

FORCESPRO

FORCESPRO

Version 5.1.0

FORCESPRO User Manual

Embotech AG

Giessereistrasse 18

CH-8005 Zürich

www.embotech.com

info@embotech.com

Contents

1	Introduction	1
1.1	Troubleshooting and support	3
1.2	Licensing	3
1.3	Citing FORCESPRO	4
1.4	Product Life Cycle	4
1.5	Release Notes	5
1.6	Version history of manual	14
2	License Variants	15
2.1	Variant Summary	15
2.2	Variant S	16
2.3	Variant M	16
2.4	Variant L	17
3	Installation	19
3.1	Obtaining FORCESPRO	19
3.2	Installation of the MATLAB Client	19
3.3	Installation of the Python Client	20
4	Backward Compatibility	25
4.1	Determining Client Version	25
4.2	Changes from Version 5.0.1	26
4.3	Changes from Version 5.0.0	26
4.4	Changes from Version 4.3.0	26
4.5	Changes from Version 4.2.0	26
4.6	Changes from Version 4.1.0	27
5	Y2F Interface	29
5.1	Installing Y2F	29
5.2	Generating a solver	30
5.3	Calling the solver	30
5.4	Solver info	30
5.5	Performance	31
5.6	Examples	32
6	MathWorks Linear MPC Plugin	33
6.1	Different types of solvers	34
6.2	Generating a QP solver from an MPC object	35
6.3	Solving a QP from MPC online data	38
6.4	Using the FORCESPRO MPC Simulink block	38
6.5	Deploy to dSpace MicroAutoBox II using the FORCESPRO MPC Simulink block	41
6.6	Examples	43
7	MathWorks Nonlinear MPC Plugin	55
7.1	Introduction	55
7.2	Defining a nonlinear model	57
7.3	Generating an NLP solver	57

7.4	Simulation in MATLAB and Simulink	63
7.5	Code generation in MATLAB and Simulink	64
7.6	Examples	64
8	Low-level interface	75
8.1	Supported problem class	76
8.2	Multistage struct	76
8.3	Dimensions	77
8.4	Cost function	77
8.5	Equality constraints	77
8.6	Lower and upper bounds	78
8.7	Polytopic constraints	78
8.8	Quadratic constraints	79
8.9	Binary constraints	80
8.10	Declaring parameters	80
8.11	Declaring Solver Outputs	80
8.12	Dumping and Loading Models	82
8.13	Generating the solver	82
8.14	Calling the generated low-level solver	82
9	High-level Interface	85
9.1	Supported problems	87
9.2	Expressing the optimization problem in code	88
9.3	Generating a solver	98
9.4	Calling the solver	99
9.5	External function evaluations in C	103
9.6	Calling the nonlinear functions from Matlab or Python	107
9.7	Mixed-integer nonlinear solver	109
9.8	Sequential quadratic programming algorithm	112
9.9	Differences between the MATLAB and the Python client	115
9.10	Examples	116
10	Simulating your custom controller in Simulink®	117
10.1	Configuration of a custom linear MPC controller using the FORCESPRO Simulink® GUI	117
10.2	Getting Started - Basic MPC Regulation State Feedback Example	120
10.3	Real-time control with the Simulink block	123
11	Examples	127
11.1	How to	127
11.2	Y2F interface: Basic example	144
11.3	Y2F interface: Trajectory Optimization for Quadrotor Flight	150
11.4	Low-level interface: Active Suspension Control	154
11.5	Low-level interface: Robust estimation (Kalman filter)	160
11.6	Low-level interface: Spacecraft Rendezvous	164
11.7	Low-level interface: DC/DC converter	167
11.8	High-level interface: Basic example	174
11.9	High-level interface: Obstacle avoidance (MATLAB & Python)	178
11.10	High-level interface: Indoor localization (MATLAB & Python)	188
11.11	High-level interface: Path tracking example (MATLAB)	192
11.12	High-level interface: Legacy path tracking example (MATLAB & Python)	203
11.13	High-level interface: Rate Constraints	215
11.14	High-level interface: Soft Constraints	220
11.15	Controlling a crane using a FORCESPRO NLP solver	224
11.16	Real-time SQP Solver: Robotic Arm Manipulator (MATLAB & Python)	227
11.17	Controlling a DC motor using a FORCESPRO SQP solver	235
11.18	Mixed-integer nonlinear solver: F8 Crusader aircraft	240
12	Parametric problems	249

12.1	Defining parameters	249
12.2	Example	250
12.3	Parametric Quadratic Constraints	251
12.4	Diagonal Hessians	251
12.5	Sparse Parameters	251
12.6	Special Parameters	252
12.7	Python: Column vs Row Major Storage Format	252
13	Code Deployment	253
13.1	Main Targets	253
13.2	dSPACE deployment through Simulink Coder	257
13.3	dSPACE deployment through ConfigurationDesk	274
13.4	Speedgoat	294
13.5	Speedgoat QNX	312
14	Licensing	327
14.1	Machine Identification	327
14.2	Static License	328
14.3	License Files	328
14.4	Floating Licenses	329
15	Solver Options	333
15.1	General options	335
15.2	High-level interface options	352
15.3	Convex branch-and-bound options	362
15.4	Solve methods	363
16	Modelling Utilities	371
16.1	Interpolations (e.g. splines)	371
16.2	Smooth Approximations	373
17	Dumping Problem Formulation and Data	375
17.1	Why to use the dump tool?	375
17.2	How to use the dump tool?	376
18	Frequently asked questions	387
18.1	Features of FORCESPRO	387
18.2	Issues during code generation	388
18.3	Issues when running the solver	389
18.4	Simulink interface	391
18.5	Code deployment	392
18.6	Other topics	392
	Bibliography	395

Chapter 1

Introduction

- *Troubleshooting and support*
- *Licensing*
 - *Commercial licensing*
 - *Academic licensing*
- *Citing FORCESPRO*
- *Product Life Cycle*
- *Release Notes*
 - *New features in FORCESPRO 5.1.0*
 - *Improvements in FORCESPRO 5.1.0*
 - *Bug Fixes in FORCESPRO 5.1.0*
 - *New features in FORCESPRO 5.0.1*
 - *Improvements in FORCESPRO 5.0.1*
 - *Bug Fixes in FORCESPRO 5.0.1*
 - *New features in FORCESPRO 5.0.0*
 - *Improvements in FORCESPRO 5.0.0*
 - *Bug Fixes in FORCESPRO 5.0.0*
 - *New features in FORCESPRO 4.4.0*
 - *Improvements in FORCESPRO 4.4.0*
 - *Bug Fixes in FORCESPRO 4.4.0*
 - *Improvements in FORCESPRO 4.3.1*
 - *Bug Fixes in FORCESPRO 4.3.1*
 - *New features in FORCESPRO 4.3.0*
 - *Improvements in FORCESPRO 4.3.0*
 - *Bug Fixes in FORCESPRO 4.3.0*
 - *Improvements in FORCESPRO 4.2.1*
 - *Bug Fixes in FORCESPRO 4.2.1*

- *New features in FORCESPRO 4.2.0*
- *Improvements in FORCESPRO 4.2.0*
- *Improvements in FORCESPRO 4.1.1*
- *Bug Fixes in FORCESPRO 4.1.1*
- *New features in FORCESPRO 4.1.0*
- *Improvements in FORCESPRO 4.1.0*
- *Bug Fixes in FORCESPRO 4.1.0*
- *New features in FORCESPRO 4.0.0*
- *Improvements in FORCESPRO 4.0.0*
- *Bug Fixes in FORCESPRO 4.0.0*
- *New features in FORCESPRO 3.1.0*
- *Improvements in FORCESPRO 3.1.0*
- *Bug Fixes in FORCESPRO 3.1.0*
- *Improvements in FORCESPRO 3.0.1*
- *Bug Fixes in FORCESPRO 3.0.1*
- *New features in FORCESPRO 3.0.0*
- *Improvements in FORCESPRO 3.0.0*
- *Bug Fixes in FORCESPRO 3.0.0*
- *New features in FORCESPRO 2.0.0*
- *Improvements in FORCESPRO 2.0.0*
- *Bug Fixes in FORCESPRO 2.0.0*
- *New features in FORCESPRO 1.9.1*
- *Improvements in FORCESPRO 1.9.1*
- *New features in FORCESPRO 1.9.0*
- *Improvements in FORCESPRO 1.9.0*
- *Bug Fixes in FORCESPRO 1.9.0*
- *New features in FORCESPRO 1.8.0*
- *Improvements in FORCESPRO 1.8.0*
- *Bug Fixes in FORCESPRO 1.8.0*
- *New features in FORCESPRO 1.7.0*
- *Improvements in FORCESPRO 1.7.0*
- *Bug Fixes in FORCESPRO 1.7.0*
- *Version history of manual*

This is a user manual for FORCESPRO, a commercial tool for generating highly customized optimization solvers that can be deployed on all embedded computers. FORCESPRO is intended to be used in situations where the same optimization problem has to be solved many times, possibly in real-time, with varying data, i.e. there is sufficient time in the design stage for generating a customized solution for the problem you want to solve.

The code generation engine in FORCESPRO extracts the structure in your optimization problem and automatically synthesizes a custom optimization solver. The resulting C code can

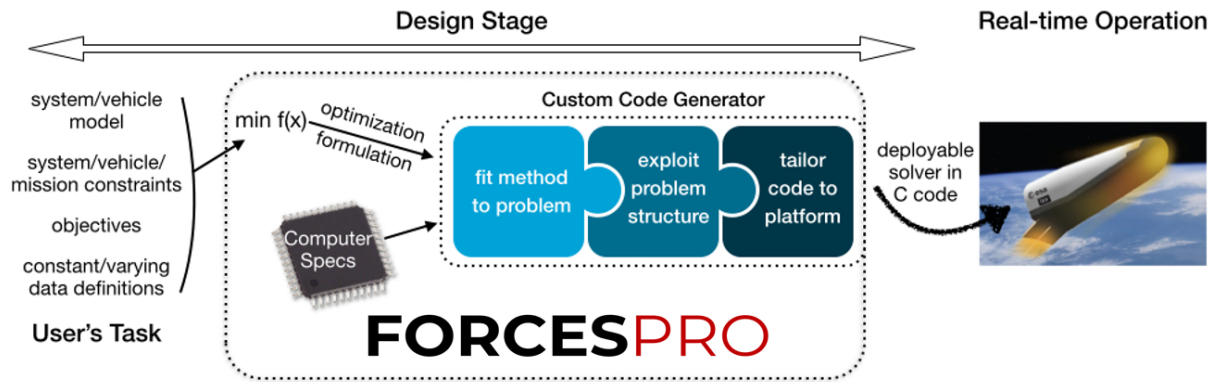


Figure 1.1: Overview of FORCESPRO.

only solve one optimization problem (with certain data changing), hence it is typically many times more efficient and smaller code size than general-purpose optimization solvers. The generated C code is also library-free and uses no dynamic memory allocation making it suitable for safe deployment on real-time autonomous systems.

This document will show you how to input your optimization problem description for code generation in FORCESPRO. It is important to point out that FORCESPRO is not a tool for transforming a problem specification into an optimization problem description. This responsibility lies with the user.

1.1 Troubleshooting and support

FORCESPRO typically returns meaningful error messages when code generation errors occur due to invalid user inputs. When encountering other errors please consult our documentation which is included in the FORCESPRO client and is also available on all FORCESPRO servers. In case you cannot find a solution to your problem please submit a bug report to support@embotech.com.

Much effort has gone into making this interface easy to use. We welcome all your suggestions for further improving the usability of the tool. Requests for special functionality for your particular problem will also be considered by our development team. For all requests and feedback please contact support@embotech.com.

1.2 Licensing

1.2.1 Commercial licensing

FORCESPRO licenses are available through a subscription model. There are four types of licenses, as seen below:

- **Engineer License:** For generating FORCESPRO solvers. Charged per engineer computer.
- **Software Testing License (Sil/CI):** For running FORCESPRO solvers on a desktop PC or a server for simulation and (automated) testing. No physical system is controlled. Charged per platform running the solver.
- **Floating License:** For running FORCESPRO solvers on servers or virtualised environments (such as Docker containers) without permanently mapping the license to a hardware system. Charged per number of platforms able to concurrently run the solver. Currently available only on Linux x86/x86_64.

- **Hardware Testing License (HiL/Field Testing):** For controlling a physical system (i.e. the target platform may also be an ECU or a rapid prototyping platform). Charged per platform running the solver.

For more information regarding licensing please check on our [website](#) or contact sales@embotech.com.

FORCESPRO licenses are available in variants S, M and L. For more information please check the section [License Variants](#)

1.2.2 Academic licensing

Users at degree granting institutions can have access to the **Engineer License** version of FORCESPRO free of charge provided they are not doing research for an industrial partner. **Software Testing** and **Hardware Testing** licenses are also available at highly reduced rates.

1.3 Citing FORCESPRO

If you use FORCESPRO in published scientific work, please cite the following two papers:

```
@misc{FORCESPro,
  Author      = "Alexander Domahidi and Juan Jerez",
  Howpublished = "Embotech AG, url=https://embotech.com/FORCES-Pro",
  Title       = "FORCES Professional",
  Year        = "2014--2019"
}
```

```
@article{FORCESNLP,
  Author      = "A. Zanelli and A. Domahidi and J. Jerez and M. Morari",
  Title       = "FORCES NLP: an efficient implementation of interior-point...
               methods for multistage nonlinear nonconvex programs",
  Journal     = "International Journal of Control",
  Year        = "2017",
  Pages       = "1-17"
}
```

1.4 Product Life Cycle

A new major or minor version of FORCESPRO is released every quarter, with patch releases in between. These new versions contain new functionalities and improvements in terms of speed and robustness.

In order to be able to add novel features and improve existing ones at a high pace, FORCESPRO uses continuous deployment as development policy. That also implies that we have to ask users to update their clients if they want to benefit from the latest version of FORCESPRO. In rare cases, this may also mean breaking backward compatibility (see also Section [Backward Compatibility](#)) requiring users to either make the necessary changes in their own code or to stick with an older version (and the corresponding server for code generation).

We guarantee that the codegen servers of any new version of FORCESPRO will be kept available for at least one year, starting from their respective release dates. [Table 1.1](#) lists all release dates since version 1.7.0 along with the actual or planned date for the corresponding code generation server to go offline. In case you need an older version of FORCESPRO to be available beyond the scheduled offline date, please contact support@embotech.com so we can work out a solution for you.

Table 1.1: Release Dates and Codegen Server Availabilities

FORCESPRO Version	Release Date	Actual or <i>Planned</i> Date Server goes Offline
1.7.0	2019-03-08	2019-10-01
1.8.0	2019-06-13	2020-04-01
1.9.0	2019-09-05	2020-05-15
1.9.1	2019-10-18	2020-10-01
2.0.0	2019-12-17	2020-12-15
3.0.0	2020-04-09	2021-03-15
3.0.1	2020-05-26	2021-05-31
3.1.0	2020-07-15	2021-07-15
4.0.0	2020-09-22	2021-10-15
4.1.0	2020-11-04	2022-02-15
4.1.1	2020-12-09	2022-02-15
4.2.0	2021-02-11	2022-02-15
4.2.1	2021-03-23	2022-03-31
4.3.0	2021-05-18	2022-05-31
4.3.1	2021-06-01	2022-05-31
4.4.0	2021-06-16	2022-06-30
5.0.0	2021-09-09	2022-09-30
5.0.1	2021-10-21	2022-10-31
5.1.0	2021-12-09	2022-12-31

1.5 Release Notes

1.5.1 New features in FORCESPRO 5.1.0

- Added Floating License Proxy packages for floating license connections

1.5.2 Improvements in FORCESPRO 5.1.0

- Added more advanced path tracking example to Matlab client
- Made plugin for The MathWorks Model Predictive Control Toolbox (TM) work with R2021b
- Made MATLAB client compatible with R2014b

1.5.3 Bug Fixes in FORCESPRO 5.1.0

- Robustified array conversions for Interpolation in Python client
- Bugfix in SQP solver to use correct tolerances in underlying QP solver
- Fixed issue in SQP log when showing solvetime
- Small bugfix in loading of symbolic dumps in MATLAB

1.5.4 New features in FORCESPRO 5.0.1

- Added MEX interfaces and Python interfaces for calling nonlinear callback functions stand-alone on user side

1.5.5 Improvements in FORCESPRO 5.0.1

- Re-enabled generation of ADMM solvers via Python client
- Extended code generation floating license options; improved floating licensing's performance and robustness
- Added files for requirements in Python client and made suds package optional

1.5.6 Bug Fixes in FORCESPRO 5.0.1

- Bugfix in callback evaluations function of SQP solver
- Bugfix for detection of affine inequalities in SQP solver in Python client
- Fixed MISRA C issues when using SQP solver or using float callbacks with chainrule integrators
- Fixed issue with loading old dumps in Python

1.5.7 New features in FORCESPRO 5.0.0

- Added improved symmetric indefinite linear solver and iterative refinement
- Added CasADi 3.5.5 support also to Python client and made it default AD tool in both clients
- Added support for Python 3.9

1.5.8 Improvements in FORCESPRO 5.0.0

- Added Y2F example for optimizing trajectory of quadrotor flight
- Added support for server connection via RestAPI
- Added option to export lower triangular BFGS

1.5.9 Bug Fixes in FORCESPRO 5.0.0

- Minor bugfixes in low-level and high-level interface solver interface
- Fix to handle scalar input arguments to interpolations in Python client
- Added fixes for size one parameters
- Improved adherence to C90 standard and MISRA C rules
- Bugfix concerning nonlinear inequalities detection in Python client

1.5.10 New features in FORCESPRO 4.4.0

- Implemented linear subsystem exploitation for explicit chainrule integrator RK4
- Implemented chainrule variant for integrator IRK2
- Added support for dSPACE SCALEXIO and dSPACE MicroLabBox
- Added functionality to use interpolations (such as splines) inside symbolic problem formulations to both Matlab and Python client

1.5.11 Improvements in FORCESPRO 4.4.0

- Added Python variant of ForcesMin/ForcesMax, wrapped into new modelling sub-package

1.5.12 Bug Fixes in FORCESPRO 4.4.0

- Fixed minor issues with return flags of SQP solver, e.g. in case of license error

1.5.13 Improvements in FORCESPRO 4.3.1

- Added support for server connection via proxy in Python client

1.5.14 Bug Fixes in FORCESPRO 4.3.1

- Fixed bug for code option `threadSafeExpert` causing two static variables
- Added missing code option `nlp.max_num_threads` to Python client

1.5.15 New features in FORCESPRO 4.3.0

- Added support to formulate and solve multi-stage nonlinear MPC problems with The MathWorks Model Predictive Control Toolbox (TM)
- Added code option `threadSafeExpert` to give users full control over memory allocation when running multiple instances of an `PDIP_NLP` or `PDIP` solver
- Added support for CasADi 3.5.5 in the MATLAB client

1.5.16 Improvements in FORCESPRO 4.3.0

- Made CasADi 3.5.1 default AD tool also in the MATLAB client
- Added support for single (stacked) solution vector for solvers `PDIP_NLP` and `SQP_NLP`
- Added more thorough check for identical stages in MATLAB client along with new code option `nlp.strictCheckDistinctStages`
- Let `FORCESversion` also return planned offline date of client version
- Added new client examples demonstrating how to formulate problems comprising soft and rate constraints using the high-level interface

1.5.17 Bug Fixes in FORCESPRO 4.3.0

- Fixed freeing of DLLs in Python Client
- Fixed issue with code option `noVariableElimination` is used along with linear solver `normal_eqs` in MATLAB client

1.5.18 Improvements in FORCESPRO 4.2.1

- Added msgpack support for MacOS
- Added separate optlevel options for host and target
- Improved robustness of client connection to the codegen server
- Added support for custom parameters in Python client

1.5.19 Bug Fixes in FORCESPRO 4.2.1

- Bugfix in QP solver caused by code optimization for source in src_target folder
- Fixed bug in ADMM method

1.5.20 New features in FORCESPRO 4.2.0

- Added support for dumping of problem formulation from C
- Added support for NI cRIO platforms
- Created Simulink Fingerprinters for platforms with Simulink Model deployment
- Added Speedgoat (for MATLAB R2020b and later) example for The MathWorks Model Predictive Control Toolbox (TM)
- Added support for single precision callbacks, i.e. mixed-precision NLP solution

1.5.21 Improvements in FORCESPRO 4.2.0

- Changed to new server communication in MATLAB client for improved safety and connection stability
- Reenabled chainrule integrators as default integrator when using continuous dynamics, and fixed performance issues
- Extended Speedgoat support to more MATLAB/Simulink Real-Time releases

1.5.22 Improvements in FORCESPRO 4.1.1

- Improved hashing of sparse linear algebra routines
- Fixed MATLAB network communication, replaced deprecated SOAP methods with new ones, enabled with `legacyNetworkConnections = 0`
- Parallel BFGS updates with `compact_code = 0` (default)
- Prevent MATLAB client to overwrite user script if solver has same filename
- Throw proper exceptions when block structure is not detected in sparse parametric equalities in low-level interface
- Parallel callbacks evaluation with `compact_code = 1` and `parallel >= 1`
- Reverted to legacy integrators in default behaviour
- Added code generation compatibility with MATLAB 2016a
- Various fixes and updates in the API of the Python dump tool

1.5.23 Bug Fixes in FORCESPRO 4.1.1

- Fixed FORCESconfigureClient to work on all OS
- Fixed codegen failure with compact_code related to nonlinear inequalities
- Disabled compact_code when initial equality constraint not eliminated (D0)
- Restored functionality to collect variable declarations at beginning of CasADi callbacks (only if c90 code option is set)
- Bug fix for copy of scalar parameters with compact_code = 1

1.5.24 New features in FORCESPRO 4.1.0

- Code-generated explicit integrators and sensitivity with chain rule and variational differential equation
- Python dump tool and compatible MATLAB dump tool
- Option for adding a single external callback instead of adding all callbacks externally
- Added solver and webcompiler support for speedgoat (for MATLAB R2020b and later)

1.5.25 Improvements in FORCESPRO 4.1.0

- Scalar parameters are not treated as arrays anymore for compatibility with MATLAB Coder. To enable the previous behaviour set code option size_one_param_as_array = 1
- Separated CasADi and Symbolic math toolbox callbacks to have more control over dynamics callbacks.
- Introduce code option separateCasadiFiles which when set to 1 ensures old callback file structure (separate model files).
- Replaced old obstacle avoidance client examples for python and MATLAB by new interactive ones
- Added path tracking example for the python and the MATLAB client

1.5.26 Bug Fixes in FORCESPRO 4.1.0

- Fixed Simulink and standalone Python interface using scalar parameters
- Fixed some openmp issues and added number of threads as runtime parameter

1.5.27 New features in FORCESPRO 4.0.0

- Support for FORCESPRO NLP solvers (PDIP_NLP and SQP_NLP) in The MathWorks Model Predictive Control Toolbox (TM)
- Solver timeout option for PDIP_NLP, SQP_NLP and PDIP
- New code option exportBFGS which enables export of BFGS diagonal on every stage

1.5.28 Improvements in FORCESPRO 4.0.0

- Server now returns `interface/definitions.py` file independent of whether the request was sent from the MATLAB or Python client
- Added support for symbolic step size in Python integrators
- Added connection tester for the FORCESPRO server
- Added new parameter type `Adense` to allow copy of dense A matrix to sparse internally. Should be used within Model Predictive Control Toolbox plugin only!
- New option `nlp.parametricBFGSinit` for initializing BFGS matrix as a run-time parameter

1.5.29 Bug Fixes in FORCESPRO 4.0.0

- Fixed export of root relaxation solution in MINLP solver
- Fixed number of outputs in ADMM method
- Added fix for floattype 'int' and 'short'
- Fixed issue occurring in Python client when all initial or all final variables are fixed
- Fixed reading issue in csmatio library

1.5.30 New features in FORCESPRO 3.1.0

- High-level Python interface for NLP solvers

1.5.31 Improvements in FORCESPRO 3.1.0

- Vectorized outer product on one-stage dense QP problems in double precision on Intel platforms
- Refactoring of clients and server to enable standalone release
- Check for vectorization instructions in Python client, refactored C code in DLL
- Made variables in generated interface static
- Improved efficiency of CasADi file postprocessing in MATLAB client
- Export of dual variables in solver `PDIP_NLP`
- Fixed `updateClient` scripts to delete old data
- Made `FORCES_NLP` return dumped formulation even if an error occurs during execution
- Allow to specify directory when saving dumped problem formulation/instance

1.5.32 Bug Fixes in FORCESPRO 3.1.0

- Fix in detection of selection matrix
- Fix in CasADi for linux systems
- Fixed bug with stacked parametric bounds
- Updated accessing of Stage properties to work with obfuscation

- fix issue with variable number of equality constraints in convex problems
- Fixed issue in CasADi code generation
- Fixed internal rounding heuristic in MINLP solver

1.5.33 Improvements in FORCESPRO 3.0.1

- New `nlp.stack_parambounds` for stacking parametric bounds over stages with solvers PDIP_NLP and SQP_NLP
- Support for MicroAutoBox III

1.5.34 Bug Fixes in FORCESPRO 3.0.1

- Bug fix in fraction to boundary rule
- Bug fixes for specific compilation settings
- Fixed download of CasADi for macos
- Fixed bug in model files declarations in `casadi2forces` with solver SQP_NLP

1.5.35 New features in FORCESPRO 3.0.0

- Real-time sequential quadratic programming solver via code option SQP_NLP
- Support for MathWorks Symbolic Math Toolbox and CasADi 3.5.1 (with limitations)
- Code option `nlp.compact_code` for generating small-size code on long horizon problems
- Support for license files
- Option for dumping problem formulation and data for support

1.5.36 Improvements in FORCESPRO 3.0.0

- Revamped licensing system
- Removed object files from downloaded solver package

1.5.37 Bug Fixes in FORCESPRO 3.0.0

- Fixed bug with number of stages and integer guess in MINLP solver

1.5.38 New features in FORCESPRO 2.0.0

- Introduced support for FORCESPRO QP solvers in the The MathWorks Model Predictive Control Toolbox (TM)
- Created new examples for the MPC Toolbox plugin

1.5.39 Improvements in FORCESPRO 2.0.0

- Made tolerances on equalities, inequalities, stationarity and complementarity run-time parameters in NLP solver
- Automatic disabling of vectorization when some matrix parameters are sparse

1.5.40 Bug Fixes in FORCESPRO 2.0.0

- Fixed linking issue with avx on linux host
- Fixed mex interface to not copy empty parameters
- Fixed bug with MINLP solver exitflag on infeasible problems

1.5.41 New features in FORCESPRO 1.9.1

- Adapted FORCESPRO license check to portal database
- Adapted floating license database checks to portal database
- Made linear algebra vectorization stage dependent

1.5.42 Improvements in FORCESPRO 1.9.1

- Fixed numerical bug in NLP line-search

1.5.43 New features in FORCESPRO 1.9.0

- New code-generation options for AVX and NEON vectorization
- New code generation options and parameters to provide an integer guess to the MINLP solver
- New runtime parameter parallelStrategy for MINLP solver
- Created dedicated Floating License web Server

1.5.44 Improvements in FORCESPRO 1.9.0

- Changed floating license communication to http
- Enabled user-defined outputs in MINLP solver
- Added code option c90 to add extra C definitions in CasADi model files
- Added openmp flag to nvidia webcompiler
- Added support for Python 3.6
- Updated usysid files in client

1.5.45 Bug Fixes in FORCESPRO 1.9.0

- Fixed bug with constraints handling in code-generation
- Fixed memory bug in MINLP solver
- Fixed bug in parameters indexing in client. Parameters are now indexed with a fixed number of digits depending on the horizon length. 1 digit below 10, 2 digits between 10 and 100 excluded,...
- Fixed bug with stacked parameter `ineq.p.b`

1.5.46 New features in FORCESPRO 1.8.0

- Mixed-integer nonlinear solver with parallelizable search and other customization features
- Support for the Speedgoat platform
- Support for the Integrity ARM platform
- Support for Docker containers
- Updated `newParam` API to allow for parameters stacked over stages

1.5.47 Improvements in FORCESPRO 1.8.0

- Improved performance of `compactSparse` feature
- Added custom headers to specify platforms

1.5.48 Bug Fixes in FORCESPRO 1.8.0

- Fixed numerical bug in v1.7.0

1.5.49 New features in FORCESPRO 1.7.0

- MISRA 2012 compliance, no mandatory or required violations in generated C code
- Added support for dSPACE MicroAutoBox II
- Added support for ARM Cortex A72 platforms
- Added support for MinGW as a mex compiler
- New code option `compactSparse` for smaller code and faster compilation of sparse problems
- Added `threadSafeStorage` option, enabling creation of thread-safe solvers (requires C11 compilers)

1.5.50 Improvements in FORCESPRO 1.7.0

- Improved codegen speed for sparse problems
- Improved web compilation to reduce http timeouts
- Secure client-server communication under custom embotech domain
- Improved portability of functions used

- Added display of license and solver expiration as well as generation id on header files
- Updated `FORCEScleanup` to include all solver related files
- Improved messages and warnings returned from FORCESPRO client
- Now passing iteration number to function evaluations
- Added new error code for invalid parameter initial values

1.5.51 Bug Fixes in FORCESPRO 1.7.0

- Changed default server when default server file is missing
- Always check for default server files when choosing server to use
- Corrected the logic for updating the best solution found so far (NLP)
- Fixed sparse linear algebra routine names

1.6 Version history of manual

The version history of this document is presented in *Version history of FORCESPRO manual*.

Table 1.2: Version history of FORCESPRO manual

Version	Revision	Date	Reason for change
1	0	2017-04-10	Initial version
2	0	2018-09-27	Overhaul of outdated manual
2	1	2018-11-19	Add dSPACE code deployment
3	0	2019-02-20	Updated manual for v1.7.0
4	0	2019-06-04	Updated manual for v1.8.0
4	1	2019-08-29	Updated manual for v1.9.0
5	0	2019-10-10	Updated manual for v1.9.1
6	0	2019-12-09	Updated manual for v2.0.0
7	0	2020-04-07	Updated manual for v3.0.0
7	1	2020-05-26	Updated manual for v3.0.1
7	2	2020-07-13	Updated manual for v3.1.0
8	0	2020-09-21	Updated manual for v4.0.0
8	1	2020-10-30	Updated manual for v4.1.0
8	2	2020-12-07	Updated manual for v4.1.1
8	3	2021-02-09	Updated manual for v4.2.0
8	4	2021-03-18	Updated manual for v4.2.1
8	5	2021-05-11	Updated manual for v4.3.0
8	6	2021-05-31	Updated manual for v4.3.1
8	7	2021-06-15	Updated manual for v4.4.0
9	0	2021-09-08	Updated manual for v5.0.0
9	1	2021-10-20	Updated manual for v5.0.1
9	2	2021-12-08	Updated manual for v5.1.0

Chapter 2

License Variants

- *Variant Summary*
- *Variant S*
- *Variant M*
- *Variant L*

Each problem type requires a dedicated solver method in order to be solved quickly and efficiently. FORCESPRO is available in different variants in order to adapt to each user's needs. When receiving a FORCESPRO license on the portal(<https://my.embotech.com>) a user can select one of the available variants which is best suited for the problem to be solved. At any point, a user can decide to upgrade to a larger variant in order to include additional solver methods in their available toolset for FORCESPRO.

The available variants are (smaller variants are included in larger ones):

- **S** (*Variant S*)
- **M** (*Variant M*)
- **L** (*Variant L*)

2.1 Variant Summary

In the tables below you can find a summary of the components provided with each variant of FORCESPRO.

Table 2.1: Problem types supported for each variant

	S	M	L
Problem Type			
LP	✓	✓	✓
QP	✓	✓	✓
QCQP	✓	✓	✓
BI-QP		✓	✓
NLP (SQP)		✓	✓
NLP (IP)			✓
MINLP			✓

Table 2.2: Interfaces provided for each variant

	S	M	L
Interface			
MATLAB Low-Level	✓*	✓	✓
Python Low-Level	✓*	✓	✓
MATLAB Y2F	✓	✓	✓
MathWorks MPC Toolbox™ (Linear MPC)	✓	✓	✓
MATLAB High-Level		✓**	✓
Python High-Level		✓**	✓
MathWorks MPC Toolbox™ (Nonlinear MPC)		✓**	✓
* No Binary Constraints			
** Only with SQP method			

2.2 Variant S

This variant is used for generation of convex solvers. This variant should be used for solving:

- LP problems
- QP problems
- QCQP problems

This variant is delivered with the following interfaces:

- MATLAB Low-level Interface (*Low-level interface*)
- Python Low-level Interface (*Low-level interface*)
- MATLAB Y2F Interface (*Y2F Interface*)
- MathWorks Model Predictive Control Toolbox™ - Linear MPC (*MathWorks Linear MPC Plugin*)

2.3 Variant M

This variant further enables the generation of SQP solvers for NLPs and the solution of Binary-Integer QPs. This variant should be used for solving:

- Binary-Integer QP problems (*Binary constraints*)
- NLP Problems using SQP methods (*Sequential quadratic programming algorithm*)

This variant is delivered with the following interfaces:

- MATLAB High-level Interface (*High-level Interface*) with `codeoptions.solvermethod = 'SQP_NLP'`;
- Python High-level Interface (*High-level Interface*) with `codeoptions.solvermethod = 'SQP_NLP'`
- MathWorks Model Predictive Control Toolbox™ - Nonlinear MPC (*MathWorks Nonlinear MPC Plugin*) with `options.SolverType = 'SQP'`;

2.4 Variant L

This variant provides the full experience of FORCESPRO and enables all its features. This variant further enables the solution of:

- NLP problems with Interior-Point Methods and SQP
- MINLP problems (*Mixed-integer nonlinear solver*)

This variant is delivered with the following interfaces:

- MATLAB High-level Interface (*High-level Interface*) with full support
- Python High-level Interface (*High-level Interface*) with full support
- MathWorks Model Predictive Control Toolbox™ - Nonlinear MPC (*MathWorks Nonlinear MPC Plugin*) with full support

Chapter 3

Installation

3.1 Obtaining FORCESPRO

FORCESPRO is a client-server code generation system. The user describes the optimization problem using the client software, which communicates with the server for code generation (and compilation if applicable). The client software is the same for all users, independent of their license type.

In order to obtain FORCESPRO, follow the steps below:

1. Inquire a license from <https://www.embotech.com/products/forcespro/licensing/> or by directly contacting licenses@embotech.com.
2. After receiving a license, if registered on the portal, the FORCESPRO client can be downloaded from the portal after assigning an Engineering Node. For more information see <https://my.embotech.com/readme>. Otherwise the FORCESPRO client will be sent to you via email.
3. Unzip the downloaded client into a convenient folder.

Note: The FORCESPRO client contains several inner ZIP-files for the Python client named *forcesproXY.zip*. These do not need to be extracted!

3.2 Installation of the MATLAB Client

- *System requirements*
- *Keeping FORCESPRO up to date*

Add the path of the downloaded folder `FORCES_PRO` to the MATLAB path by using the command `addpath DIRNAME`, e.g. by typing:

```
addpath /home/user/FORCES_PRO
```

on your MATLAB command prompt. Alternatively, you can add the path of the `FORCES_PRO` folder via the graphical user interface of MATLAB as seen in [Figure 3.1](#).

Having added the root folder of the FORCESPRO MATLAB client to the MATLAB path one configures the client to the specific MATLAB version by running

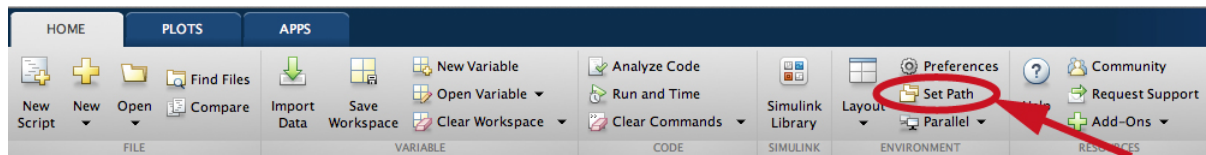


Figure 3.1: Adding the `FORCES_PRO` folder to the MATLAB path.

```
FORCESconfigureClient;
```

in the MATLAB command window. After the FORCESPRO MATLAB client has been configured one can save the MATLAB path in order to always have access to FORCESPRO when initiating a new MATLAB session. Alternatively one perform the above 2 steps whenever initiating a new MATLAB session.

3.2.1 System requirements

FORCESPRO is supported on Windows, macOS and the different Linux distributions.

For the MATLAB and Simulink interfaces, 32 or 64 bit MATLAB 2012b (or higher) is required. Older versions might work but have not been tested. A MEX compatible C compiler is also required. A list of compilers that are supported by MATLAB can be found in https://www.mathworks.com/support/sysreq/previous_releases.html.

Run:

```
mex -setup
```

to configure your C compiler in MATLAB.

3.2.2 Keeping FORCESPRO up to date

FORCESPRO is actively developed and client modifications are frequent. Whenever your client version is not synchronized with the server version, you will receive a code generation error notifying you that your client is out of date.

To update your client simply type:

```
updateClient
```

on your MATLAB command prompt. `updateClient` without any arguments uses the default embotech server to grab the client, and updates all corresponding client files. The command:

```
updateClient (URL)
```

overrides the default server selection and uses the server located at URL instead.

Alternatively, the FORCESPRO client may also be updated through Python, see [Keeping FORCESPRO up to date](#).

3.3 Installation of the Python Client

• [Quick Guide](#)

- *Windows (PowerShell)*
- *Linux Ubuntu*
- *Mac*
- *Requirements*
 - *Python*
 - *Python Packages*
 - *Available Compiler*
- *Adding the FORCESPRO Python Client to your Python path*
 - *Option A: Setting the PYTHONPATH environment variable*
 - *Option B: Setting sys.path inside Python scripts*
- *Keeping FORCESPRO up to date*

FORCESPRO offers a Python interface that enables user to formulate a optimization problem, generating a solver for it through communication with the FORCESPRO server, and calling the generated solver directly from Python. It is contained within the FORCESPRO client package together with the MATLAB Client, which can be obtained with a valid license as described in *Obtaining FORCESPRO*.

3.3.1 Quick Guide

This section describes the most common commands needed to go from a blank system to generating and executing the first solver for different operating systems. Before doing so, you may want to double-check the section *Requirements* below, in particular with respect to supported versions of Python and external packages.

In the following, we assume you have obtained the FORCESPRO client as described in *Obtaining FORCESPRO*, and unzipped its files into the directory */path/to/forces/pro* on Unix platforms or *C:\path\to\forces\pro* on Windows. The following installation instructions slightly differ for the operating systems supported, so please refer to the appropriate section.

Windows (PowerShell)

```
C:\PythonXY\Scripts\pip.exe install -r C:\path\to\forces\pro\requirements.txt
$env:PYTHONPATH="C:\path\to\forces\pro"
C:\PythonXY\python.exe ↵
↪C:\path\to\forces\pro\examples\Python\HighLevelInterface\RobotArmRTI\robot_sim.py
```

Linux Ubuntu

```
pip3 install -r /path/to/forces/pro/requirements.txt
sudo apt-get install gcc libomp-dev
export PYTHONPATH="/path/to/forces/pro":$PYTHONPATH
python3 /path/to/forces/pro/examples/Python/HighLevelInterface/RobotArmRTI/robot_
↪sim.py
```

Mac

```
xcode-select --install
brew install python3 libomp
python3 -m pip install -r /path/to/forces/pro/requirements.txt
export PYTHONPATH="/path/to/forces/pro":$PYTHONPATH
python3 /path/to/forces/pro/examples/Python/HighLevelInterface/RobotArmRTI/robot_
↪sim.py
```

This assumes you have the Homebrew package manager already installed. If not, run the following before any of the above instructions:

```
/bin/bash -c "$(curl -fsSL https://raw.githubusercontent.com/Homebrew/install/
↪master/install.sh)"
```

3.3.2 Requirements

The Python client has been tested with the following configurations:

Python

A Python installation is required. Note that only compiled Python bytecode for the versions listed below is currently shipped with the client:

- Python 2.7 (low-level convex problems only)
- Python 3.6
- Python 3.7
- Python 3.8
- Python 3.9

If you require a different version, please contact us at forces@embotech.com.

For purposes of readability, for Windows, we will assume you have installed the respective Python version into `C:\PythonXY` (where X is the major version number and Y the minor version number) throughout the rest of this documentation. On Linux and Mac, we assume you have Python 3 available in your `PATH` as `python3`, and Python 2.7 as `python`.

Python Packages

For any Python version, the following packages from the Python package index (PyPI) must be installed in the `PYTHONPATH`:

- **numpy** (Tested with version 1.18.3)
- **scipy** (Tested with version 1.4.1)
- **casadi** (Version 3.5.1 or 3.5.5 required; only for high-level interface)
- **matplotlib** (Required only for plotting in the example code)
- **requests** (Required for server connections)

All of these packages can be conveniently installed through the command-line by running the following command from a terminal (Linux, Mac):

```
pip3 install -r /path/to/forces/pro/requirements.txt
```


Or, on Windows:

```
C:\PythonXX\Scripts\pip.exe install -r C:\path\to\forces\pro\requirements.txt
```

Note: The FORCESPRO client provides the option to connect to the code generation server using WSDL instead of RestAPI. This adds the dependency to the *suds-community* package. To install this through pip, the file *requirementsWSDL.txt* in the FORCESPRO client directory can be used (*pip install -r /path/to/forces/pro/requirementsWSDL.txt*).

Available Compiler

Nonlinear symbolic problem formulations are translated into C code by the FORCES PRO client. In order to generate solvers for these kinds of problems, a C compiler and linker must thus be present on the host machine. The following compilers have been tested and are supported by the FORCESPRO Python client:

- On Windows: Microsoft Visual Studio C Compiler 2019 and 2015 (Can be obtained by downloading the Microsoft Visual Studio Community IDE)
- On Linux: GNU Compiler Collection (GCC), tested with version 9.3.0
- On Mac: Apple clang version 11.0.3 (Can be obtained by installing the XCode command-line tools)

Additionally, on Linux, the following package must be installed if you wish to generate solvers making use of parallel execution (*options.parallel = True*) or mixed-integer nonlinear problem (MINLP) solvers:

```
sudo apt-get install libomp-dev
```

On Mac, for parallel solver generation and MINLP-problems, the following package must be installed through Homebrew:

```
brew install libomp
```

3.3.3 Adding the FORCESPRO Python Client to your Python path

Once the FORCESPRO client has been downloaded and the requirements have been installed as outlined above, you will need to tell the Python interpreter where to look for the *forcespro* and *forcespro.nlp* packages which implement the FORCESPRO client interface in Python. Doing so will allow you to write *import forcespro* or *import forcespro.nlp* in your scripts to import the FORCESPRO functionality. To make the FORCESPRO client available this way, you have several options:

Option A: Setting the *PYTHONPATH* environment variable

Add the FORCESPRO client directory to your *PYTHONPATH* before calling any scripts that require FORCESPRO from the command line. In a Windows PowerShell this is done by:

```
$env:PYTHONPATH="C:\path\to\forces\pro"
```

In Windows *cmd.exe*:

```
set PYTHONPATH=C:\path\to\forces\pro
```

On Unix (Linux and Mac):

```
export PYTHONPATH=/path/to/forces/pro
```

After doing so, you can call any script that requires FORCESPRO, and the script may include *import forcespo* or *import forcespro.nlp* statements without needing to know where your actual FORCESPRO client directory is.

Option B: Setting *sys.path* inside Python scripts

Add the FORCESPRO client directory to *sys.path* before importing:

```
import sys
sys.path.insert(0, '/path/to/forces/pro') # On Unix
sys.path.insert(0, 'C:\\path\\to\\forces\\pro') # On Windows, note the doubly-
↳ escaped backslashes
import forcespro
import forcespro.nlp
```

Note that this reduces the portability of any scripts using FORCESPRO, as it hard-codes the location of FORCESPRO inside the script.

3.3.4 Keeping FORCESPRO up to date

In order to obtain the latest version of the FORCESPRO client, a Python script for automatic upgrading is available.

In order to use it, navigate to the FORCESPRO client directory and execute the *update-Client.py* script in Python.

```
$ cd /path/to/forces/pro
$ python updateClient.py
```

Alternatively, the FORCESPRO client can also be updated through MATLAB, see *Keeping FORCESPRO up to date*.

Chapter 4

Backward Compatibility

- *Determining Client Version*
- *Changes from Version 5.0.1*
- *Changes from Version 5.0.0*
- *Changes from Version 4.3.0*
- *Changes from Version 4.2.0*
- *Changes from Version 4.1.0*

FORCESPRO uses continuous deployment as development policy, which may cause also minor new versions not to behave identical to previous ones. This chapter summarizes code-generation options that either recently changed default behaviour or were introduced to allow restoring behaviour of a previous FORCESPRO version.

4.1 Determining Client Version

For determining the current version of your client, you may invoke the following command:

Matlab

Python

```
VER = FORCESversion();
```

```
# not yet supported for Python client
```

The code-generation servers of FORCESPRO only remain available for a certain period of time (but for at least one year after release, see *Product Life Cycle*). The date when the codegen server of the current client version is planned to go offline can be retrieved as second output argument of the same command:

Matlab

Python

```
[VER, OFFLINEDATE] = FORCESversion();
```

```
# not yet supported for Python client
```

4.2 Changes from Version 5.0.1

From version 5.0.1, license options for FORCESPRO code generation are set in `codeoptions.license`. Previous options:

- `codeoptions.useFloatingLicense`
- `codeoptions.license_file_name`

have now been replaced by:

- `codeoptions.license.use_floating_license`
- `codeoptions.license.static_license_file_name`

The old options are still available in 5.0.1 for backwards compatibility but the new options override them when set.

4.3 Changes from Version 5.0.0

From version 5.0.0, FORCESPRO uses CasADi v3.5.5 as default AD tool for both Matlab and Python client. The following code-generation option can be used for reverting to previous FORCESPRO behaviour (since v4.3.0) using CasADi v3.5.1:

- `codeoptions.nlp.ad_tool = 'casadi-3.5.1'`

From version 5.0.0, FORCESPRO uses an improved implementation of the linear solver as default whenever `nlp.linear_solver` is set to `'symm_indefinite'`. The following code-generation option can be used for reverting to previous FORCESPRO behaviour:

- `codeoptions.nlp.linear_solver = 'symm_indefinite_legacy'`

From version 5.0.0, FORCESPRO uses RestAPI for server communications. To revert to previous communication methods, the following options can be used (see [MATLAB network communications/Python network communications](#)):

Matlab

Python

```
codeoptions.server_connection = ForcesWeb.ServerConnections.WSDL
codeoptions.server_connection = ForcesWeb.ServerConnections.WSDL_legacy
```

```
codeoptions.server_connection = 'WSDL'
```

4.4 Changes from Version 4.3.0

From version 4.3.0, FORCESPRO uses CasADi v3.5.1 as default AD tool for both Matlab and Python client. The following code-generation option can be used for reverting to previous FORCESPRO behaviour using CasADi v2.4.2:

- `codeoptions.nlp.ad_tool = 'casadi-2.4.2'`

4.5 Changes from Version 4.2.0

From version 4.2.0, the following code-generation options can be used for reverting to previous FORCESPRO behaviours:

- `codeoptions.legacyNetworkConnections = 1`. From version 4.2.0, a new communication method is used to connect to the codegen service for safety and stability reasons. Use this option to use the legacy method of communication.
- `codeoptions.platform = 'Speedgoat-Legacy-x86'`. From version 4.2.0, use this option for Mobile Speedgoat platforms on earlier versions of MATLAB (earlier than R2018b).

From version 4.2.0, the option `codeoptions.platform = 'Speedgoat-x86'` supports MATLAB versions from R2018b till R2020a, while option `codeoptions.platform = 'Speedgoat-QNX'` supports MATLAB R2020b and later.

4.6 Changes from Version 4.1.0

From version 4.1.0, the following code-generation options can be used for reverting to previous FORCESPRO behaviours:

- `codeoptions.separateCasadiFiles = 1`. From version 4.1.0, the old `_model` files are all gathered in a single `_casadi` file. Use this option to enable the old behaviour, i.e. splitted model files.
- `codeoptions.size_one_param_as_array = 1`. From version 4.1.0, when using the PDIP_NLP method only, all parameters of size one are treated as scalars by default in order to be compatible with the Matlab coder. This option enables users to revert to the previous behaviour, i.e. scalar parameters as arrays of size one.

Chapter 5

Y2F Interface

- *Installing Y2F*
- *Generating a solver*
- *Calling the solver*
- *Solver info*
 - *Exitflags*
 - *Additional diagnostics*
- *Performance*
- *Examples*

YALMIP is a high-level modeling language for optimization in MATLAB. It is very convenient to use for modeling various optimization problems, including convex quadratic programs, for example. YALMIP allows you to write self-documenting code that reads very much like a mathematical description of the optimization model.

To combine the computational efficiency of FORCESPRO with the ease-of-use of YALMIP, we have created the interface **Y2F**. Y2F very efficiently detects the inherent structure in the optimization problem, and uses the FORCESPRO backend to generate efficient code for it. All you need to do is to replace YALMIP's `optimizer` function, which pre-builds the optimization problem such that subsequent evaluations become very inexpensive, by Y2F's `optimizerFORCES` function, which is fully API-compatible with `optimizer`.

This interface is provided with all variants of FORCESPRO, starting with *Variant S*.

You can read more about the concept of YALMIP's `optimizer` [here](#).

Important: The Y2F interface supports convex decision making problems, with or without binary variables.

5.1 Installing Y2F

Y2F is included in the FORCESPRO client. If `optimizerFORCES` is not found on your MATLAB path, you need to add the `FORCES_PRO/Y2F/Y2F` directory to it, e.g. by typing:

```
addpath /home/user/FORCES_PRO/Y2F/Y2F
```

on your MATLAB command prompt.

Of course, you also need a working installation of YALMIP, which you can download from <https://yalmip.github.io/download/>.

5.2 Generating a solver

A YALMIP model consists of a constraint object, which we name `const` and an objective function `obj`. You can create an `optimizer` object that has most of the work YALMIP needs to do before calling a solver (called canonicalization) already saved. The only parts missing are the parameters of the problem, which you can specify when calling `optimizer`:

```
P = optimizer(Con, Obj, Options, Parameters, WantedVariables); % YALMIP syntax
```

With Y2F, you can have the same syntax but creating a FORCESPRO solver:

```
P = optimizerFORCES(Con, Obj, Options, Parameters, WantedVariables,   
↳ [ParameterNames], [OutputNames]);
```

where `Options` is a FORCESPRO codeoptions struct (see the *Solver Options* section for more information). The two last arguments are optional cell arrays of strings specifying the names of the parameters and the wanted variables. These will be used for naming e.g. the in- and output ports of the generated Simulink block.

5.3 Calling the solver

There are several ways of calling the generated solver:

1. Using the `optimizerFORCES` object, which again is API compatible with YALMIP's `optimizer` object:

```
[wantedVariableValues, exitflag, info] = P{Parameters}; % YALMIP syntax
```

2. Using the generated Matlab (MEX) interface (type `help solvname` at the Matlab command prompt for more information):

```
problem.ParameterName1 = value1; problem.ParameterName2 = value2;   
[output, exitflag, info] = solvname(problem);   
wantedVariable = output.outputName1;
```

3. Via the generated Simulink block (see `interfaces` folder of the generated code).

5.4 Solver info

5.4.1 Exitflags

One should always check whether the solver has exited without an error before using the solution. Possible values of `exitflag` are presented in [Table 5.1](#).

Table 5.1: Exitflag values

Exitflag	Description
1	Optimal solution found to the requested accuracy.
2	(for branch-and-bound) A feasible point has been identified for which the objective value is no more than <code>codeoptions.mip.mipgap*100</code> per cent worse than the global optimum. (for convex solver) Solver timeout has been reached.
0	Timeout – maximum number of iterations or maximum computation time of <code>codeoptions.mip.timeout</code> (only branch-and-bound) reached. The returned solution is the best one found so far.
-1	(only branch-and-bound) Infeasible problem (problems solving the root relaxation to desired accuracy).
-2	(only branch-and-bound) Out of memory – cannot fit branch and bound nodes into pre-allocated memory.
-7	The convex solver could not proceed due to stalled line search. The problem might be infeasible. Otherwise, please submit a bug report to support@embotech.com including all data necessary to reproduce the problem. You can also run <code>FORCESdiagnostics</code> on your problem to check for most common errors in the formulation.
-10	The convex solver could not proceed due to an internal error. The problem might be infeasible. Otherwise, please submit a bug report to support@embotech.com including all data necessary to reproduce the problem. You can also run <code>FORCESdiagnostics</code> on your problem to check for most common errors in the formulation.
-100	License error. If you have generated code with a simulation license, it will run only on the machine from which the code has been generated. In some cases, e.g. when connected to a VPN network, the FORCESPRO license checker produces a false negative. Re-run the code generation script in this case to make sure licensing information is correctly set.

5.4.2 Additional diagnostics

The solver returns additional information to the optimizer in the `info` struct. Some of the fields are described in Table 5.2. Depending on the method used, there will also be other fields describing the quality of the returned result.

Table 5.2: Info values

Info	Description
<code>info.it</code>	Number of iterations. In branch-and-bound mode this is the number of convex problems solved in total.
<code>info.solvetime</code>	Total computation time in seconds.
<code>info.pobj</code>	Value of the objective function.
<code>info.it2opt</code>	(only branch-and-bound) Number of convex problems solved for finding the optimal solution. Note that often the optimal solution is found early in the search, but in order to certify (sub-)optimality, all branches have to be explored.

5.5 Performance

A performance measurement for the interface when compared to other solvers called via YALMIP and to the same problem formulated via the low-level interface of FORCESPRO (2 states, 1 input, box constraints, varying horizon) is presented in Figure 5.1. In this example, the

code generated directly from YALMIP is about 10 times faster than other solvers, and only a factor 2 slower than the code generated with the low-level interface of FORCESPRO.

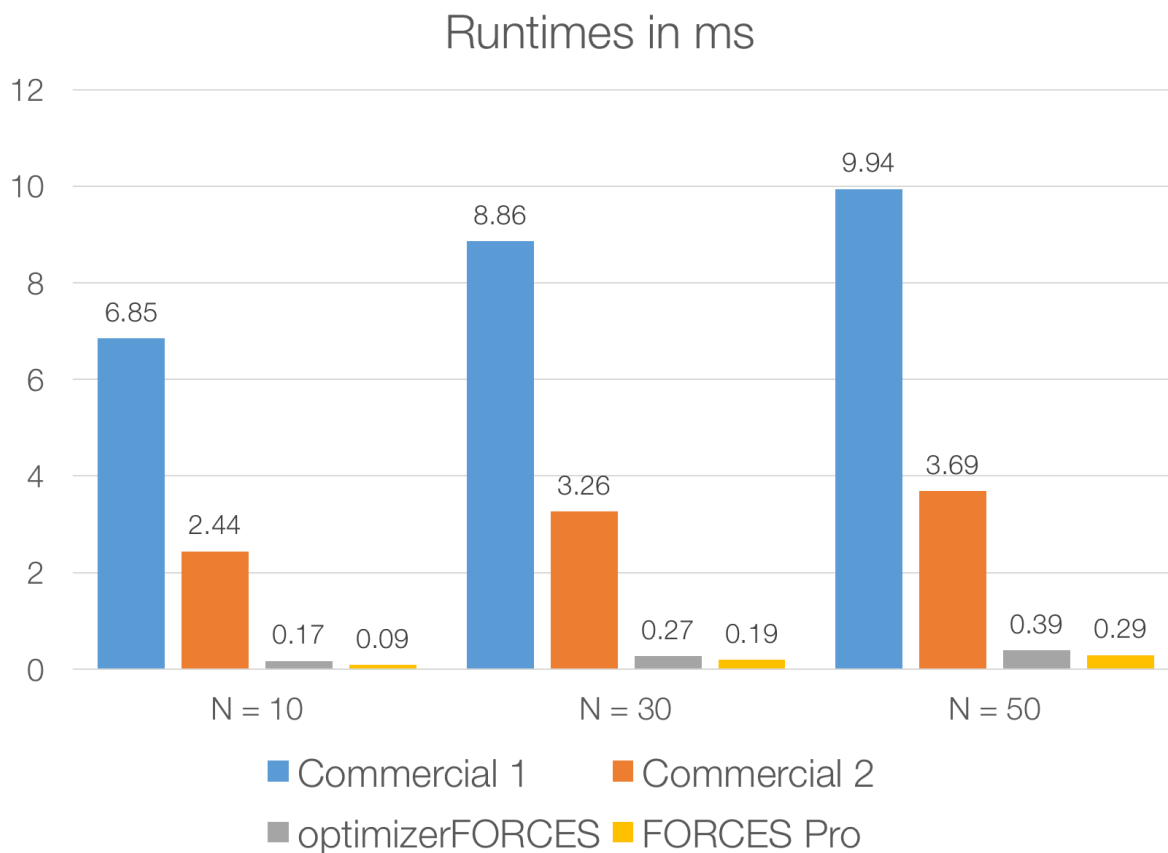


Figure 5.1: Performance comparison of the Y2F interface of FORCESPRO.

5.6 Examples

- *Y2F interface: Basic example*: Learn how to formulate problems in YALMIP easily, and then use the Y2F interface to generate code with FORCESPRO.
- *Y2F interface: Trajectory Optimization for Quadrotor Flight*: A more complex example optimizing the trajectory of a quadrotor within safe flight corridors.

Chapter 6

MathWorks Linear MPC Plugin

- *Different types of solvers*
- *Generating a QP solver from an MPC object*
- *Solving a QP from MPC online data*
- *Using the FORCESPRO MPC Simulink block*
- *Deploy to dSpace MicroAutoBox II using the FORCESPRO MPC Simulink block*
- *Examples*

As a result of a long-term collaboration, MathWorks Inc. and Embotech AG developed a MATLAB® plugin for FORCESPRO. Users are now able to use the FORCESPRO solver in MATLAB® and Simulink® from within the MATLAB® **Model Predictive Control Toolbox**. The plugin leverages the powerful design capabilities of the Model Predictive Control Toolbox™ and the computational performance of FORCESPRO. With FORCESPRO 2.0, toolbox users can now easily define challenging control problems and solve long-horizon MPC problems more efficiently.

Model Predictive Control Toolbox™ provides functions, an **app**, and Simulink® blocks for designing and simulating model predictive controllers. The toolbox enables users to readily specify plant and disturbance models, horizons, constraints, and weights. User-friendly control design capabilities of Model Predictive Control Toolbox™, combined with the powerful numerical algorithms of FORCESPRO, enables code deployment of the FORCESPRO solver on real-time hardware from within MATLAB® and Simulink®, in addition to the QP solvers shipped by MathWorks. The new FORCESPRO interface comes with various features such as Simulink blocks that can generate code runnable on embedded targets such as dSpace. The parameters of the MPC algorithm, such as plant and disturbance model, prediction horizon, constraints and move-blocking strategy can be specified directly. The toolbox enables users to run closed-loop simulations and evaluation of controller performance. User-friendly MPC design capabilities are combined with the powerful numerical algorithms of FORCESPRO. This combination of the Model Predictive Control Toolbox™ and FORCESPRO enables code deployment on real-time hardware. The generated code is highly optimized for fast computations and low memory footprint.

This interface is provided with all variants of FORCESPRO, starting with *Variant S*. It is compatible with MATLAB R2019b, 2020a and 2020b.

The plugin mainly consists of the three following MATLAB commands which are described in details in this chapter:

- `mpcToForces` for generating a FORCESPRO solver from an MPC object designed by the Model Predictive Control Toolbox
- `mpcmoveForces` for calling the generated solver on a specific MPC problem instance

- `mpcCustomSolver` for using the FORCESPRO dense QP solver as a custom solver

An auxiliary file is also exposed to the users for generating different solvers options, namely `mpcToForcesOptions`.

The following LTI MPC features are supported:

- Continuous and discrete time plant models
- Move blocking
- Measured disturbances
- Unmeasured disturbances
- Disturbance and noise models
- Uniform or time-varying weights on outputs, manipulated variables, manipulated variables rates and a global slack variable
- Uniform or time-varying bounds on outputs, manipulated variables and manipulated variables rates
- Soft constraints
- Signal previewing on reference and measured disturbances
- Scale factors
- Nominal values
- Online updates of weights and constraints
- Built-in and custom state estimators

Currently, convex quadratic programs are supported by the MATLAB plugin. Extensions to adaptive and linear time-varying are under development. The current limitations of the plugin are the following:

- Mixed input-output constraints are not covered
- Offdiagonal terms on the hessian of the objective cannot be implemented
- Unconstrained problems are not supported
- No single-precision solvers, only double precision currently
- No suboptimal solutions

6.1 Different types of solvers

The plugin converts an MPC object (weights, bounds, horizons, prediction model) into a quadratic program (QP) formulated via the FORCESPRO API. One key design decision is to choose the decision variables in the quadratic program. There are two classic choices and they lead to two different formulations:

- **Dense QP**, where only the manipulated variables MV or ΔMV are decision variables. In this case, the hessian and linear constraints matrices are stored as dense matrices.
- **Sparse QP**, where MV , ΔMV , the outputs OV and the states X are decision variables. In this case, all matrices have a block sparse structure as in *Low-level interface*.

Typically, a dense QP has fewer optimization variables, zero equality constraints and many inequality constraints. Although the sparse QP is generally much larger than the dense QP its structure can be efficiently exploited to reduce the solve times. Besides, the dense formulation has an inherent flaw, which is that the condition number increases with the horizon

length, especially when the plant states have large contributions to the plant inputs and outputs. Thus, the best solution is to allow users to switch to the sparse formulation, which prevents numerical blow-ups when the plant is unstable. Nevertheless, the dense formulation can be beneficial in terms of solve time when there is an important amount of move-blocking.

6.2 Generating a QP solver from an MPC object

Given an MPC object created by the `mpc` command, users can generate a QP solver tailored to their specific problem via the following command:

```
% mpcobj is the output of mpc(...)
% options is the output of mpcToForcesOptions(...)

[coredata, statedata, onlinedata] = mpcToForces(mpcobj, options);
```

Two types of QP solvers can be generated via `mpcToForces`: a **sparse** solver that corresponds to a multi-stage formulation as in *Low-level interface* and a **dense** solver that corresponds to a one-stage QP with inequality constraints only.

The API of `mpcToForces` is described in more details in the tables below. The `mpcToForces` command expects an MPC object **mpcobj** and a structure **options** generated by `mpcToForcesOptions` as inputs.

Table 6.1: `mpcToForces` inputs

Input	Description
mpcobj	LTI MPC controller designed by Model Predictive Control Toolbox
options	Object that provides solver generation options.

The outputs of `mpcToForces` consist of three structures **coredata**, **statedata** and **onlinedata**. The FORCESPRO server generates two types of solvers:

- *customForcesSparseQP* when the option 'sparse' is set. An m file named 'custom-ForcesSparseQP.m' with the corresponding mex interface as well as the solver libraries and header in the 'customForcesSparseQP' folder. In this particular case (sparse), the name of the solver can be set by users.
- *customForcesDenseQP* when the option 'dense' is set. An m file named 'customForces-DenseQP.m' with the corresponding mex interface as well as the solver libraries and header in the 'customForcesDenseQP' folder. In this particular case (dense), the solver name cannot be changed by users.

Table 6.2: *mpcToForces* outputs

Output	Type	Description
coredata	Structure	Stores constant data needed to construct quadratic program at run-time
statedata	Structure	Represents prediction model states and last optimal MV. The index k stands for the current simulation time. It contains 4 fields: When built-in state estimation is used: Plant is the estimated plant state $x_p[k k-1]$ Disturbance is the estimated disturbance states $x_d[k k-1]$ Noise is the estimated measurement noise states $x_n[k k-1]$ LastMove is the optimal manipulated variables at the previous sample time In this case, users should not manually change any field at run-time. When custom state estimation is used: Plant is the estimated plant state $x_p[k k]$ Disturbance is the estimated disturbance states $x_d[k k]$ Noise is the estimated noise states $x_n[k k]$ LastMove is the optimal manipulated variables at the previous solve In this case, user should manually update Plant, Disturbance (if used), Noise (if used) fields at run-time but leave LastMove alone.
onlinedata	Structure	Represent online signals It contains up to three fields: signals, a structure containing following fields: ref (references of Output Variables) mvTarget (references of Manipulated Variables) md (when Measured Disturbance is present) ym (when using the built-in estimator) externalMV (when UseExternalMV is true in the options object) weights, a structure containing the following fields: y (when UseOnlineWeightOV is enabled) u (when UseOnlineWeightMV is enabled) du (when UseOnlineWeightMVRate is enabled) ecr (when UseOnlineWeightECR is enabled) constraints, a structure containing the following fields: vmin (when UseOnlineConstraintOVMin is enabled) vmax (when UseOnlineConstraintOVMax is enabled) umin (when UseOnlineConstraintMVMin) umax (when UseOnlineConstraintMVMax) dumin (when UseOnlineConstraintMVRateMin) dumax (when UseOnlineConstraintMVRateMax)

In order to provide the code-generation options to *mpcToForces*, the user needs to run the command *mpcToForcesOptions* with one of the following two arguments as input:

- “dense” for generating the options of a one-stage dense QP solvers
- “sparse” for generating the options a multi-stage QP solver.

The structures provided by the *mpcToForcesOptions* command have the following MPC related fields in common between the “dense” and “sparse” case:

- *SkipSolverGeneration*. When set to *True*, only structures are returned. If set to *False*, a solver mex interface is generated and the structures are returned. Default value is *False*.

- *UseOnlineWeightOV*. When set to *True*, it allows Output Variables weights to vary at run time. Default is *False*.
- *UseOnlineWeightMV*. When set to *True*, it allows Manipulated Variables weights to vary at run time. Default is *False*.
- *UseOnlineWeightMVRate*. When set to *True*, it allows weights on the Manipulated Variables rates to vary at run time. Default is *False*.
- *UseOnlineWeightECR*. When set to *True*, it allows weights on the ECR to change at run time. Default is *False*.
- *UseOnlineConstraintOVMax*. When set to *True*, it allows updating the upper bounds on Output Variables at run time. Default is *False*.
- *UseOnlineConstraintOVMin*. When set to *True*, it allows updating the lower bounds on Output Variables at run time. Default is *False*.
- *UseOnlineConstraintMVMax*. When set to *True*, it allows updating the upper bounds on Manipulated Variables at run time. Default is *False*.
- *UseOnlineConstraintMVMin*. When set to *True*, it allows updating the lower bounds on Manipulated Variables at run time. Default is *False*.
- *UseExternalMV*. When set to *True*, the actual Manipulated Variable applied to the plant at time $k - 1$ is provided as output. Default is *False*.
- *UseMVTarget*. When set to *True*, an MV reference signal is provided via the `onlinedata` structure. In this case, MV weights should be positive for proper tracking. When false, the MV reference is the nominal value by default and MV weights should be zero to avoid unexpected behaviour. Default is *False*.

Both the “dense” and “sparse” options structures have the following solver related fields in common:

- *ForcesServer* is the FORCESPRO server url. Default is forces.embotech.com.
- *ForcesMaxIteration* is the maximum number of iterations in a FORCESPRO solver. Default value is 50.
- *ForcesPrintLevel* is the logging level of the FORCESPRO solver. If equal to 0, there is no output. If equal to 1, a summary line is printed after each solve. If equal to 2, a summary line is printed at every iteration. Default value is 0.
- *ForcesInitMethod* is the initialization strategy used for the FORCESPRO interior point algorithm. If equal to 0, the solver is cold-started. If equal to 1, a centered start is computed. Default value is 1.
- *ForcesMu0* is the initial barrier parameter. It must be finite and positive. Its default value is equal to 10. A small value close to 0.1 generally leads to faster convergence but may be less reliable.
- *ForcesTolerance* is the tolerance on the infinity norm of the residuals of the inequality constraints. It must be positive and finite. Its default value is 10^{-6} .
- *ForcesTargetPlatform* for choosing a target platform to deploy the solver. Currently, dSpace, Speedgoat and BeagleBone-Blue are supported.

In the “sparse” solver case, there are four more fields:

- *SolverName* for customizing the solver name.
- *UseOnlineConstraintMVRateMax* for setting MVRate upper bounds.
- *UseOnlineConstraintMVRateMin* for setting MVRate lower bounds.
- *UseOneSlackVariablePerStep* to enable one slack variable per prediction step.

6.3 Solving a QP from MPC online data

Once a QP solver has been generated it can be used to solve online MPC problems via the MATLAB command `mpcmoveForces` as follows

```
% the coredata, statedata and onlinedata structures are outputs of
↳mpcToForces

[mv, statedata, info] = mpcmoveForces(coredata, statedata, onlinedata);
```

The outputs of the `mpcmoveForces` command are described below. In the table below n_m denotes the number of manipulated variables, n_x stands for the state dimension of the system implemented in the MPC object, p is the prediction horizon and k is the current solve time instant.

Table 6.3: `mpcmoveForces` outputs

Output	Type	Description
mv	Vector of size n_m	Optimal manipulated variables at current solve time instant
statedata	Structure	Initialized by <code>mpcToForces</code>
info	Structure	Information about the FORCESPRO solve U_{opt} is a $p \times n_m$ matrix for the optimal manipulated variables over the prediction horizon k to $k + p - 1$ Y_{opt} is a $p \times n_y$ matrix for the optimal output variables over the prediction horizon $k + 1$ to $k + p$ X_{opt} is a $p \times n_x$ matrix for the optimal state variables over the prediction horizon $k + 1$ to $k + p$ $Slack$ is a $p \times 1$ vector of slack variables $Exitflag$ is the FORCESPRO solve exit flag. If it is equal to 1, an optimal solution has been found. If it is equal to 0, the maximum number of solver iterations has been reached. A negative flag means that the solver failed to find a feasible solution. $Iterations$ is the number of solver iterations upon convergence or failure $Cost$ is the cost returned by the solver

6.4 Using the FORCESPRO MPC Simulink block

Both the FORCESPRO sparse and dense solvers can be used inside Simulink. The dense QP formulation is usable from the shipped Simulink MPC controller block directly. For this, the following steps are needed:

- Generate a custom dense FORCESPRO solver

```
options = mpcToForcesOptions('dense');
mpcToForces(mpcobj, options);
```

- Set the following settings in the MPC object

```
mpcobj.Optimizer.CustomSolver = true;
mpcobj.Optimizer.CustomSolverCodeGen = true;
```

The FORCESPRO sparse QP solver is also available via the Model Predictive Control Toolbox in Simulink. A dedicated block has been implemented for this purpose. All features of the MATLAB plugin are available through this Simulink block, namely measured disturbances,

external manipulated variables, references for manipulated variables, custom state estimation as well as online weights and constraints. Configuring the block is done via the user interface shown in [Figure 6.1](#) below. Currently only the sparse QP solver can be used via the Simulink API.

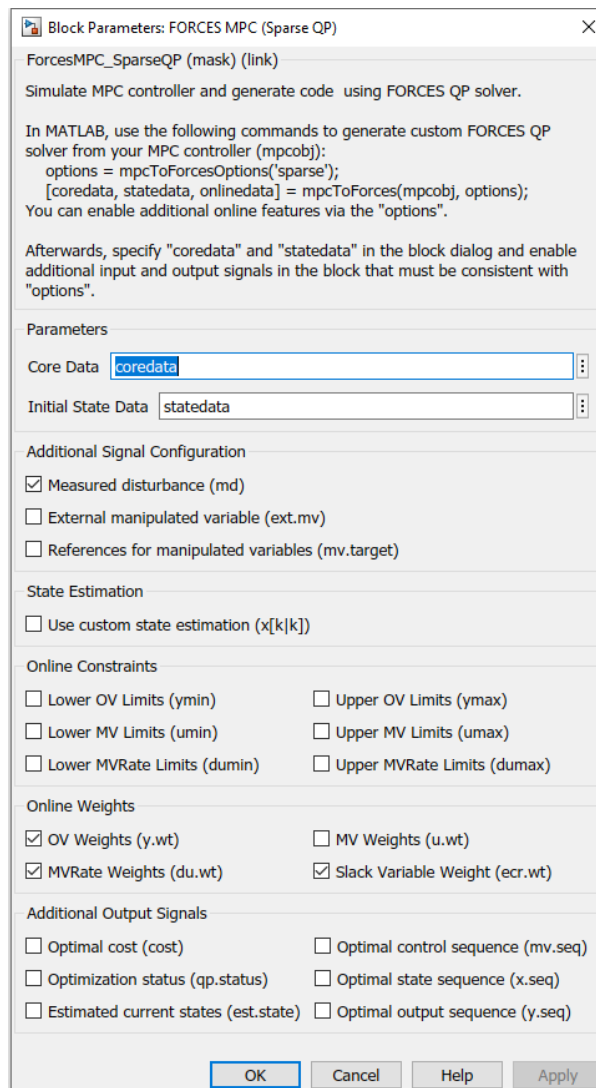


Figure 6.1: FORCESPRO MPC block configuration window

In order to run a simulation using the FORCESPRO Simulink block, a solver first needs to be generated via the following code for instance:

```
%% Generate FORCESPRO sparse QP solver
options = mpcToForcesOptions('sparse');
% For this example we need to specify that online weights on the outputs,
% the input rates and the ECR slacks are used
options.UseOnlineWeightOV = true;
options.UseOnlineWeightMVRate = true;
options.UseOnlineWeightECR = true;
[coredata, statedata, onlinedata] = mpcToForces(mpcobj, options);
```

The structures *coredata* and *statedata* needed by the FORCESPRO solver are then provided to the Simulink block via the window shown in [Figure 6.1](#).

- *coredata* is the variable name of the core data structure generated by *mpcToForces* in the base workspace.

- *initial state data* is the variable name of the state data structure generated by *mpcToForces* in the base workspace. The user is expected to populate this structure with initial states of the plant and disturbances.
- *md* checkbox should be selected if MD channels exist in the MPC object.
- *x[k/k]* checkbox needs to be selected for using a custom state estimator.
- Optional outputs provide more information. It is recommended to monitor the *qp.status* port to check whether the MPC block produces a feasible solution.

The integration of the FORCESPRO MPC block in a Simulink model is shown in Figure 6.2 below.

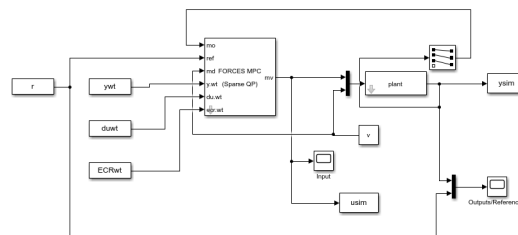


Figure 6.2: Simulink model illustrating the integration of the FORCESPRO MPC block

The Simulink model can be run either by clicking on the Run button in Simulink or from MATLAB using the `sim` command.

```
% Start simulation.
mdl = 'forcesmpc_onlinetuning';
open_system(mdl);           % Open Simulink(R) Model
sim(mdl);                   % Start Simulation
```

Finally, the FORCESPRO MPC block is available via the Library browser once the user has updated his client to the latest version of FORCES, as shown in Figure 6.3 below.

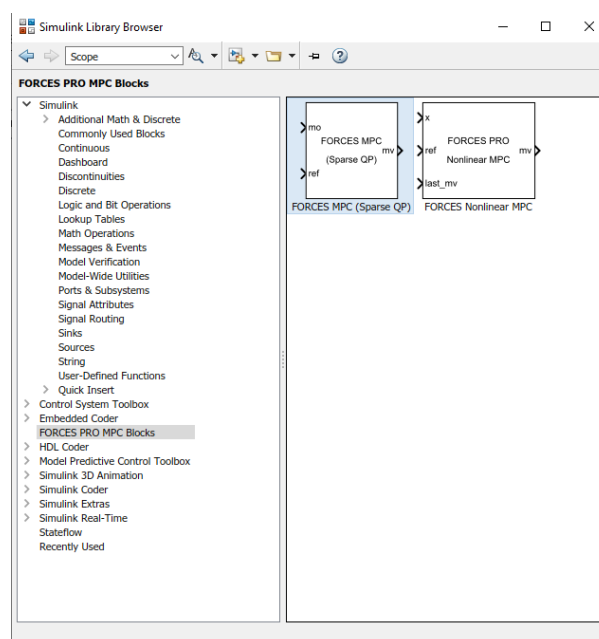


Figure 6.3: FORCESPRO MPC block in the library browser

6.5 Deploy to dSpace MicroAutoBox II using the FORCE-SPRO MPC Simulink block

The FORCESPRO sparse solvers can be used inside Simulink to deploy to dSpace MicroAutoBox II. All features of the MATLAB plugin are available through this Simulink block, namely measured disturbances, external manipulated variables, references for manipulated variables, custom state estimation as well as online weights and constraints. Configuring the block is done via the user interface shown in Figure 6.4 below.

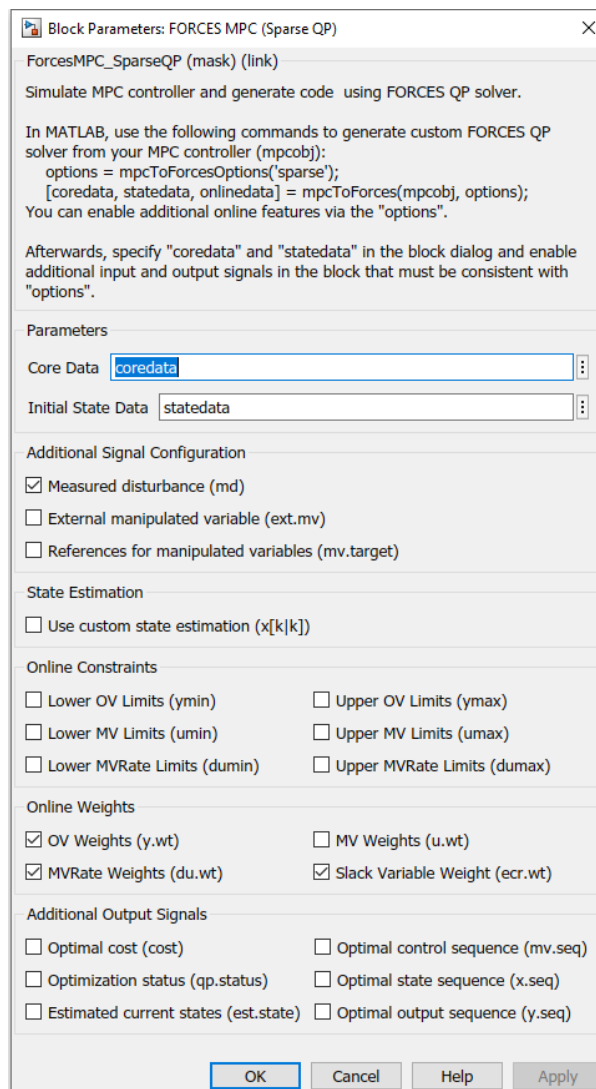


Figure 6.4: FORCESPRO MPC block configuration

- 1) In order to run an MPC simulation in dSPACE using the FORCESPRO block, a solver first needs to be generated via the following code:

```
%% Generate FORCESPRO sparse QP solver
options = mpcToForcesOptions('sparse');
% For this example we need to specify that online weights on the outputs,
% the input rates and the ECR slacks are used
```

(continues on next page)

(continued from previous page)

```
options.UseOnlineWeightOV = true;
options.UseOnlineWeightMVRate = true;
options.UseOnlineWeightECR = true;
options.ForcesTargetPlatform = 'dSPACE-MABII';

[coredata, statedata, onlinedata] = mpcToForces(mpcobj, options);
```

- 2) Note that the option *ForcesTargetPlatform* needs to be specified. The structures *coredata* and *statedata* needed by the FORCESPRO solver are then provided to the Simulink block via the window shown in [Figure 6.4](#). The integration of the FORCESPRO MPC block in a Simulink model is shown in [Figure 6.5](#) below.

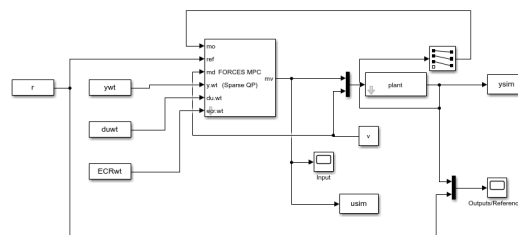


Figure 6.5: FORCESPRO MPC block integration in a Simulink model

- 3) When creating the Simulink Model, in the Configurations, in the “Code Generation” tab, set the options (see [Figure 6.6](#) below):
 - System target file: `rti1401.tlc`
 - Language: C
 - Generate makefile: On
 - Template makefile: `rti1401.tmf`
 - Make command: `make_rti`
- 4) The Simulink model can be used for Code Generation from MATLAB in the usual way.

```
% Start Code Generation.
mdl = 'forcesmpc_onlinetuning_dSpace_MicroAutoBoxII';
open_system(mdl);           % Open Simulink(R) Model
load_system(mdl);          % Load Simulink(R) Model
rtwbuild(mdl);             % Start Code Generation
```

- 5) After code generation the dspace compiler (Microtec PowerPC) generated files to use to run your model on the MicroAutoBox II (see [Figure 6.7](#)).
- 6) Open dSpace Control Desk and select create new project (see [Figure 6.8](#)).
- 7) Name the project and the experiment (see [Figure 6.9](#) and [Figure 6.10](#)).
- 8) Select the platform to which you will deploy the generated executable (see [Figure 6.11](#)).
- 9) Import the variable description file `forcesmpc_onlinetuning_dSpace_MicroAutoBoxII.sdf` in order to have access to the model variables and see the results of the execution (see [Figure 6.12](#) and [Figure 6.13](#)).
- 10) Click Finish to create the project (see [Figure 6.14](#)).
- 11) On the project layout select the tab Variables and on the `forcesmpc_onlinetuning_dSpace_MicroAutoBoxII` category expand Model Root (see [Figure 6.15](#)).

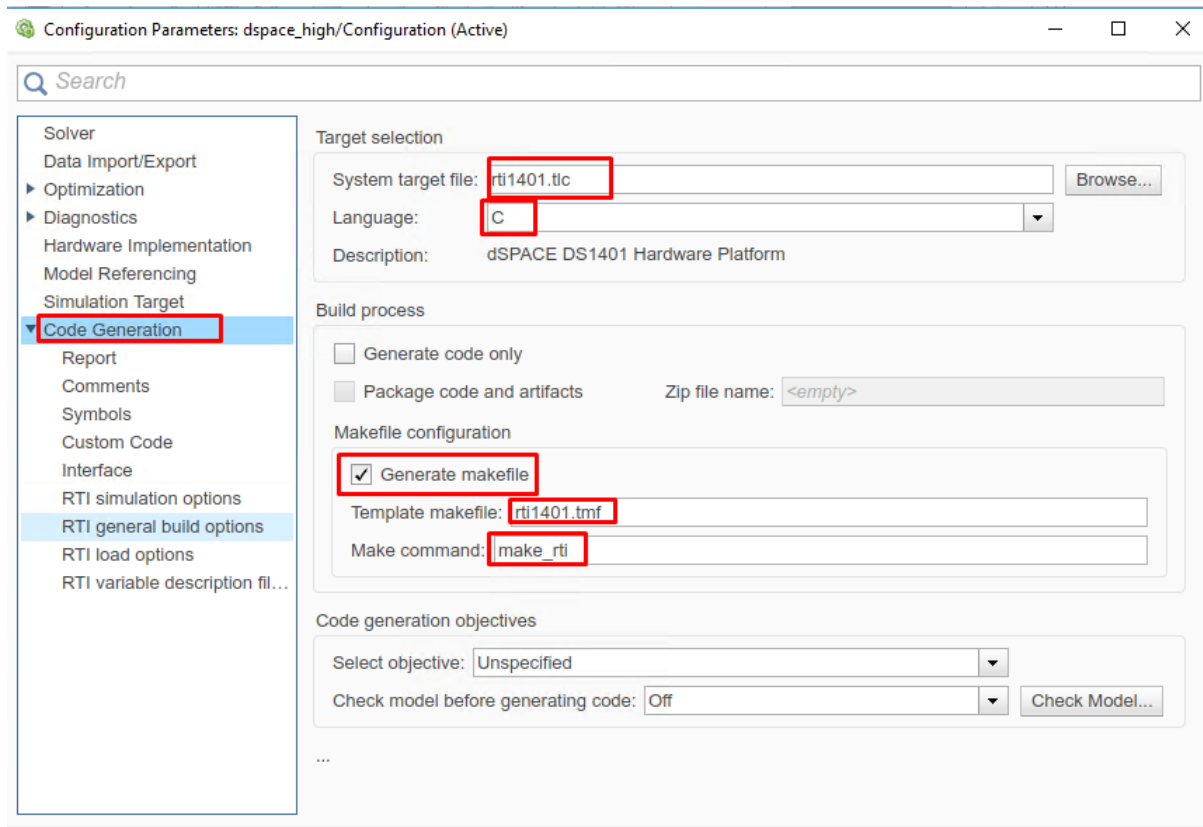


Figure 6.6: Configure Code Generation for dSPACE MicroAutoBox II

- 12) Select **FORCES MPC (Sparse QP)** and Drag & Drop all the output variables together to the Layout. In the opened menu select **Time Plotter** (see Figure 6.16).
- 13) Drag & Drop the output variables again and now choose **Display** (see Figure 6.17).
- 14) To see all the plots concurrently right-click on the left of the Y-axis and select **YAxes-view> Horizontal stacked** (see Figure 6.18).
- 15) Select the **Platforms/Devices** tab. Right-Click on your platform and select **Real-Time Application> Load**. Choose the executable file `forcesmpc_onlinetuning_dSpace_MicroAutoBoxII.ppc` (see Figure 6.19 and Figure 6.20).
- 16) Select **Go Online** and **Start Measuring** to see the results. (see Figure 6.21 and Figure 6.22).

6.6 Examples

The plugin comes with several examples to demonstrate its functionalities and flexibility.

You can find the MATLAB code of this example to try them out for yourself in the `examples/matlab/mpc-toolbox-plugin/linearModels` folder that comes with your client.

The packaged examples are the following ones:

- `forcesmpc_cstr.m` is a linear time-invariant (LTI) MPC example with unmeasured outputs. It also shows how to use the MATLAB Coder for generating and running *mpcmoves* as a mex interface, which results in lower simulation times.

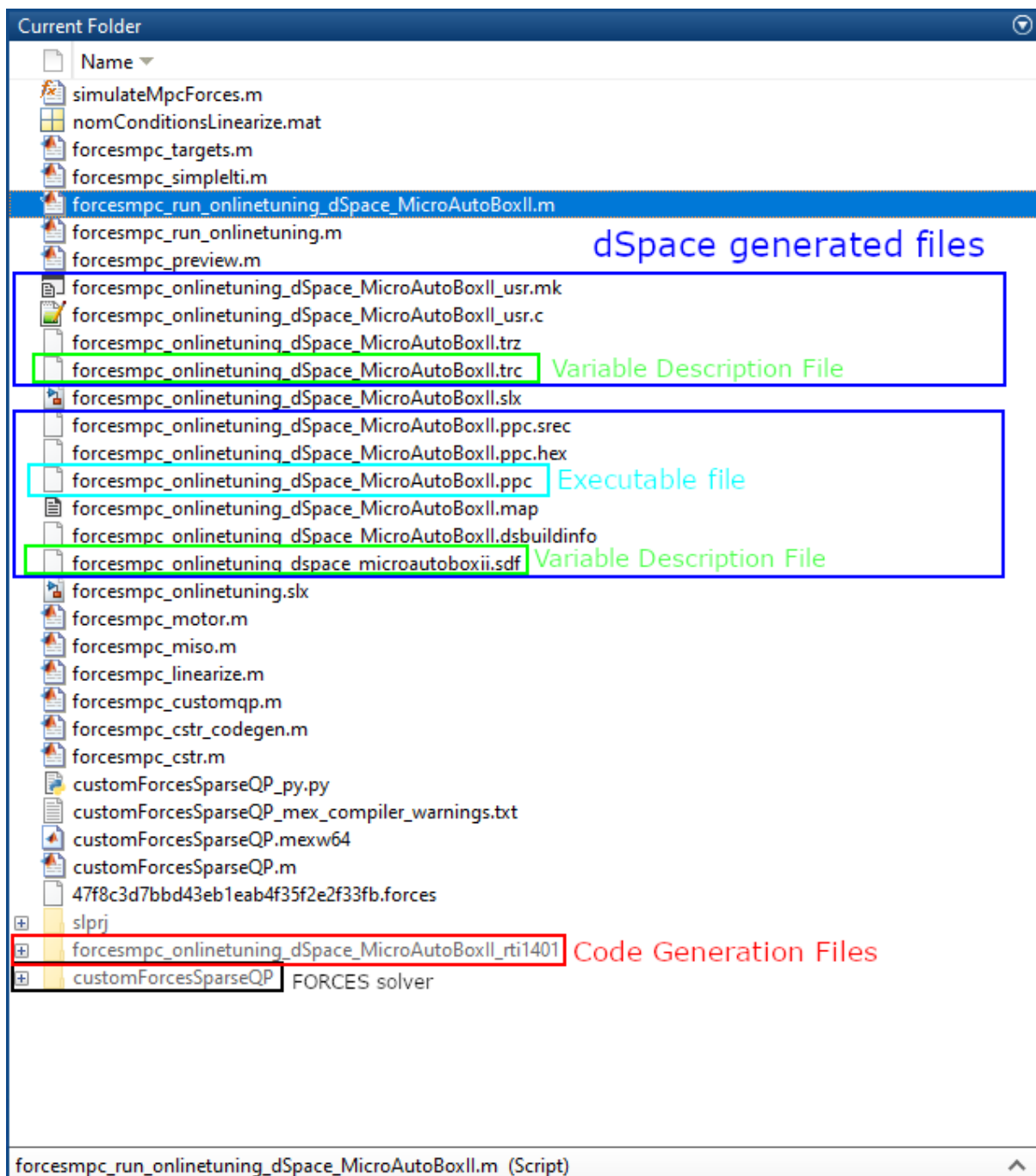


Figure 6.7: The generated files from the Simulink Code Generation

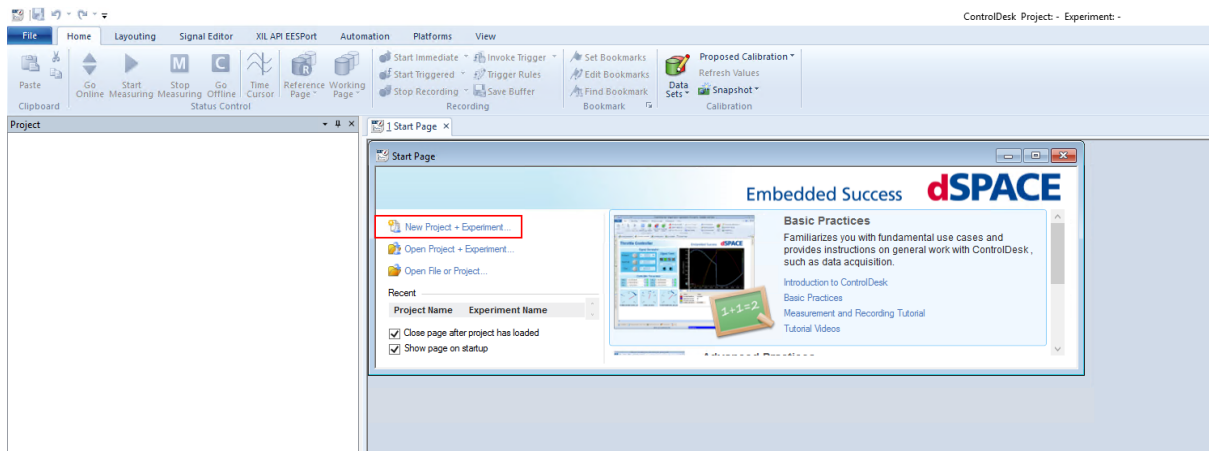
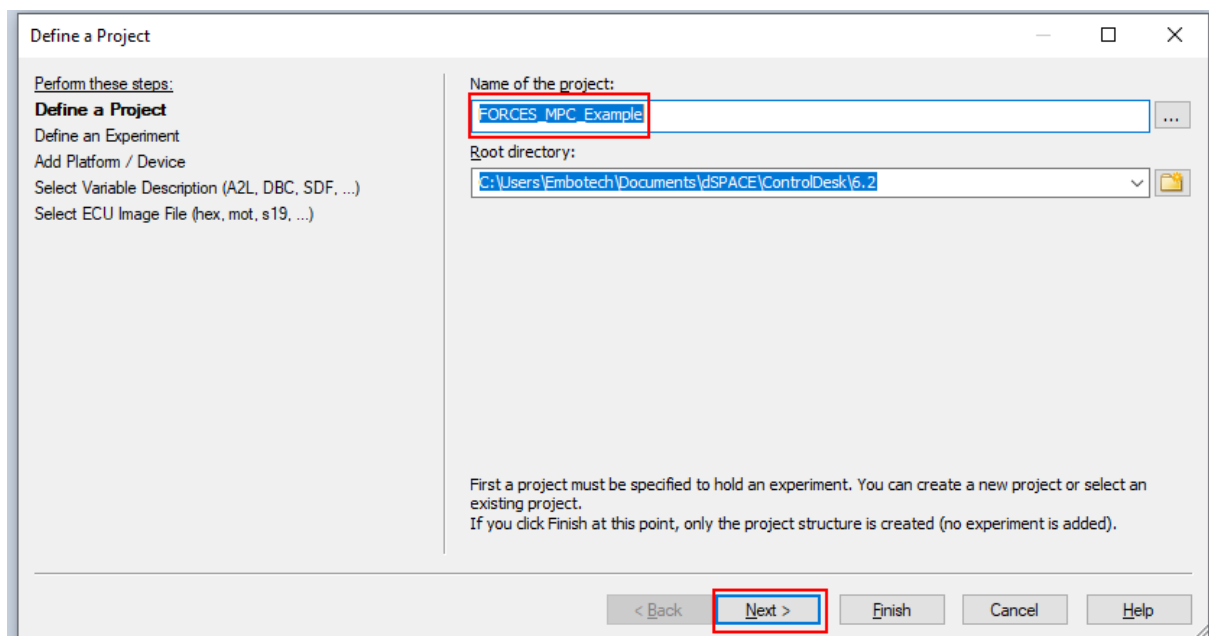


Figure 6.8: Start a new project



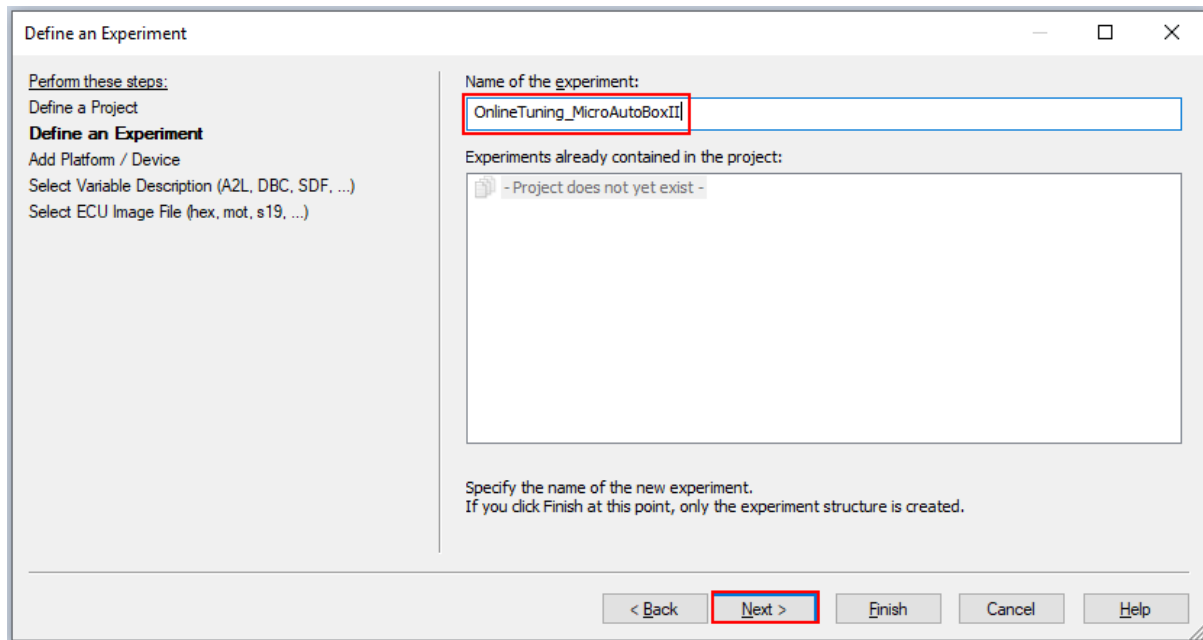


Figure 6.10: Name your experiment

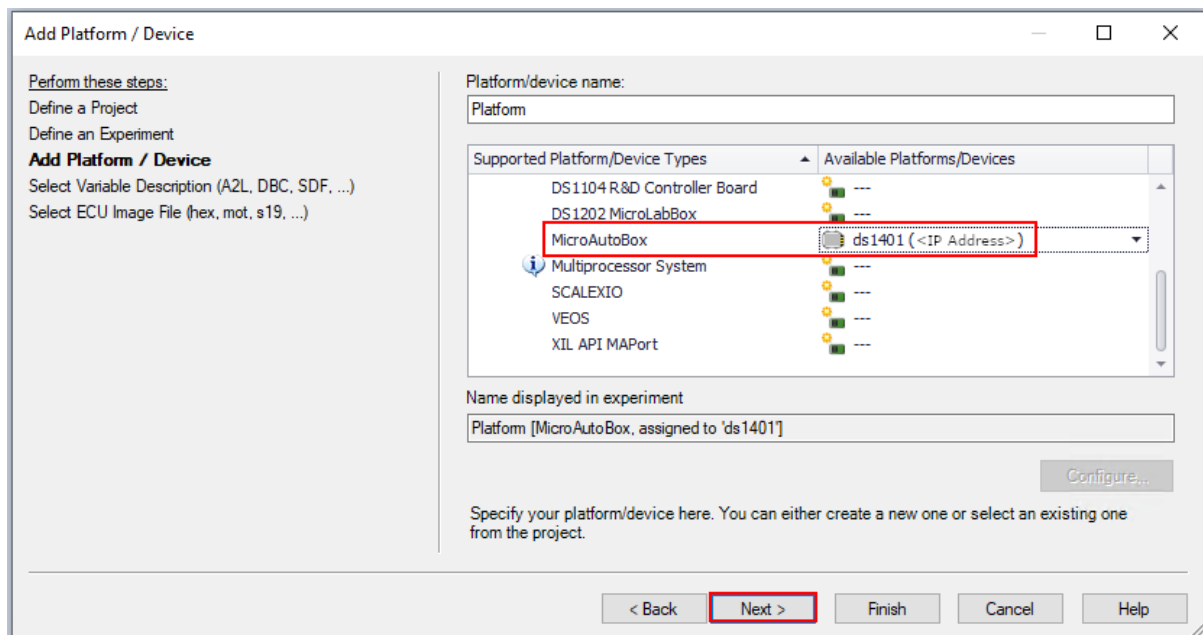


Figure 6.11: Select the MicroAutoBox platform

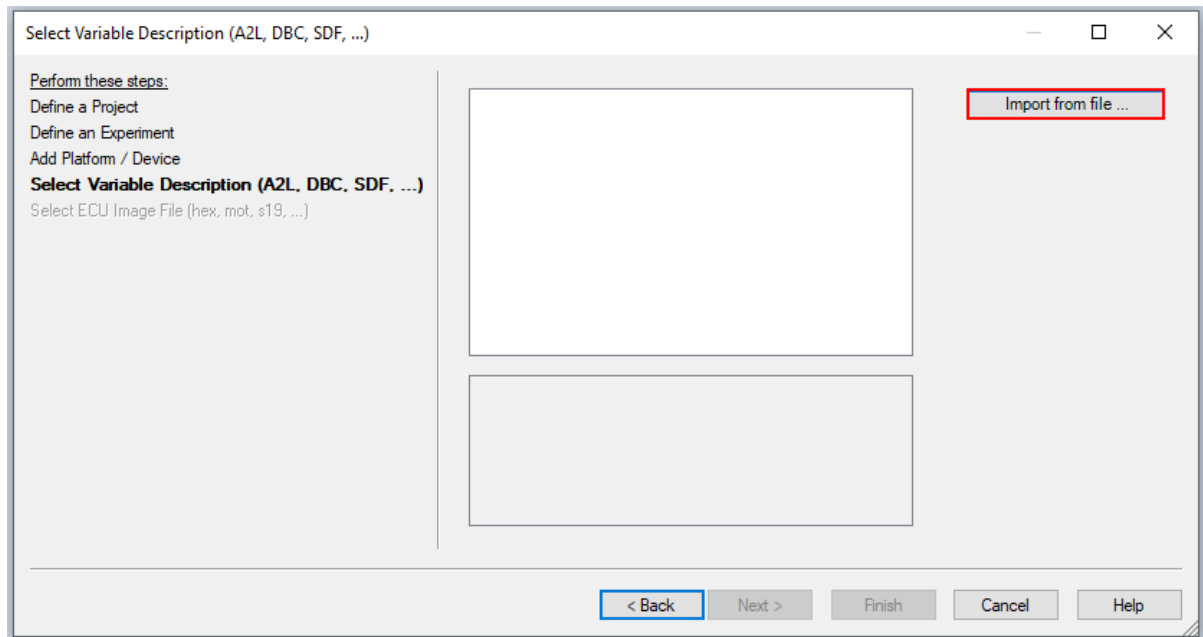


Figure 6.12: Import the variable description file

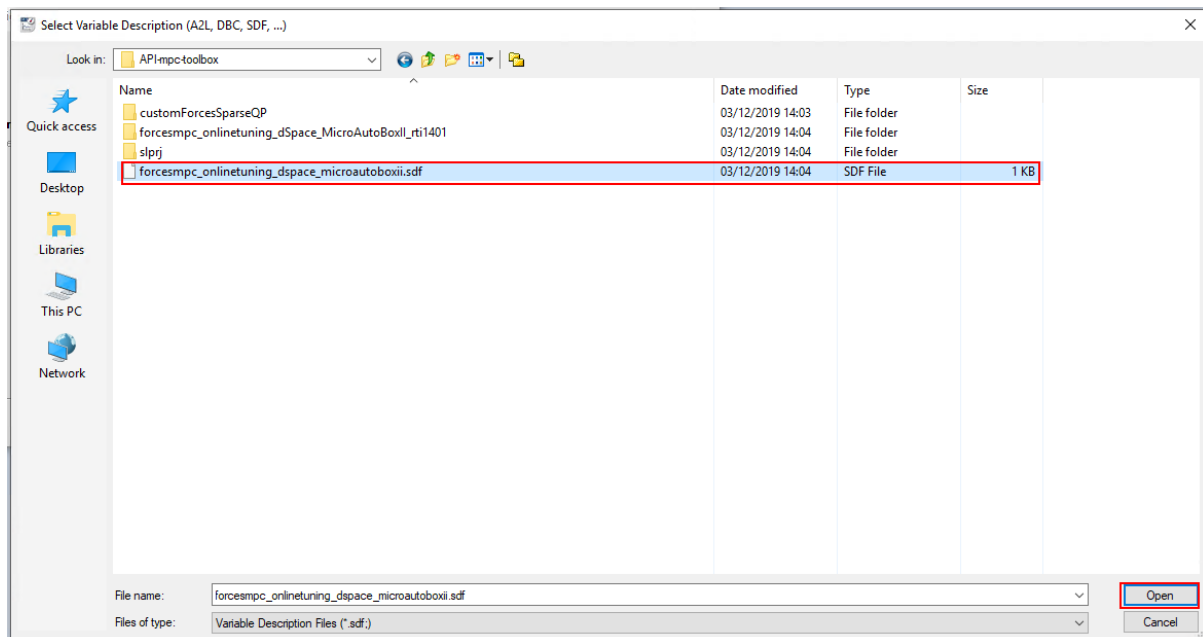


Figure 6.13: Select the sdf file with the variables description

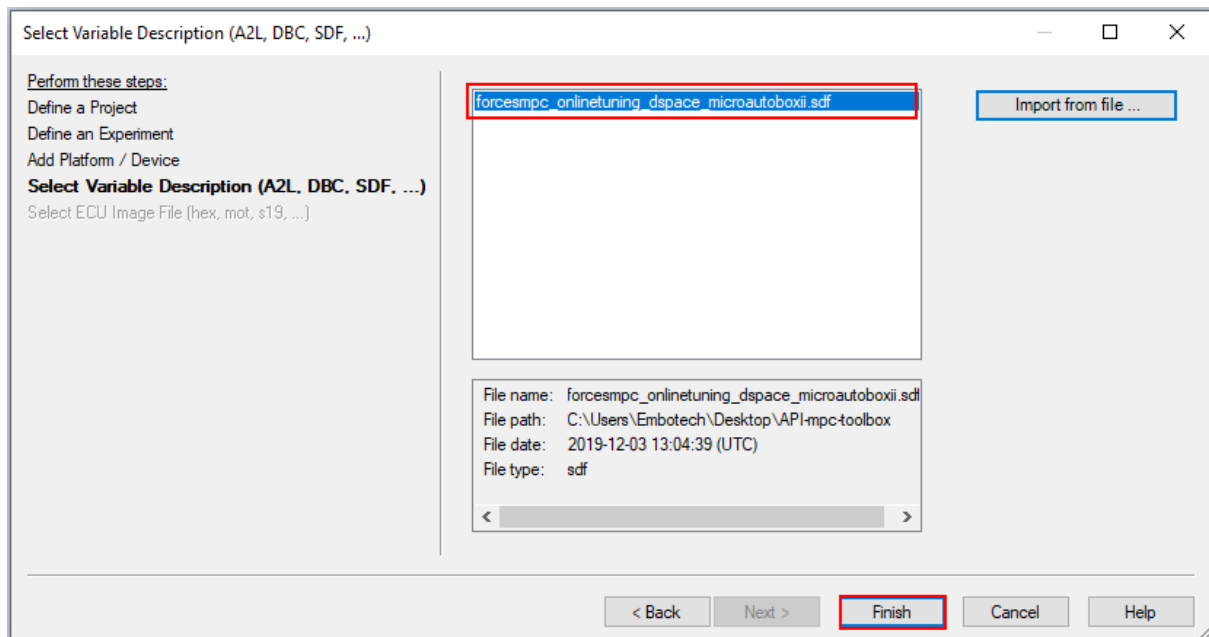


Figure 6.14: Click Finish to create the project

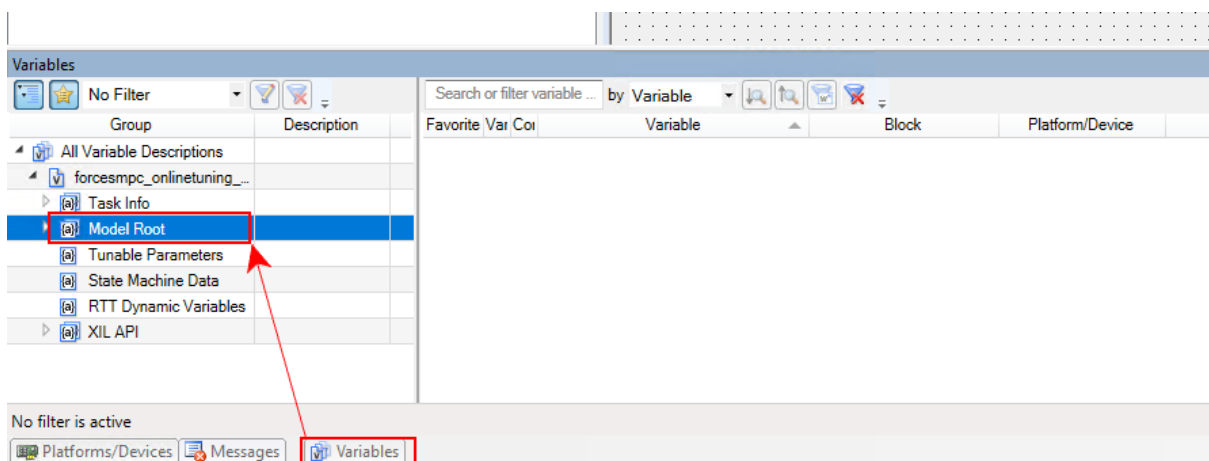


Figure 6.15: Find the model root in the variables tab

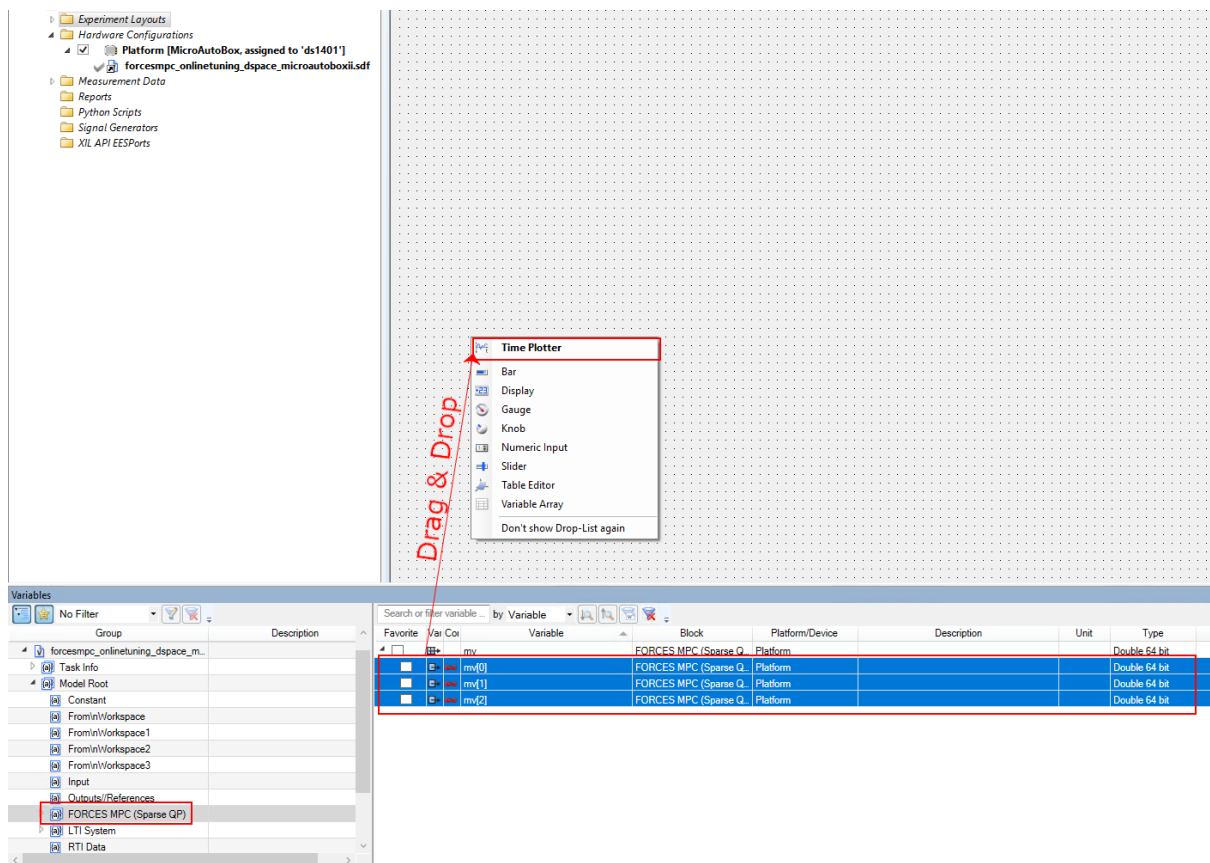


Figure 6.16: Add the variables as plots

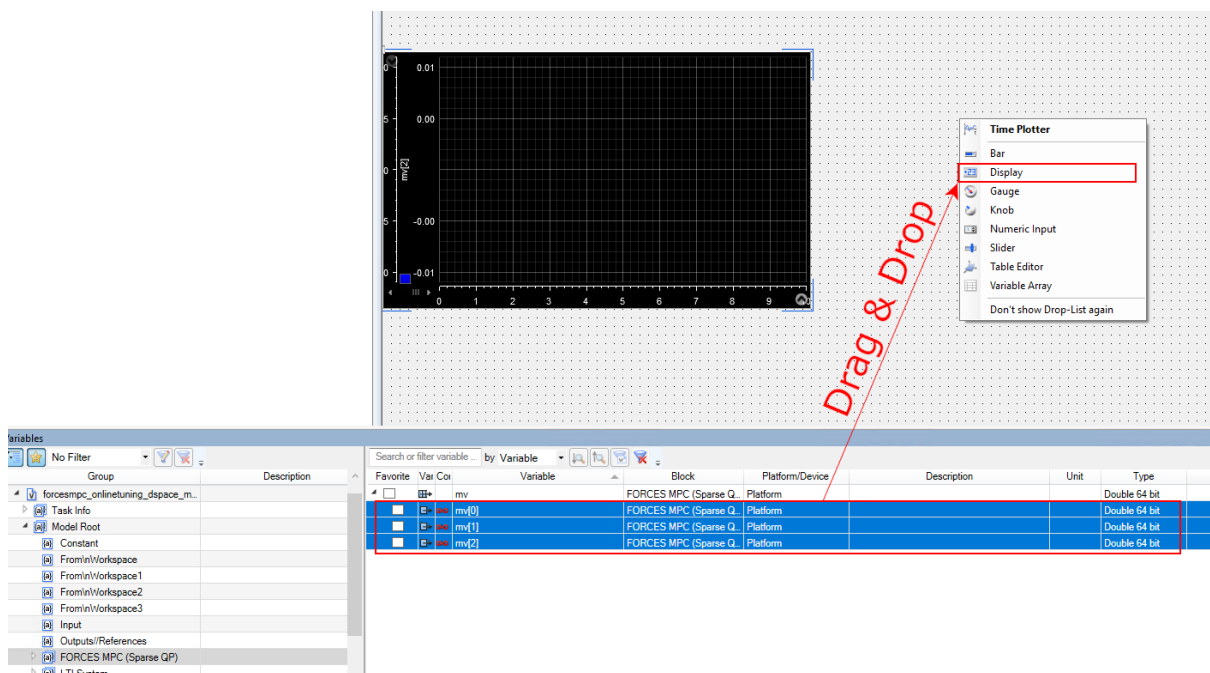


Figure 6.17: Add the variables as displays

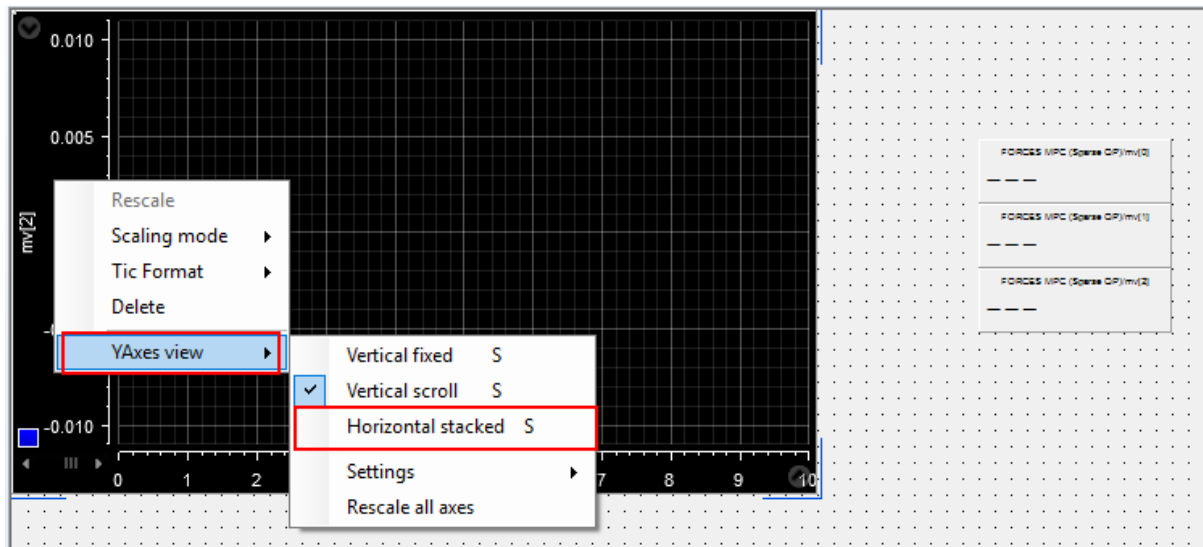


Figure 6.18: Select to show all the signals on the same plot with their own Y-axes

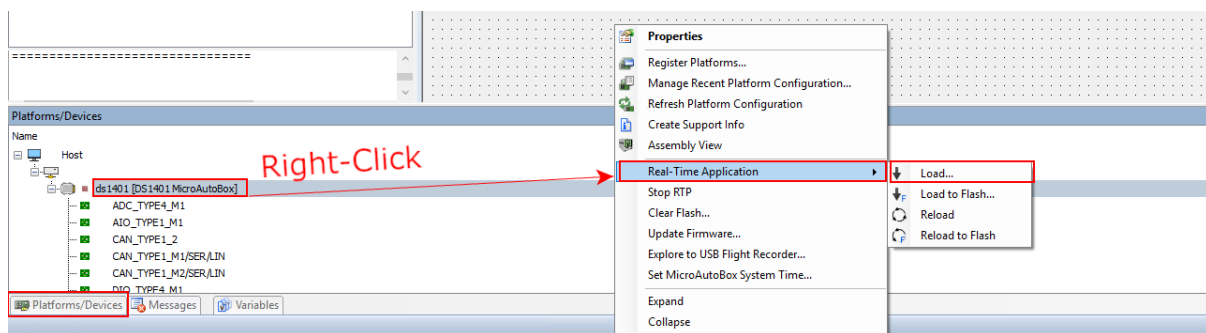


Figure 6.19: Load the application on the dSPACE MicroAutoBox II

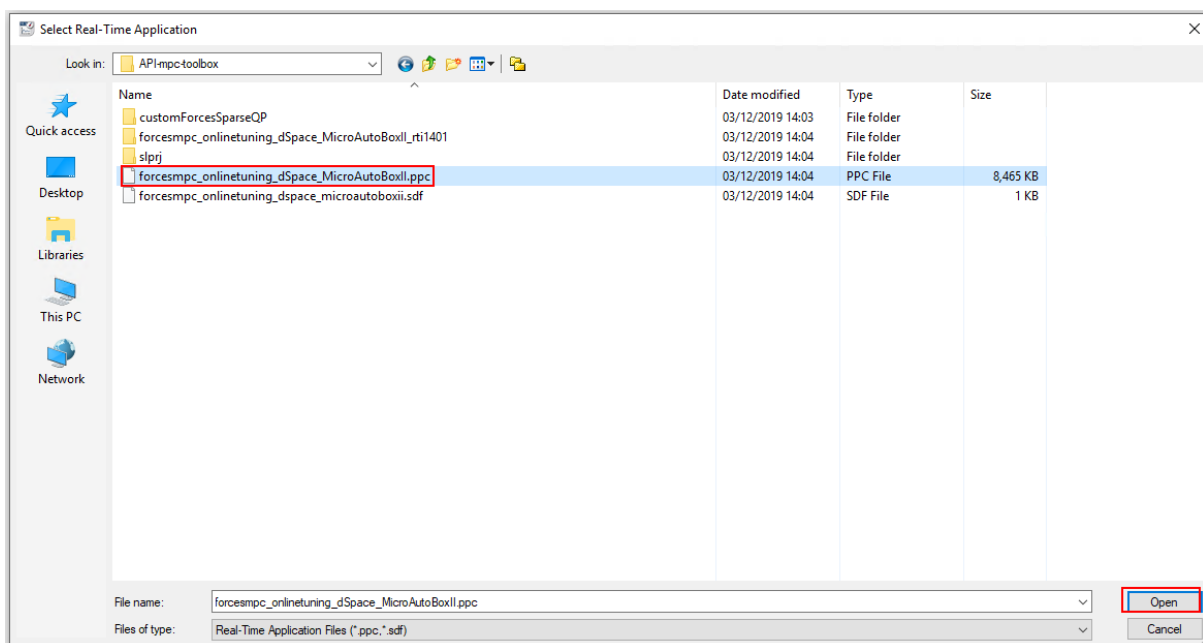


Figure 6.20: Select the executable to run the experiment

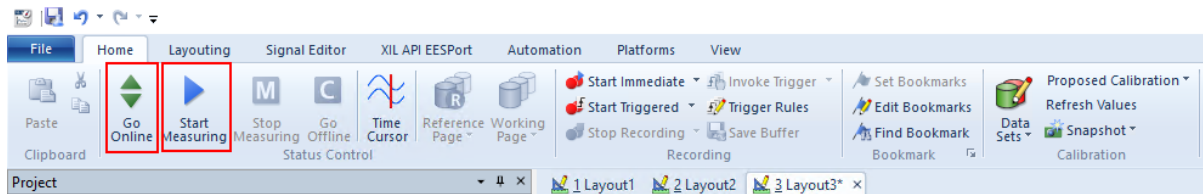


Figure 6.21: Buttons Go Online and Start Measuring to receive execution results

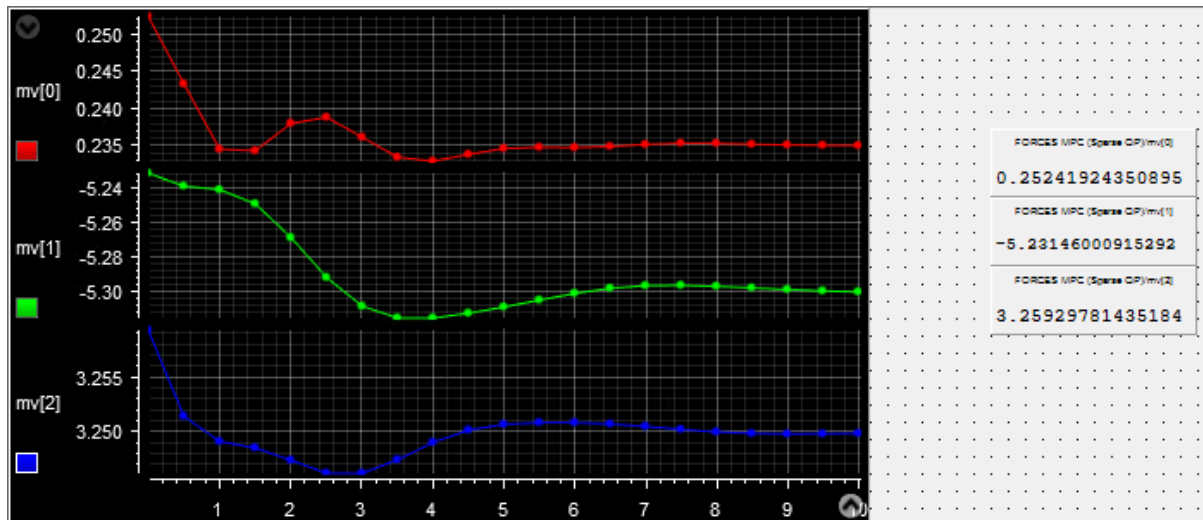


Figure 6.22: Plots and results from experiment on dSPACE MicroAutoBox II

- `forcesmpc_targets.m` is an LTI MPC example with a reference on one manipulated variables
- `forcesmpc_preview.m` is an LTI MPC example with previewing on the output reference and the measured disturbance
- `forcesmpc_motor.m` is an LTI MPC example with state and input constraints
- `forcesmpc_miso.m` is an LTI MPC example with one measured output, one manipulated variable, one measured disturbance, and one unmeasured disturbance
- `forcesmpc_simplelti.m` demonstrates a simple LTI MPC designed
- `forcesmpc_linearize.m` is an example of linear MPC around an operating point of a nonlinear system.
- `forcesmpc_customqp.m` shows how to use the FORCESPRO dense QP solver as a custom solver in an MPC object
- `forcesmpc_run_onlinetuning.m` demonstrates how to run the MPC Simulink block.
- `forcesmpc_run_onlinetuning_dSpace_MicroAutoBoxII.m` demonstrates how to generate code for dSpace MicroAutoBox II using the MPC Simulink block.

The `forcesmpc_linearize.m` example is described in more details below. First, the linearized model and the operating point are loaded from a MAT file.

```
%% Load plant model linearized at its nominal operating point (x0, u0, y0)
load('nomConditionsLinearize.mat');
```

An MPC controller object is then created with a prediction horizon of length $p = 20$, a control horizon $m = 3$ and a sampling period $T_s = 0.1$ seconds as explained [here](#).

```
%% Design MPC Controller
% Create an MPC controller object with a specified sample time |Ts|,
% prediction horizon |p|, and control horizon |m|.
Ts = 0.1;
p = 20;
m = 3;
mpcobj = mpc(plant,Ts,p,m);
```

Nominal values need to be set in the MPC object.

```
% Set the nominal values in the controller.
mpcobj.Model.Nominal = struct('X',x0,'U',u0,'Y',y0);
```

Constraints are set on the manipulated variables and an output reference signal is provided.

```
% Set the manipulated variable constraint.
mpcobj.MV.Max = 0.2;

% Specify the reference value for the output signal.
r0 = 1.5*y0;
```

From the MPC object and a structure of options, a FORCESPRO solver can be generated.

```
% Create options structure for the FORCESPRO sparse QP solver
options = mpcToForcesOptions();
% Generates the FORCESPRO QP solver
[coredata, statedata, onlinedata] = mpcToForces(mpcobj, options);
```

Once a reference signal has been constructed, the simulation can be run using `mpcmoveForces`.

```
for t = 1:Tf
    % A measurement noise is simulated
    Y(:, t) = dPlant.C * (X(:, t) - x0) + dPlant.D * (U(:, t) - u0) + y0 + 0.01 * randn;
    % Prepare inputs of mpcmoveForces
    onlinedata.signals.ref = r(t:min(t+mpcobj.PredictionHorizon-1,Tf),:);
    onlinedata.signals.ym = Y(:, t);
    % Call FORCESPRO solver
    [mv, statedata, info] = mpcmoveForces(coredata, statedata, onlinedata);
    if info.ExitFlag < 0
        warning('Internal problem in FORCESPRO solver');
    end
    U(:, t) = mv;
    X(:, t+1) = dPlant.A * (X(:, t) - x0) + dPlant.B * (U(:, t) - u0) + x0;
end
```

The resulting input and output signals are shown in Figure [Figure 6.23](#) and Figure [Figure 6.24](#) respectively.

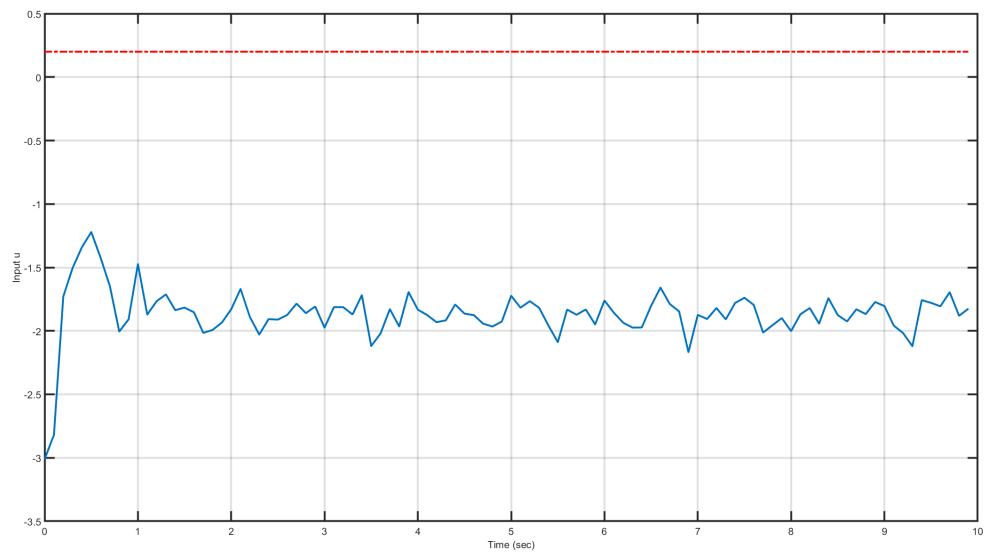


Figure 6.23: Manipulated variable computed by the FORCESPRO plugin.

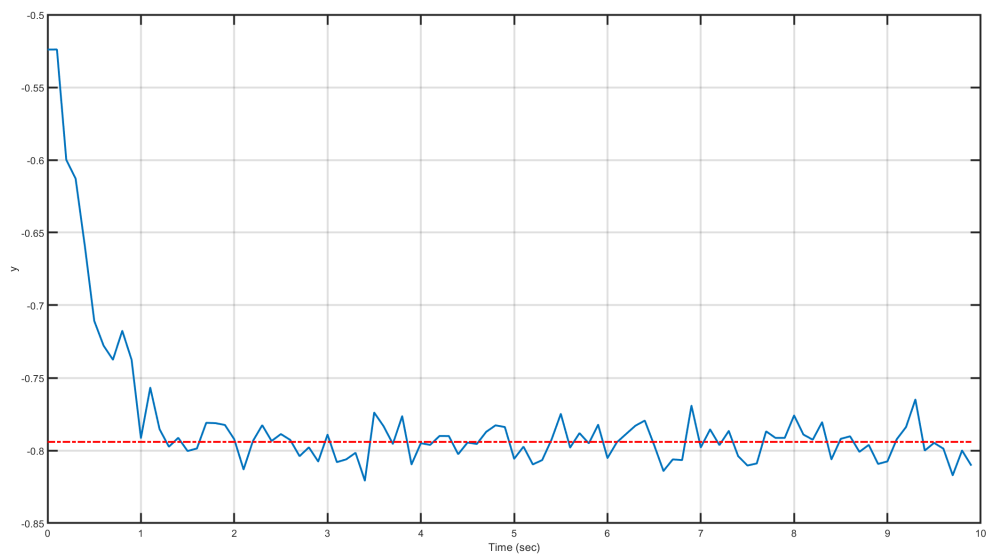


Figure 6.24: Output variable computed by the FORCESPRO plugin.

Chapter 7

MathWorks Nonlinear MPC Plugin

- *Introduction*
- *Defining a nonlinear model*
- *Generating an NLP solver*
 - *Using an “nlmpc” object*
 - *Using an “nlmpcMultistage” object*
- *Simulation in MATLAB and Simulink*
- *Code generation in MATLAB and Simulink*
- *Examples*
 - *Controlling a CSTR reactor*
 - * *Creating an NLMPC object*
 - * *Specifying solver options*
 - * *Generating the NLP solver*
 - * *Calling the solver*
 - * *Results*
 - *Lane following example*
 - * *Create an NLMPC object*
 - *Deploying the Lane Following Model on Speedgoat*
 - *Rocket landing example*
 - * *The dynamical model*
 - * *Constructing a NLMPCMultistage object*
 - * *Specifying solver options and generating a solver*
 - * *Results*

7.1 Introduction

As a result of a long-term collaboration, MathWorks Inc. and Embotech AG have extended the Model Predictive Control Toolbox™ with a plugin for the FORCESPRO nonlinear solvers. Users

are now able to use the FORCESPRO nonlinear interior-point (IP) and sequential quadratic programming (SQP) solvers in MATLAB® and Simulink® from within the MATLAB® **Model Predictive Control Toolbox** within the **nonlinear MPC API**. This plugin leverages the powerful design capabilities of the Model Predictive Control Toolbox™ and the computational performance of FORCESPRO. FORCESPRO extends the Model Predictive Control Toolbox with code-generated IP and SQP solvers that are not based on finite-difference derivatives computation, resulting in faster convergence. Thanks to FORCESPRO, the nonlinear API now comes with two classes of nonlinear solvers compatible with code generation that can be deployed to various real-time targets.

Generating a FORCESPRO solver through the Model Predictive Control Toolbox plugin is done by first generating either a *nlmpcMultistage* object (see [here](#)) or a *nlmpc* object (see [here](#)). The *nlmpcMultistage* formulation of a nonlinear MPC problem offers maximum flexibility and customizability while also ensures optimal performance. Meanwhile, the *nlmpc* formulation of a nonlinear MPC problem is very easy and requires a minimal amount of coding to get started. The different aspects of generating these different objects will be covered in details below.

Depending on the object chosen, the FORCESPRO nonlinear MPC plugin consists of two API methods:

- *nlmpc*
 - *nlmpcToForces* generates a FORCESPRO nonlinear solver from a nonlinear MPC (*nlmpc*) object designed by the Model Predictive Control Toolbox
 - *nlmpcmoveForces* calls the generated solver to calculate optimal control actions
- *nlmpcMultistage*
 - *nlmpcMultistageToForces* generates a FORCESPRO nonlinear solver from a nonlinear MPC multistage (*nlmpcMultistage*) object designed by the Model Predictive Control Toolbox
 - *nlmpcmoveForcesMultistage* calls the generated solver to calculate optimal control actions

The nonlinear plugin also comes with Simulink® libraries that enable users to run the FORCESPRO solvers from within their Simulink® models. The generation of FORCESPRO nonlinear solvers from *nlmpc* objects is supported from MATLAB R2020a while generation from *nlmpcMultistage* objects is supported from MATLAB R2021a.

This interface is provided with **Variant L** and partially with **Variant M** of FORCESPRO.

Important: Note that when generating a FORCESPRO solver using a *nlmpcMultistage* object there is the following caveat concerning declaration of model functions: For any stage cost, equality and inequality constraint function, if it is defined differently than any other stage, it must be specified in a separate MATLAB function. In other words, do not define different cost and constraint terms in a single function using a switch yard based on stage number. Instead, use different functions, one for each unique definition.

For example, do *not* use a single cost function and assign it to every stage like showed in the following code-snippet:

```
% THIS WILL NOT WORK CORRECTLY!
function cost = LaneFollowingCostFcn(stage,x,u,dmv,para)
Wx = [0; 0; 0.05; 0; 3; 0];
Wdmv = [0.1; 0.2];
ref = [0; 0; para(2); 0; 0; 0];
p = para(1)
if stage==1
cost = (Wdmv.*dmv)'*(Wdmv.*dmv);
elseif stage==(p+1)
```

(continues on next page)

(continued from previous page)

```

    cost = (Wx.*(x-ref))'*(Wx.*(x-ref));
else
    cost = (Wx.*(x-ref))'*(Wx.*(x-ref)) + (Wdmv.*dmv)'*(Wdmv.*dmv);
end

```

Instead, split it into three functions and assign them to 1, 2 to p and $p + 1$ respectively.

7.2 Defining a nonlinear model

In order to call the FORCESPRO code generation, both a `nlimpc` object as well as a `nlimpcMultistage` object need to be built from a *Model*. The process is essentially the same as the one described [here](#). However one should note that the FORCESPRO code generation ignores the jacobian functions that may be provided in *Jacobian.StateFcn* and *Jacobian.OutputFcn*, since these will be automatically generated by the automatic differentiation tool [CasADi](#). Moreover, the following requirements on the fields *Model.StateFcn* and *Model.OutputFcn* need to be fulfilled for the plugin to work seamlessly:

- they must be the name of a function file, not an anonymous functions
- they must be compatible with MATLAB code generation
- they must follow CasADi coding conventions. Most importantly, the state derivative $dxdt$ has to be built explicitly, as shown below.

```
dxdt = [expression; expression; ...]
```

As a word of caution, the following code snippet will result in an undesired behaviour from CasADi.

```

dxdt = x; % Do not write this, CasADI takes it as reference !
dxdt(1,1) = a1*x(1) + a2*x(2) + b1*u(2);
dxdt(2,1) = a3*x(1) + a4*x(2) + b2*u(2);
dxdt(3,1) = x(2)*x(1) + x(4);
dxdt(4,1) = (1/tau)*(-x(4) + u(1));
dxdt(5,1) = x(1) + x(3)*x(6);
dxdt(6,1) = x(2) - 0*x(3);

```

FORCESPRO calls the model functions from its own objects, which follow an assignment by reference convention, hence the assignment $dxdt = x$ is made by reference. This implies that updating $dxdt$ also changes x , which builds the wrong symbolic dynamics.

For `nlimpc` objects, if the model contains a parameter, it must be a single vector parameter. In other words, users need to set `nlobj.Model.NumberOfParameters = 1` and at run-time write `onlinedata.Parameter = value` where value is a column vector.

7.3 Generating an NLP solver

7.3.1 Using an “nlimpc” object

When generating a FORCESPRO solver using an `nlimpc` object, the main difference compared to the existing nonlinear MPC from The MathWorks based on the `fmincon` solver from the Optimization Toolbox is a code generation step that takes the nonlinear MPC object as argument. This is needed in order to build a mex interface for a FORCESPRO nonlinear solver that is customized to the model provided by the user.

Given an NLMPC object created by the `nlpmpc` command, users can generate an IP or SQP nonlinear solver tailored to their specific problem via the following command:

```
% nlobj is the output of nlpmpc(...)
% options is the output of nlpmpcToForcesOptions(...)

[coredata, onlinedata] = nlpmpcToForces(nlobj, options);
```

Two types of nonlinear solvers can be generated via `nlpmpcToForces`: a nonlinear interior-point solver and a sequential quadratic programming solver whose features are covered in details in *Sequential quadratic programming algorithm*.

The `nlpmpcToForces` API is described in more details in the tables below. The `nlpmpcToForces` command expects an NLMPC object **nlobj** and a structure **options** as arguments. It also has a few limitations as it currently does not support custom cost and constraints. Instead one should in this case use an `nlpmpcMultistage` object to represent custom cost and constraints. It also requires double precision.

Table 7.1: `nlpmpcToForces` arguments

Input	Description
nlobj	NMPC object constructed by Model Predictive Control Toolbox (see here)
options	Object that provides solver generation options.

The outputs of `nlpmpcToForces` consist of two structures **coredata**, a structure containing the constant NLMPC information used by `nlpmpcmoveForces` and **onlinedata**, a structure that allows you to specify online signals such as `x`, `lastMV`, `ref`, `MVTarget`, `md` as well as weights or bounds used by `nlpmpcmoveForces`.

In order to provide the solver options to `nlpmpcToForces`, the user needs to run the command `nlpmpcToForcesOptions`. The options structure contains the following fields:

- **SolverName**. This is the solver name used by MEX and C files. Its default value is `myForcesNLPsSolver`.
- **SolverType**. This option specifies which FORCESPRO nonlinear programming solver to use. Its default value is `InteriorPoint`. To use the FORCESPRO SQP algorithm set the value to `SQP`.
- **SkipSolverGeneration**. This option indicates whether `nlpmpcToForces` should generate the custom NLP solver. When true, `nlpmpcToForces` will return structures without re-generating the MEX and C files. Its default value is `false`.
- **Server**. This option specifies the FORCESPRO server address for remote solver generation. Its default value is <https://forces.embotech.com>.
- **PrintLevel**. This option specifies the amount of information displayed in the solver log.
 - 0: no output will be written
 - 1: summary line of each solve
 - 2: summary line of each iteration

Its default value is 0.

- **IntegrationMethod**. This option specifies the choice of integration scheme. I.e. the way in which the continuous dynamics are discretized. This field is only available from MATLAB R2021a onwards. The different integration schemes are
 - "IRK2": Implicit Runge Kutta method of order 2
 - "RK4": Explicit Runge Kutta method of order 4

Its default value is "IRK2".

- *IntegrationNodes*. This option specifies the the number of intermediate points between t and $t + T_s$ during numerical integration of a continuous time model. Use larger values when the plant is stiff at the price of computational efficiency. Its default value is 1. The approach used here is referred to as *direct multiple shooting*.
- *x0*. This option is used to create initial guess of optimal state trajectory at cold start. It must be a column vector of n_x -by-1. The typical value should be the initial state of the prediction model. If it is left empty, zeros will be used for cold start. Its default value is [].
- *mv0*. This option is used to create initial guess of optimal manipulated variable trajectory at cold start. It must be a column vector of n_{mv} -by-1. The typical value should be the last known control action. If it is left empty, zeros will be used for cold start.
- *Parameter*. This option should be specified if the prediction model has a parameter. It must be a column-vector and it can be updated at run-time.
- *UseMVTARGET*. This option enables/disables MV reference signal. When equal to *true*, the MV reference signal is provided via the `onlinedata` structure. When equal to *false*, the MV reference is 0 by default. In this case, MV weights should be zero to avoid unexpected behavior. Default value is *false*.
- *UseOnlineWeightOV*. This option enables/disables online OV weight change. When equal to *true*, OV weight needs to be provided via `onlinedata` structure. Its default value is *false*.
- *UseOnlineWeightMV*. This option enables/disables online MV weight change. When equal to *true*, MV weight needs to be provided via `onlinedata` structure. Its default value is *false*.
- *UseOnlineWeightMVRate*. This option enables/disables online MVRate weight change. When equal to *true*, MVRate weight needs to be provided via `onlinedata` structure. Its default value is *false*.
- *UseOnlineWeightECR*. This field enables/disables online ECR weight change. When equal to *true*, ECR weight needs to be provided via `onlinedata` structure. Its default value is *false*.
- *UseOnlineConstraintStateMax*. This option enables/disables online state upper bound change. When equal to *true*, state upper bound needs to be provided via `onlinedata` structure. Its default value is *false*.
- *UseOnlineConstraintStateMin*. This field enables/disables online state lower bound change. When equal to *true*, state lower bound needs to be provided via `onlinedata` structure. Its default value is *false*.
- *UseOnlineConstraintOVMax*. This field enables/disables online OV upper bound change. When equal to *true*, OV upper bound needs to be provided via the `onlinedata` structure. Its default value is *false*.
- *UseOnlineConstraintOVMin*. This option enables/disables online OV lower bound change. When equal to *true*, OV lower bound needs to be provided via the `onlinedata` structure. Its default value is *false*.
- *UseOnlineConstraintMVMax*. This field enables/disables online MV upper bound change. When equal to *true*, MV upper bound needs to be provided via the `onlinedata` structure. Its default value is *false*.
- *UseOnlineConstraintMVMin*. This field enables/disables online MV lower bound change. When equal to *true*, MV lower bound needs to be provided via the `onlinedata` structure. Its default value is *false*.
- *UseOnlineConstraintMVRateMax*. This option enables/disables online MVRate upper bound change. When equal to *true*, MVRate upper bound needs to be provided via the `onlinedata` structure. Its default value is *false*.

- *UseOnlineConstraintMVRateMin*. This option enables/disables online MVRate lower bound change. When equal to *true*, MVRate lower bound needs to be provided via the *onlinedata* structure. Its default value is *false*.

The following set of options are specific to the nonlinear interior point solver:

- *IP_MaxIteration*. This field specifies the maximum number of iterations in the interior point solver. When the maximum number of iterations is reached (i.e. ExitFlag is 0), the NLP solver aborts calculations and the result should be discarded. Default value is 200.
- *IP_Mu0*. This field specifies initial barrier parameter. It must be positive and its default value is 0.1.
- *IP_BarrierStrategy*. This option specifies the strategy used to update the barrier parameter at every iteration of the nonlinear interior point solver. It needs to be either *monotone* or *logo*. *logo* often leads to faster convergence, while *monotone* may help convergence for difficult problems. Default value is *logo*.
- *IP_LinearSolver*. This option sets the linear solver. It must be either *normal_eqs*, *symm_indefinite*, *symm_indefinite_fast* or *symm_indefinite_legacy*. With *normal_eqs*, the KKT system is solved in normal equations form. With *symm_indefinite*, the KKT system is solved with an improved variant of '*symm_indefinite_legacy*' introduced in FORCESPRO version 5.0.0. With *symm_indefinite_legacy*, the KKT system is solved using block-indefinite factorizations. With *symm_indefinite_fast*, the KKT system is solved in symmetric indefinite form, using regularization and positive definite Cholesky factorizations only. Default value is *normal_eqs*.
- *IP_EqualityTolerance*. This option specifies the tolerance on the nonlinear equality constraints used by the nonlinear interior point solver. It must be positive. Default value is 10^{-6} .
- *IP_InequalityTolerance*. This field specifies the tolerance on the nonlinear inequality constraints used by the interior-point solver. It needs to be positive and its default value is 10^{-6} .
- *IP_StationarityTolerance*. This option specifies the tolerance on the stationarity measure used in the nonlinear interior point solver. It needs to be positive and its default value is 10^{-5} .

The following set of options are specific to the sequential quadratic programming solver:

- *SQP_MaxIteration*. This field specifies the maximum number of iterations used by the inner QP solver. Its default value is 50.
- *SQP_MaxQPS*. This enables the SQP solver to solve a fixed amount of quadratic approximations at every call to the solver. In general, the more quadratic approximations are solved, the more accurate control performance is achieved. The tradeoff is that the solve time also increases. The default value is 1.
- *SQP_RegHessian*. This field stands for the level of regularization of the hessian approximation. Increasing this parameter may help if the SQP solver returns exitflag -8 on your problem. The default value is $5 \cdot 10^{-9}$.
- *SQP_EqualityTolerance*. This option specifies the tolerance on the nonlinear equality constraints. It must be positive and its default value is 10^{-6} .
- *SQP_InequalityTolerance*. This option specifies the tolerance on the linear inequality constraints. It must be positive and its default value is 10^{-6} .
- *SQP_StationarityTolerance*. This field specifies the tolerance on stationarity. It must be positive and its default value is 10^{-5} .

7.3.2 Using an “nlmpcMultistage” object

When generating a FORCESPRO solver using an `nlmpcMultistage` object, the main difference compared to the existing nonlinear MPC from The MathWorks based on the `fmincon` solver from the Optimization Toolbox is a code generation step that takes the nonlinear MPC object as argument. This is needed in order to build a mex interface for a FORCESPRO nonlinear solver that is customized to the model provided by the user.

Given an `nlmpcMultistage` object, users can generate an IP nonlinear solver tailored to their specific problem via the following command:

```
% nlmul is the output of nlmpcMultistage(...)
% options is the output of nlmpcMultistageToForcesOptions(...)

[coredata, onlinedata] = nlmpcMultistageToForces(nlmul, options);
```

The `nlmpcMultistageToForces` API allows the user to customize the generated solver to a much higher extend than that of the `nlmpc` object. In particular it supports a different cost function associated with each stage, with the restriction that each cost function can only depend on the optimization variables of a single stage.

The `nlmpcMultistageToForces` API is described in more details in the tables below. The `nlmpcMultistageToForces` command expects an `nlmpcMultistage` object **nlmul** and a structure **options** as arguments.

Table 7.2: `nlmpcMultistageToForces` arguments

Input	Description
nlmul	<code>nlmpcMultistage</code> object constructed by Model Predictive Control Toolbox (see here)
options	Object that provides solver generation options.

The outputs of `nlmpcMultistageToForces` consist of two structures **coredata**, a structure containing the constant NLMPCMultistage information used by `nlmpcmoveForcesMultistage` and **onlinedata**, a structure that allows you to specify online signals such as `x`, `lastMV`, `ref`, `MVTarget`, `md` as well as weights or bounds used by `nlmpcmoveForces`.

In order to provide the solver options to `nlmpcmoveForcesMultistage`, the user needs to run the command `nlmpcMultistageToForcesOptions`. The options structure contains the following fields:

- **SolverName**. This is the solver name used by MEX and C files. Its default value is `myForcesNLPSolver`.
- **SolverType**. This option specifies which FORCESPRO nonlinear programming solver to use. Currently the only options is `InteriorPoint`.
- **SkipSolverGeneration**. This option indicates whether `nlmpcToForces` should generate the custom NLP solver. When true, `nlmpcMultistageToForces` will return structures without regenerating the MEX and C files. Its default value is `false`.
- **Server**. This option specifies the FORCESPRO server address for remote solver generation. Its default value is <https://forces.embotech.com>.
- **PrintLevel**. This option specifies the amount of information displayed in the solver log.
 - 0: no output will be written
 - 1: summary line of each solve
 - 2: summary line of each iteration

Its default value is 0.

- *IntegrationMethod*. This option specifies the choice of integration scheme. I.e. the way in which the continuous dynamics are discretized. This field is only available from MATLAB R2021a onwards. The different integration schemes are
 - "IRK2": Implicit Runge Kutta method of order 2
 - "RK4": Explicit Runge Kutta method of order 4
- *IntegrationNodes*. This option specifies the the number of intermediate points between t and $t + T_s$ during numerical integration of a continuous time model. Use larger values when the plant is stiff at the price of computational efficiency. Its default value is 1. The approach used here is referred to as *direct multiple shooting*.
- *x0*. This option is used to create initial guess of optimal state trajectory at cold start. It must be a column vector of n_x -by-1. The typical value should be the initial state of the prediction model. If it is left empty, zeros will be used for cold start. Its default value is [].
- *mv0*. This option is used to create initial guess of optimal manipulated variable trajectory at cold start. It must be a column vector of n_{mv} -by-1. The typical value should be the last known control action. If it is left empty, zeros will be used for cold start.
- *NumInequalityConstraints*. Must be a $(p + 1)$ -by-1 vector where each entry specifies the number of inequality constraints generated by the `IneqConFcn` at that stage. Leave it [] if no `IneqConFcn` is defined in the `nlmpcMultistage` object.
- *NumEqualityConstraints*. Must be a p -by-1 vector where each entry specifies the number of equality constraints generated by the `EqConFcn` at that stage. Leave it [] if no `EqConFcn` is defined in the `nlmpcMultistage` object.
- *UseOnlineConstraintStateMax*. This option enables/disables online state upper bound change. When equal to *true*, state upper bound needs to be provided via `onlinedata` structure. Its default value is *false*.
- *UseOnlineConstraintStateMin*. This field enables/disables online state lower bound change. When equal to *true*, state lower bound needs to be provided via `onlinedata` structure. Its default value is *false*.
- *UseOnlineConstraintMVMax*. This field enables/disables online MV upper bound change. When equal to *true*, MV upper bound needs to be provided via the `onlinedata` structure. Its default value is *false*.
- *UseOnlineConstraintMVMin*. This field enables/disables online MV lower bound change. When equal to *true*, MV lower bound needs to be provided via the `onlinedata` structure. Its default value is *false*.
- *UseOnlineConstraintMVRateMax*. This option enables/disables online MVRate upper bound change. When equal to *true*, MVRate upper bound needs to be provided via the `onlinedata` structure. Its default value is *false*.
- *UseOnlineConstraintMVRateMin*. This option enables/disables online MVRate lower bound change. When equal to *true*, MVRate lower bound needs to be provided via the `onlinedata` structure. Its default value is *false*.
- *UseOnlineTerminalState*. This option enables/disables online terminal state condition. When equal to *true*, terminal state values need to be provided via the `onlinedata` structure. Its default value is *false*.

The following set of options are specific to the nonlinear interior point solver:

- *IP_MaxIteration*. This field specifies the maximum number of iterations in the interior point solver. When the maximum number of iterations is reached (i.e. `ExitFlag` is 0), the NLP solver aborts calculations and the result should be discarded. Default value is 200.
- *IP_Mu0*. This field specifies initial barrier parameter. It must be positive and its default value is 0.1.

- *IP_BarrierStrategy*. This option specifies the strategy used to update the barrier parameter at every iteration of the nonlinear interior point solver. It needs to be either *monotone* or *loqo*. *loqo* often leads to faster convergence, while *monotone* may help convergence for difficult problems. Default value is *loqo*.
- *IP_LinearSolver*. This option sets the linear solver. It must be either *normal_eqs*, *symm_indefinite*, *symm_indefinite_fast* or *symm_indefinite_legacy*. With *normal_eqs*, the KKT system is solved in normal equations form. With *symm_indefinite*, the KKT system is solved with an improved variant of '*symm_indefinite_legacy*' introduced in FORCESPRO version 5.0.0. With *symm_indefinite_legacy*, the KKT system is solved using block-indefinite factorizations. With *symm_indefinite_fast*, the KKT system is solved in symmetric indefinite form, using regularization and positive definite Cholesky factorizations only. Default value is *normal_eqs*.
- *IP_EqualityTolerance*. This option specifies the tolerance on the nonlinear equality constraints used by the nonlinear interior point solver. It must be positive. Default value is 10^{-6} .
- *IP_InequalityTolerance*. This field specifies the tolerance on the nonlinear inequality constraints used by the interior-point solver. It needs to be positive and its default value is 10^{-6} .
- *IP_StationarityTolerance*. This option specifies the tolerance on the stationarity measure used in the nonlinear interior point solver. It needs to be positive and its default value is 10^{-5} .

7.4 Simulation in MATLAB and Simulink

Once a FORCESPRO nonlinear solver has been generated by calling either `nlpmpcToForces` or `nlpmpcMultistageToForces`, optimal control moves can be calculated in MATLAB by using either `nlpmpcmoveForces` or `nlpmpcmoveForcesMultistage` depending on the case. This API method expects a **coredata** structure as returned by `nlpmpcToForces` or `nlpmpcMultistageToForces` as well as the other inputs described in Table below.

Table 7.3: *nlpmpcmoveForces* and *nlpmpcMultistageToForces* arguments

Input	Description
coredata	A structure containing the constant controller settings. It is generated by the <code>nlpmpcToForces</code> method and used as a constant
x	A n_x -by-1 column vector, representing the current prediction model states
lastMV	A nmv -by-1 column vector, representing the control action applied to the plant at the previous control interval
onlinedata	A structure containing run time signals

The outputs of `nlpmpcmoveForces` and `nlpmpcMultistageToForces` are described in the table below.

Table 7.4: *nlpmpcmoveForces* and *nlpmpcMultistageToForces* outputs

Output	Description
mv	Optimal control moves computed by a FORCESPRO solver
onlinedata	A structure prepared for the next control, containing e.g. the initial guess.
info	A structure containing extra information about the solver run

7.5 Code generation in MATLAB and Simulink

The `nlmpcmoveForces` and `nlmpcmoveForcesMultistage` commands can be turned into a MEX interface named `nlmpcmove_<solvername>` by means of the `SkipSolverGeneration`. If the option is set to `true`, then no MEX interface is built by the MATLAB Coder. If it is set to `false`, then the `nlmpcmove` MEX interface is generated and compiled, which requires the MATLAB Coder.

7.6 Examples

Here we present the following examples to illustrate the workflow of the FORCESPRO plugin for the MPC Toolbox:

- Example [Controlling a CSTR reactor](#) illustrates how to generate a FORCESPRO solver from an NLMPC object directly in MATLAB®.
- Example [Lane following example](#) illustrates how to generate a FORCESPRO solver from an NLMPC object and run it based on the `nlmpc` Simulink block.
- Example [Rocket landing example](#) illustrates how to generate a FORCESPRO solver from an NLMPCMultistage object.

7.6.1 Controlling a CSTR reactor

In this example we create a nonlinear MPC controller for a CSTR reactor using the MathWorks Nonlinear MPC Plugin. The objective is to control the concentration CA of reagent A .

You can find the code of this example to try it out for yourself in the `examples/matlab/mpc-toolbox-plugin/nonlinearModels/nlmpc_cstr` folder that comes with your FORCESPRO client.

Click [here](#) for a detailed description of the model. The state of our plant will be denoted by x , while our control input will be denoted by u .

x_1 : Reactor temperature (K)

x_2 : Concentration of A in reactor tank $\left(\frac{kgmol}{m^3}\right)$

u_1 : Jacket coolant temperature (K)

u_2 : Concentration of A in inlet feed stream $\left(\frac{kgmol}{m^3}\right)$

u_3 : Inlet feed stream temperature (K)

The system dynamics are given by the following first order differential equation

$$\begin{aligned}\dot{x}_1 &= (u_3 - x_1) + 0.3 \cdot (u_1 - x_1) + 11.92 \cdot 27944640 \cdot \exp\left(\frac{-5894.14}{x_1}\right) \cdot u_2 \\ \dot{x}_2 &= (u_2 - x_2) - 27944640 \cdot \exp\left(\frac{-5894.14}{x_1}\right) \cdot u_2\end{aligned}$$

For the purpose of this demonstration the MATLAB function describing the state dynamics will be denoted by `exocstrStateFcnCT`. Our output y is simply given by the concentration of A :

$$y = x_2$$

Creating an NLMPC object

The MATLAB function implementing this output will be denoted by *exocstrOutputFcn*. With the implemented *exocstrStateFcnCT* and *exocstrOutputFcn* MATLAB functions at hand we can go ahead create our NLMPC object. The following code-snippet constructs the NLMPC object and specifies our model.

```
nx = 2;
ny = 1;
nu = 3;
nlobj = nlmpc(nx,ny,'MV',1,'MD',[2 3]);
Ts = 0.5;
nlobj.Ts = Ts;
nlobj.PredictionHorizon = 6;
nlobj.ControlHorizon = [2 2 2];
nlobj.MV.RateMin = -5;
nlobj.MV.RateMax = 5;
nlobj.Model.StateFcn = 'exocstrStateFcnCT';
nlobj.Model.OutputFcn = 'exocstrOutputFcn';
```

Specifying solver options

The following specifies the code options specific to FORCESPRO's MathWorks Nonlinear MPC Plugin:

```
options = nlmpcToForcesOptions();
options.SolverName = 'CstrSolver';
options.SolverType = 'SQP';
options.IntegrationNodes = 5;
options.SQP_MaxQPS = 5;
options.SQP_MaxIteration = 500;
options.x0 = [311.2639; 8.5698];
options.mv0 = 298.15;
```

Generating the NLP solver

Once we have our NLMPC object and our options we can generate an NLP solver through the *nlmpcToForces* function:

```
[coredata, onlinedata] = nlmpcToForces(nlobj,options);
```

Calling the solver

This will generate our NLP solver named *CstrSolver*. We can call this solver in two different ways:

- Through the generic *nlmpcmoveForces* function which comes with the FORCESPRO MathWorks Nonlinear MPC Plugin
- Or through the generated MEX function *nlmpcmove_CstrSolver* (the name of the MEX is always "nlmpc_<solver name>"). In general it is advantageous from a performance perspective to use the MEX over the generic *nlmpcmoveForces* function.

Calling the NLP solver through the generic *nlmpcmoveToForces* can be done as in the following code-snippet:

```
onlinedata.md = [10 298.15];  
[mv, onlinedata, info] = nlmpcmoveForces(coredata,x,mv,onlinedata);
```

And the MEX can be called as follows:

```
[mv, onlinedata, info] = nlmpcmove_CstrSolver(x,mv,onlinedata);
```

Results

The NLP solver generated through the above code-snippets were applied in a simulation for 200 seconds. As can be seen in the plots [Figure 7.1](#), [Figure 7.2](#) and [Figure 7.3](#) the generated solver succeeds in controlling the CSTR reactor with a very fast solvetime while the output stays close to the reference.

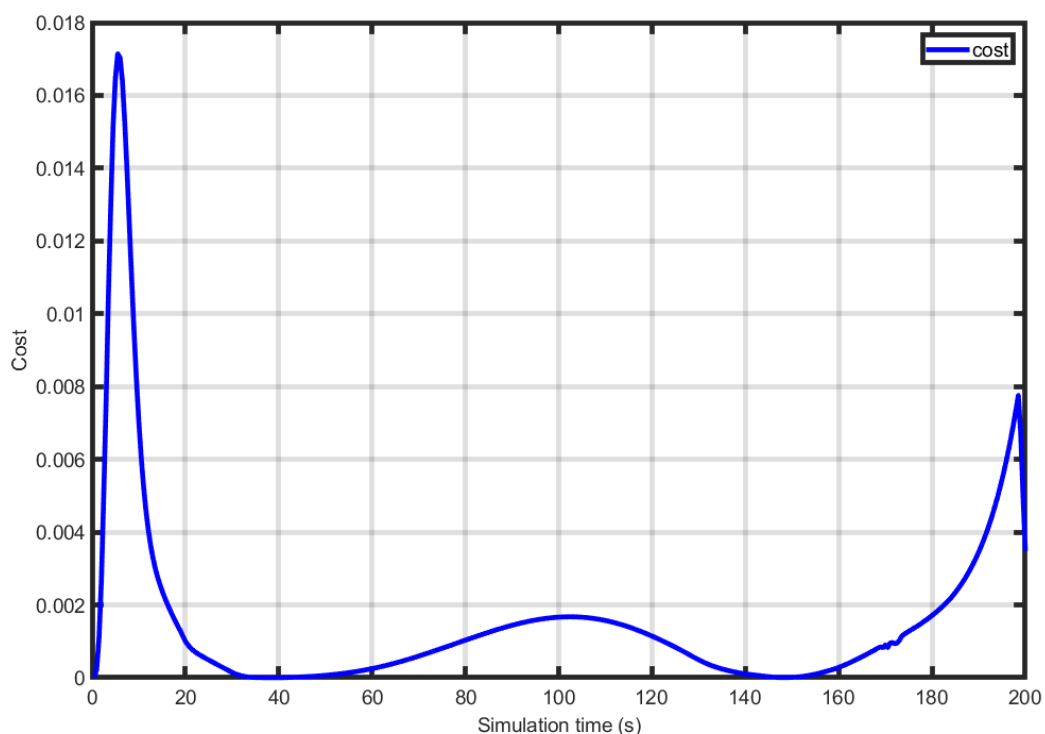


Figure 7.1: Cost as a function of time.

7.6.2 Lane following example

In this example, the use of the nlmpc plugin in Simulink is described. The example consists in making a vehicle follow a central line while keeping a user-specified velocity.

You can find the code of this example to try it out for yourself in the `examples/matlab/mpc-toolbox-plugin/nonlinearModels/lane_following` folder that comes with your FORCESPRO client.

Create an NLMP object

An nlmpc object with measured and unmeasured disturbance is first created.

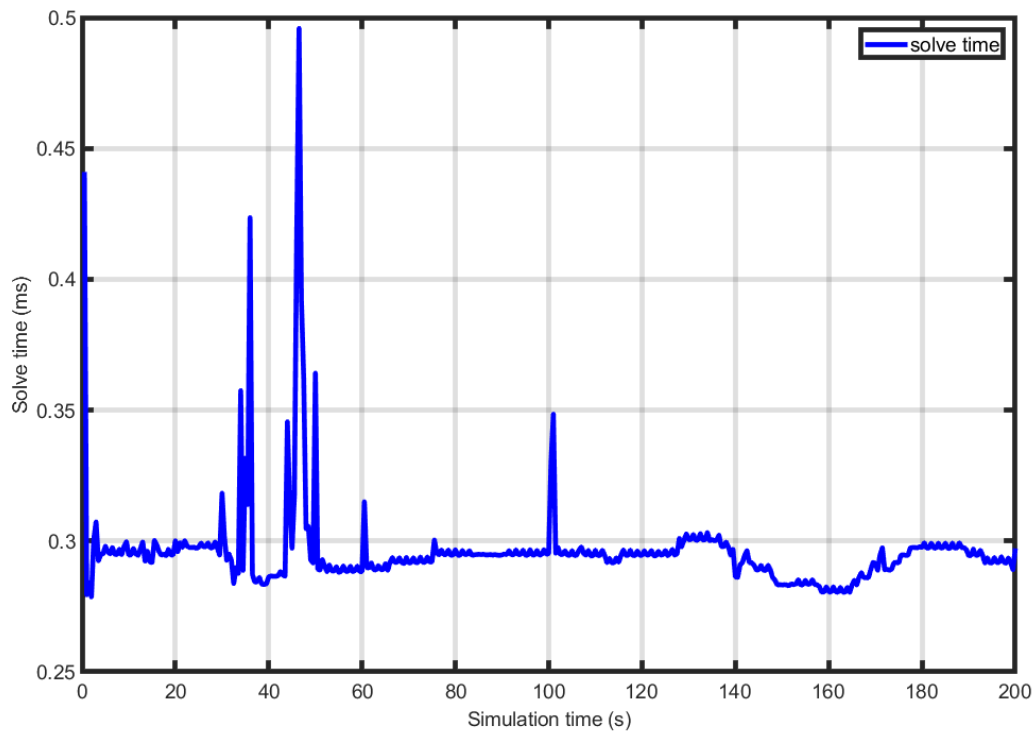


Figure 7.2: Solve time as a function of simulation time.

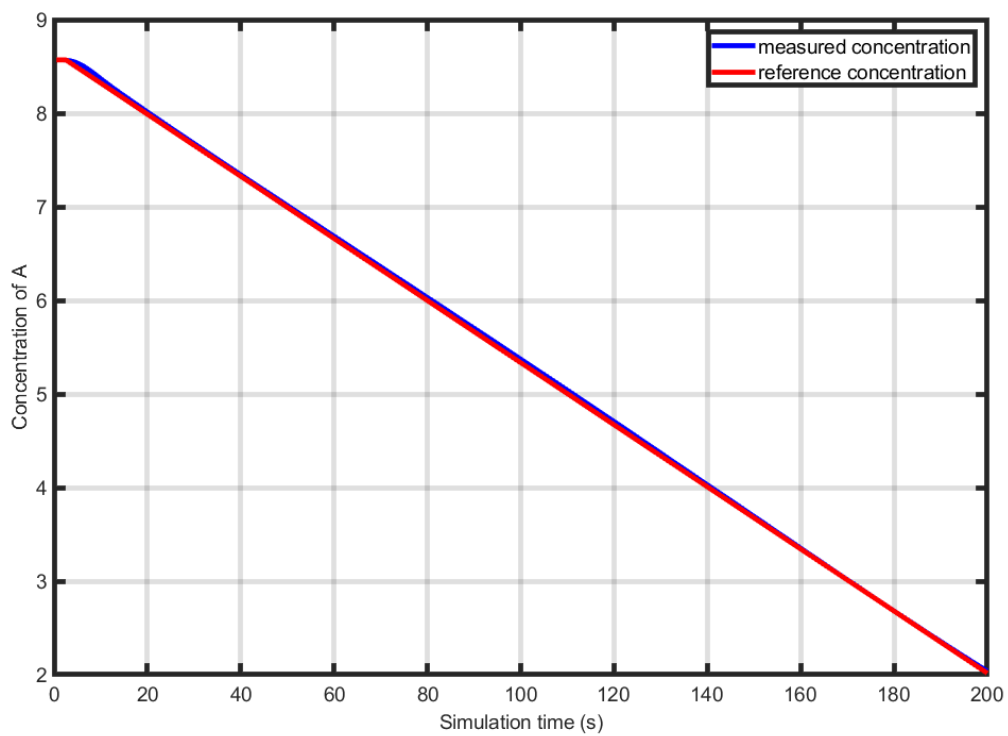


Figure 7.3: Concentration of A as a function of simulation time.

```
nlobj = nlmpc(7,3,'MV',[1 2],'MD',3,'UD',4);
```

The NMPC controller sample time, prediction horizon and control horizon are then specified.

```
nlobj.Ts = Ts;
nlobj.PredictionHorizon = 10;
nlobj.ControlHorizon = 2;
```

The dynamics are provided as a function name.

```
nlobj.Model.StateFcn = 'LaneFollowingStateFcn';
```

The output variables returned by *LaneFollowingOutputFcn* are the longitudinal velocity, the lateral deviation and the sum of the yaw angle and yaw angle output disturbance

```
nlobj.Model.OutputFcn = 'LaneFollowingOutputFcn';
```

Bound constraints are set on the manipulated (input) variables.

```
nlobj.MV(1).Min = -3;      % Maximum acceleration 3 m/s^2
nlobj.MV(1).Max = 3;      % Minimum acceleration -3 m/s^2
nlobj.MV(2).Min = -1.13;  % Minimum steering angle -65
nlobj.MV(2).Max = 1.13;   % Maximum steering angle 65
```

Scaling factors are incorporated on output and manipulated variables to optimize solver performance.

```
nlobj.OV(1).ScaleFactor = 15; % Typical value of longitudinal velocity
nlobj.OV(2).ScaleFactor = 0.5; % Range for lateral deviation
nlobj.OV(3).ScaleFactor = 0.5; % Range for relative yaw angle
nlobj.MV(1).ScaleFactor = 6;   % Range of steering angle
nlobj.MV(2).ScaleFactor = 2.26; % Range of acceleration
nlobj.MD(1).ScaleFactor = 0.2; % Range of Curvature
```

Weights on outputs and the rates of manipulated variables are set in the NLMPC object objective function.

```
nlobj.Weights.OutputVariables = [1 1 0];

%%
% Penalize acceleration change more for smooth driving experience.
nlobj.Weights.ManipulatedVariablesRate = [0.3 0.1];
```

A nonlinear interior-point FORCESPRO solver is generated from a customizable options structure.

```
options = nlmpcToForcesOptions();
% Set solver name
options.SolverName = 'LaneFollowSolver';
% Choose solver type 'InteriorPoint' or 'SQP'
options.SolverType = 'InteriorPoint';
% x0 and u0 are used to create a primal initial guess
options.x0 = x0;
options.mv0 = u0;
tm = tic;
[coredata, onlinedata] = nlmpcToForces(nlobj,options);
tBuild = toc(tm);
```

The FORCESPRO NLMPC Simulink block can then be used seamlessly. It is available in the Simulink Library Browser in the *Model Predictive Control Toolbox* section, as shown in [Figure 7.4](#).

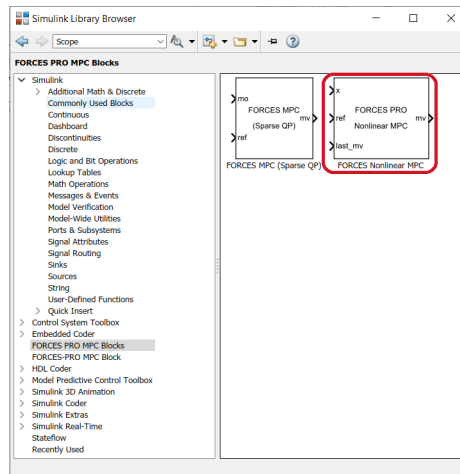


Figure 7.4: FORCESPRO NMPC block.

In order to run the nonlinear interior-point solver, the *coredata* structure returned by *nlmpcToForces* must be provided in the block mask, as shown in Figure 7.5.

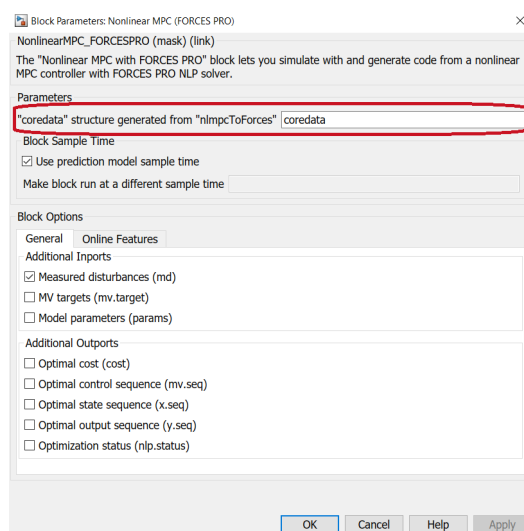


Figure 7.5: FORCESPRO NMPC block mask.

The Simulink model can finally be run using the *sim* command.

```
sim('LaneFollowingNMPC')
```

Results are shown in Figures 7.6 and 7.7.

Simulink Coder (R) enables users to generate an executable from the FORCESPRO NLMPC block, so that it can be deployed for real-time applications.

7.6.3 Deploying the Lane Following Model on Speedgoat

The lane following model in Figure 7.8 can be easily deployed on Speedgoat platforms by means of the code below.

```
% Choose Speedgoat x86 platform to run FORCESPRO solver
options.ForceTargetPlatform = 'Speedgoat-x86';
```

(continues on next page)

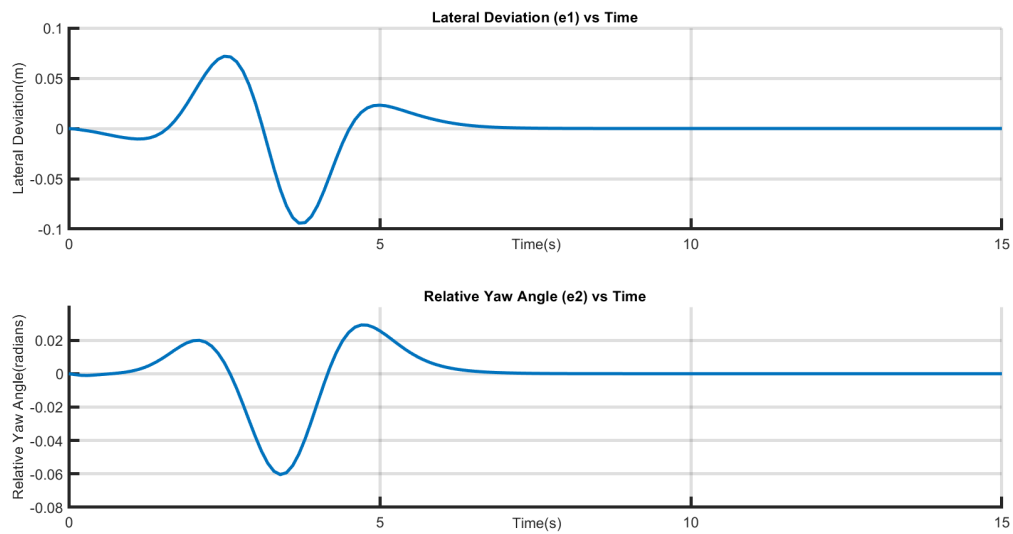


Figure 7.6: Vehicle lateral deviation.

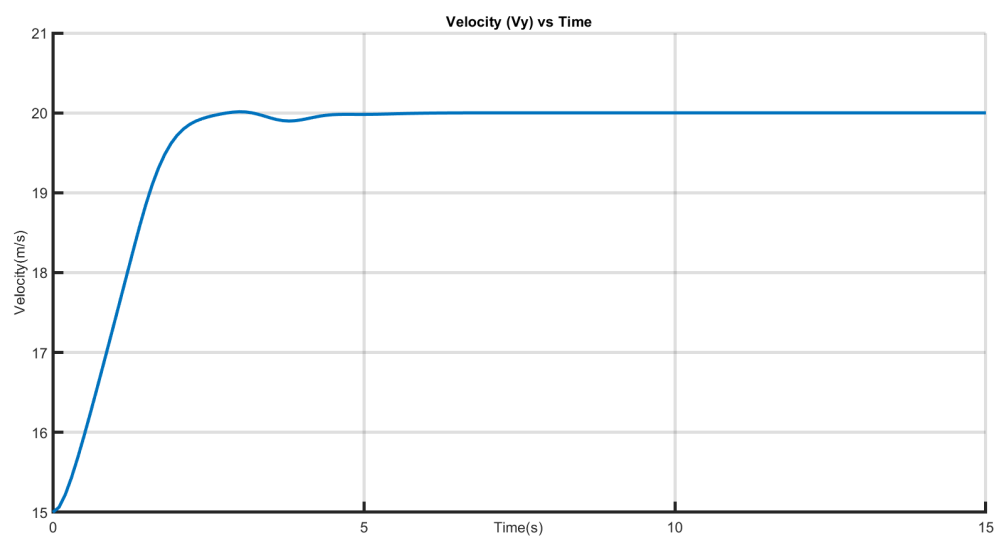


Figure 7.7: Vehicle velocity.

(continued from previous page)

```

% x0 and u0 are used to create a primal initial guess
options.x0 = x0;
options.mv0 = u0;
% Generate FORCESPRO solver
tm = tic;
[coredata, onlinedata] = nlmpcToForces(nlobj,options);
tBuild = toc(tm);

%%
% Start code generation for Speedgoat x86
mdl = 'LaneFollowingNMPC_Speedgoat_x86';
open_system(mdl);                                % Open Simulink(R) Model
load_system(mdl);                                % Load Simulink(R) Model
rtwbuild(mdl);                                    % Start Code Generation

% Deploy application from the start
tg = slrt;
if(~strcmpi(tg.Application, 'loader'))
    tg.unload();
end
tg.load(mdl);

% Execute application
tg.start();
while(strcmpi(tg.Status, 'running'))
    pause(Ts);
end
scope1 = tg.getscope(1);
scope2 = tg.getscope(2);
scope3 = tg.getscope(3);

```

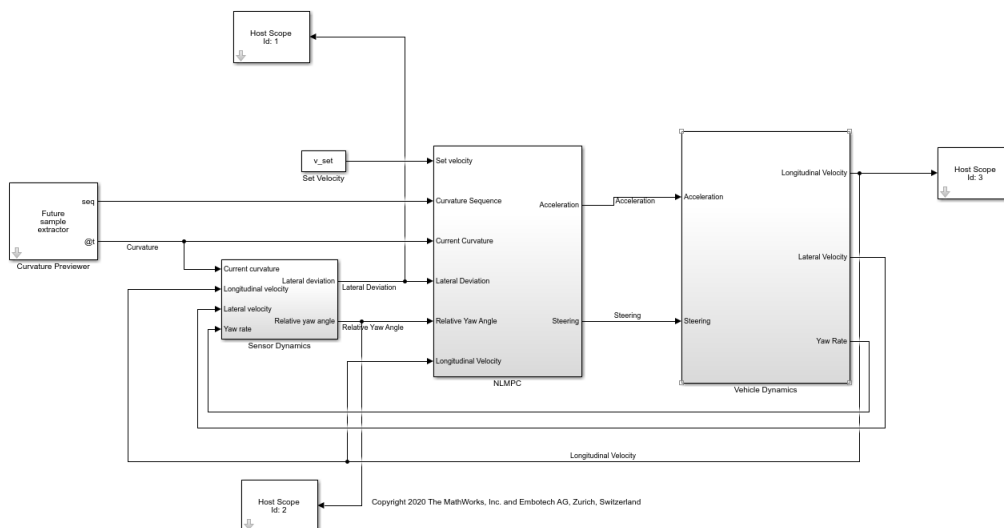


Figure 7.8: Simulink Real-Time Lane Following model for Speedgoat deployment.

All the files necessary to run this example can be downloaded [here](#).

7.6.4 Rocket landing example

In this example we consider the motion planning problem of landing a rocket safely. The FORCESPRO solver is generated using a NLMPCCMultistage object. We will cover the details of the model below. For further details, see [here](#).

You can find the code of this example to try it out for yourself in the `examples/matlab/mpc-toolbox-plugin/nonlinearModels/rocket_planner` folder that comes with your FORCESPRO client.

The dynamical model

The model we consider is a first-principles non-linear dynamical model. The state x of our system is 6-dimensional while the control u is 2-dimensional. The interpretation of the different states/control inputs is given as follows:

- u_1 : Left thrust (N)
- u_2 : Right thrust (N)
- x_1 : Horizontal position of the center of gravity (m)
- x_2 : Vertical position of the center of gravity (m)
- x_3 : Tilt with respect to the center of gravity (r)
- $x_4 = \frac{dx_1}{dt}$ ($\frac{m}{s}$)
- $x_5 = \frac{dx_2}{dt}$ ($\frac{m}{s}$)
- $x_6 =$ Angular velocity ($\frac{r}{s}$)

The differential equation governing the dynamics is given by

$$\begin{aligned}\dot{x}_1 &= x_4 \\ \dot{x}_2 &= x_5 \\ \dot{x}_3 &= x_6 \\ \dot{x}_4 &= \frac{-\sin(x_3)(u_1 + u_2)}{m} \\ \dot{x}_5 &= \frac{\cos(x_3)(u_2 - u_1)}{m} - g \\ \dot{x}_6 &= \frac{2L_2(u_2 - u_1)}{mL_1^2},\end{aligned}$$

where we use of the following constants:

Name	Value	Description
L_1	$10m$	Center of gravity to top/bottom end
L_2	$5m$	Center of gravity to left/right end
m	$1kg$	Mass of rocket
g	$9.806\frac{m}{s^2}$	Gravitational constant

Constructing a NLMPCMultistage object

The first step to generate a FORCESPRO solver is to construct a `nlmpcMultistage` object and set the constraints on our manipulated variables (*MV*) and states (*State*).

```
% Construct nlmpcMultistage object and set dynamics
Ts = 0.2;
pPlanner = 50;
planner = nlmpcMultistage(pPlanner, 6, 2);
planner.Ts = Ts;

% Limit thrusts between 0 and 8 Newton
planner.MV(1).Min = 0;
planner.MV(1).Max = 8;
```

(continues on next page)

(continued from previous page)

```
planner.MV(2).Min = 0;
planner.MV(2).Max = 8;

% Specify lower bound on y-axis to avoid crashing
planner.States(2).Min = 10;
```

Then we specify the state transition function along with a cost function for every stage. Note that these functions are specified via the of the function.

```
planner.Model.StateFcn = 'RocketStateFcn';
for ct=1:pPlanner
    planner.Stages(ct).CostFcn = 'RocketPlannerCostFcn';
end
```

Specifying solver options and generating a solver

Once we have defined our `nlmpcMultistage` object *planner* we need to specify information about the solver we would like to generate. This can be done through the options generated by *nlmpcMultistageToForcesOptions*

```
%% Generate FORCES NLP Solver
options = nlmpcMultistageToForcesOptions;
options.Server = 'https://forces.embotech.com/';
options.x0 = x0;
options.mv0 = u0;
options.UseOnlineConstraintMVMin = true;
options.UseOnlineConstraintMVMax = true;
options.UseOnlineConstraintStateMin = true;
```

With both our *options* and *nlmpcMultistage* object at hand we can go ahead and generate the FORCESPRO solver:

```
[coredata, onlinedata, model] = nlmpcMultistageToForces(planner, options);
```

Results

In plot [Figure 7.9](#) the optimal trajectory for landing the rocket is displayed. As can be observed in the generated animation which appears when running the code (see [Figure 7.10](#)), the FORCESPRO solver manages to control the rocket and land it safely.

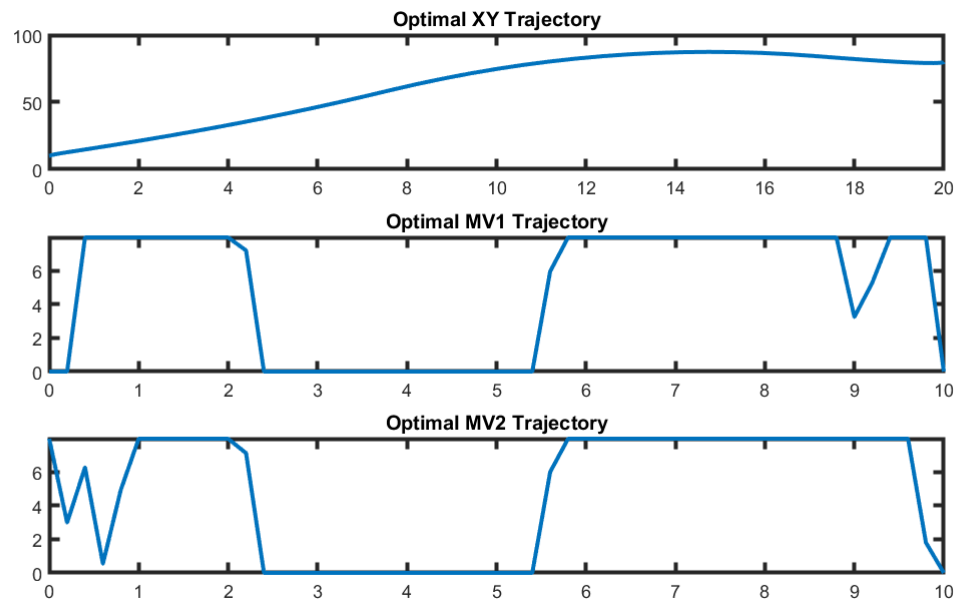


Figure 7.9: Optimal rocket trajectory.

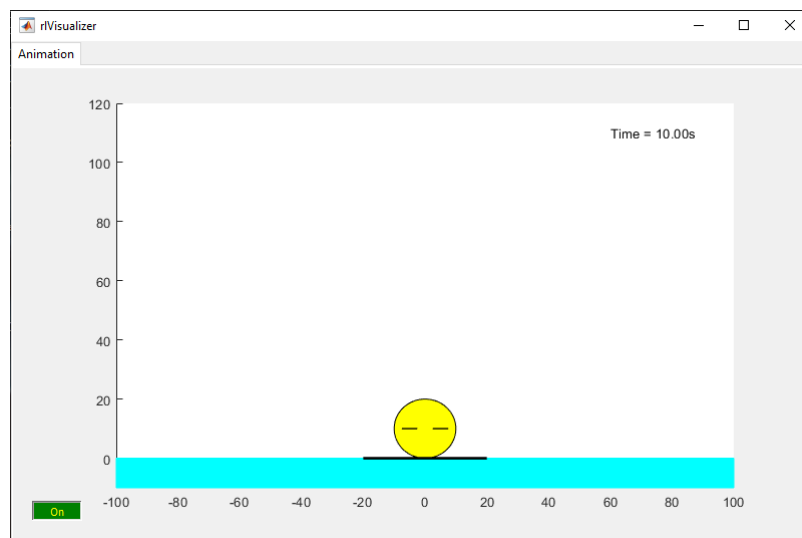


Figure 7.10: Rocket lander animation generated when running the rocket lander example.

Chapter 8

Low-level interface

- *Supported problem class*
- *Multistage struct*
- *Dimensions*
- *Cost function*
- *Equality constraints*
- *Lower and upper bounds*
- *Polytopic constraints*
- *Quadratic constraints*
 - *Example*
- *Binary constraints*
- *Declaring parameters*
- *Declaring Solver Outputs*
 - *Example*
- *Dumping and Loading Models*
- *Generating the solver*
- *Calling the generated low-level solver*

FORCESPRO supports designing solvers and controllers via MATLAB and Python scripts. When using the MATLAB client, a Simulink block is always created such that you can plug your advanced formulation directly into your simulation models, or download it to a real-time target platform.

The low-level interface gives advanced optimization users the full flexibility when designing custom optimization solvers and MPC controllers based on non-standard formulations.

This interface is provided with all variants of FORCESPRO, starting with *Variant S*.

8.1 Supported problem class

The FORCESPRO low-level interface supports the class of **convex multistage quadratically constrained programs (QCQPs)** of the form

$$\begin{array}{ll}
 \text{minimize} & \sum_{i=1}^N \frac{1}{2} z_i^\top H_i z_i + f_i^\top z_i & (\text{separable objective}) \\
 \text{subject to} & D_1 z_1 = c_1 & (\text{initial equality}) \\
 & C_{i-1} z_{i-1} + D_i z_i = c_i, \quad i = 2, \dots, N & (\text{inter-stage equality}) \\
 & \underline{z}_i \leq z_i & (\text{lower bound}) \\
 & z_i \leq \bar{z}_i & (\text{upper bound}) \\
 & A_i z_i \leq b_i & (\text{polytopic inequalities}) \\
 & z_i^\top Q_{i,k} z_i + L_{i,k}^\top z_i \leq r_{i,k} & (\text{quadratic inequalities})
 \end{array}$$

for $i = 1, \dots, N$ and $k = 1, \dots, M$. To obtain a solver for this optimization program using the FORCESPRO client, you need to define all data in the problem, that is the matrices H_i , A_i , $Q_{i,j}$, D_i , C_i and the vectors \underline{z}_i , \bar{z}_i , b_i , $L_{i,k}$, $r_{i,k}$, c_i , in a MATLAB struct or Python dictionary, along with the corresponding dimensions. The following steps will take you through this process. Importantly, the matrices H_i and $Q_{i,j}$ should all be positive definite.

Note: FORCESPRO supports all problem data to be parametric, i.e. to be unknown at code generation time. Read [Section 12](#) to learn how to use parameters correctly.

In the following, we describe how to model a problem of the above form with FORCESPRO. First make sure that the FORCESPRO client is on the MATLAB/Python path. See [Section 3](#) for more details on how to set up the MATLAB client and [Section 3.3](#).

After the `PYTHONPATH` has been appropriately set up to include your FORCESPRO client directory (see [Section 3.3.3](#)), Python users have to import the FORCESPRO module and their user ID.

```
import forcespro
import get_userid
```

8.2 Multistage struct

First, an empty struct/class has to be initialized, which contains all fields needed and initialises matrices and vectors to empty matrices. The command

Matlab

Python

```
stages = MultistageProblem(N);
```

```
stages = forcespro.MultistagePoblem(N) # 0-indexed
```

creates such an empty structure/class of length N . Once this structure/class has been created, the corresponding matrices, vectors and dimensions can be set for each element of stages.

8.3 Dimensions

In order to define the dimensions of the stage variables z_i , the number of lower and upper bounds, the number of polytopic inequality constraints and the number of quadratic constraints use the following fields:

Matlab

Python

```
stages(i).dims.n = ...; % length of stage variable z_i
stages(i).dims.r = ...; % number of equality constraints
stages(i).dims.l = ...; % number of lower bounds
stages(i).dims.u = ...; % number of upper bounds
stages(i).dims.p = ...; % number of polytopic constraints
stages(i).dims.q = ...; % number of quadratic constraints
```

```
# 0-indexed
stages.dims[i]['n'] = ... # length of stage variable z_i
stages.dims[i]['r'] = ... # number of equality constraints
stages.dims[i]['l'] = ... # number of lower bounds
stages.dims[i]['u'] = ... # number of upper bounds
stages.dims[i]['p'] = ... # number of polytopic constraints
stages.dims[i]['q'] = ... # number of quadratic constraints
```

8.4 Cost function

The cost function is, for each stage, defined by the matrix H_i and the vector f_i . These can be set by

Matlab

Python

```
stages(i).cost.H = ...; % Hessian
stages(i).cost.f = ...; % linear term
```

```
# 0-indexed
stages.cost[i]['H'] = ... # Hessian
stages.cost[i]['f'] = ... # linear term
```

Note: whenever one of these terms is zero, you have to set them to zero (otherwise the default of an empty matrix is assumed, which is different from a zero matrix).

H_i should be square of size $\text{dims}[i]['n'] / \text{stages}(i).\text{dims}.n$ and f_i should also be of that length. It does not matter whether you use a column or row vector for f .

8.5 Equality constraints

The equality constraints for each stage, which are given by the matrices C_{i-1} , D_i and the vector c_i , have to be provided in the following form:

The matrices C_{i-1} , D_i should have dimension $\text{dims}[i]['r']$ by $\text{dims}[i]['n']$ and c_i should be of length $\text{dim}[i]['r']$.

Note the index shift in C_{i-1} . In particular you should take care, that the vertical dimension of C_{i-1} matches $\text{dim}[i]['r']$ and not $i-1$.

Matlab

Python

```
stages(i).eq.C = ...;
stages(i).eq.c = ...;
stages(i).eq.D = ...;
```

```
# 0-indexed
stages.eq[i]['C'] = ...
stages.eq[i]['c'] = ...
stages.eq[i]['D'] = ...
```

In many parts of the literature a different notation is given for inter-stage equality, which places the next index on the right hand side of the equation like so:

$$A_i x_i + B_i u_i = x_{i+1}, \quad i = 2, \dots, N \quad (\text{inter-stage equality})$$

Where $z_i = (u_i, x_i)$

The correct way to translate this is as follows:

$$(B_{i-1} \mid A_{i-1}) z_{i-1} + (0 \mid -\mathbf{Id}) z_i = 0$$

Where $-\mathbf{Id}$ has the matching size for x_i

For $i = 1$ (0 in Python) There is the special case of setting an `xinit` variable. This can be done by either setting $D_1 = +\mathbf{Id}$ or $c_1 = -x_{init}$, to make the signs of both sides of the equation agree.

8.6 Lower and upper bounds

Lower and upper bounds have to be set in sparse format, i.e. an index vector `lbIdx/ubIdx` that defines the elements of the stage variable z_i has to be provided, along with the corresponding upper/lower bound `lb/ub`:

These index vectors will be the same in both Matlab and Python, which means that the Python indices need to be adjusted to match Matlab's 1-indexed style.

Matlab

Python

```
stages(i).ineq.b.lbIdx = ...; % index vector for lower bounds
stages(i).ineq.b.lb = ...; % lower bounds
stages(i).ineq.b.ubIdx = ...; % index vector for upper bounds
stages(i).ineq.b.ub = ...; % upper bounds
```

```
stages.ineq[ i ]['b']['lbIdx'] = ... # index vector for lower bounds, 1-indexed
stages.ineq[ i ]['b']['lb'] = ... # lower bounds
stages.ineq[ i ]['b']['ubIdx'] = ... # index vector for upper bounds, 1-indexed
stages.ineq[ i ]['b']['ub'] = ... # upper bounds
```

Both `lb` and `lbIdx` must have length `stages(i).dims.l / stages.dims[i]['l']`, and both `ub` and `ubIdx` must have length `stages(i).dims.u / stages.dims[i]['u']`.

8.7 Polytopic constraints

In order to define the inequality $A_i z_i \leq b_i$, use

Matlab

Python

```
stages(i).ineq.p.A = ...; % Jacobian of linear inequality
stages(i).ineq.p.b = ...; % RHS of linear inequality
```

```
# 0-indexed
stages.ineq[i]['p']['A'] = ... # Jacobian of linear inequality
stages.ineq[i]['p']['b'] = ... # RHS of linear inequality
```

The matrix A must have $stages(i).dims.p / stages.dims[i][p]$ rows and $stages(i).dims.n / stages.dims[i][n]$ columns. The vector b must have $stages(i).dims.p / stages.dims[i][p]$ rows.

8.8 Quadratic constraints

Similar to lower and upper bounds, quadratic constraints are given in sparse form by means of an index vector, which determines on which variables the corresponding quadratic constraint acts.

Matlab

Python

```
stages(i).ineq.q.idx = { idx1, idx2, ...}; % index vectors
stages(i).ineq.q.Q = { Q1, Q2, ...}; % Hessians
stages(i).ineq.q.l = { L1, L2, ...}; % linear terms
stages(i).ineq.q.r = [ r1; r2; ... ]; % RHSs
```

```
stages.ineq[i]['q']['idx'] = ... # index vectors, 1-indexed
stages.ineq[i]['q']['Q'] = ... # Hessians
stages.ineq[i]['q']['l'] = ... # linear terms
stages.ineq[i]['q']['r'] = ... # RHSs
```

If the index vector $idx1$ has length m_1 , then the matrix Q must be square and of size $m_1 \times m_1$, the column vector l_1 must be of size m_1 and r_1 is a scalar. Of course this dimension rules apply to all further quadratic constraints that might be present. Note that L_1, L_2 etc. are column vectors in MATLAB!

Since multiple quadratic constraints can be present per stage, in MATLAB we make use of the cell notation for the Hessian, linear terms, and index vectors. In Python we make use of Python object arrays for the Hessians, linear terms, and index vectors.

8.8.1 Example

To express the two quadratic constraints

$$\begin{aligned} z_{3,3}^2 + 2z_{3,5}^2 - z_{3,5} &\leq 3 \\ 5z_{3,1}^2 &\leq 1 \end{aligned}$$

on the third stage variable, use the code

Matlab

Python

```
stages(3).ineq.q.idx = { [3 5], [1] } % index vectors
stages(3).ineq.q.Q = { [1 0; 0 2], [5] }; % Hessians
stages(3).ineq.q.l = { [0; -1], [0] }; % linear terms
stages(3).ineq.q.r = [ 3; 1 ]; % RHSs
```

```
stages.ineq[3-1]['q']['idx'] = np.zeros((2,), dtype=object) # index vectors
stages.ineq[3-1]['q']['idx'][0] = np.array([3,5])
stages.ineq[3-1]['q']['idx'][1] = np.array([1])
stages.ineq[3-1]['q']['Q'] = np.zeros((2,), dtype=object) # Hessians
stages.ineq[3-1]['q']['Q'][0] = np.array([1.0 0], [0 2.0])
stages.ineq[3-1]['q']['Q'][1] = np.array([5])
stages.ineq[3-1]['q']['l'] = np.zeros((2,), dtype=object) # linear terms
stages.ineq[3-1]['q']['l'][0] = np.array([0], [-1])
stages.ineq[3-1]['q']['l'][1] = np.array([0])
stages.ineq[3-1]['q']['r'] = np.array([3], [1]) # RHSs
```

8.9 Binary constraints

To declare binary variables, you can use the *bidx* field of the *stages* struct or object. For example, the following code declares variables 3 and 7 of stage 1 to be binary:

Matlab

Python

```
stages(1).bidx = [3 7]
```

```
stages.bidx[0] = np.array([3, 7])
```

That's it! You can now generate a solver that will take into account the binary constraints on these variables. If binary variables are declared, FORCESPRO will add a branch-and-bound procedure to the standard convex solver it generates.

8.10 Declaring parameters

FORCESPRO is a parametric solver. As such, it is necessary to specify which parts of the model are to be parametric.

For a detailed introduction to setting parameters, see the section [Section 12](#).

A common choice of parameter is an x_{init} value. To set this, use the following:

Matlab

Python

```
parameter = addParam('xinit', 1, 'eq.c')
```

```
stages.addParam("xinit", [1], 'eq.c') # 1-indexed
```

8.11 Declaring Solver Outputs

FORCESPRO gives you full control over the part of the solution that should be outputted by the solver. It is also possible to obtain the Lagrange multipliers of certain constraints. To define a standard output as a slice of the primal solution vector, use the function

Matlab

Python

```
output = newOutput(name, maps2stage, idxWithinStage)
```

```
stages.newOutput(name, maps2stage, idxWithinStage)
```

where `name` is the name you give to the output (you will need this to read it after calling the solver). The index vector (or integer) `maps2stage` defines to which stage this output maps to. The last argument, `idxWithinStage` allows the user to select which indices from the stage vector should be outputted by the solver.

To define an output as a slice of certain Lagrange multipliers, use the function

Matlab

Python

```
output = newOutput(name, maps2stage, idxWithinStage, maps2const)
```

```
stages.newOutput(name, maps2stage, idxWithinStage, maps2const)
```

where the remaining argument `maps2const` specifies the constraint associated with the Lagrange multipliers being requested.

Table 8.1: Possible string values for argument `maps2const`

maps2const	Constraint
r	Equalities
u	Upper bounds
l	Lower bounds
p	Polytopic bounds

8.11.1 Example

To define an output to be the first two elements of the primal solution vector, use the following command:

Matlab

Python

```
output1 = newOutput('u0', 1, 1:2)
```

```
stages.newOutput('u0', 1, range(1,3))
```

To define an output to be the first and third indices of the Lagrange multipliers for the equality constraints of the second stage, use the following command:

Matlab

Python

```
output2 = newOutput('dual_eq0', 2, [1 3], 'r')
```

```
stages.newOutput('dual_eq0', 2, [1,3], 'r')
```

8.12 Dumping and Loading Models

To dump a low-level formulation, simply run:

Matlab

Python

```
not implemented
```

```
save_all(stages)
```

Available options are listed in detail in [Section 17](#).

Note that, unlike in the high-level implementation, specifying *options* or *outputs* does nothing and is ignored, as these should be included in the *stages* object.

8.13 Generating the solver

After the optimization problem has been formulated into a structure *stages*, an optimized solver can be generated. To do so, the solver requires a name and a number of solver options, as described in [Section 15](#).

Matlab

Python

```
codeoptions = getOptions('solver name');
generateCode(stages, params, codeoptions, outputs);
```

```
options = forcespro.CodeOptions('solver_name')
stages.codeoptions = options
stages.generateCode(get_userid.user_id)
```

8.14 Calling the generated low-level solver

After solver generation has completed, the solver itself (as a compiled library) as well as several interfacing files will become available in your working directory. These files are named according to what you named your solver; in the following we assume “SOLVER_NAME”. Calling the solver from MATLAB or Python is then as simple as:

Matlab

Python

```
problem = {} % a struct of solver parameters
SOLVER_NAME(problem)
```

```
import SOLVER_NAME_py # notice the _py suffix
problem = {} # a dictionary of solver parameters
SOLVER_NAME_py.SOLVER_NAME_solve(problem)
```

Note: Don't give your solver the same name as the script you are calling it from. Doing so will overwrite your calling script with the solver interface. For example, in a script named *test_problem.m*, choose a name such as *test_solver* instead of *test_problem*.

Note: The high-level Python interface provides more convenient access to solvers generated using the high-level interface. This method of calling a solver is only available for solvers generated through the low-level interface, and high-level solvers can only be called from Python through the means described in the high-level interface documentation.

Chapter 9

High-level Interface

- *Supported problems*
 - *Canonical problem for discrete-time dynamics*
 - *Continuous-time dynamics*
 - *Other variants*
 - *Function evaluations*
- *Expressing the optimization problem in code*
 - *Model Initialization*
 - * *Model Initialization in Matlab*
 - * *Model Initialization in Python*
 - *Dimensions*
 - *Objective*
 - *Equalities*
 - * *Discrete-time*
 - * *Continuous-time*
 - *Initial and final conditions*
 - *Inequalities*
 - *Variations*
 - * *Varying dimensions, parameters, constraints, or functions*
 - * *Providing analytic derivatives*
 - *Single precision callbacks*
- *Generating a solver*
 - *Declaring outputs*
- *Calling the solver*
 - *Initial guess*
 - *Initial and final conditions*
 - *Real-time parameters*

- *Tolerances as real-time parameters*
- *Exitflags and quality of the result*
- *External function evaluations in C*
 - *Interface*
 - * *Expected function signature*
 - * *Custom data structures as parameters*
 - *Supplying function evaluation information*
 - *Rules for function evaluation code*
 - *Matrix format*
 - *Multiple source files*
 - *Stage-dependent functions*
- *Calling the nonlinear functions from Matlab or Python*
 - *Calling the nonlinear functions from MATLAB*
 - *Calling the nonlinear functions from Python*
- *Mixed-integer nonlinear solver*
 - *Writing a mixed-integer model*
 - *Mixed-integer solver customization via user callbacks*
 - *Providing a guess for the incumbent*
- *Sequential quadratic programming algorithm*
 - *How to generate a SQP solver*
 - *The hessian approximation and line search settings*
 - *Controlling the initial guess at run-time*
 - *Additional code options specific to the SQP-RTI solver*
- *Differences between the MATLAB and the Python client*
- *Examples*

The FORCESPRO high-level interface gives optimization users a familiar easy-to-use way to define an optimization problem. The interface also gives the advanced user full flexibility when importing external C-coded functions to evaluate the quantities involved in the optimization problem.

This interface is provided with *Variant L* and partially with *Variant M* of FORCESPRO.

Important: Starting with FORCESPRO 1.8.0, the solver generated from the high-level interface supports nonlinear and convex decision making problems with integer variables.

Note: The high-level Python interface expects 0-based indices in the model formulation, such as for the indices in *lbidx*, *ubidx*, *hlidx*, *huidx*, *xinitidx* and *xfinalidx*, as is usual in Python programs. Note that this is contrary to the low-level interface, which requires 1-based indices for these fields.

9.1 Supported problems

9.1.1 Canonical problem for discrete-time dynamics

The FORCESPRO NLP solver solves (potentially) non-convex, finite-time nonlinear optimal control problems with horizon length N of the form:

$$\begin{aligned}
 & \text{minimize} && \sum_{k=1}^{N-1} f_k(z_k, p_k) && \text{(separable objective)} \\
 & \text{subject to} && z_1(\mathcal{I}) = z_{\text{init}} && \text{(initial equality)} \\
 & && E_k z_{k+1} = c_k(z_k, p_k) && \text{(inter-stage equality)} \\
 & && z_N(\mathcal{N}) = z_{\text{final}} && \text{(final equality)} \\
 & && \underline{z}_k \leq z_k \leq \bar{z}_k && \text{(upper-lower bounds)} \\
 & && F_k z_k \in [\underline{z}_k, \bar{z}_k] \cap \mathbb{Z} && \text{(integer variables)} \\
 & && \underline{h}_k \leq h_k(z_k, p_k) \leq \bar{h}_k && \text{(nonlinear constraints)}
 \end{aligned}$$

for $k = 1, \dots, N$, where $z_k \in \mathbb{R}^{n_k}$ are the optimization variables, for example a collection of inputs, states or outputs in an MPC problem; $p_k \in \mathbb{R}^{l_k}$ are real-time data, which are not necessarily present in all problems; the functions $f_k : \mathbb{R}^{n_k} \times \mathbb{R}^{l_k} \rightarrow \mathbb{R}$ are stage cost functions; the functions $c_k : \mathbb{R}^{n_k} \times \mathbb{R}^{l_k} \rightarrow \mathbb{R}^{w_k}$ represents (potentially nonlinear) equality constraints, such as a state transition function; the matrices E_k are used to couple variables from the $(k+1)$ -th stage to those of stage k through the function c_k ; and the functions $h_k : \mathbb{R}^{n_k} \times \mathbb{R}^{l_k} \rightarrow \mathbb{R}^{m_k}$ are used to express potentially nonlinear, non-convex inequality constraints. The index sets \mathcal{I} and \mathcal{N} are used to determine which variables are fixed to initial and final values, respectively. The initial and final values z_{init} and z_{final} can also be changed in real-time. At every stage k , the matrix F_k is a selection matrix that picks some coordinates in vector z_k .

All real-time data is coloured in red. Additionally, when integer variables are modelled, they need to be declared as real-time parameters. See Section *Mixed-integer nonlinear solver*.

To obtain a solver for this optimization problem using the FORCESPRO client, you need to define all functions involved (f_k, c_k, h_k) along with the corresponding dimensions.

9.1.2 Continuous-time dynamics

Instead of having discrete-time dynamics as can be seen in Section 9.1.1, we also support using continuous-time dynamics of the form:

$$\dot{x} = f(x, u, p)$$

and then discretizing this equation by one of the standard integration methods. See Section 9.2.4 for more details.

9.1.3 Other variants

Not all elements in Section 9.1.1 have to be necessarily present. Possible variants include problems:

- where all functions are fixed at code generation time and do not need extra real-time data p ;
- with no lower (upper) bounds for variable $z_{k,i}$, then $\underline{z}_i \equiv -\infty$ ($\bar{z}_i \equiv +\infty$);
- without nonlinear inequalities h ;
- with $N = 1$ (single stage problem), then the inter-stage equality can be omitted;

- that optimize over the initial value z_{init} and do not include the initial equality;
- that optimize over the final value z_{final} and do not include the final equality.
- mixed-integer nonlinear programs, where some variables are declared as integers. See Section *Mixed-integer nonlinear solver* for more information about the MINLP solver.

9.1.4 Function evaluations

The FORCESPRO NLP solver requires external functions to evaluate:

- the cost function terms $f_k(z_k)$ and their gradients $\nabla f_k(z_k)$,
- the dynamics $c_k(z_k)$ and their Jacobians $\nabla c_k(z_k)$, and
- the inequality constraints $h_k(z_k)$ and their Jacobians $\nabla h_k(z_k)$.

The FORCESPRO code generator supports the following ways of supplying these functions:

1. Automatic C-code generation of these functions from MATLAB using a supported automatic differentiation (AD) tool, such as *CasADi*. This happens automatically in the background, as long as the AD tool is found on your system. By doing so, the user does not need to adhere to any tool-specific syntax but can use standard MATLAB commands to define the necessary functions instead (which are then automatically converted to match the specifics of the chosen AD tool). This is the recommended way of getting started with FORCESPRO NLP. See Section 9.2 to learn how to use this approach.
2. C-functions (source files). These can be hand-coded, or generated by any automatic differentiation tool. See Section 9.5 for details on how to provide own function evaluations and derivatives to FORCESPRO.

9.2 Expressing the optimization problem in code

When solving nonlinear programs of the type in Section 9.1.1, FORCESPRO requires the functions f, c, h and their derivatives (Jacobians) to be evaluated in each iteration. There are two ways for accomplishing this: either implement all function evaluations in C by some other method (by hand or by another automatic differentiation tool), or use an AD tool integrated with FORCESPRO, such as the open-source package *CasADi* (see *Automatic differentiation tool* for a list of all supported tools). This is the easiest option to quickly get started with solving NLPs, and it generates efficient code. However, if you prefer other AD tools, see Section 9.5 to learn how to provide your own derivatives to FORCESPRO NLP solvers. This section will describe the *CasADi*-based approach in detail, using either the MATLAB or the Python client of FORCESPRO. Please note that even though both the MATLAB and the Python client are intended to behave largely identical, there are some differences between the two clients. For details, refer to *Differences between the MATLAB and the Python client*.

9.2.1 Model Initialization

Model Initialization in Matlab

In the MATLAB high-level interface, the formulation of the optimization problem is given through a simple structure array. In the following, we will describe the problem in such an array named *model*. It is advisable to zero-initialize this variable at the beginning of your script such that no values set in previous iterations of your script interfere with this run:

```
model = {}
```

Model Initialization in Python

In the high-level Python interface, optimization problems are described through objects of different types, depending on the problem. The following classes are available:

- **SymbolicModel** - Allows you to describe your optimization problem using regular Python functions. These functions will be evaluated symbolically by CasADi to create optimized C code. Note that this model is meant to be used for nonlinear models. If you wish to express a convex model symbolically, consider using the *ConvexSymbolicModel* or forcing generation of a nonconvex solver by setting the option *forcenonconvex* to *True*.
- **ExternalFunctionModel** - Enables more flexibility in describing nonlinear problems by allowing any external function to be used as objective function and constraints. This requires C code or already compiled code (object files or shared libraries) from any language. The approach using external function evaluations for your objective function and constraints is described in *External function evaluations in C*, including the required call signature of the callback function.
- **ConvexSymbolicModel** - FORCESPRO can generate different solvers for convex problems.

Whichever model you choose, it can be initialized with no arguments, or with a single argument denoting the number of stages N in the problem:

```
import forcespro.nlp
model = forcespro.nlp.SymbolicModel(50)
```

Note that most symbolic problem descriptions will also require the Numpy and CasADi packages, so it is a good idea to import them at the beginning:

```
import numpy as np
import casadi
```

9.2.2 Dimensions

In order to define the dimensions of the stage variables z_i , the number of equality and inequality constraints and the number of real-time parameters use the following fields (properties) in the client:

Matlab

Python

```
model.N = 50;    % length of multistage problem
model.nvar = 6;  % number of stage variables
model.neq = 4;   % number of equality constraints
model.nh = 2;    % number of nonlinear inequality constraints
model.npar = 0;  % number of runtime parameters
```

```
model.N = 50      # not required if already specified in initializer
model.nvar = 6    # number of stage variables
model.neq = 4     # number of equality constraints
model.nh = 2      # number of nonlinear inequality constraints
model.npar = 0    # number of runtime parameters
```

If the dimensions vary for different stages use arrays of length N . See [Section 9.2.7](#) for an example.

9.2.3 Objective

The high-level interface allows you to define the objective function using a handle to a MATLAB or Python function that evaluates the objective. This function is called with the variables of one stage as its first argument, i.e. a vector of *model.nvar* entries. FORCESPRO will process the given function symbolically and generate the necessary C code to be included in the solver.

Matlab

Python

```
model.objective = @eval_obj; % handle to objective function
```

```
model.objective = eval_obj # eval_obj is a Python function
```

For instance, the function could be:

Matlab

Python

```
function f = eval_obj ( z )
    F = z(1);
    s = z(2);
    y = z(4);
    f = -100*y + 0.1*F^2 + 0.01* s^2;
end
```

```
def eval_obj(z):
    F = z[0]
    s = z[1]
    y = z[3]
    return -100*y + 0.1*F**2 + 0.01*s**2
```

If the cost function varies for different stages use a cell array of function handles of length *N* in MATLAB, or a list of function handles in Python. See [Section 9.2.7](#) for an example.

Note: Python and MATLAB use different indexing bases. The first element of any variable has index 1 in MATLAB, whereas it is accessed at offset 0 in Python!

The objective evaluation function can optionally accept an additional argument *p* which serves as a run-time parameter. In order to be able to change the terms in the cost function during runtime, one can define the objective function as:

Matlab

Python

```
function f = eval_obj ( z, p )
    F = z(1);
    s = z(2);
    y = z(4);
    f = -100*y + p(1)*F^2 + p(2)* s^2;
end
```

```
def eval_obj(z, p):
    F = z[0]
    s = z[1]
    y = z[3]
    return -100*y + p[0]*F**2 + p[1]*s**2
```

The length of this additional parameter vector in each stage is given by *model.npar*.

9.2.4 Equalities

Discrete-time

For discrete-time dynamics, one can define a handle to a function evaluating c as shown below. The selection matrix E that determines which variables are affected by the inter-stage equality must also be filled. For performance reasons, it is recommended to order variables such that the selection matrix has the following structure:

Matlab

Python

```
model.eq = @eval_dynamics;      % handle to inter-stage function
model.E = [zeros(4,2), eye(4)]; % selection matrix
```

```
model.eq = eval_dynamics # handle to inter-stage function
model.E = np.concatenate([np.zeros((4, 2)), np.eye(4)], axis=1) # selection matrix
```

If the equality constraint function varies for different stages use a cell array (or list in Python) of function handles of length $N - 1$, and similarly for E_k . See [Section 9.2.7](#) for an example.

Continuous-time

For continuous-time dynamics, FORCESPRO requires you to describe the dynamics of the system in the following form:

$$\dot{x} = f(x, u, p)$$

where x are the states of the system, u are the inputs and p a vector of parameters, e.g. the mass or inertia. The selection matrix E determines which components of the stage variable z_i are to be considered state x or input u in this representation.

For example, let's assume that the system to be controlled has the dynamics:

$$\dot{x} = p_1 x_1 x_2 + p_2 u$$

In order to discretize the system for use with FORCESPRO we have to:

1. Implement the continuous-time dynamics as a function:

Matlab

Python

```
function xdot = continuous_dynamics(x, u, p)
    xdot = p(1)*x(1)*x(2) + p(2)*u;
end
```

```
def continuous_dynamics(x, u, p):
    return p[0]*x[0]*x[1] + p[1]*u[0]
```

Note that in general the parameter vector p can be omitted if there are no parameters. You can also implement short functions as anonymous function handles:

Matlab

Python

```
continuous_dynamics_anonymous = @(x,u,p) p(1)*x(1)*x(2) + p(2)*u;
```

```
continuous_dynamics_anonymous = lambda x, u, p: p[0]*x[0]*x[1] + p[1]*u[0]
```

2. Tell FORCESPRO that you are using continuous-time dynamics by setting the `continuous_dynamics` field of the `model` to a function handle to one of the functions above:

Matlab

Python

```
model.continuous_dynamics = @continuous_dynamics;
```

```
model.continuous_dynamics = continuous_dynamics
```

or, if you are using anonymous functions:

Matlab

Python

```
model.continuous_dynamics = @continuous_dynamics_anonymous;
```

```
model.continuous_dynamics = continuous_dynamics_anonymous
```

3. Use the selection matrix E to link the stage variables z_i with the states x and inputs u of the continuous dynamics function:

Matlab

Python

```
model.E = [zeros(2, 1), eye(2)]
```

```
model.E = np.concatenate([np.zeros((2, 1)), np.eye(2)], axis=1)
```

Components of z_i are considered as state variables x according to the order prescribed by the selection matrix. If an entire k -th column of the selection matrix is zero, the k -th component of z_i is not governed by a dynamic equation and thus considered as input u .

4. Choose one of the integrator functions from the *Integrators* section (the default is ERK4):

Matlab

Python

```
codeoptions.nlp.integrator.type = 'ERK2';
codeoptions.nlp.integrator.Ts = 0.1;
codeoptions.nlp.integrator.nodes = 5;
```

```
codeoptions.nlp.integrator.type = 'ERK2'
codeoptions.nlp.integrator.Ts = 0.1
codeoptions.nlp.integrator.nodes = 5
```

where the integrator type is set using the `type` field of the options struct `codeoptions.nlp.integrator`. The field `Ts` determines the absolute time between two integration intervals, while `nodes` defines the number of intermediate integration nodes within that integration interval. In the example above, we use 5 steps to integrate for 0.1 seconds, i.e. each integration step covers an interval of 0.02 seconds.

9.2.5 Initial and final conditions

The indices affected by the initial and final conditions can be set as follows:

Matlab

Python

```
model.xinitidx = 3:6;    % indices affected by initial condition
model.xfinalidx = 5:6;  % indices affected by final condition
```

```
model.xinitidx = range(2, 6)    # indices affected by the initial condition
model.xfinalidx = range(4, 6)   # indices affected by the final condition
```

Note: Python and MATLAB use different indexing bases. The first variable in a stage has index 1 in MATLAB, whereas it is accessed at offset 0 in Python! Further note that Python's *range* does not include the upper limit, thus:

```
list(range(2, 6)) == [2, 3, 4, 5] # does not include upper limit
```

9.2.6 Inequalities

A function evaluating nonlinear inequalities can be provided in a similar way, for example:

Matlab

Python

```
function h = eval_const(z)
    x = z(3);
    y = z(4);
    h = [x^2 + y^2;
        (x+2)^2 + (y-2.5)^2];
end
```

```
def eval_const(z):
    x = z[2]
    y = z[3]
    return np.array([x**2 + y**2;
                    (x+2)**2 + (y-2.5)**2])
```

Note: For Python installations with Numpy version 1.20 onwards it is advised to use CasADi arrays and CasADi functions (where available) for the implementation of the functions assigned to: **model.objective**, **model.eq**, **model.ineq**, **model.continuous_dynamics** for the problem formulation in order to ensure maximum compatibility between CasADi and the FORCESPRO Python client.

The simple bounds and the nonlinear inequality bounds can have `+inf` and `-inf` elements, but must be the same length as the field `nvar` and `nh`, respectively:

Matlab

Python

```
model.ineq = @eval_const;          % handle to nonlinear constraints
model.hu = [9, +inf];              % upper bound for nonlinear constraints
model.hl = [1, 0.95^2];            % lower bound for nonlinear constraints
```

(continues on next page)

(continued from previous page)

```
model.ub = [+5, +1, 0, 3, 2, +pi];    % simple upper bounds
model.lb = [-5, -1, -3, -inf, 0, 0]; % simple lower bounds
```

```
model.ineq = eval_const                # handle to nonlinear constraints
model.hu = [9, +float('inf')]          # upper bound for nonlinear_
↳constraints
model.hl = [1, 0.95**2]                # lower bound for nonlinear_
↳constraints
model.ub = [+5, +1, 0, 3, 2, +np.pi]  # simple upper bounds
model.lb = [-5, -1, -3, -float('inf'), 0, 0] # simple lower bounds
```

Note: While the FORCESPRO Python client does not require you to use numpy arrays, we encourage their use for vector- and matrix-valued properties of the model, as it simplifies calculations for the user. Therefore, any of the above properties can also be set to Numpy arrays instead of lists. If lists are given, these are converted to Numpy arrays internally.

If the constraints vary for different stages, use cell arrays of length N for any of the quantities defined above. See *Varying dimensions, parameters, constraints, or functions* section for an example.

Bounds `model.lb` and `model.ub` can be made parametric by leaving said fields empty and using the `model.lbidx` and `model.ubidx` fields to indicate on which variables lower and upper bounds are present. The numerical values will then be expected at runtime. For example, to set parametric lower bounds on states 1 and 2, and parametric upper bounds on states 2 and 3, use:

Matlab

Python

```
% Lower bounds are parametric (indices not mentioned here are -inf)
model.lbidx = [1 2]';

% Upper bounds are parametric (indices not mentioned here are +inf)
model.ubidx = [2 3]';

% lb and ub have to be empty when using parametric bounds
model.lb = [];
model.ub = [];
```

```
# Lower bounds are parametric (indices not mentioned here are -inf)
model.lbidx = [0, 1]

# Upper bounds are parametric (indices not mentioned here are +inf)
model.ubidx = [1, 2]

# There is no need to specify model.lb or model.ub to empty lists if
# model.lbidx or model.ubidx are set, and any non-empty value is disallowed.
```

and then specify the exact values at runtime through the fields `lb01–lbN` and `ub01–ubN`:

Matlab

Python

```
% Specify lower bounds
problem.lb01 = [0 0]';
problem.lb02 = [0 0]';
% ...
```

(continues on next page)

(continued from previous page)

```
% Specify upper bounds
problem.ub01 = [3 2]';
problem.ub02 = [3 2]';
% ...
```

```
# Specify lower bounds
problem["lb01"] = [0, 0]
problem["lb02"] = [0, 0]

# Specify upper bounds
problem["ub01"] = [3, 2]
problem["ub02"] = [3, 2]
```

Tip: One could use `problem.(sprintf('lb%02u',i))` in an `i`-indexed loop to set the parametric bounds more easily in the MATLAB client. Similarly, the parametric bounds for the stages can be set using `problem["{:02d}"].format(i+1)` in Python. Alternatively, consider using the option `stack_parambounds`, described below.

If the `model.lbidx` and `model.ubidx` fields vary for different stages use cell arrays of length N . From Release 3.0.1, the parametric bounds can be stacked on one same array covering all stages. To enable this behaviour, users need to set the following code-generation option:

Matlab

Python

```
codeoptions.nlp.stack_parambounds = 1;
```

```
codeoptions.nlp.stack_parambounds = True
```

This option is effective for both the `PDIP_NLP` and `SQP_NLP` solve methods and works with bounds on variables and inequalities. At run-time, users can then write

Matlab

Python

```
% Lower and upper bounds stacked over all stages
problem.lb = [0 0 0 0 ...];
problem.ub = [3 2 3 2 ...];
```

```
# Lower and upper bounds stacked over all stages
problem["lb"] = [0, 0, 0, 0, ...]
problem["ub"] = [3, 2, 3, 2, ...]
```

Alternatively, if you want to use the same bounds across all stages:

Matlab

Python

```
problem.lb = repmat([0, 0], 1, model.N);
problem.ub = repmat([3, 2], 1, model.N);
```

```
problem["lb"] = np.tile([0, 0], (model.N,))
problem["ub"] = np.tile([3, 2], (model.N,))
```

9.2.7 Variations

Varying dimensions, parameters, constraints, or functions

The example described above has the same dimensions, bounds and functions for the whole horizon. One can define varying dimensions using arrays and varying bounds and functions using MATLAB cell arrays or Python lists. For instance, to remove the first and second variables from the last stage one could write the following:

Matlab

Python

```
for i = 1:model.N-1
    model.nvar(i) = 6;
    model.objective{i} = @(z) -100*z(4) + 0.1*z(1)^2 + 0.01*z(2)^2;
    model.lb{i} = [-5, -1, -3, 0, 0, 0];
    model.ub{i} = [+5 , +1, 0, 3, 2, +pi];
    if i < model.N-1
        model.E{i} = [zeros(4, 2), eye(4)];
    else
        model.E{i} = eye(4);
    end
end

model.nvar(model.N) = 4;
model.objective{model.N} = @(z) -100*z(2);
model.lb{model.N} = [-3, 0, 0, 0];
model.ub{model.N} = [ 0, 3, 2, +pi];
```

```
model = forcespro.nlp.SymbolicModel(50) # to set values stage-wise, the model_
↳ must be initialized this way

for i in range(0,model.N-1):
    model.nvar[i] = 6
    model.objective[i] = lambda z: -100*z[3] + 0.1*z[0]**2 + 0.01*z[1]**2
    model.lb[i] = [-5, -1, -3, 0, 0, 0]
    model.ub[i] = [+5 , +1, 0, 3, 2, +np.pi]
    if i < model.N-2:
        model.E[i] = np.concatenate([np.zeros(4, 2), np.eye(4)], axis=1)
    else:
        model.E[i] = np.eye(4)

model.nvar[-1] = 4
model.objective[-1] = lambda z: -100*z[1]
model.lb[-1] = [-3, 0, 0, 0]
model.ub[-1] = [ 0, 3, 2, +np.pi]
```

It is also typical for model predictive control problems (MPC) that only the last stage differs from the others (excluding the initial condition, which is handled separately). Instead of defining cell arrays as above for all stages, FORCESPRO offers the following shorthand notations that alter the last stage:

- `nvarN`: number of variables in last stage
- `nparN`: number of parameters in last stage
- `objectiveN`: objective function for last stage
- `EN`: selection matrix E for last stage update
- `nhN`: number of inequalities in last stage
- `ineqN`: inequalities for last stage

Add any of these fields to the `model` struct/object to override the default values, which is to make everything the same along the horizon. For example, to add a terminal cost that is a factor 10 higher than the stage cost:

Matlab

Python

```
model.objectiveN = @(z) 10*model.objective(z);
```

```
model.objectiveN = lambda z: 10*model.objective(z)
```

Providing analytic derivatives

The algorithms inside FORCESPRO need the derivatives of the functions describing the objective, equality and inequality constraints. The code generation engine uses algorithmic differentiation (AD) to compute these quantities. Instead, when analytic derivatives are available, the user can provide them using the fields `model.dobjective`, `model.deq`, and `model.dineq`.

Note that the user must be particularly careful to make sure that the provided functions and derivatives are consistent, for example:

Matlab

Python

```
model.objective = @(z) z(3)^2;  
model.dobjective = @(z) 2*z(3);
```

```
model.objective = lambda z: z[2]**2  
model.dobjective = lambda z: 2*z[2]
```

The code generation system will not check the correctness of the provided derivatives.

9.2.8 Single precision callbacks

Evaluating objective function, dynamics and constraints as well as their respective derivatives may take a significant part of the overall solution time (both total and per iteration). In such situations solution time and memory consumption may be sped up by evaluating those functions in single, rather than double precision arithmetic. This can be done by specifying

Matlab

Python

```
codeoptions.callback_floattype = 'float';
```

```
# not yet supported
```

Note that this will allow to run the NLP solver in mixed-precision arithmetic, where the callbacks are evaluated in single precision, but the overall algorithm in double precision. In order for this to work well, all callbacks functions need to be numerically well-posed and overall accuracy requirements of the solution must not be too high. In particular, when using that feature, you may need to reduce some of the accuracy settings (such as `codeoptions.nlp.TolStat`) by one or two orders of magnitude, see [Accuracy requirements](#).

Note: Single precision callbacks are currently supported for legacy and chainrule integrators, but not yet for VDE integrators. Also, this features is currently only available via the Matlab

client.

9.3 Generating a solver

In addition to the definition of the NLP, solver generation requires an (optional) set of options for customization (see the *Solver Options* section for more information). Using the default solver options we generate a solver using:

Matlab

Python

```
% Get the default solver options
codeoptions = getOptions('FORCESNLPsolver');

% Generate solver
FORCES_NLP(model, codeoptions);
```

```
# Get the default solver options
options = forcespro.CodeOptions('FORCESNLPsolver')

# Generate solver for previously initialized model
solver = model.generate_solver(options)
```

As the solver is generated, several files are downloaded into the current working directory of the calling script, including the compiled solver itself and MATLAB/Python interfaces for calling it.

Note: In the Python client, *generate_solver()* returns a **solver object**. This object can be used to call the solver. To get a solver object for a previously generated solver in some directory */path/to/solver*, use:

```
import forcespro.nlp
solver = forcespro.nlp.Solver.from_directory('/path/to/solver')
```

9.3.1 Declaring outputs

By default, the solver returns the solution vector for all stages as multiple outputs. Alternatively, the user can pass a third argument to the function *FORCES_NLP* with an array that specifies what the solver should output. For instance, to define an output, named *u0*, to be the first two elements of the solution vector at stage 1, use the following commands:

Matlab

Python

```
output1 = newOutput('u0', 1, 1:2);
FORCES_NLP(model, codeoptions, output1);
```

```
output_1 = ("u0", 0, [0, 1], "")
model.generate_solver(options, [output_1])
```

Additionally, you can request that the solver returns the solution vectors for all different stages “stacked” together into a single vector, say called *so1*, by using the following commands:

Matlab

Python

```
output1 = newOutput('sol');
FORCES_NLP(model, codeoptions, output1);
```

```
output1 = ("sol", [], [])
model.generate_solver(options, [output1])
```

Important: When using the MINLP solver and defining outputs, all integer variables need to be specified as custom outputs.

The dual variables at the solution returned by FORCESPRO provide useful information on the problem sensitivity. They can be exported from the nonlinear solver as well by giving the `maps2const` field one of the following values:

- `'nl_eq_dual'` for the dual variables associated to equality constraints
- `'nl_lb_var_dual'` for the dual variables associated to lower bounds on variables
- `'nl_ub_var_dual'` for the dual variables associated to upper bounds on variables
- `'nl_ip_ineq_dual'` for the dual variables associated to nonlinear inequalities
- `'nl_ineq_slack'` for the dual variables associated to slacks on nonlinear inequalities.

An example of exporting the marginals associated to nonlinear equalities is shown in the code snippet below.

```
outputs(4) = newOutput('dual_eq0', 1:model.N, 1:2, 'nl_eq_dual');
```

9.4 Calling the solver

After code generation has been successful, one can obtain information about the real-time data needed to call the generated solver by typing:

Matlab

Python

```
help FORCESNLPsolver
```

```
# Assuming `solver` is the return value of a `model.generate_solver()` call
solver.help()
```

In Python, a previously generated solver can be loaded as follows:

```
import forcespro.nlp
solver = forcespro.nlp.Solver.from_directory("/path/to/generated/solver/")
solver.help()
```

9.4.1 Initial guess

The FORCESPRO NLP solver solves NLPs to local optimality, hence the resulting optimal solution depends on the initialization of the solver. One can also choose another initialization point when a better guess is available. The following code sets the initial point to be in the middle of all bounds:

Matlab

Python

```
x0i = model.lb + (model.ub - model.lb) / 2;
x0 = repmat(x0i', model.N, 1);
problem.x0 = x0;
```

```
xi = (model.lb + model.ub) / 2 # assuming lb and ub are numpy arrays
x0 = np.tile(xi, (model.N,))
problem = {"x0": x0}
```

9.4.2 Initial and final conditions

If there are initial and/or final conditions on the optimization variables, the solver will expect the corresponding runtime fields:

Matlab

Python

```
problem.xinit = model.xinit;
problem.xfinal = model.xfinal;
```

```
problem = {"xinit": np.array([1, 2, 3]),
           "xfinal": np.array([4, 5, 6])}
```

Note that the Python client does not allow setting *model.xinit* or *model.xfinal* properties, as those are run-time parameters not needed at solver generation time.

9.4.3 Real-time parameters

Whenever there are any runtime parameters defined in the problem, i.e. the field *npar* is not zero, the solver will expect the following field containing the parameters for all the N stages stacked in a single vector:

Matlab

Python

```
problem.all_parameters = repmat(1.0, model.N, 1);
```

```
problem["all_parameters"] = np.tile(1.0, (model.N,))
```

9.4.4 Tolerances as real-time parameters

From FORCESPRO 2.0 onwards, the NLP solver tolerances can be made real-time parameters, meaning that they do not need to be set when generating the solver but can be changed at run-time when calling the generated solver. The code-snippet below shows how to make the tolerances on the gradient of the Lagrangian, the equalities, the inequalities and the complementarity condition parametric. Essentially, when the tolerances are declared nonpositive at code-generation, the corresponding run-time parameter is created in the solver.

Matlab

Python

```
codeoptions.nlp.TolStat = -1; % Tolerance on gradient of Lagrangian
codeoptions.nlp.TolEq = -1; % Tolerance on equality constraints
codeoptions.nlp.TolIneq = -1; % Tolerance on inequality constraints
codeoptions.nlp.TolComp = -1; % Tolerance on complementarity
```

```
codeoptions.nlp.TolStat = -1 # Tolerance on gradient of Lagrangian
codeoptions.nlp.TolEq = -1 # Tolerance on equality constraints
codeoptions.nlp.TolIneq = -1 # Tolerance on inequality constraints
codeoptions.nlp.TolComp = -1 # Tolerance on complementarity
```

Once the tolerance has been declared nonpositive and the solver has been generated, the corresponding parameter can be set at run-time as follows:

Matlab

Python

```
problem.ToleranceStationarity = 1e-1;
problem.ToleranceEqualities = 1e-1;
problem.ToleranceInequalities = 1e-1;
problem.ToleranceComplementarity = 1e-1;
```

```
problem["ToleranceStationarity"] = 1e-1
problem["ToleranceEqualities"] = 1e-1
problem["ToleranceInequalities"] = 1e-1
problem["ToleranceComplementarity"] = 1e-1
```

Tip: We do not recommend changing the tolerance on the complementarity condition since it is used internally to update the barrier parameter. Hence loosening it may hamper the solver convergence.

9.4.5 Exitflags and quality of the result

Once all parameters have been populated, the MEX interface of the solver can be used to invoke it:

Matlab

Python

```
[output, exitflag, info] = FORCESNLPsolver(problem);
```

```
output, exitflag, info = solver.solve(problem)
```

The possible exitflags are documented in [Table 9.1](#). The exitflag should always be checked before continuing with program execution to avoid using spurious solutions later in the code. Check whether the solver has exited without an error before using the solution. For example, in MATLAB, we suggest to use an assert statement:

Matlab

Python

```
assert(exitflag == 1, 'Some issue with FORCESPRO solver');
```

```
assert exitflag == 1, "Some issue with FORCESPRO solver"
```

Table 9.1: Exitflag values

Exitflag	Description
1	Local optimal solution found (i.e. the point satisfies the KKT optimality conditions to the requested accuracy).
0	Maximum number of iterations reached. You can examine the value of optimality conditions returned inside the <code>info</code> struct by FORCESPRO to decide whether the point returned is acceptable.
-4	Wrong number of inequalities input to solver.
-5	Error occurred during matrix factorization.
-6	NaN or INF occurred during functions evaluations.
-7	The solver could not proceed. Most likely cause is that the problem is infeasible. Try formulating a problem with slack variables (soft constraints) to avoid this error.
-8	The internal QP solver could not proceed. This exitflag can only occur when using the <i>Sequential quadratic programming algorithm</i> . The most likely cause is that an infeasible QP or a numerical unstable QP was encountered. Try increasing the hessian regularization parameter <code>reg_hessian</code> if this exitflag is encountered (see <i>SQP specific codeoptions</i>).
-10	NaN or INF occurred during evaluation of functions and derivatives. If this occurs at iteration zero, try changing the initial point. For example, for a cost function $1/\sqrt{x}$ with an initialization $x_0 = 0$, this error would occur.
-11	Invalid values in problem parameters.
-100	License error. This typically happens if you are trying to execute code that has been generated with a Simulation license of FORCESPRO on another machine. Regenerate the solver using your machine.

Besides the exitflag, the solver also returns an information structure containing detailed KPIs on the solver performance. All its entries are listed and explained in Table 9.2. Those values may also be useful in case the solver exitflag has been 0, which means the solver did not fail but reached the maximum number of iterations. In that case, one should at least check whether the “solution” returned is sufficiently feasible. This can be done by examining `res_eq` and `res_ineq`, respectively, to check whether equality and inequality constraints are satisfied up to a sufficiently small tolerance. The exact tolerances to check may be strongly application dependent.

Note: Applying a premature “solution” returned along with an exitflag of 0 to control your system may have undesired effects to the behaviour of that system. Only do so if you fully understand what you are doing.

Table 9.2: Info struct entries

Fieldname	Description
<code>it</code>	Number of solver iterations that led to this result
<code>res_eq</code>	Maximum norm of equality constraint residual
<code>res_ineq</code>	Maximum norm of inequality constraint residual
<code>rsnorm</code>	Maximum norm of stationarity condition
<code>rcompnorm</code>	Maximum norm of violations of the complementarity conditions
<code>pobj</code>	Primal objective value (as provided by the user)
<code>mu</code>	Duality measure
<code>solvetime</code>	Time needed to run the solver (wall clock time)
<code>fevalsttime</code>	Time needed just for function evaluations of all user callbacks inside the solver (wall clock time)

9.5 External function evaluations in C

This approach allows the user to integrate existing efficient C implementations to evaluate the required functions and their derivatives with respect to the stage variable. This gives the user full flexibility in defining the optimization problem. In this case, the functions do not necessarily have to be differentiable, although the convergence of the algorithm is not guaranteed if they are not. When following this route the user does not have to provide MATLAB code to evaluate the objective or constraint functions. However, the user is responsible for making sure that the provided derivatives and function evaluations are coherent. The FORCESPRO NLP code generator will not check this.

9.5.1 Interface

Expected function signature

There are two ways in which a user can supply custom functions written in C:

- Either she can supply all functions (`model.objective`, `model.eq`, `model.ineq` etc.)
- Or she can supply one or a few of these together with its differential/Jacobian.

Depending on the case, the user will have to supply different information when generating a FORCESPRO solver.

When supplying all functions, the user will have to supply a single C function having the following signature:

```
void myfunctions (
    double *x, /* primal vars */
    double *y, /* eq. constraint multipliers */
    double *l, /* ineq . constraint multipliers */
    double *p, /* runtime parameters */
    double *f, /* objective function ( incremented in this function ) */
    double *nabla_f, /* gradient of objective function */
    double *c, /* dynamics */
    double *nabla_c, /* Jacobian of the dynamics ( column major ) */
    double *h, /* inequality constraints */
    double *nabla_h, /* Jacobian of inequality constraints ( column major ) */
    double *H, /* Hessian ( column major ) */
    int stage, /* stage number (0 indexed ) */
    int iteration, /* Solver iteration count */
    int threadID /* Thread id */
)
```

If instead the user wants to supply just a single function she will have to supply a single C function having the following signature:

```
void function (
    const double * const x, /* primal vars */
    const double * const p, /* runtime parameters */
    double * const zeroOrderFcn, /* Zero order function */
    double * const firstOrderFcn, /* first order Fcn */
    const int stage, /* stage number (0 indexed ) */
    const int threadID /* thread number */
)
```

where `zeroOrderFcn` and `firstOrderFcn` denote the function which the user wants to supply, together with its differential/Jacobian respectively. E.g. if the user were to add the objective function and its differential externally, the function might look as follows:

```

void objective (
    const double * const x, /* primal vars */
    const double * const p, /* runtime parameters */
    double * const obj, /* objective function */
    double * const nabra_obj, /* jacobian of objective fcn */
    const int stage, /* stage number (0 indexed ) */
    const int threadID /* thread number */
)

```

Note: External C-functions should have the same name as the file it is contained in, minus the file extension. E.g. in the above example the source file containing the definition of the function `objective` would have to have the name `objective.c`. If all functions are provided as external C functions through the FORCESPRO Python client, then one can provide a different name for the function and the file.

Custom data structures as parameters

If you have an advanced data structure that holds the user-defined run-time parameters, and you do not want to serialize it into an array of doubles to use the interface above, you can invoke the option:

```
codeoptions.customParams = 1;
```

```
options.customParams = 1
```

When doing this, it is important to note that run-time parameters can only be passed to externally provided functions. In particular, if some but not all function evaluations are provided externally, one will have to set `model.npar = 0`. When using custom parameters, if all functions are provided externally, the expected function signature is:

```

void myfunctions (
    double *x, /* primal vars */
    double *y, /* eq. constraint multipliers */
    double *l, /* ineq. constraint multipliers */
    void *p, /* runtime parameters (passed as void pointer) */
    double *f, /* objective function ( incremented in this function ) */
    double *nabra_f, /* gradient of objective function */
    double *c, /* dynamics */
    double *nabra_c, /* Jacobian of the dynamics ( column major ) */
    double *h, /* inequality constraints */
    double *nabra_h, /* Jacobian of inequality constraints ( column major ) */
    double *H, /* Hessian ( column major ) */
    int stage, /* stage number (0 indexed ) */
    int iteration, /* Solver iteration count */
    int threadID /* Thread id */
)

```

If instead only some of the functions are provided, the expected function signature of these is

```

void function (
    const double * const x, /* primal vars */
    void * const p, /* runtime parameters passed as void pointer */
    double * const zeroOrderFcn, /* Zero order function */
    double * const firstOrderFcn, /* first order Fcn */
    const int stage, /* stage number (0 indexed ) */

```

(continues on next page)

(continued from previous page)

```
const int threadID /* thread number */
)
```

At run time you can then pass arbitrary data structures to your own function by setting the pointer in the params struct:

```
myData p; /* define your own parameter structure */
/* ... */ /* fill it with data */

/* Set parameter pointer to your data structure */
mySolver_params params; /* Define solver parameters */
params.customParams = &p;

/* Call solver (assuming everything else is defined) */
mySolver_solv(&params, &output, &info, stdout, &external_func);
```

Note: Setting customParams to 1 will disable building high-level interfaces. Only C header- and source files will be generated. As a consequence, if CasADi is used to generate some of the function evaluations, the generated source code will have to be compiled by the user.

Note: When using custom parameters, generating callback code automatically is only supported for CasADi 3.5.x only.

9.5.2 Supplying function evaluation information

In MATLAB, if the user wants to supply all functions externally she can let the code generator know about the path to the C files implementing the necessary function as follows:

```
model.extfuncs = 'C/myfunctions.c';
```

Alternatively she could supply either one of the functions `model.objective`, `model.eq` or `model.ineq` together with its differential by specifying the path to the corresponding C source file in the corresponding field of `model.extfuncs` as follows:

```
model.extfuncs.objective = 'C/myobjective.c'; % adding model.objective externally %
model.extfuncs.dynamics = 'C/mydynamics.c'; % adding model.eq externally %
model.extfuncs.inequalities = 'C/myinequalities.c'; % adding model.ineq externally
↪ %
```

As noted above, FORCESPRO derives the function name used for the callback from the file name; the function must therefore have the same name as the file in which it is contained.

In Python, if the user wishes to add ALL functions externally she would use a *ExternalFunctionModel* as follows:

```
model = forcespro.nlp.ExternalFunctionModel(50)
model.add_auxiliary(["helper_functions.c", "compiled_helper_functions.obj"])
model.set_main_callback("myfunctions.c", function="myfunctions")
```

Herein, the `add_auxiliary()` method is used to add any helper C source files or object files that should be compiled and linked against, and the `set_main_callback()` function is used to define the path to a C source file or compiled object file, as well as the name of an exported function that conforms to the call signature given above. This function will be used to evaluate any nonlinear constraints and the objective function.

Alternatively, in order to add a single function externally the user would use the *SymbolicModel* and add the C source files containing code for the external functions through *model.extfuncs* as follows:

```
model = forcespro.nlp.SymbolicModel(50)
model.extfuncs.objective = "myobjective.c"
model.extfuncs.dynamics = "mydynamics.c"
model.extfuncs.inequalities = "myinequalities.c"
model.add_c_source("extra_source.c")
```

where the *extra_source.c* are additional C source files needed for evaluating some or all of the external functions.

9.5.3 Rules for function evaluation code

The contents of the function have to follow certain rules. We will use the following example to illustrate them:

```
/* cost */
if (f)
{ /* notice the increment of f */
    (*f) += -100*x[3] + 0.1* x[0]*x[0] + 0.01*x [1]*x [1];
}
/* gradient - only nonzero elements have to be filled in */
if ( nabra_f )
{
    nabra_f [0] = 0.2*x[0];
    nabra_f [1] = 0.02*x[1];
    nabra_f [3] = -100;
}

/* eq constr */
if (c)
{
    vehicle_dyanmics (x, c);
}
/* jacobian equalities ( column major ) */
if ( nabra_c )
{
    vehicle_dyanmics_jacobian (x, nabra_c );
}

/* ineq constr */
if (h)
{
    h[0] = x [2]*x[2] + x[3]*x [3];
    h[1] = (x[2]+2)*(x[2]+2) + (x[3] -2.5)*(x[3] -2.5);
}
/* jacobian inequalities ( column major )
- only non - zero elements to be filled in */
if ( nabra_h )
{
    /* column 3 */
    nabra_h [4] = 2*x [2];
    nabra_h [5] = 2*x[2] + 4;
    /* column 4 */
    nabra_h [6] = 2*x [3];
    nabra_h [7] = 2*x[3] - 5;
}
```

Notice that every function evaluation is only carried out if the corresponding pointer is not

null. This is used by the FORCESPRO NLP solver to call the same interface with different pointers depending on the functions that it requires.

9.5.4 Matrix format

Matrices are assumed to be stored in dense column major format. However, only the non-zero components need to be populated, as FORCESPRO NLP makes sure that the arrays are initialized to zero before calling this interface.

9.5.5 Multiple source files

The use of multiple C files is also supported. In the example above, the functions `dynamics` and `dynamics_jacobian` are defined in another file and included as external functions using:

```
extern void dynamics ( double *x, double *c);  
extern void dynamics_jacobian ( double *x, double *J);
```

In MATLAB, to let the code generator know about the location of these other files use a string with spaces separating the different files. In Python, use the `add_auxiliary()` method:

Matlab

Python

```
codeoptions.nlp.other_srcs = 'C/dynamics.c';
```

```
model.add_auxiliary('C/dynamics.c')
```

9.5.6 Stage-dependent functions

Whenever the cost function in one of the stages is different from the standard cost function f , one can make use of the argument `stage` to evaluate different functions depending on the stage number. The same applies to all other quantities.

9.6 Calling the nonlinear functions from Matlab or Python

From FORCESPRO version 5.0.1 onwards it is possible to evaluate the nonlinear functions and their derivatives directly in Matlab or Python. This can be very useful for debugging a FORCESPRO solver. This in particular can be useful when calling the generated solver returns an exitflag `-6`, `-8` or `-10`. For help on how to do this, see *Real-time SQP Solver: Robotic Arm Manipulator (MATLAB & Python)* and *Issues when running the solver*.

9.6.1 Calling the nonlinear functions from MATLAB

When generating a FORCESPRO solver one can request the FORCESPRO client to also generate a MEX entry point to any of the nonlinear functions (equality constraints, inequality constraints and objective function) so that one can evaluate these along with their derivatives directly in MATLAB. This is done via the following three options:

- `dynamics`: In order to generate a MEX interface for the equality constraints, set `codeoptions.MEXinterface.dynamics = 1`.

- `inequalities`: In order to generate a MEX interface for the inequality constraints, set `codeoptions.MEXinterface.inequalities = 1`.
- `objective`: In order to generate a MEX interface for the objective function, set `codeoptions.MEXinterface.objective = 1`.

The generated MEX entry point carries the name `<solver name>_dynamics`, `<solver name>_inequalities` or `<solver name>_objective` depending on the case.

The first argument to each of these generated MEX entry points is the primal variable z_k and the second argument is the real-time parameter p_k (see *Canonical problem for discrete-time dynamics*), both passed as column vectors. Additionally a third argument can be passed, which indicates the stage (1-based) at which the function should be evaluated. Each of the generated MEX entry points output two variables: The first is the constraint/objective evaluated at the supplied point and the second is its jacobian with respect to z_k . E.g. in order to generate a solver named `FORCESsolver` and generate a MEX entry point for the inequality constraints, one would proceed as follows:

```
model = getModel();
codeoptions = getOptions('FORCESsolver');
codeoptions.MEXinterface.inequalities = 1;
FORCES_NLP(model, codeoptions);
```

Now one can evaluate the inequality constraints on stage 8 at the point $z_8 = (4.0, 3.0, 2.4)^T$ with real-time parameters given by $p_8 = (3.4, 2.1)^T$ by doing

```
z = [4.0; 3.0; 2.4];
p = [3.4; 2.1];
ineq, jacineq = FORCESsolver_inequalities(z,p,8);
```

which stores the values of the inequality constraints in `ineq` and their jacobian in `jacineq`.

Note: If there are no real-time parameters one simply passes an empty array: `ineq, jacineq = FORCESsolver_inequalities(z, [], 8)`

9.6.2 Calling the nonlinear functions from Python

When generating a solver one obtains a solver object

```
solver = model.generate_solver(options)
```

or

```
import forcespro.nlp
solver = forcespro.nlp.Solver.from_directory('/path/to/solver')
```

and one can directly evaluate any of the nonlinear functions (equality constraints, inequalities or objective function) via the solver object's methods. The methods for doing so are `dynamics`, `ineq` and `objective`. Each of these functions take as a first input the primal variable z_k and the real-time parameter p_k as a second input, if the problem formulation has real-time parameters (see *Canonical problem for discrete-time dynamics*). All of these inputs are expected to be passed as numpy arrays. Recall that the way in which states and inputs are "organized" into z_k is determined by `model.E`. Additionally a stage input can be given in order to compute the dynamics at a given stage (it is not necessary to supply this argument if the same dynamics are used throughout the entire horizon). This stage input should give the 0-based number of the corresponding stage. The first output of each of these function is the evaluated constraint/objective and the second output is the derivative with respect to z_k . E.g. in order to evaluate the equality constraints at stage number 7 on the primal variable $z_8 = (4.0, 3.0, 2.4)^T$ in a formulation where there are no real-time parameters, one would do as follows:

```
import numpy as np
import forcespro.nlp

solver = forcespro.nlp.Solver.from_directory('/path/to/solver')
z = np.array([4.0, 3.0, 2.4])
c, jacc = solver.dynamics(z, stage=7)
```

This stores the value of the equality constraints in the numpy array `c` and its jacobian in the numpy array `jacc`.

9.7 Mixed-integer nonlinear solver

From FORCESPRO 1.8.0, mixed-integer nonlinear programs (MINLPs) are supported. This broad class of problems encompasses all nonlinear programs with some integer decision variables.

This interface is provided with *Variant L* of FORCESPRO.

9.7.1 Writing a mixed-integer model

In order to use this feature, the user has to declare lower and upper bounds on **all variables** as parametric, as shown in the code below.

Matlab

Python

```
model.lb = [];
model.ub = [];
```

```
model.lbidx = range(0, model.nvar)
model.ubidx = range(0, model.nvar)
```

The user is then expected to provide lower and upper bounds as run-time parameters. FORCESPRO switches to the MINLP solver as soon as some variables are declared as integers in any stage. This information can be provided to FORCESPRO via the `intidx` array at every stage. An example is shown below.

Matlab

Python

```
%% Add integer variables to existing nonlinear model
for s = 1:5
    model.intidx{s} = [4, 5, 6];
end
```

```
# Add integer variables to existing nonlinear model
for s in range(0, 5):
    model.intidx[s] = [3, 4, 5]
```

In the above code snippet, the user declares variables 4, 5 and 6 (3, 4 and 5 in Python's zero-based indexing) as integers from stage 1 to 5 (stages 0 to 4 in Python's zero-based indexing). The values that can be taken by an integer variable are derived from its lower and upper bounds. For instance, if the variable lies between -1 and 1 , then it can take integer values -1 , 0 or 1 . If a variable has been declared as integer and does not have lower or upper bounds, FORCESPRO raises an exception during code generation. Stating that a variable has lower and upper bounds should be done via the arrays `lbidx` and `ubidx`. For instance, in the code

below, variables 1 to 6 (0 to 5 in Python) in stage 1 (0) have lower and upper bounds, which are expected to be provided at run-time.

Matlab

Python

```
model.lbidx{1} = 1 : 6;
model.ubidx{1} = 1 : 6;
```

```
model.lbidx[0] = range(0, 6)
model.ubidx[0] = range(0, 6)
```

The FORCESPRO MINLP algorithm is based on the well-known branch-and-bound algorithm but comes with several customization features which generally help for improving performance on some models by enabling the user to provide application specific knowledge into the search process. At every node of the search tree, the FORCESPRO nonlinear solver is called in order to compute a solution of a relaxed problem. The generated MINLP solver code can be customized via the options described in [Table 9.3](#), which can be changed before running the code generation.

One of the salient features of the MINLP solver is that the branch-and-bound search can be run in parallel on several threads. Therefore the search is split in two phases. It starts with a sequential branch-and-bound and switches to a parallelizable process when the number of nodes in the queue is sufficiently high. The node selection strategy can be customized in both phases, as described in [Table 9.3](#).

Table 9.3: FORCESPRO MINLP solver options

Code generation setting	Values	Default
<code>minlp.int_gap_tol</code>	Any value ≥ 0	0.001
<code>minlp.max_num_nodes</code>	Any value ≥ 0	10000
<code>minlp.seq_search_strat</code>	'BEST_FIRST', 'BREADTH_FIRST', 'DEPTH_FIRST'	'BEST_FIRST'
<code>minlp.par_search_strat</code>	'BEST_FIRST', 'BREADTH_FIRST', 'DEPTH_FIRST'	'BEST_FIRST'
<code>minlp.max_num_threads</code>	Any nonnegative value preferably smaller than 8	4
<code>minlp.output_relaxation</code>	0 or 1	0

- The `minlp.int_gap_tol` setting corresponds to the final optimality tolerance below which the solver is claimed to have converged. It is the difference between the objective incumbent, which is the best integer feasible solution found so far and the lowest lower bound. As the node problems are generally not convex, it can be expected to become negative. FORCESPRO claims convergence to a local minimum only when the integrality gap is nonnegative and below the tolerance `minlp.int_gap_tol`.
- The `minlp.max_num_nodes` setting is the maximum number of nodes which can be explored during the search.
- The `minlp.seq_search_strat` setting is the search strategy which is used to select candidate nodes during the sequential search phase.
- The `minlp.par_search_strat` setting is the search strategy which is used to select candidate nodes during the parallelizable search phase.
- The `minlp.max_num_threads` setting is the maximum number of threads allowed for a parallel search. The actual number of threads on which the branch-and-bound algorithm can be run can be set as a run-time parameter, as described below.
- The `minlp.output_relaxation` setting enables users to export the primal outputs of the root relaxation. With this option set to 1, the server automatically generates one additional output for every defined output. The name of the root relaxation output is the name of the output followed by `_relax`.

Note: The MINLP solver is currently constrained to run on one thread on MacOS, meaning that `minlp.max_num_threads` is automatically set to 1 on MacOS.

Important: When generating a MINLP solver for MacOS the thread local feature (`codeoptions.threadSafeStorage`) is automatically set to 0 so if a dynamic library is used for a MINLP solver in a MacOS environment then one should not run at the same time more than one solvers linked to that library. A workaround for this would be to use the static library which is not bound by this restriction.

The FORCESPRO MINLP solver also features settings which can be set at run-time. These are the following:

- `minlp.numThreadsBnB`, the number of threads used to parallelize the search. Its default value is 1, if not provided by the user.
- `minlp.solver_timeout`, the maximum amount of time allowed for completing the search. Its default value is 1.0 seconds, if not set by the user.
- `minlp.parallelStrategy`, the method used for parallelizing the mixed-integer search (from FORCESPRO 1.9.0). Value 0 (default) corresponds to a single priority queue shared between threads. Value 1 corresponds to having each thread managing its own priority queue.

9.7.2 Mixed-integer solver customization via user callbacks

For advanced users, the mixed-integer branch-and-bound search can be customized after the rounding and the branching phases. In the rounding phase, an integer feasible solution is computed after each relaxed problem solve. The user is allowed to modify the rounded solution according to some modelling requirements and constraints. This can be accomplished via the `postRoundCallback_template.c` file provided in the FORCESPRO client. This callback is applied at every stage in a loop and updates the relaxed solution stage-wise. It needs to be provided before code generation, as shown in the following code snippet.

Matlab

Python

```
%% Add post-rounding callback to existing model
postRndCall = fileread('postRoundCallback_template.c'); % The file name can be_
↳changed by the user
model.minlpPostRounding = postRndCall;
```

```
with open('postroundCallback_template.c') as f:
    model.minlpPostRounding = f.read()
```

The branching process can be customized in order to discard some nodes during the search. To do so, the user is expected to overwrite the file `postBranchCallback_template.c` and pass it to FORCESPRO before generating the MINLP solver code.

Matlab

Python

```
%% Add as post-branching callbacks as you want
postBranchCall_1 = fileread('postBranchCallback_template_1.c');
postBranchCall_2 = fileread('postBranchCallback_template_2.c');
postBranchCall_3 = fileread('postBranchCallback_template_3.c');
model.minlpPostBranching{1} = postBranchCall_1;
```

(continues on next page)

(continued from previous page)

```
model.minlpPostBranching{2} = postBranchCall_2;
model.minlpPostBranching{3} = postBranchCall_3;
```

```
# Add as post-branching callbacks as you want
with open('postBranchCallback_template_1.c') as f:
    model.minlpPostBranching[0] = f.read()
with open('postBranchCallback_template_2.c') as f:
    model.minlpPostBranching[1] = f.read()
with open('postBranchCallback_template_3.c') as f:
    model.minlpPostBranching[2] = f.read()
```

In each of those callbacks, the user is expected to update the lower and upper bounds of the sons computed during branching given the index of the stage in which the branched variables lies, the index of this variable inside the stage and the relaxed solution at the parent node.

9.7.3 Providing a guess for the incumbent

Internally, the mixed-integer branch-and-bound computes an integer feasible solution by rounding. Moreover, since version 1.9.0, users are allowed to provide an initial guess for the incumbent. At code-generation, the following options need to be set:

- `minlp.int_guess`, which tells whether an integer feasible guess is provided by the user (value 1). Its default value is 0.
- `minlp.int_guess_stage_vars`, which specifies the indices of the integer variables that are user-initialized within one stage (MATLAB based indexing). If `minlp.int_guess = 1`, a parameter `int_guess` needs to be set at every stage. An example can be found there *Mixed-integer nonlinear solver: F8 Crusader aircraft*.

Another important related option is `minlp.round_root`. If set to 1, the solution of the root relaxation is rounded and set as incumbent if feasible. Its default value is 1. The mixed-integer solver behaviour differs depending on the combinations of options. The different behaviours are listed below.

- If `minlp.int_guess = 0` and `minlp.round_root = 1`, then the solution of the root relaxation is taken as incumbent (if feasible). This is the default behaviour.
- If `minlp.int_guess = 1` and `minlp.round_root = 0`, then the incumbent guess provided by the user is tested after the root solve. If feasible, it is taken as incumbent. Note that the user is allowed to provide guesses for a few integers per stage only. In this case, the other integer variables are rounded to the closest integer.
- If `minlp.int_guess = 1` and `minlp.round_root = 1`, then the rounded solution of the root relaxation and the user guess are compared. The best integer feasible solution in terms of primal objective is then taken as incumbent.

This feature is illustrated in Example *Mixed-integer nonlinear solver: F8 Crusader aircraft*. The ability of providing an integer guess for the incumbent is a key feature to run the mixed-integer solver in a receding horizon setting.

9.8 Sequential quadratic programming algorithm

The FORCESPRO real-time sequential quadratic programming (SQP) algorithm allows one to solve problems of the type specified in the section *High-level Interface*. The algorithm iteratively solves a convex quadratic approximations of the (generally non-convex) problem. Moreover, the solution is stored internally in the solver and used as an initial guess for the next time the solver is called. This and other features enables the solver to have fast solvetimes

(compared to the interior point method), particularly suitable for MPC applications where the sampling time or the computational power of the hardware is small.

Important: The SQP algorithm currently only supports affine inequalities. This means that all the inequality functions $h_k, k = 1, \dots, N$ from (9.1.1) must be *affine* functions of the variable z_k (not necessarily of p_k).

Moreover, the SQP algorithm currently does not support problems comprising final equality constraints (specified via `model.xfinalidx`).

9.8.1 How to generate a SQP solver

To generate a FORCESPRO sequential quadratic programming real-time iteration solver one sets

Matlab

Python

```
codeoptions.solvemethod = 'SQP_NLP';
```

```
codeoptions.solvemethod = "SQP_NLP"
```

(see [Generating a solver](#)). In addition to the general code options specified in the previous section here are some of the important code options one can use to customize the generated SQP solver.

By default the FORCESPRO SQP solver solves a single convex quadratic approximation. This accomplishes a fast solvetime compared to a “full” sequential quadratic programming solver (which solves quadratic approximations to the nonlinear program until a KKT point is reached). The user might prefer to manually allow the SQP solver to solve multiple quadratic approximations: By setting

Matlab

Python

```
codeoptions.sqp_nlp.maxqps = k;
```

```
codeoptions.sqp_nlp.maxqps = k
```

for a positive integer k one allows the solver to solve k quadratic approximations at every call to the solver. In general, the more quadratic approximations which are solved, the higher the control performance. The tradeoff is that the solvetime also increases.

9.8.2 The hessian approximation and line search settings

The SQP code generation currently supports two different types of hessian approximations. A good choice of hessian approximation can often improve the number of iterations required by the solver and thereby its solvetime. The default option for a SQP solver is the BFGS hessian approximation. When the objective function of the optimization problem is a least squares cost it is often beneficial to use the Gauss-Newton hessian approximation instead. To enable this option one proceeds as specified in the sections [Hessian approximation](#) and [Gauss-Newton options](#). When the Gauss-Newton hessian approximation is chosen one can also disable the the internal linesearch by setting

Matlab

Python

```
codeoptions.sqp_nlp.use_line_search = 0;
```

```
options.sqp_nlp.use_line_search = False
```

A linesearch is required to ensure global convergence of an SQP method, but is not needed in a real-time context when a Gauss-Newton hessian approximation is used.

Note: One cannot disable the line search when using the BFGS hessian approximation.

9.8.3 Controlling the initial guess at run-time

Upon the first call to the generated FORCESPRO SQP solver one needs to specify a primal initial guess (`problem.x0`, see also *Initial guess*). The default behaviour of the FORCESPRO SQP solver is to use the solution from the previous call as initial guess in every subsequent call to it. However, one can also manually set an initial guess in subsequent calls to the solver. Whether a manual initial guess (provided through `problem.x0`) will be used or the internally stored solution from the previous call will be used can be controlled by the field `problem.reinitialize` of the `problem` struct which is passed as an argument to the solver when it is called.

The `reinitialize` field can take two values: 0 or 1. For the default usage of the solver

Matlab

Python

```
problem.reinitialize = 0;
```

```
problem["reinitialize"] = False
```

should be used. This choice results in the solver using the solution from the previous call as initial guess. This feature is useful when running the real-time iteration scheme because it ensures that the initial guess is close to the optimal solution. If you want to specify an initial guess at run-time, you will need to set

Matlab

Python

```
problem.reinitialize = 1;
```

```
problem["reinitialize"] = True
```

So in summary: The first time the solver is called the initial guess the solver will use has to be provided by `problem.x0`. In all subsequent calls the solver will only make use of `problem.x0` as its initial guess if `problem.reinitialize = 1`.

9.8.4 Additional code options specific to the SQP-RTI solver

In addition to the above codeoptions, the following options are specific to the SQP algorithm. Each of these options can be supplied when generating a solver as a field of `codeoptions.sqp_nlp` (e.g. `codeoptions.sqp_nlp.TolStat`).

Table 9.4: SQP specific codeoptions

option	Possible values	Default value	Description
TolStat	positive	10^{-6}	Set the stationarity tolerance required for terminating the algorithm (the tolerance required to claim convergence to a KKT point).
TolEq	positive	10^{-6}	Set the feasibility tolerance required for terminating the algorithm (the tolerance required to claim convergence to a feasible point).
reg_hessian	positive	$5 \cdot 10^{-9}$	Set the level of regularization of the hessian approximation (often increasing this parameter can help if the SQP solver returns exitflag -8 for your problem)
qpinit	0 or 1	0	Set the initialization strategy for the internal QP solver. 0 = cold start and 1 = centered start. See also <i>Solver Initialization</i> (note however, that for the SQP solver qpinit=2 is not possible).

In addition to these options one can also specify the maximum number of iterations the internal QP solver is allowed to run in order to solve the quadratic approximation. If one wishes the QP solver use no more than k iterations to solve a problem one sets

```
codeoptions.maxit = k;
```

Note: The SQP algorithm currently does not support parallel execution, i.e. setting `codeoptions.parallel` will have no effect.

9.9 Differences between the MATLAB and the Python client

The Python NLP interface is largely similar to the MATLAB interface, but does come with some language- and implementation-specific differences.

- All indices in the problem formulation are expected to be 0-based in Python, as is usual in this language. This does not include the indices of the generated solver, however, where outputs are named `x01`, `x02`, ... as in MATLAB. Thus, the problem formulation *before generation* requires 0-based indices, whereas the returned solver from the server uses 1-based indices. This also does not apply to the low-level Python interface, where indices are 1-based even in the model formulation.
- In the Python client, different model objects must be used when using external functions or symbolic expressions, namely `nlp.ExternalFunctionModel()` and `nlp.SymbolicModel()`. Furthermore, if the high-level interface is to be used for convex problems, this is only possible using the `nlp.ConvexSymbolicModel()`. This is different from the MATLAB client, where the `FORCES_NLP` function accepts problems of any kind and switches to the appropriate solver automatically.
- When using the Python client with a `nlp.SymbolicModel()`, the C code generated for symbolic expressions is currently not entirely identical to the code generated by MATLAB. While the actual expression evaluation code generated by CasADi is the same, the structure of the files varies. Specifically, the MATLAB client creates individual C files for each problem stage with distinct symbolic expressions (leading to varying file names when changing the problem horizon) whereas all functions are gathered in one

file in the Python client. Yet, the Python client does add one additional file for the FORCESPRO-CasADi glue code, which is not present when using the MATLAB client. Lastly, function names of the evaluation functions differ.

If you want to get the same code for MATLAB and Python, you must generate the CasADi C code from one of both clients and then supply this code as an external function in the other client.

9.10 Examples

- *High-level interface: Basic example*: In this example, you learn the basics in how to use FORCESPRO to create an MPC regulation controllers.
- *High-level interface: Obstacle avoidance (MATLAB & Python)*: This example uses a simple nonlinear vehicle model to illustrate the use of FORCESPRO for real-time trajectory planning around non-convex obstacles.
- *High-level interface: Indoor localization (MATLAB & Python)*: This examples describes a nonlinear optimization approach for the indoor localization problem.
- *Mixed-integer nonlinear solver: F8 Crusader aircraft*: In this example, you learn the basics in how to use FORCESPRO MINLP solver to solve a mixed-integer optimal control problem.
- *Real-time SQP Solver: Robotic Arm Manipulator (MATLAB & Python)*: This example describes how to apply the FORCESPRO SQP solver to control a robotic arm.
- *Controlling a DC motor using a FORCESPRO SQP solver*: This example describes how to apply the FORCESPRO SQP solver to control a DC motor.
- *Controlling a crane using a FORCESPRO NLP solver*: This example describes how to apply the FORCESPRO interior point NLP solver to control a crane.

Chapter 10

Simulating your custom controller in Simulink®

FORCESPRO provides a Simulink® interface for easy simulation of your custom controllers within existing Simulink® diagrams. Once code has been generated the block transforms into a new block with the appropriate number of ports for your specific configuration. Depending on your controller configuration you will have different input and output ports on your block. The port labels are self-explanatory. Just wire the ports of the FORCESPRO block to other blocks in you Simulink diagram and run the simulation.

Note: We recommend *not* to use this Simulink interface anymore as it will be deprecated in a future release. Instead, use the Simulink S-function that is generated along with your FORCESPRO solver inside the `interface` folder.

Watch an introductory video on how to use the FORCESPRO Simulink® interface [here](#)

10.1 Configuration of a custom linear MPC controller using the FORCESPRO Simulink® GUI

- *Model*
- *Control Objectives*
- *System Constraints*
- *Estimator Settings*

The Simulink® GUI for FORCESPRO is an easy and intuitive way to design model-based optimal controllers that can take decisions considering future information and system constraints. The general supported problem formulation is as follows:

Given a measurement or estimate of the current state of the system, x , and possibly:

- an estimate for an additive disturbance, w_k
- the previous control command, u_{prev} ,
- the output reference to track, $y_{ref,k}$

the controller decides the future control actions u_0, u_1, \dots, u_{N-1} , and the resulting predicted state trajectory x_1, x_2, \dots, x_N , over the prediction horizon, N , in order to optimize the control

objectives

$$\sum_{k=0}^{N-1} (x_{k+1} - x_{ss,k})^T Q_k (x_{k+1} - x_{ss,k}) + (u_{k+1} - u_{ss,k})^T Q_k (u_{k+1} - u_{ss,k}) + \Delta u_k^T T_k \Delta u_k$$

where

$$\begin{pmatrix} A_k - I & B_k \\ C & 0 \end{pmatrix} \begin{pmatrix} x_{ss,k} \\ u_{ss,k} \end{pmatrix} = \begin{pmatrix} 0 \\ y_{ref,k} \end{pmatrix}$$

$$\Delta u_0 = u_0 - u_{prev},$$

$$\Delta u_0 = u_k - u_{k-1}, \quad k = 1, \dots, N-1$$

subject to a linear mode of the system

$$x_1 = A_0 x + B_0 u_0 + w_0$$

$$x_{k+1} = A_k x_k + B_k u_k + w_k, \quad \text{for all } k = 1, \dots, N-1$$

$$y_k = C x_k, \quad \text{for all } k = 1, \dots, N$$

and satisfying the *system constraints*

$$y_k \in \mathbb{Y}_k, \quad \text{for all } k = 1, 2, \dots, N$$

$$u_k \in \mathbb{U}_k, \quad \text{for all } k = 0, 1, \dots, N-1$$

$$\Delta u_k \in \mathbb{V}_k, \quad \text{for all } k = 0, 1, \dots, N-1$$

The settings for your particular controller can be specified by editing the mask of the FORCE-SPRO Simulink block. To start a new controller design copy the block in `MPC_lib_2012b.mdl` to your Simulink diagram and give a name to your controller. Double click on the new block and configure the different parameters as described here:

10.1.1 Model

Describe your linear state-space model of the system.

- *Time* : Choose whether your state-space model is described using differential equations or using a discrete update equation.
- *Type* : Choose whether your model has an extra affine term, i.e. is *w* present?
- *Sampling time* : If you are loading a continuous-time model specify the sampling time in seconds.
- *System matrices* : Specify the workspace variables describing the different system matrices *A*, *B*, *C*, and *w*, if present, vector *w*.
- *Parameters* : Some variables are allowed to be parameters at design time, i.e. they can change dynamically during runtime. To allow this feature mark the appropriate check boxes to determine whether the parameter changes over the prediction horizon.
- *System dimensions* : If one or more system matrices are parameters you might need to specify any unresolved system dimensions.

10.1.2 Control Objectives

The control objectives are typically a trade-off between how well the controller tracks the output reference and how much input action it uses.

- *Tracking options*: Check if the controller is tracking an output reference or leave unchecked if the controller is regulating to the origin. If the controller is tracking a reference, specify whether the output reference y_{ref} will be provided, or whether the steady-state offset-free state and input references, x_{ss} and u_{ss} , have already been calculated. Also specify if the reference is changing over time and whether the changes are known ahead of time or not ($y_{ref,k} = y_{ref}$). If reference changes are known ahead of time, the controller can use this preview information to improve the control performance.
- *Input slew rate penalty*: Check if the controller should also attempt to minimize the actuator changes between control samples. If the checkbox is left unmarked, the weight matrix T is set to zero.
- *Terminal cost*: If the checkbox is marked the state penalty matrix for the last stage becomes $Q_N := P$, where P is the solution of the discrete-time Ricatti equation. Note that the matrix P can only be computed when matrices A , B , C , and R are known at design time, i.e. they are not runtime parameters. In general, having a terminal cost allows for a reduced prediction horizon but imposes certain restrictions on the optimization methods that can be used.
- *Control horizon*: Specify the number of samples that the controller looks into the future. In general, a longer control horizon can improve control performance but leads to longer computation times.
- *Weighting matrices*: Check if the weighting matrices on the outputs, Q , on the inputs, R , and on the input rates, T , are available and specify the corresponding workspace variables. If no weighting matrices are available specify the relative importance for tracking/regulation of the different outputs, inputs and slew rates. A high weight on an output tells the controller to focus on improving the tracking performance on that output. A high weight on an input tells the controller to use less of that input.
- *Parameters*: The penalty matrices can also be parameters at design time and change dynamically at runtime. To allow this feature mark the appropriate check boxes to determine whether the parameter changes over the prediction horizon.

10.1.3 System Constraints

Describe system limits that cannot be exceeded due to physical, safety, economic or regulatory reasons.

- *Constraint list*: Check which output, input, and slew rate constraints are present. For each constraint specify the upper and lower bounds. Note that an empty bound implies a one-sided constraint, e.g. $0 \leq u_1$.
- *Soft constraints*: Output constraints can be specified to be soft to prevent infeasible problems. In this case a slack variable, δ , is introduced resulting in the constraint.

$$\begin{aligned} -23\delta \leq y_2 \leq 23 + \delta, \\ \delta \geq 0. \end{aligned}$$

- *Parameters*: Upper and lower bounds can also be defined as runtime parameters. To allow this feature mark the appropriate check boxes to determine whether the parameter changes over the prediction horizon.

10.1.4 Estimator Settings

Describe additional characteristics for your customized solver.

- *Data type* : Choose the data type used by the solver. For some embedded platforms, floating-point computations (specially double precision) will incur significant computational delays. In the standard and premium versions of FORCESPRO fixed-point data types can lead to reduced computation times depending on the platform, but this imposes certain restrictions on the optimization methods that can be used.
- *Optimization method* : The basic version of FORCESPRO always uses a Primal-Dual Interior-Point (PDIP) method to implement the optimal controller. In the standard and premium versions of FORCESPRO one can select other alternative methods, such as ADMM and DFGM, that can lead to reduced computation times. One can also let FORCESPRO choose the most appropriate optimization method for your problem.
- *Number of iterations* : Specify the maximum number of iterations used in the optimization algorithm. One can also let FORCESPRO determine the number of iterations for your problem.
- *Method-specific options* : For some methods the user can choose values for certain parameters to tune the performance of the method.
- *Platform* : In the standard and premium versions of FORCESPRO one can choose the platform that the solver will run on to obtain customized code for the particular platform. For desktop based platforms, choose 'x86_64' for 64-bit platforms and 'x86' for 32-bit platforms. For embedded platforms, choose between 'x86', 'ARM Cortex M3 and M4', 'ARM Cortex A9', 'Tricore', 'PowerPC', or get a customized circuit design described in VHDL. Note that additional add-ons for FORCESPRO are required to generate code for different target platforms.
- *Description* : Add an optional description for your controller that can be used later to identify the settings for a particular controller instance in your web workspace.
- *Solve information* : Mark this check box to obtain runtime information from the solver that can be used to diagnose problems.

Once all the necessary solver options have been specified a custom solver for your controller can be built by executing the command `configure_block`. The command returns an error if any essential information is missing or if the license type is not valid. Note that this command transforms the block to make it ready for simulation. Once a controller has been generated you can change the configuration by double clicking the block and running `configure_block` again.

Several instance of the FORCESPRO block can exist in the same Simulink® diagram.

10.2 Getting Started - Basic MPC Regulation State Feedback Example

This example will show how to get started with the Simulink® interface of FORCESPRO by designing an MPC regulator for the system below.

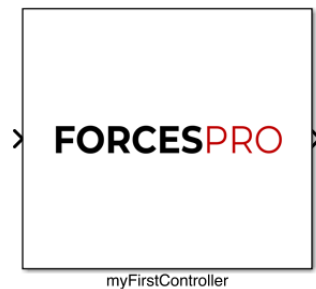
You can find the Matlab code of this example to try it out for yourself in the `examples` folder that comes with your client.

$$x_{k+1} = \begin{pmatrix} 0.7115 & -0.4345 \\ 0.4345 & 0.8853 \end{pmatrix} x_k + \begin{pmatrix} 0.2173 \\ 0.0573 \end{pmatrix} u_k$$

$$y_k = \begin{pmatrix} 0 & 1 \end{pmatrix} x_k$$

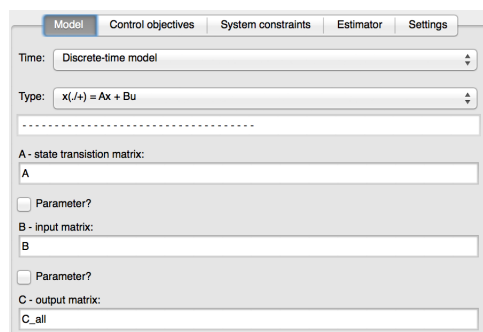
In addition to the task of steering the two states to zero, there are constraints on the single actuator u and on the second state x_2 . We require that the actuator u does not exceed $[-5, 5]$ and the state $x_2 \geq 0$ for all time. After downloading the files we can start with the design of the controller. First load the data from `myFirstController_data.mat` into the workspace and then open the Simulink® model `myFirstController_sim.slx`.

Then copy the FORCESPRO Simulink® block `MPC_lib_2012b.mdl` into your Simulink® diagram. Give the block a name. Here we will call it `myFirstController`.



We are now ready to configure the controller. Double-click on the block and go to the 'Model' tab to enter the details of the system that we want to control. The model described above has already been discretized with a sampling time of 0.1 seconds. We therefore choose 'Discrete-time model' and chose the type of state-space model (we have no additive term g in this example). Enter the state transition matrix A , the input matrix B and the output matrix C_{all} . Notice that we use C_{all} , which is just the identity matrix, instead of C , since we want to regulate both states, not just the output of the system.

We are now ready to configure the controller. Double-click on the block and go to the 'Model' tab to enter the details of the system that we want to control. The model described above has already been discretized with a sampling time of 0.1 seconds. We therefore choose 'Discrete-time model' and chose the type of state-space model (we have no additive term g in this example). Enter the state transition matrix A , the input matrix B and the output matrix C_{All} . Notice that we use C_{All} , which is just the identity matrix, instead of C , since we want to regulate both states, not just the output of the system.



In the 'Control Objective' tab we choose a prediction horizon of 10 steps, i. e. the controller looks 1 second into the future. We will input the relative weights manually. We weight the importance of regulating the states 10 times higher then reducing the use of the actuator.

You are encouraged to change these weights and observe the effect on the control behaviour.

In the 'System Constraints' tab we input the details of the constraints described above. The second state must remain positive, whereas the first state is left unconstrained. We also have a constraint on the actuator. We enter the lower bound -5 and the upper bound 5 . We can also check the option 'Soft Constraint' for the output constraint to prevent infeasibility problems in the solver.

Model Control objectives System constraints Estimator Settings

☐ Reference tracking?
☐ Penalize the input slew rate?
☐ Use unconstrained LQR gain as terminal cost?

Control/prediction horizon (steps):
 10

☐ Load weighing matrices?

Relative importance of output/state 1:
 10

Relative importance of output/state 2:
 10

Relative importance of input 1 magnitude:
 1

Model Control objectives System constraints Estimator Settings

.....

☐ Constraints on output 1?

☒ Constraints on output 2?
 Constraint type: Bound constraints
 Lower bound:
 0
☐ Lower bound - Parameter?
 Upper bound:
☐ Upper bound - Parameter?
☒ Soft constraint

☒ Constraints on input 1 magnitude?
 Constraint type: Bound constraints
 Lower bound:
 -5
☐ Lower bound - Parameter?
 Upper bound:
 5
☐ Upper bound - Parameter?

☐ Constraints on input 1 slew rate?

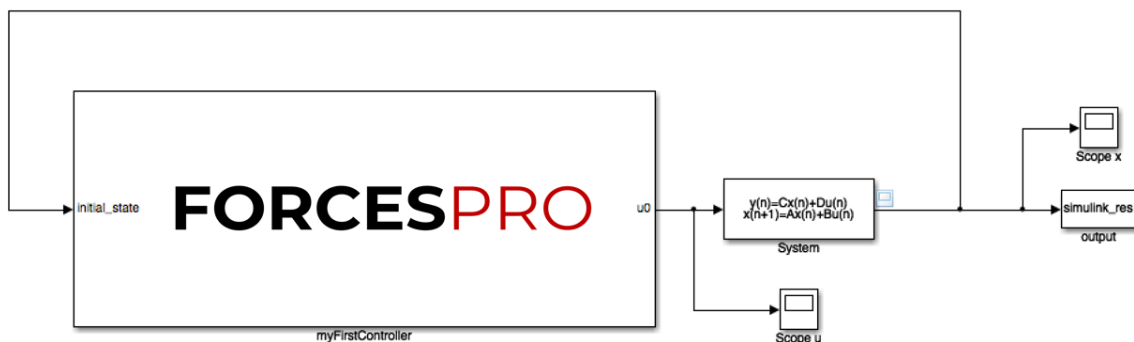
Since we are designing a state feedback controller we will leave the only option in the 'Estimator' tab as 'State Feedback'. There will be no estimator built into the FORCESPRO block.

If we wish the controller to give information on the optimization process at each time step we check the option 'Get Solve Information' in the 'Settings' tab. The controller will have an additional output from which we can read this information.

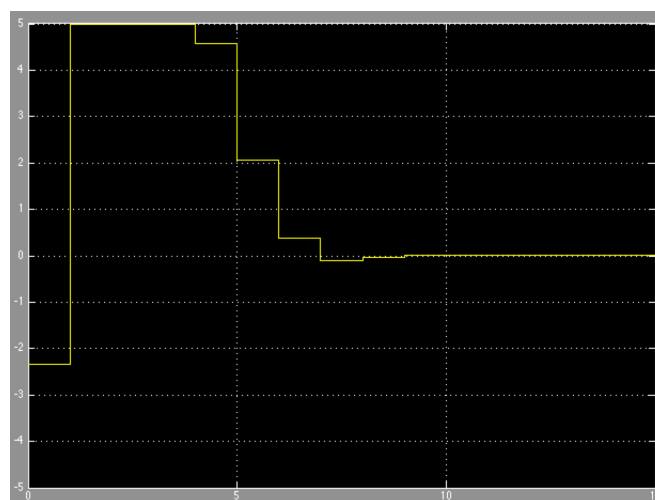
We are now ready to configure the controller. Simply type

```
>> configure_block
```

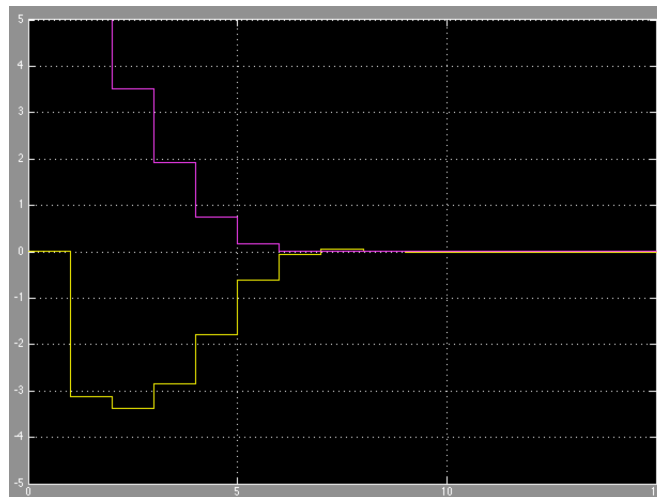
in the MATLAB® command prompt. This will send a request to the server which will generate a custom controller for your problem. The code is downloaded to your machine and the FORCESPRO block is automatically updated and made ready for simulation on your Simulink® diagram. We can connect the ports of the controller to the rest of the system and run the simulation.



From the left plot we can see that the actuator remains in the allowed range. The right plot shows how the second state x_2 is always non-negative (purple graph in the right plot) and both states are regulated to zero.



10.3 Real-time control with the Simulink block



• Input and Output Ports in the Compact Interface

When a user generates a new solver from either the graphical Simulink interface, or the textual MATLAB or Python interfaces, several Simulink blocks are automatically created in the 'interfaces' folder. These blocks are useful to interface the solver with other Simulink models for simulation, or for deployment in embedded prototyping hardware using tools such as dSpace MicroAutobox or Simulink Coder.

In the following we describe the difference between the different available Simulink interfaces.

10.3.1 Input and Output Ports in the Compact Interface

For every solver, there are two Simulink interfaces generated: a standard interface; and a compact interface, which groups parameters and outputs. For problems with many parameters and outputs, the compact interface is more suitable because it reduces the number of ports and connections that need to be wired up to the rest of the Simulink model.

The criteria for grouping parameters is the following: parameters of the same type that have the same number of rows are grouped together into a single stacked parameter. These parameters are stacked horizontally, e.g. if there are two parameters mapping to `eq.c`, both of size 3×1 , they will be grouped into a new parameter of size 3×2 . The new parameter will get the name `c`.

To illustrate the conversion consider a problem with the following parameters and with the corresponding standard (non-compact) Simulink block:

Name	maps2data	Dimensions
<code>Amat1</code>	<code>eq.D</code>	2×4
<code>Amat2</code>	<code>eq.D</code>	3×4
<code>Amat3</code>	<code>eq.D</code>	3×4
<code>Amat4</code>	<code>eq.D</code>	3×4
<code>linterm1</code>	<code>cost.f</code>	4×1
<code>linterm2</code>	<code>cost.f</code>	4×1
<code>linterm3</code>	<code>cost.f</code>	4×1
<code>linterm4</code>	<code>cost.f</code>	4×1

For the compact Simulink block, parameters `linterm1`, `linterm2`, `linterm3` and `linterm4` are stacked together into a new parameter `f` (because the problem data they map to is `cost`).



f). For the parameters mapping to `eq.D`, `Amat2`, `Amat3` and `Amat4` can be stacked into the new parameter `D`. `Amat1` is not included into the new parameter because it has two rows and the concatenation is not possible with the other parameters, which all have three rows. Parameters are always stacked horizontally according to the stage number they map to.

Name	maps2data	Dimensions
<code>D</code>	<code>eq.D</code>	3x12
<code>f</code>	<code>cost.f</code>	4x4
<code>Amat1</code>	<code>eq.D</code>	2x4



The port dimensions of any FORCESPRO Simulink block can be checked by double-clicking the block and clicking the 'Help' button.

Chapter 11

Examples

11.1 How to

11.1.1 Basic Example

Consider the following linear MPC problem with lower and upper bounds on state and inputs, and a terminal cost term:

$$\begin{aligned} & \text{minimize} && x_N^\top P x_N + \sum_{i=0}^{N-1} x_i^\top Q x_i + u_i^\top R u_i \\ & \text{subject to} && x_0 = \mathbf{x} \\ & && x_{i+1} = A x_i + B u_i \\ & && \underline{x} \leq x_i \leq \bar{x} \\ & && \underline{u} \leq u_i \leq \bar{u} \end{aligned}$$

This problem is parametric in the initial state \mathbf{x} and the first input u_0 is typically applied to the system after a solution has been obtained. The following code generates a function that takes $-Ax$ as a calling argument and returns u_0 , which can then be applied to the system.

Here is the Matlab code:

```
%% FORCES multistage form
% assume variable ordering zi = [ui, xi+1] for i=1...N-1

stages = MultistageProblem(N); % get stages struct of length N

for i = 1:N

    % dimension
    stages(i).dims.n = nx+nu; % number of stage variables
    stages(i).dims.r = nx;    % number of equality constraints
    stages(i).dims.l = nx+nu; % number of lower bounds
    stages(i).dims.u = nx+nu; % number of upper bounds

    % cost
    if( i == N )
        stages(i).cost.H = blkdiag(R,P); % terminal cost (Hessian)
    else
        stages(i).cost.H = blkdiag(R,Q);
    end
    stages(i).cost.f = zeros(nx+nu,1); % linear cost terms
```

(continues on next page)

(continued from previous page)

```

% lower bounds
stages(i).ineq.b.lbidx = 1:(nu+nx); % lower bound acts on these indices
stages(i).ineq.b.lb = [umin; xmin]; % lower bound for this stage variable

% upper bounds
stages(i).ineq.b.ubidx = 1:(nu+nx); % upper bound acts on these indices
stages(i).ineq.b.ub = [umax; xmax]; % upper bound for this stage variable

% equality constraints
if( i < N )
    stages(i).eq.C = [zeros(nx,nu), A];
end
if( i>1 )
    stages(i).eq.c = zeros(nx,1);
end
stages(i).eq.D = [B, -eye(nx)];
end

% RHS of first eq. constr. is a parameter: stages(1).eq.c = -A*x0
params(1) = newParam('minusA_times_x0',1,'eq.c');

```

You can find the Matlab code of this example to try it out for yourself in the examples folder that comes with your client.

And here's the Python code:

```

# FORCESPRO multistage form
# assume variable ordering zi = [ui, xi+1] for i=1...N-1

stages = forcespro.MultistageProblem(N) # get stages struct of length N

for i in range(N):

    # dimensions
    stages.dims[ i ]['n'] = nx+nu # number of stage variables
    stages.dims[ i ]['r'] = nx     # number of equality constraints
    stages.dims[ i ]['l'] = nx+nu # number of lower bounds
    stages.dims[ i ]['u'] = nx+nu # number of upper bounds

    # cost
    if ( i == N-1 ):
        stages.cost[ i ]['H'] = np.vstack((np.hstack((R,np.zeros((nu,
→nx)))), np.hstack((np.zeros((nx,nu)),P))))
    else:
        stages.cost[ i ]['H'] = np.vstack((np.hstack((R,np.zeros((nu,
→nx)))), np.hstack((np.zeros((nx,nu)),Q))))
        stages.cost[ i ]['f'] = np.zeros((nx+nu,1)) # linear cost terms

    # lower bounds
    stages.ineq[ i ]['b']['lbidx'] = range(1,nu+nx+1) # lower bound acts on_
→these indices
    stages.ineq[ i ]['b']['lb'] = np.concatenate((umin,xmin),0) # lower bound_
→for this stage variable

    # upper bounds
    stages.ineq[ i ]['b']['ubidx'] = range(1,nu+nx+1) # upper bound acts on_
→these indices
    stages.ineq[ i ]['b']['ub'] = np.concatenate((umax,xmax),0) # upper bound_
→for this stage variable

    # equality constraints

```

(continues on next page)

(continued from previous page)

```

if ( i < N-1 ):
    stages.eq[i]['C'] = np.hstack((np.zeros((nx,nu)),A))
if ( i>0 ):
    stages.eq[i]['c'] = np.zeros((nx,1))
    stages.eq[i]['D'] = np.hstack((B,-np.eye(nx)))

# RHS of first eq. constr. is a parameter: stages(1).eq.c = -A*x0
stages.newParam('minusA_times_x0', [1], 'eq.c')
# define output of the solver
stages.newOutput('u0', 1, range(1,nu+1))

```

11.1.2 How to Incorporate Preview Information in the MPC Problem

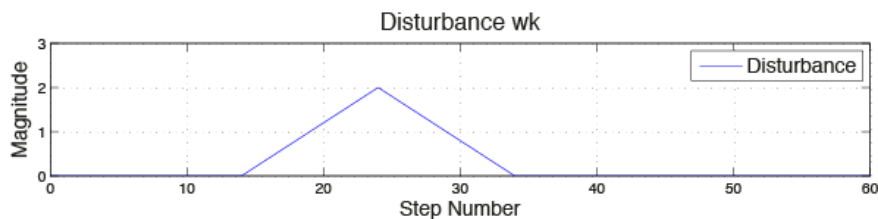
- *Introduction*
- *Use preview information in the Simulink® interface*
- *Use preview information in the MATLAB® interface*
- *Comparison of MPC with Preview and Standard MPC*

Introduction

In this example the following discrete-time system is considered:

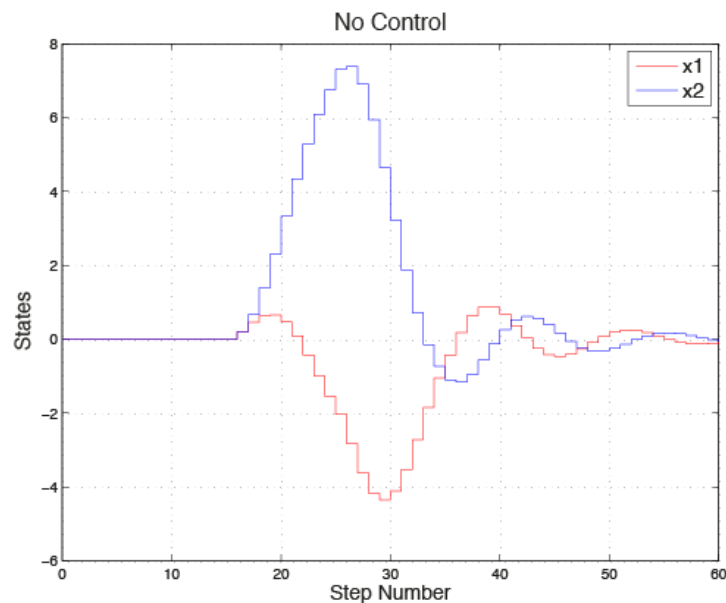
$$x_{k+1} = \begin{pmatrix} 0.7115 & -0.4345 \\ 0.4345 & 0.8853 \end{pmatrix} x_k + \begin{pmatrix} 1 \\ 1 \end{pmatrix} u_k + \begin{pmatrix} 1 \\ 1 \end{pmatrix} w_k$$

The control objective is to regulate the two states to zero using the input u_k , while a disturbance w_k is acting on the system. The disturbance w_k gets predicted for a horizon of length $N = 10$, which is equal to the control horizon of the model predictive control problem solved at each time step by the FORCESPRO controller. At each time step k , a predicted disturbance for the next N steps is considered by the FORCESPRO controller. For the cost function of the MPC problem, it is assumed that the relative importance of regulating the two states to zero is ten times as high as the penalty on applying an input. Further it is demanded, that the input magnitude of the input signal u lies in the range $[-1.8, 1.8]$. The initial state of the system is set to zero, i. e. $x_0 = [0; 0]$.



One can see that the disturbance drives the states far away from the desired value. In this example it is shown how FORCESPRO can significantly improve the dynamical behaviour by using the concept of ‘preview’ when such future information is available.

To implement a FORCESPRO controller with ‘preview’ one can either use the Simulink® interface or the MATLAB® interface. Here both options are presented. The result is the same.



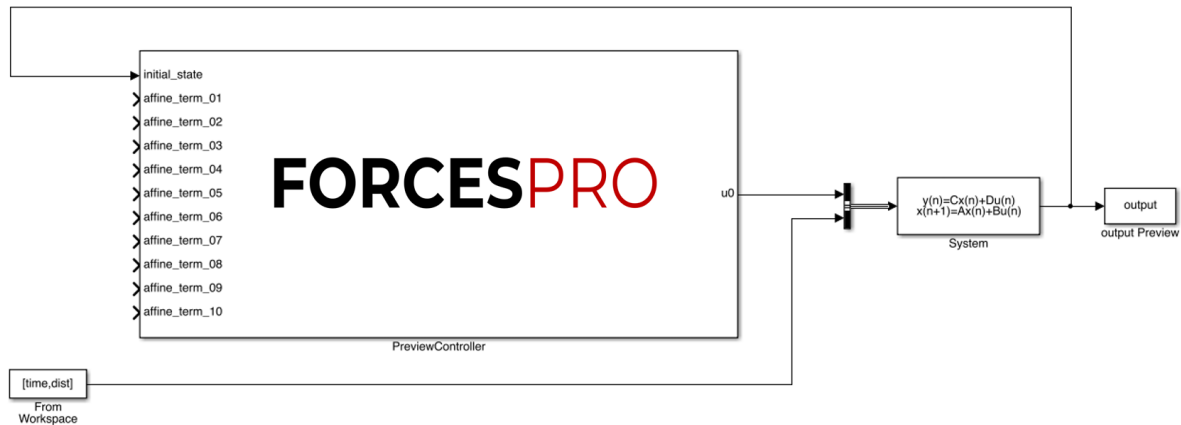
Use preview information in the Simulink® interface

To implement a FORCESPRO controller which makes use of preview information, drag the `LTI_MPC` block from the `LTI_MPC_lib` from the `FORCES_PRO` folder into the Simulink® model. After renaming the block, double click on it and chose in the tab `Model` the settings shown on the right side. In this example, the preview information comes through the additive term g . Check the option `parameter`. g is a parameter because at each time instant new disturbance predictions enter the controller. Also note that the additive term g is not constant over time, i.e. the disturbance prediction can vary over the prediction horizon.

The rest of the configuration of the FORCESPRO block is the same as for the design of a standard MPC regulator described [here](#). After finishing the configuration, type `configure_block` to obtain a customized solver for your controller.

The controller is now configured and the number of inputs ports to the controller is determined by the length of the preview horizon.

Add the data of the disturbance and its preview from the workspace to model and start the



simulation. To see the impact of using preview information see the section [Comparison of MPC with Preview and Standard MPC](#) below.

You can find the Matlab code of this example to try it out for yourself in the `examples` folder that comes with your client. When running this example the code will automatically generate the Simulink block.

Use preview information in the MATLAB® interface

The same problem can be solved using the MATLAB® Interface. The multistage problem is constructed as shown in the simple example [here](#) and is then extended as shown below.

As in the Simulink® interface, the parametric additive terms g have to be defined. At each stage of the multistage problem, the equality constraint change, therefore we have to define a parameter for each stage. In the definition of the parameters, `distx` represents the name of the predicted disturbance at stage x of the multistage problem.

During runtime, the preview information is mapped to these parameters.

```
% RHS of first eq. constr. is a parameter: z1=-A*x0 -Bw*Road
parameter(1) = newParam('minusA_times_x0_BwDist',1,'eq.c');
% Parameter of Preview
parameter(2) = newParam('dist1',2,'eq.c');
parameter(3) = newParam('dist2',3,'eq.c');
parameter(4) = newParam('dist3',4,'eq.c');
parameter(5) = newParam('dist4',5,'eq.c');
parameter(6) = newParam('dist5',6,'eq.c');
parameter(7) = newParam('dist6',7,'eq.c');
parameter(8) = newParam('dist7',8,'eq.c');
parameter(9) = newParam('dist8',9,'eq.c');
parameter(10) = newParam('dist9',10,'eq.c');
```

After setting up the multistage problem with the parametric equality constraints, configure the solver settings (i. e. define solver output and solver options), the solver can be generated by using the command `generateCode(...)`. With the function provided by FORCESPRO, the system is now ready for simulation.

Comparison of MPC with Preview and Standard MPC

Figure 11.2 shows the dynamics of the system using a non-preview controller and a preview controller designed using FORCES Pro. One can see that the maximum deviation of the two states from their desired value is reduced by a factor 18, and 11, respectively. Compared to the

open loop case, the magnitude of the deviation is reduced by a factor of 47, and 34, respectively.

Figure 11.1 shows the control action of both controllers. As expected, the input signal remains in the allowed range. One can see how the preview controller makes use of future information to provide a more aggressive control action that results in improved system performance.

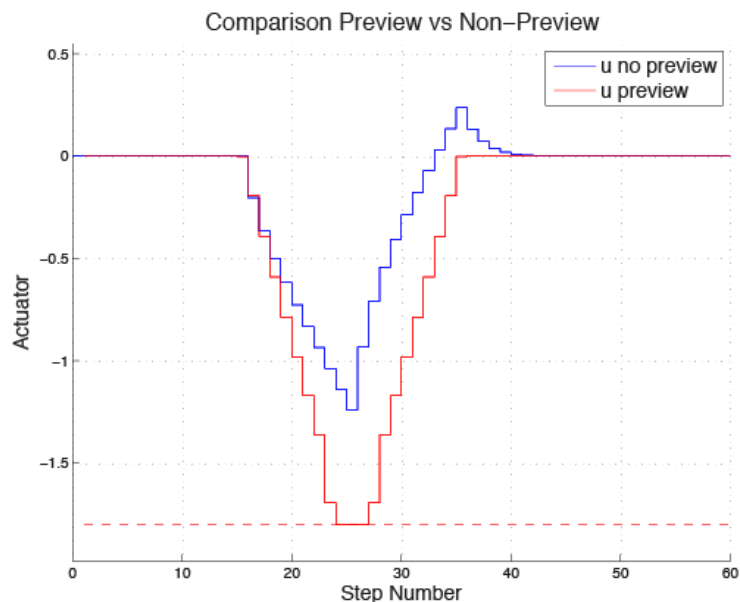


Figure 11.1: Comparison preview vs. non-preview

11.1.3 HOW TO: Implement an MPC Controller with a Time-Varying Model

- *Introduction*
- *Implementation*
- *Comparison of the two approaches*

Introduction

This 'HOW TO' explains how FORCESPRO can be used to handle time-varying models to achieve better control performance than a standard MPC controller. For this example it is assumed that the time-varying model consists of four different systems. This could be four models derived from a nonlinear system at four operating points or from a periodic system. The systems are listed below. The first system is a damped harmonic oscillator, while the second system has eigenvalues on the right plane and is therefore unstable. System three is also a damped oscillator, but differs from system one. System four is an undamped harmonic

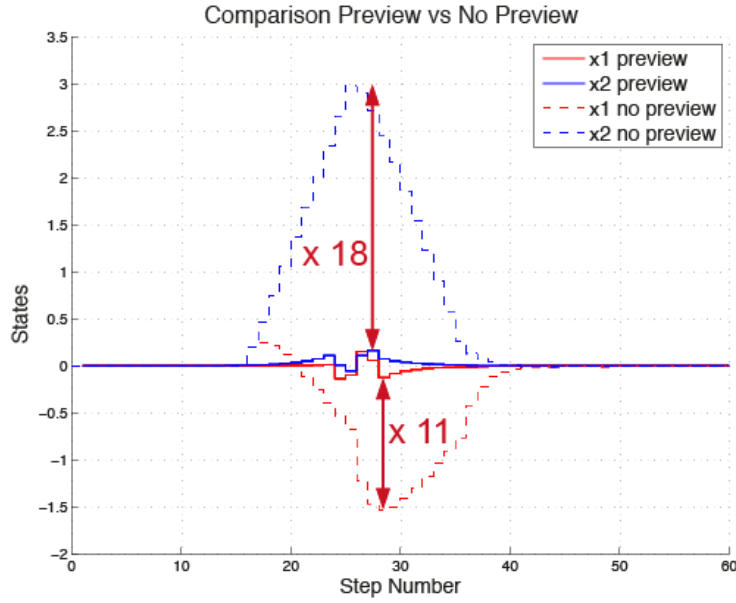


Figure 11.2: Comparison preview vs. no preview

oscillator.

$$\text{System 1: } x_{k+1} = \begin{pmatrix} 0.7115 & -0.6 \\ 0.6 & 0.8853 \end{pmatrix} x_k + \begin{pmatrix} 0.2173 \\ 0.0573 \end{pmatrix} u_k$$

$$\text{System 2: } x_{k+1} = \begin{pmatrix} 0.9 & 0.5 \\ 0.5 & 1 \end{pmatrix} x_k + \begin{pmatrix} 0 \\ 0.0666 \end{pmatrix} u_k$$

$$\text{System 3: } x_{k+1} = \begin{pmatrix} 0.7115 & -0.5 \\ 0.5 & 1 \end{pmatrix} x_k + \begin{pmatrix} 0.5 \\ 0.01 \end{pmatrix} u_k$$

$$\text{System 4: } x_{k+1} = \begin{pmatrix} 0 & 0.9 \\ -1 & 0 \end{pmatrix} x_k + \begin{pmatrix} 0 \\ 0.2 \end{pmatrix} u_k$$

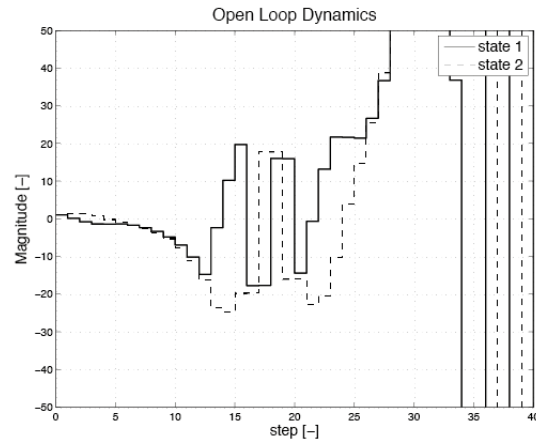
In this example we assume that system 1 is active for the first 4 steps. Then at step 5 the model changes to system 2, which stays active for 8 steps. Then we switch to system 3 for the following 3 steps and finally system 4 is active for the next 5 steps. This pattern is periodic, i. e. every 20 steps the cycle starts again. Also we have an initial condition of $x_0 = [1; 1]$, a prediction horizon $N = 15$ and the simulation runs for 40 steps.

The open loop dynamics of this time-varying model are shown on the right. One can see that the system becomes unstable. The goal is to regulate both states to zero while satisfying the different input constraints on each system. The constraints on the model are $u \in [-3, 5]$, $u \in [-5.5, 5.5]$, $u \in [-3, 5]$ and $u \in [-0.45, 4.5]$ for systems 1, 2, 3 and 4, respectively.

At each step k FORCESPRO takes the changing state space matrices and the corresponding input constraints into account, in order to regulate both states to zero as fast as possible. The following section shows how a controller for this problem can be implemented using the FORCESPRO MATLAB® Interface.

Implementation

The FORCESPRO MATLAB® Interface is used to pose a multistage problem as described [here](#). When taking the changing dynamics over the prediction horizon into account, the matrices C_{i-1} and D_i of the inter-stage equality have to be defined as parameters for each prediction step i . Additionally the lower bounds \underline{z}_i and the upper bounds \bar{z}_i on the optimization variable have to be defined as parameters as they also change over the prediction



horizon. Also, the initial condition has to be set as a parameter. The code below shows the multistage problem and the commands to design the controller using FORCESPRO.

```
%% Multistage Problem: Varying Model in Prediction Horizon
stages = MultistageProblem(N); % get stages struct of length N

% Initial Equality
% c_1 = -A*x0
parameter(1) = newParam('minusA_times_x0',1,'eq.c');

for i = 1:N
    % dimension
    stages(i).dims.n = nx+nu; % number of stage variables
    stages(i).dims.r = nx; % number of equality constraints
    stages(i).dims.l = nu; % number of lower bounds
    stages(i).dims.u = nu; % number of upper bounds

    % lower bounds
    stages(i).ineq.b.lbidx = 1; % lower bound acts on these indices
    parameter(1+i) = newParam(['u',num2str(i),'min'],i,'ineq.b.lb');

    % upper bounds
    stages(i).ineq.b.ubidx = 1; % upper bound acts on these indices
    parameter(1+N+i) = newParam(['u',num2str(i),'max'],i,'ineq.b.ub');

    % cost
    stages(i).cost.H = blkdiag(R,Q);
    stages(i).cost.f = zeros(nx+nu,1);

    % Equality constraints
    if( i>1 )
        stages(i).eq.c = zeros(nx,1);
    end
    % Inter-Stage Equality
    % D_i*z_i = [B_i -I]*z_{i-1}
    parameter(1+2*N+i) = newParam(['D_',num2str(i)],i,'eq.D');
    if( i < n )
        % C_{i-1}*z_{i-1} = [0 A_i]*z_{i-1}
        parameter(1+3*N+i) = newParam(['C_',num2str(i)],i,'eq.C');
    end
end

% define outputs of the solver
outputs(1) = newOutput('u0',1,1);
% solver settings
```

(continues on next page)

(continued from previous page)

```
codeoptions = getOptions('Time_Varying_Model_wP');
% generate code
generateCode(stages,parameter,codeoptions,outputs);
```

You can find the Matlab code of this example to try it out for yourself in the `examples` folder that comes with your client.

Comparison of the two approaches

The two plots in [Figure 11.3](#) and [Figure 11.4](#) respectively, show the difference between the response of a controller that assumes constant matrices A and B over the whole prediction horizon, and a controller that considers the changing dynamics, e. g. at time step 0 the second controller knows that system 1 will only be active for the first 4 steps. The left plot shows the system response and the right plot shows the actuator signals and the varying system constraints.

Both controllers can satisfy the constraints. To quantify the improvement in control performance, the cost function $\sum_{k=1}^N x_k^T Q x_k + u_k^T R u_k$ can be evaluated for the whole simulation length of $n = 40$. For the controller that uses a fixed model for the prediction horizon, the closed loop cost for regulating the states to zero is 2163.2. With the FORCESPRO time-varying controller the costs is reduced to 457.5. This is a cost reduction of almost 80%.

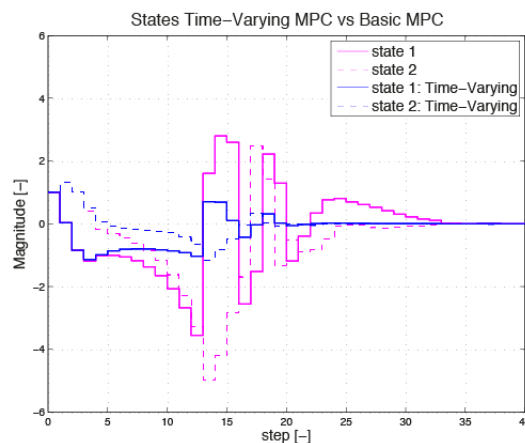


Figure 11.3: States Time-varying MPC vs. basic MPC

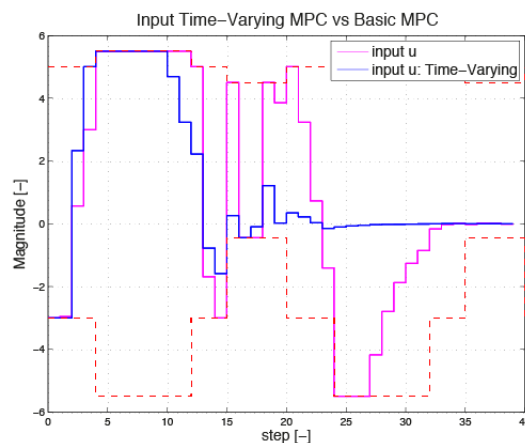


Figure 11.4: Input Time-varying MPC vs. basic MPC

11.1.4 How to Implement 1-Norm and Infinity-Norm Cost Functions

- *Introduction*
- *1-norm reformulation*
- *∞ -norm formulation*

Introduction

In this example we use the system described in the *Basic MPC Example*, but we will implement non-quadratic costs of the type

$$\|Ru_i\|_1$$

or

$$\|Qx_i\|_\infty$$

which are sometimes more meaningful for certain applications.

In both cases we will have to introduce slack variables and additional constraints, hence the optimization problem will become more challenging to solve, even if the cost function becomes linear instead of quadratic.

1-norm reformulation

The 1-norm is the absolute sum of a vector, hence a 1-norm penalty on the actuators can be a more meaningful objective when, for instance, the fuel consumption is directly proportional to actuation. The 1-norm also induces sparsity in the solution vector, i.e. a 1-norm cost leads to solutions where actuators are not used at all if possible, which can more accurately represent the objective of minimising wear in certain applications.

To formulate a 1-norm cost as an optimization problem we introduce one slack variable ϵ_j per vector element of Ru_i (i.e. such that the vector ϵ has the same length as the vector Ru_i) and add it to the polytopic constraints. As a result, the problem

$$\begin{array}{ll} \text{minimize} & \|Ru_i\|_1 \\ \text{subject to} & \text{constraints} \end{array}$$

is transformed into the problem

$$\begin{array}{ll} \text{minimize} & \sum_j \epsilon_j \\ \text{subject to} & \pm Ru_i \leq \epsilon \\ & \text{constraints} \end{array}$$

The following MATLAB code shows how to model a problem with 1-norm penalties on the actuators and quadratic penalties on the states with FORCESPRO. In particular, note the changes to the cost function and the introduction of polytopic constraints.

```
%% FORCES multistage form
% assume variable ordering zi = [ui, xi+1, ei] for i=1...N-1

stages = MultistageProblem(N); % get stages struct of length N
```

(continues on next page)

(continued from previous page)

```

for i = 1:N

    % dimension
    stages(i).dims.n = nx+2*nu; % number of stage variables
    stages(i).dims.r = nx;      % number of equality constraints
    stages(i).dims.l = nx+nu;   % number of lower bounds
    stages(i).dims.u = nx+nu;   % number of upper bounds
    stages(i).dims.p = 2*nu;    % number of polytopic constraints

    % cost
    if( i == N )
        stages(i).cost.H = blkdiag(zeros(nu),P,zeros(nu)); % terminal cost
    else
        stages(i).cost.H = blkdiag(zeros(nu),Q,zeros(nu));
    end
    stages(i).cost.f = [zeros(nx+nu,1); ones(nu,1)]; % linear cost terms

    % lower bounds
    stages(i).ineq.b.lbidx = 1:(nu+nx); % lower bound acts on these indices
    stages(i).ineq.b.lb = [umin; xmin]; % lower bound for this stage variable

    % upper bounds
    stages(i).ineq.b.ubidx = 1:(nu+nx); % upper bound acts on these indices
    stages(i).ineq.b.ub = [umax; xmax]; % upper bound for this stage variable

    % polytopic bounds
    stages(i).ineq.p.A = [ R, zeros(nu,nx), -eye(nu); ...
                          -R, zeros(nu,nx), -eye(nu) ];
    stages(i).ineq.p.b = zeros(2*nu,1);

    % equality constraints
    if( i < N )
        stages(i).eq.C = [zeros(nx,nu), A, zeros(nx,nu) ];
    end
    if( i>1 )
        stages(i).eq.c = zeros(nx,1);
    end
    stages(i).eq.D = [B, -eye(nx), zeros(nx,nu)];
end

% RHS of first eq. constr. is a parameter: stages(1).eq.c = -A*x0
params(1) = newParam('minusA_times_x0',1,'eq.c');

```

You can download the Matlab code of this example using this [link](#).

∞ -norm formulation

The ∞ -norm is the maximum absolute value in a vector, hence an ∞ -norm penalty on the states tries to minimise the maximum deviation of any state from the setpoint rather than the combined deviation of all the states in the system.

To formulate an ∞ -norm cost as an optimization problem we need to introduce a single slack variable *epsilon* and add polytopic constraints. As a result, the problem

$$\begin{aligned}
 & \text{minimize} && \|Qx_i\|_{\infty} \\
 & \text{subject to} && \text{constraints}
 \end{aligned}$$

is transformed into the problem

$$\begin{aligned} & \text{minimize} \quad \epsilon \\ & \text{subject to} \quad \pm Qx_i \leq \mathbf{1}^T \epsilon \\ & \quad \quad \quad \text{constraints} \end{aligned}$$

where the vector $\mathbf{1} = [1 \dots 1]$ has the same length as the vector Qx_i .

The following MATLAB code shows how to model a problem with ∞ -norm penalties on the states and quadratic penalties on the inputs with FORCESPRO. In particular, note the changes to the cost function and the introduction of polytopic constraints. Also note that we only need to add one more variable per stage.

```
%% FORCES multistage form
% assume variable ordering zi = [ui, xi+1, ei] for i=1...N-1

stages = MultistageProblem(N); % get stages struct of length N

for i = 1:N

    % dimension
    stages(i).dims.n = nx+nu+1; % number of stage variables
    stages(i).dims.r = nx;      % number of equality constraints
    stages(i).dims.l = nx+nu;   % number of lower bounds
    stages(i).dims.u = nx+nu;   % number of upper bounds
    stages(i).dims.p = 2*nx;    % number of polytopic constraints

    % cost
    if( i == N )
        stages(i).cost.H = blkdiag(R,zeros(nx),0); % terminal cost
        % (Hessian)
    else
        stages(i).cost.H = blkdiag(Q,zeros(nx),0);
    end
    stages(i).cost.f = [zeros(nx+nu,1); 1]; % linear cost terms

    % lower bounds
    stages(i).ineq.b.lbidx = 1:(nu+nx); % lower bound acts on these indices
    stages(i).ineq.b.lb = [umin; xmin]; % lower bound for this stage variable

    % upper bounds
    stages(i).ineq.b.ubidx = 1:(nu+nx); % upper bound acts on these indices
    stages(i).ineq.b.ub = [umax; xmax]; % upper bound for this stage variable

    % polytopic bounds
    if( i == N )
        stages(i).ineq.p.A = [ zeros(nx,nu), P, -ones(nx,1); ...
                                zeros(nx,nu), -P, -
                                ones(nx,1)];
    else
        stages(i).ineq.p.A = [ zeros(nx,nu), Q, -ones(nx,1); ...
                                zeros(nx,nu), -Q, -
                                ones(nx,1)];
    end
    stages(i).ineq.p.b = zeros(2*nx,1);

    % equality constraints
    if( i < N )
        stages(i).eq.C = [zeros(nx,nu), A, zeros(nx,1)];
    end
    if( i>1 )
        stages(i).eq.c = zeros(nx,1);
    end
end
```

(continues on next page)

(continued from previous page)

```

end
stages(i).eq.D = [B, -eye(nx), zeros(nx,1)];
end

% RHS of first eq. constr. is a parameter: stages(1).eq.c = -A*x0
params(1) = newParam('minusA_times_x0',1,'eq.c');

```

Here you can download the Matlab code of this example.

11.1.5 HOW TO: Implement Rate Constraints

- *Problem formulation*
- *Implementation*
- *Simulation Results*

Problem formulation

In this example it is illustrated how slew rate constraints on a system's actuators can be incorporated in the controller design. As a real world example one could think of an airplane, where the elevator cannot be switched instantaneously from one position to another, i. e. has a limited slew rate. Here the concept of constraints on the slew rate is shown on the following system:

$$x_{k+1} = \begin{pmatrix} 0.7115 & -0.4345 \\ 0.4345 & 0.8853 \end{pmatrix} x_k + \begin{pmatrix} 0.2173 \\ 0.0573 \end{pmatrix} u_k \Leftrightarrow x_{k+1} = Ax_k + Bu_k$$

To have a bound on the slew rate, $u_k - u_{k-1}$ has to lie in some range, i. e.

$$\Delta u_{min} \leq u_k - u_{k-1} \leq \Delta u_{max}.$$

One option to set the constraints on the slew rate is to augment the state as follows:

$$\hat{x}_k = \begin{pmatrix} x_k \\ u_{k-1} \end{pmatrix} \Leftrightarrow \hat{x}_{k+1} = \begin{pmatrix} A & B \\ 0 & I \end{pmatrix} \hat{x}_k + \begin{pmatrix} B \\ I \end{pmatrix} \hat{u}_k \Leftrightarrow \hat{x}_{k+1} = \hat{A}\hat{x}_k + \hat{B}\hat{u}_k$$

where \hat{u} is defined as $u_k - u_{k-1}$. To implement the problem using FORCESPRO, the multistage problem has to be defined as stated [here](#). The optimization variable is $z_i = [\hat{u}_i \quad \hat{x}_{i+1}]^T$.

$$\begin{aligned}
& \hat{x}_{k+1} = \hat{A}\hat{x}_k + \hat{B}\hat{u}_k \\
& \Delta u_{min} \leq \hat{u} \leq \Delta u_{max} \\
& u_{min} \leq u \leq \Delta u_{max} \\
& \Downarrow \\
& \text{minimize} \quad \frac{1}{2} \sum_{i=1}^N z_i^T H_i z_i \\
& \text{subject to} \quad D_1 z_1 = c_1 \\
& \quad \quad \quad C_{i-1} z_{i-1} + D_i z_i = c_i \\
& \quad \quad \quad z_{min} \leq z_i \leq z_{max}
\end{aligned}$$

The details on how the first equality and the interstage equality look like and how the constraints are implemented can be seen in the MATLAB® code below.

Implementation

```

%% FORCES multistage form
% assume variable ordering zi = [uhat_i, xhat_{i+1}] for i=1...N-1

stages = MultistageProblem(N); % get stages struct of length N

for i = 1:N

    % dimension
    stages(i).dims.n = 4; % number of stage variables
    stages(i).dims.r = 3; % number of equality constraints
    stages(i).dims.l = 2; % number of lower bounds: minimal slew rate and_
↪minimal input
    stages(i).dims.u = 2; % number of upper bounds: maximal slew rate and_
↪maximal input

    % cost
    if( i == N )
        stages(i).cost.H = blkdiag(R_sr, [P, zeros(2,1); zeros(1,2), 0]);
↪% terminal cost (Hessian)
    else
        stages(i).cost.H = blkdiag(R_sr, [Q, zeros(2,1); zeros(1,2), R]);
    end
    stages(i).cost.f = zeros(3,1); % linear cost terms

    % lower bounds
    stages(i).ineq.b.lbidx = [1,4]; % indices of lower bounds
    stages(i).ineq.b.lb = [dumin; umin]; % lower bounds

    % upper bounds
    stages(i).ineq.b.ubidx = [1,4]; % indices of upper bounds
    stages(i).ineq.b.ub = [dumax; umax]; % upper bounds

    % equality constraints
    if( i < N )
        stages(i).eq.C = [zeros(3,1), [ A, B; zeros(1, 2), 1]];
    end
    if( i>1 )
        stages(i).eq.c = zeros(3,1);
    end
    stages(i).eq.D = [[B;1], -eye(3)];

end

% RHS of initial equality constraint is a parameter
parameter(1) = newParam('minusAhat_times_xhat0',1,'eq.c');

% Define outputs of the solver
output(1) = newOutput('uhat',1,1);

% Solver settings
codeoptions = getOptions('RateConstraints_Controller');

% Generate code
generateCode(stages,parameter,codeoptions,output);

```

You can download the Matlab code of this example to try it out for yourself [here](#)

Simulation Results

For simulation the following specifications are assumed: the initial condition $x_0 \in [-2; 6]$, the input signal u is in the range $[-0.5, 2]$ and the constraints on the slew rate is $\hat{u} \in [-1, 0.5]$. Figure 11.5, Figure 11.6 and Figure 11.7 show how the controller regulates both states to zero while \hat{u} and u remain in the required range.

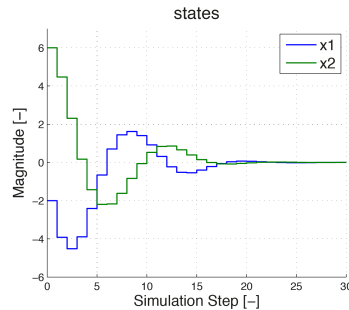


Figure 11.5: The states are both regulated to zero. No constraints are imposed on the states.

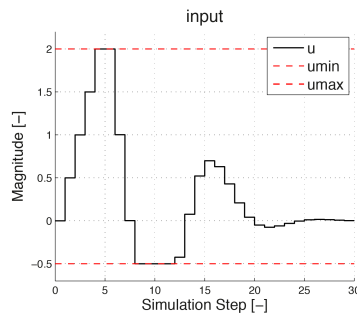


Figure 11.6: Plot of u

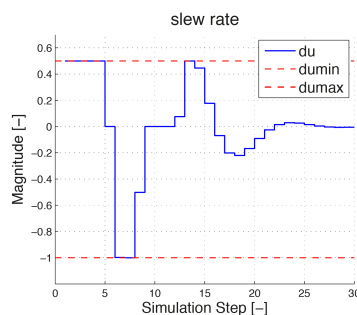


Figure 11.7: Plot of du

In Figure 11.6 and Figure 11.7 one sees how the input signal is maximally increased in the beginning with a slew rate of 0.5, until it reaches its upper bound of 2. In the figure on the right the slew rate is depicted. One can see that in the beginning, the slew rate stays at its upper bound 0.5. At simulation step 6 the input signal is maximally reduced. Again this is visible from the slew rate being at its lower bound -1 .

11.1.6 Binary MPC Example

- *Simulation result*
- *Details on problem reformulation*

Let us consider a simple MPC example where the system has inputs that can take only two values, u_{min} or u_{max} . The original problem (shown on the left) can be reformulated into the problem on the right, which corresponds to a standard form for which FORCESPRO can generate a solver. The details of the reformulation are given at the end of this example.

Simple MPC problem with discrete inputs:

$$\begin{aligned}
 &\text{minimize} && x_N^T P x_N + \sum_{i=0}^{N-1} x_i^T Q x_i + u_i^T R u_i \\
 &\text{subject to} && x_0 = x \\
 &&& x_{i+1} = A x_i + B u_i \\
 &&& x_{min} \leq x_i \leq x_{max} \\
 &&& u_i \in \{u_{min}, u_{max}\}
 \end{aligned}$$

Equivalent problem with binary inputs

$$\begin{aligned}
 &\text{minimize} && x_N^T P x_N + \sum_{i=0}^{N-1} x_i^T Q x_i + \delta_i^T \tilde{R} \delta_i + \tilde{f}^T \delta_i \\
 &\text{subject to} && x_0 = x \\
 &&& x_{i+1} = A x_i + \tilde{B} \delta_i + b \\
 &&& x_{min} \leq x_i \leq x_{max} \\
 &&& \delta_i \in \{0, 1\}^{n_u}
 \end{aligned}$$

The problem on the right can now be easily formulated in FORCESPRO. Note that the problem description is very similar to that of the simple MPC example, with the only modification that certain variables are marked to be binary. Download and run a complete simulation script to see the output.

```

nx = 2; nu = 2;

% assume variable ordering zi = [delta_i; xi+1] for i=1...N-1
stages = MultistageProblem(N);
for i = 1:N
    % dimension
    stages(i).dims.n = nx+nu; % number of stage variables
    stages(i).dims.r = nx; % number of equality constraints
    stages(i).dims.l = nx; % number of lower bounds
    stages(i).dims.u = nx; % number of upper bounds
    stages(i).bidx = 1:nu; % index of binary variables

    % cost
    if( i == N )
        stages(i).cost.H = blkdiag(Rtilde,P);
    else
        stages(i).cost.H = blkdiag(Rtilde,Q);
    end
    stages(i).cost.f = [ftilde; zeros(nx,1)];

    % lower bounds
    stages(i).ineq.b.lbidx = (nu+1):(nu+nx); % lower bound on states
    stages(i).ineq.b.lb = xmin; % upper bound values

    % upper bounds

```

(continues on next page)

(continued from previous page)

```

stages(i).ineq.b.ubidx = (nu+1):(nu+nx); % upper bound for this stage variable
stages(i).ineq.b.ub = umax; % upper bound for this stage variable

% equality constraints
if( i < N )
    stages(i).eq.C = [zeros(nx,nu), A];
end
if( i>1 )
    stages(i).eq.c = -Bconst;
end
stages(i).eq.D = [Btilde, -eye(nx)];
end

% RHS of first eq. constr. is a parameter: z1=-A*x0
params(1) = newParam('minusA_times_x0',1,'eq.c');

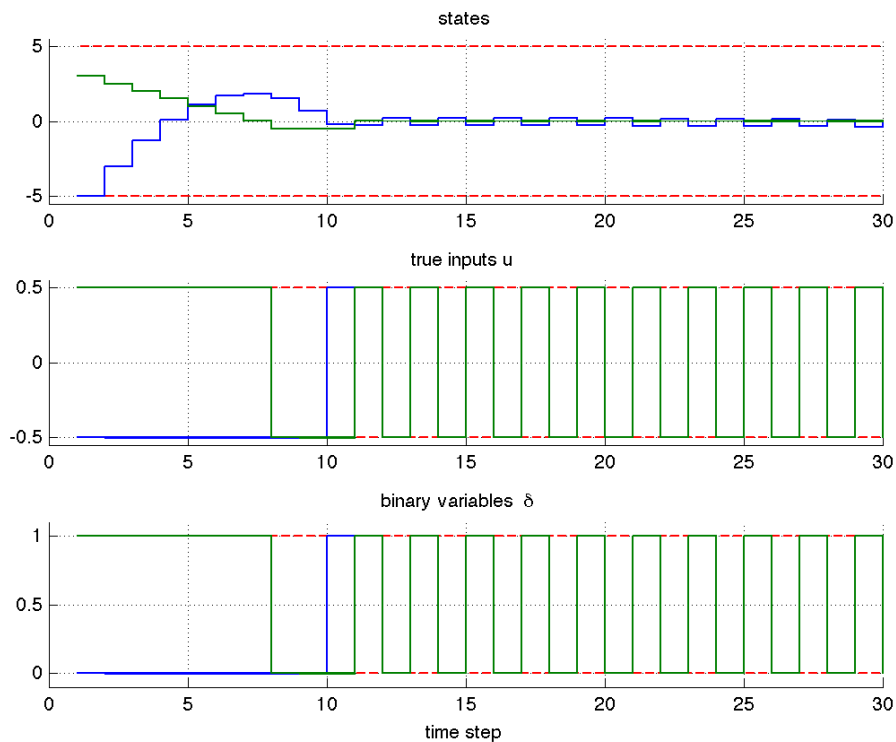
```

You can find the Matlab code of this example to try it out for yourself in the `examples` folder that comes with your client.

You can download the Python code of this example [here](#).

Simulation result

When running the example, you should see the following closed-loop behavior:



Details on problem reformulation

The reformulation is done as follows: we introduce a variable δ such that

$$\delta = 0 \Leftrightarrow u = u_{min} \quad \text{and} \quad \delta = 1 \Leftrightarrow u = u_{max}$$

This can be formulated by the equality constraint

$$u = u_{min} + \text{diag}(u_{max} - u_{min})\delta$$

where diag denotes a diagonal matrix. To keep the number of variables at a minimum, we will directly insert this equation into the dynamics:

$$\begin{aligned} x^+ &= Ax + Bu \\ &= Ax + Bu_{min} + B\text{diag}(u_{max} - u_{min})\delta \\ &= Ax + \tilde{B}\delta + b \end{aligned}$$

where $\tilde{B} := B\text{diag}(u_{max} - u_{min})$ and $b := Bu_{min}$.

Similarly for the cost function,

$$\begin{aligned} u^T Ru &= (u_{min} + \text{diag}(u_{max} - u_{min})\delta)^T R(u_{min} + \text{diag}(u_{max} - u_{min})\delta) \\ &= \delta^T \text{diag}(u_{max} - u_{min}) R \text{diag}(u_{max} - u_{min}) \delta + 2u_{min}^T \text{diag}(u_{max} - u_{min}) R \delta + \text{const} \\ &= \delta^T \tilde{R} \delta + \tilde{f}^T \delta + \text{const} \end{aligned}$$

where

$$\begin{aligned} \tilde{R} &= \text{diag}(u_{max} - u_{min}) R \text{diag}(u_{max} - u_{min}) \\ \tilde{f} &= 2R \text{diag}(u_{max} - u_{min}) u_{min} \end{aligned}$$

11.2 Y2F interface: Basic example

- *Defining the problem data*
- *Defining the MPC problem*
- *Generating a solver*
- *Calling the generated solver*
- *Simulation*
- *Results*
- *Variation 1: Parametric cost*
- *Variation 2: Time-varying dynamics*
- *Variation 3: Time-varying constraints*

Consider the following linear MPC problem with lower and upper bounds on state and inputs, and a terminal cost term:

$$\begin{aligned} \text{minimize} \quad & x_N^T P x_N + \sum_{i=0}^{N-1} x_i^T Q x_i + u_i^T R u_i \\ \text{subject to} \quad & x_0 = \underline{x} \\ & x_{i+1} = Ax_i + Bu_i \\ & \underline{x} \leq x_i \leq \bar{x} \\ & \underline{u} \leq u_i \leq \bar{u} \end{aligned}$$

This problem is parametric in the initial state \underline{x} and the first input u_0 is typically applied to the system after a solution has been obtained. Here we present the problem formulation with YALMIP, how you can use Y2F to easily generate a solver with FORCESPRO, and how you can use the resulting controller for simulation.

You can download the Matlab code of this example to try it out for yourself from https://raw.githubusercontent.com/embotech/Y2F/master/examples/mpc_basic_example.m.

Important: Make sure to have YALMIP installed correctly (run `yalmiptest` to verify this).

11.2.1 Defining the problem data

Let's define the known data of the MPC problem, i.e. the system matrices A and B , the prediction horizon N , the stage cost matrices Q and R , the terminal cost matrix P , and the state and input bounds:

```
%% MPC problem data

% system matrices
A = [1.1 1; 0 1];
B = [1; 0.5];
[nx,nu] = size(B);

% horizon
N = 10;

% cost matrices
Q = eye(2);
R = eye(1);
if exist('dlqr', 'file')
    [~,P] = dlqr(A,B,Q,R);
else
    fprintf('Did not find dlqr (part of the Control Systems Toolbox). Will use_
    ↪10*Q for the terminal cost matrix.\n');
    P = 10*Q;
end

% constraints
umin = -0.5;    umax = 0.5;
xmin = [-5; -5]; xmax = [5; 5];
```

11.2.2 Defining the MPC problem

Let's now dive in right into the problem formulation:

```
%% Build MPC problem in Yalmip

% Define variables
X = sdpvar(nx,N+1,'full'); % state trajectory: x0,x1,...,xN (columns of X)
U = sdpvar(nu,N,'full'); % input trajectory: u0,...,u_{N-1} (columns of U)

% Initialize objective and constraints of the problem
cost = 0; const = [];

% Assemble MPC formulation
for i = 1:N
    % cost
    if ( i < N )
        cost = cost + 0.5*X(:,i+1)'*Q*X(:,i+1) + 0.5*U(:,i)'*R*U(:,i);
    else
        cost = cost + 0.5*X(:,N+1)'*P*X(:,N+1) + 0.5*U(:,N)'*R*U(:,N);
    end
end
```

(continues on next page)

(continued from previous page)

```

% model
const = [const, X(:,i+1) == A*X(:,i) + B*U(:,i)];

% bounds
const = [const, umin <= U(:,i) <= umax];
const = [const, xmin <= X(:,i+1) <= xmax];
end

```

Thanks to YALMIP, defining the mathematical problem is very much like writing down the mathematical equations in code.

11.2.3 Generating a solver

We have now incrementally built up the `cost` and `const` objects, which are both YALMIP objects. Now comes the magic: use the function `optimizerFORCES` to generate a solver for the problem defined by `const` and `cost` with the initial state as a parameter, and the first input move u_0 as an output:

```

%% Create controller object (generates code)
% for a complete list of codeoptions, see
% https://www.embotech.com/FORCES-Pro/User-Manual/Low-level-Interface/Solver-
% Options
codeoptions = getOptions('simpleMPC_solver'); % give solver a name
controller = optimizerFORCES(const, cost, codeoptions, X(:,1), U(:,1), {'xinit'}, {
% 'u0'});

```

That's it! Y2F automatically figures out the structure of the problem and generates a solver.

11.2.4 Calling the generated solver

We can now use the controller object to call the solver:

```

% Evaluate controller function for parameters
[output,exitflag,info] = controller{ xinit };

```

or call the generated MEX code directly:

```

% This is an equivalent call, if the controller object is deleted from the
% workspace
[output,exitflag,info] = simpleMPC_solver({ xinit });

```

Tip: Type `help solvername` to get more information about how to call the solver.

11.2.5 Simulation

Let's now simulate the closed loop over the prediction horizon N :

```

%% Simulate
x1 = [-4; 2];
kmax = 30;
X = zeros(nx,kmax+1); X(:,1) = x1;
U = zeros(nu,kmax);

```

(continues on next page)

(continued from previous page)

```

problem.z1 = zeros(2*nx,1);
for k = 1:kmax

    % Evaluate controller function for parameters
    [U(:,k),exitflag,info] = controller{ X(:,k) };

    % Always check the exitflag in case something went wrong in the solver
    if( exitflag == 1 )
        fprintf('Time step %2d: FORCES took %2d iterations and %5.3f ', k, info.it,
↳info.solvetime*1000);
        fprintf('milliseconds to solve the problem.\n');
    else
        info
        error('Some problem in solver');
    end

    % State update
    X(:,k+1) = A*X(:,k) + B*U(:,k);
end

```

11.2.6 Results

The results of the simulation are presented in [Figure 11.8](#). The plot on the top shows the system's states over time, while the plot on the bottom shows the input commands. We can see that all constraints are respected.

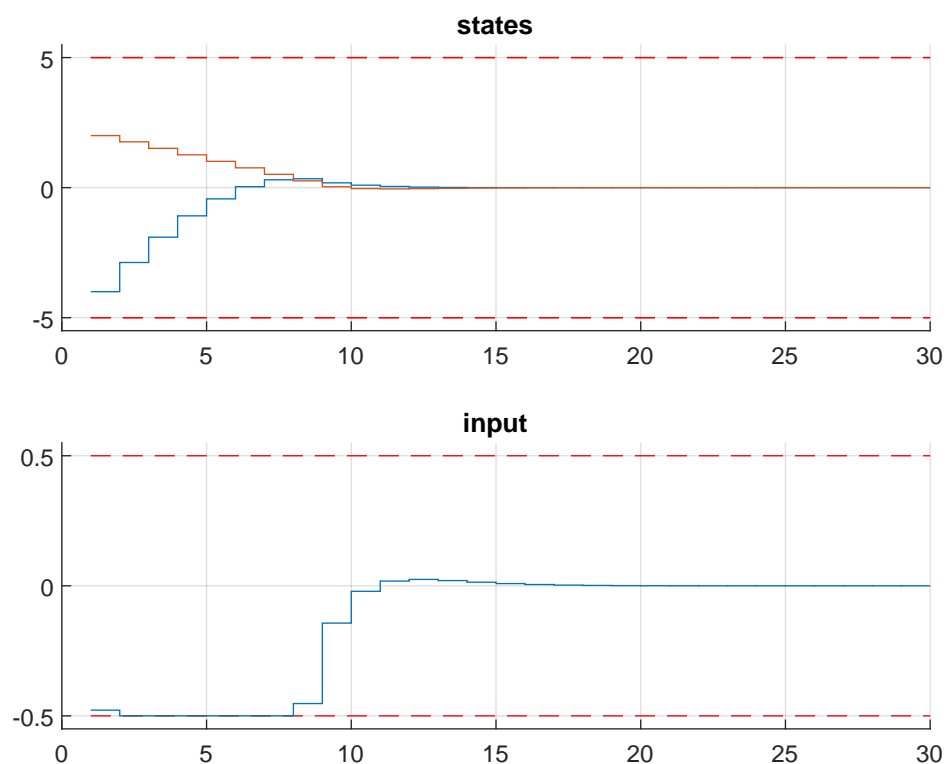


Figure 11.8: Simulation results of the states (top, in blue and red) and input (bottom, in blue) over time. The state and input constraints are plotted in red dashed lines.

11.2.7 Variation 1: Parametric cost

One possible variation is if we consider the weighting matrices Q , R and P as parameters, so that we can tune them after the code generation. The following problem is solved at each time step:

$$\begin{aligned} \text{minimize} \quad & x_N^\top P x_N + \sum_{i=0}^{N-1} x_i^\top Q x_i + u_i^\top R u_i \\ \text{subject to} \quad & x_0 = x \\ & x_{i+1} = A x_i + B u_i \\ & \underline{x} \leq x_i \leq \bar{x} \\ & \underline{u} \leq u_i \leq \bar{u} \end{aligned}$$

As usual, this problem is also parametric in the initial state x and the first input u_0 is applied to the system after a solution has been obtained. To be able to define the weighting matrices Q , R and P as parameters, first we define them as `sdpvars` and then tell `optimizerFORCES` that they are parameters:

```
% Cost matrices - these will be parameters later
Q = sdpvar(nx);
R = sdpvar(nu);
P = sdpvar(nx);

% [... formulate MPC problem in YALMIP ...]

% Define parameters and outputs
codeoptions = getOptions('parametricCost_solver'); % give solver a name
parameters   = { X(:,1), Q, R, P };
parameterNames = { 'xinit', 'Q', 'R', 'P' };
outputs      = U(:,1);
outputNames  = {'controlInput'};
controller = optimizerFORCES(const, cost, codeoptions, parameters, outputs, ...
    ↪ parameterNames, outputNames);
```

You can download the Matlab code of this variation to try it out for yourself from https://raw.githubusercontent.com/embotech/Y2F/master/examples/mpc_parametric_cost.m.

11.2.8 Variation 2: Time-varying dynamics

Another possible variation is if we consider the state-space dynamics matrices A and B as parameters, so that we can change them after the code generation. The following problem is solved at each time step:

$$\begin{aligned} \text{minimize} \quad & x_N^\top P x_N + \sum_{i=0}^{N-1} x_i^\top Q x_i + u_i^\top R u_i \\ \text{subject to} \quad & x_0 = x \\ & x_{i+1} = A x_i + B u_i \\ & \underline{x} \leq x_i \leq \bar{x} \\ & \underline{u} \leq u_i \leq \bar{u} \end{aligned}$$

As usual, this problem is also parametric in the initial state x and the first input u_0 is applied to the system after a solution has been obtained. To be able to define the state-space dynamics matrices A and B as parameters, first we define them as `sdpvars` and then tell `optimizerFORCES` that they are parameters:

```

A = sdpvar(nx,nx,'full'); % system matrix - parameter
B = sdpvar(nx,nu,'full'); % input matrix - parameter

% [... formulate MPC problem in YALMIP ...]

% Define parameters and outputs
codeoptions = getOptions('parametricDynamics_solver'); % give solver a name
parameters = { x0, A, B };
parameterNames = { 'xinit', 'Amatrix', 'Bmatrix' };
controller = optimizerFORCES(const, cost, codeoptions, parameters, U(:,1),_
↳parameterNames, {'u0'} );

```

You can download the Matlab code of this variation to try it out for yourself from https://raw.githubusercontent.com/embotech/Y2F/master/examples/mpc_parametric_dynamics.m.

11.2.9 Variation 3: Time-varying constraints

One final variation is if we consider the constraint inequalities as parameters, so that we can change them after the code generation. The inequalities are defined by a time-varying 2×2 matrix that is defined by 2 parameters:

$$R_k x \leq R_k \bar{x}$$

where k is the simulation step and the rotation matrix is defined by:

$$R_k = \begin{bmatrix} \cos(kw) & -\sin(kw) \\ \sin(kw) & \cos(kw) \end{bmatrix} = \begin{bmatrix} r_1 & -r_2 \\ r_2 & r_1 \end{bmatrix}$$

where k is the simulation step and w a fixed number. Overall, the following problem is solved at each time step:

$$\begin{aligned}
& \text{minimize} && x_N^\top P x_N + \sum_{i=0}^{N-1} x_i^\top Q x_i + u_i^\top R u_i \\
& \text{subject to} && x_0 = x \\
& && x_{i+1} = A x_i + B u_i \\
& && \underline{x} \leq x_i \leq \bar{x} \\
& && \underline{u} \leq u_i \leq \bar{u} \\
& && R_k x_i \leq R_k \bar{x}
\end{aligned}$$

As usual, this problem is also parametric in the initial state x and the first input u_0 is applied to the system after a solution has been obtained. To be able to define the rotation matrix R_k as a parameter, first we define r_1 and r_2 as sdpvars and then tell optimizerFORCES that they are parameters:

```

sdpvar r1 r2 % parameters for rotation matrix
R = [r1, -r2; r2, r1];

% [... formulate MPC problem in YALMIP ...]

% Define parameters and outputs
parameters = { X(:,1), r1, r2 };
parameterNames = { 'xinit', sprintf('cos(k*%4.2f)',w), sprintf('sin(k*%4.2f)',w) };
outputs = U(:,1);
outputNames = {'u0'};
controller = optimizerFORCES(const, cost, codeoptions, parameters, outputs,_
↳parameterNames, outputNames);

```

You can download the Matlab code of this variation to try it out for yourself from https://raw.githubusercontent.com/embotech/Y2F/master/examples/mpc_parametric_inequalities.m.

11.3 Y2F interface: Trajectory Optimization for Quadrotor Flight

- *Defining the problem parameters*
- *Defining the MPC problem*
- *Generating a solver*
- *Calling the generated solver*
- *Results*

This is a more complex example optimizing the trajectory of a quadrotor within safe flight corridors. It follows the formulation give in *S. Liu et al., "Planning Dynamically Feasible Trajectories for Quadrotors Using Safe Flight Corridors in 3-D Complex Environments," IEEE Robotics and Automation Letters, vol. 2, no. 3, pp. 1688-1695, July 2017* and makes the following assumptions:

- The system is differentially flat, with flat outputs $[x, y, z, \psi]^T$
- Piece-wise trajectory constrained by polytopes for each piece
- Trajectory segment parametrized as n -th order polynomial in time, separable in states

Based on those assumptions, the following convex QP problem needs to be solved in real-time:

$$\begin{aligned} \underset{\Phi}{\operatorname{argmin}} \quad & J = \sum_{i=0}^{N-1} \int_0^{\Delta t_i} \left\| \frac{d^4}{dt^4} \Phi_i(t) \right\|^2 dt \\ \text{subject to} \quad & \frac{d^k}{dt^k} \Phi_i(\Delta t_i) = \frac{d^k}{dt^k} \Phi_{i+1}(0) \quad k = 0, \dots, 4 \\ & A_i^T \Phi_i(t_s) < b_i \quad t_s = 0, \Delta t_s, 2\Delta t_s, \dots, t_{i+1} - t_i \\ & \Phi(t) = \begin{cases} \Phi_0(t - t_0) & t_0 \leq t < t_1 \\ \Phi_1(t - t_1) & t_1 \leq t < t_2 \\ \vdots \\ \Phi_{N-1}(t - t_{N-1}) & t_{N-1} \leq t < t_N \end{cases} \end{aligned}$$

with

$$\Phi_i(t) = \begin{bmatrix} x \Phi_i(t) \\ y \Phi_i(t) \\ z \Phi_i(t) \\ \psi \Phi_i(t) \end{bmatrix} = \begin{bmatrix} x c_i^0 & x c_i^1 & x c_i^2 & \dots & x c_i^n \\ y c_i^0 & y c_i^1 & y c_i^2 & \dots & y c_i^n \\ z c_i^0 & z c_i^1 & z c_i^2 & \dots & z c_i^n \\ \psi c_i^0 & \psi c_i^1 & \psi c_i^2 & \dots & \psi c_i^n \end{bmatrix} \begin{bmatrix} 1 \\ t \\ t^2 \\ \vdots \\ t^n \end{bmatrix}$$

This problem has $4 * (n + 1)$ optimization variables. Here we present a problem formulation with FORCESPRO's Y2F interface for YALMIP and also show how you can use the resulting controller for simulation.

You can download the code of this example to try it out for yourself (in MATLAB) by clicking [here](#).

Important: Make sure to have YALMIP installed correctly (run `yalmiptest` to verify this). Visualizations of this example additionally require the MPT Toolbox and Matlab interface for the CDD solver to be installed.

11.3.1 Defining the problem parameters

At the top of the example file, basic parameters are defined such number of states, the order of the piece-wise polynomial basis functions and number of samples to check the constraints:

```
%% Parameters
nStates = 4; % [-] Number of states
% Flat outputs [x position; y position; z position; yaw angle]
n = 8; % [-] Order of piece-wise polynomial used as basis function
nSample = 5; % [-] Number of intermediate samples (where constraints are
↳checked)

withVisualization = true; % [-] Bool if MPT Toolbox for visualization is
↳installed
bbConstr = false; % [-] true: bounding-box constraints (separable in
↳coordinates) (n=7,8,9) % false: Polyhedron along path (non-separable
↳polytopic constraints) (n=8)
```

The quadrotor is supposed to fly along piece-wise segments in 3D space that are defined by a list of way points:

```
%% WayPoints and time needed for segment
% Simple case with 3 segments
p0 = [0;0;0;0];
p1 = [1;1;1;0];
p2 = [3;1;1;pi];
p3 = [4;2;2;pi];
```

These waypoints are then used to construct artificial polyhedrons around each path segment.

11.3.2 Defining the MPC problem

Afterwards, YALMIP variables z and T are defined, gathering the trajectory parameters and the trajectory positions, respectively.

```
%% YALMIP Variables
Z = sdpvar((n+1)*nStates,N,'full'); % Trajectory parameters: z0,z1,...,z{N-1}
↳(columns of Z for N stages/segm.) % z_i = [c_0^x,c_1^x,...,c_n^x, ... (n-
↳th order polynomials -> n+1 coeff. % c_0^y,c_1^y,...,c_n^y, ...
% c_0^z,c_1^z,...,c_n^z, ...
% c_0^phi,c_1^phi,...,c_n^phi]
% where [x,y,z,phi] are the flat outputs (#
↳of flat outputs == nStates)
T = sdpvar(nStates,N+1,'full'); % Trajectory positions used as parameters
```

Afterwards, the QP formulation is setup in YALMIP syntax, including the quadratic cost function as well as various constraints.

11.3.3 Generating a solver

We have now incrementally built up the cost and `constr` objects, which are both YALMIP objects. Using the function `optimizerFORCES` to generate a solver named `TrajOptQuadrotor` that will return the optimized coefficients z_{opt} as an output:

```

%% Generate Solver
codeoptions = getOptions('TrajOptQuadrotor'); % solverName
codeoptions.optlevel = 3;
codeoptions.timing = 1;
codeoptions.BuildSimulinkBlock = 0;

controller = optimizerFORCES(constr, cost, codeoptions, T, Z, {'wayPoints'}, {'z_
↪opt'});

```

That's it! Y2F automatically figures out the structure of the problem and generates a solver.

11.3.4 Calling the generated solver

We can now use the TrajOptQuadrotor object to call the solver:

```

%% Solve
[out_opt, exitflags, info] = TrajOptQuadrotor({pathSegments});

```

Tip: Type `help TrajOptQuadrotor` to get more information about how to call the solver.

11.3.5 Results

The example also includes additional lines of code to illustrate the results.

Figure 11.9 illustrates the quadrotor flight in 3D, while Figure 11.10 shows the individual trajectories in time.

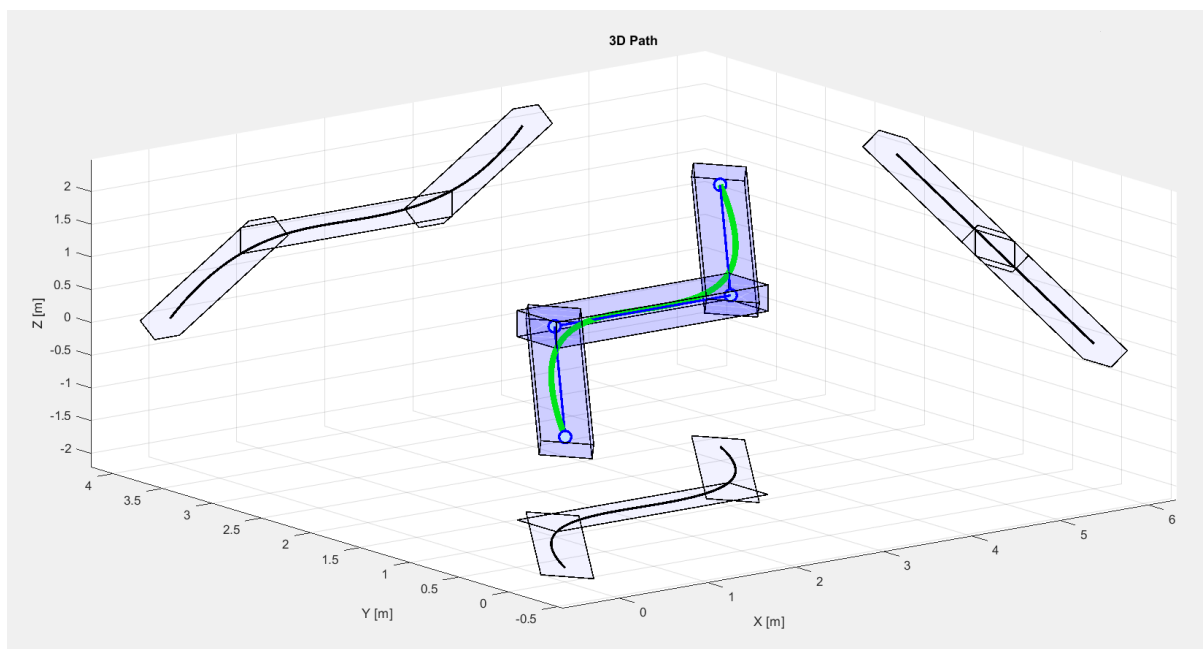


Figure 11.9: Quadrotor flight in 3D (green line) including waypoints/segments (dark blue) and bounding boxes (light blue); also projected onto each dimension.

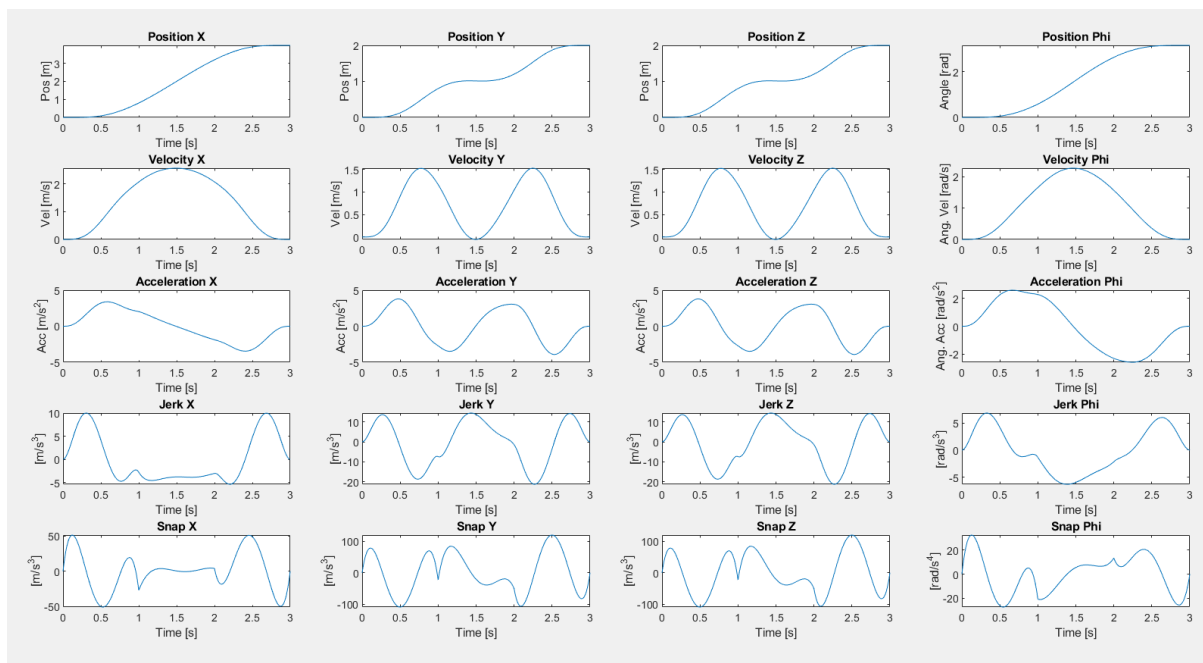


Figure 11.10: Individual trajectories of the quadrotor flight in time for all three dimensions and the angular orientation.

11.4 Low-level interface: Active Suspension Control

- *Introduction*
- *Disturbance Model: Speed Bump*
- *Implementation of Preview Information*
- *Comparison of Passive Vehicle and Active Suspension Control Using Preview Information*

11.4.1 Introduction

The concept of using future information, as described in the section *How to Incorporate Preview Information in the MPC Problem* can be applied to more advanced systems. In this example a driving vehicle is considered, equipped with sensors that measure the unevenness of the road ahead as shown in the picture below.

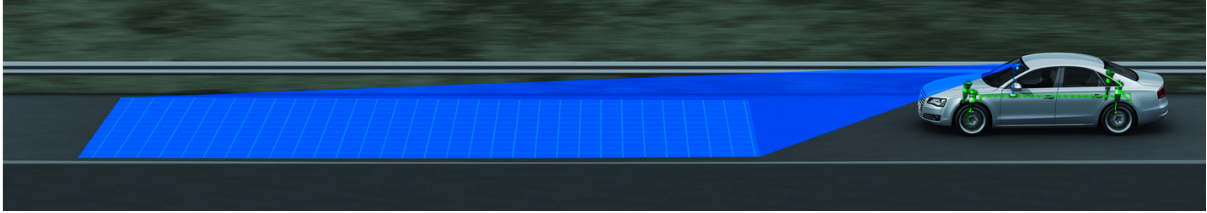


Figure 11.11: Figure borrowed from [GörSch]

The preview information can be used to improve the riding comfort, i. e. minimize the heave, pitch and roll accelerations, by actively controlling the suspension of the vehicle. This example is based on the reduced car model described in [GörSch]

The states x of the system are 'heave displacement' z_b [m], 'pitch angle' φ [rads], 'roll angle' θ [rads], 'heave velocity' \dot{z}_b [m/s], 'pitch rate' $\dot{\varphi}$ [rads/s] and 'roll rate' $\dot{\theta}$ [rads/s]. The input u [m] to the system are the 'active spring displacements'. The output y is given by the 'heave acceleration' \ddot{z}_b [m/s²], the 'pitch acceleration' $\ddot{\varphi}$ [m/s²] and the 'roll acceleration' $\ddot{\theta}$ [m/s²]. In the reduced model, the input contains not only the active spring displacements but also the measurements of the height profile of the upcoming road w and its first derivative \dot{w} .

$$x := \begin{pmatrix} \text{heave displacement [m]} \\ \text{pitch angle [rads]} \\ \text{roll angle [rads]} \\ \text{heave velocity [m/s]} \\ \text{pitch rate [rads/s]} \\ \text{roll rate [rads/s]} \end{pmatrix}$$

$$u := (\text{active spring displacements [m]})$$

$$y := \begin{pmatrix} \text{heave acceleration [m/s}^2\text{]} \\ \text{pitch acceleration [rads/s}^2\text{]} \\ \text{roll acceleration [rads/s}^2\text{]} \end{pmatrix}$$

There are constraints on the actuators, i. e. minimal and maximal adjustment track, $\underline{u} = -0.04[m]$ and $\bar{u} = 0.04[m]$. This results in the following state space system:

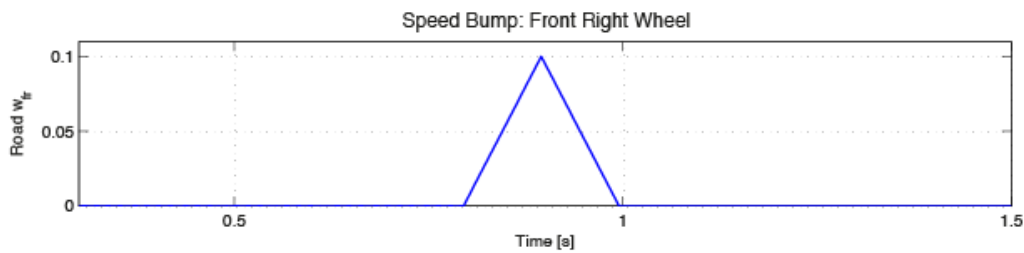
$$\dot{x}(t) = Ax(t) + B_u u(t) + B_w \begin{pmatrix} w(t) \\ \dot{w}(t) \end{pmatrix}$$

$$y(t) = Cx(t) + Du(t)$$

In the following it is shown how the FORCESPRO MATLAB Interface can be used to design a controller using preview information, substantially increasing the riding comfort compared to a vehicle with a passive suspension. The discrete vehicle model is sampled at 0.025 [s] and it is assumed that road preview information for 0.5 [s] (20 steps) is available to the controller.

11.4.2 Disturbance Model: Speed Bump

The vehicle is assumed to be driving at a constant speed of 5 [m/s] over a speed bump of length 1 [m] with a height of 0.1 [m]. The disturbance in time domain is depicted on the right side. The road bump only hits the front right wheel, while the front left wheel is not affected. The same bump will hit the rear right wheel 1.12 [s] after it hits the front wheel.



11.4.3 Implementation of Preview Information

This is a linear MPC problem with lower and upper bounds on inputs and a terminal cost term:

$$\begin{aligned} \text{minimize} \quad & x_N^T P x_N + \sum_{i=0}^{N-1} x_i^T Q x_i + u_i^T R u_i \\ \text{subject to} \quad & x_0 = x \\ & x_{i+1} = A x_i + B u_i + B_w w_i + B_w \dot{w}_i \\ & \underline{u} \leq u_i \leq \bar{u} \end{aligned}$$

At each sampling instant the initial state x and the preview information w_i and \dot{w}_i change, and the first input u_0 is typically applied to the system after an optimal solution has been obtained.

```
% Parameters: First Equation RHS
parameter(1) = newParam('minusA_times_x0_minusBw_times_w_pre',1,'eq.c');
% Paramteres: Preview Information
parameter(2) = newParam('pre2_w',2,'eq.c');
...
parameter(n) = newParam('pren_w',n,'eq.c');
...
parameter(N) = newParam('preN_w',N,'eq.c');
```

As described in the section *How to Incorporate Preview Information in the MPC Problem*, the parametric additive terms g , which corresponds to the term $B_w w_i + B_w \dot{w}_i$, has to be defined. At each stage of the multistage problem, the 'g' term (containing the preview information) in the equality constraint is different, therefore we have to define a parameter for each stage. In the definition of the parameters, 'pren_w' represents the name of the term $B_w w_n + B_w \dot{w}_n$ at stage n of the multistage problem. During runtime, the preview information is mapped to these parameters.

N is the length of the prediction horizon which is set to be equal to the preview horizon. The MATLAB code below, generates the function `VEHICLE_MPC_withPreview` that takes $-Ax$ and the additive term g as a calling argument and returns u_0 , which can then be applied to the system:

```

%% MPC with Preview
% FORCESPRO multistage form
% assume variable ordering zi = [ui; xi+1] for i=1...N-1

% Parameters: First Eq. RHS
parameter(1) = newParam('minusA_times_x0_minusBw_times_w_pre',1,'eq.c');

stages = MultistageProblem(N);
for i = 1:N

    % dimension
    stages(i).dims.n = nx+nu; % number of stage variables
    stages(i).dims.r = nx; % number of equality constraints
    stages(i).dims.l = nu; % number of lower bounds
    stages(i).dims.u = nu; % number of upper bounds

    % cost
    if( i == N )
        stages(i).cost.H = blkdiag(R,P);
    else
        stages(i).cost.H = blkdiag(R,Q);
    end
    stages(i).cost.f = zeros(nx+nu,1);

    % lower bounds
    stages(i).ineq.b.lidx = 1:nu; % lower bound acts on these indices
    stages(i).ineq.b.lb = umin*ones(4,1); % lower bound for the input signal

    % upper bounds
    stages(i).ineq.b.ubidx = 1:nu; % upper bound acts on these indices
    stages(i).ineq.b.ub = umax*ones(4,1); % upper bound for the input signal

    % equality constraints
    if( i < N )
        stages(i).eq.C = [zeros(nx,nu), Ad];
    end
    stages(i).eq.D = [Bdu, -eye(nx)];

    % Parameters for Preview
    if( i < N )
        parameter(i+1) = newParam(['pre',num2str(i+1),'_w'],i+1,'eq.c');
    end

end

% define outputs of the solver
outputs(1) = newOutput('u0',1,1:nu);

% solver settings
codeoptions = getOptions('VEHICLE_MPC_withPreview');

% generate code
generateCode(stages,parameter,codeoptions,outputs);

```

You can find the Matlab code of this example to try it out for yourself in the examples folder that comes with your client.

11.4.4 Comparison of Passive Vehicle and Active Suspension Control Using Preview Information

In Figure 11.12, Figure 11.13 and Figure 11.14, the accelerations in the direction heave, pitch and roll respectively are depicted. The blue graphs represent the controlled outputs while the red ones show the uncontrolled accelerations. One can see that the vertical dynamics of the vehicle are reduced substantially. There are smaller maximal accelerations and also less time is required to regulate the accelerations back to zero.

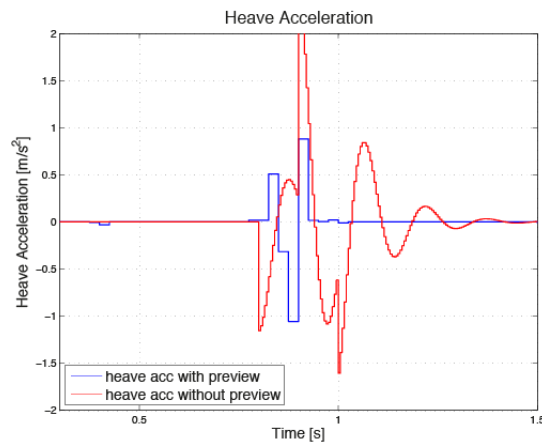


Figure 11.12: Acceleration in heave direction

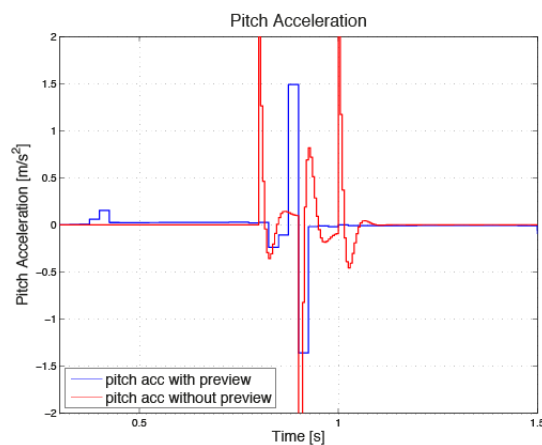


Figure 11.13: Acceleration in pitch direction

Applying Model Predictive Control with Preview using FORCESPRO the riding comfort is improved significantly with minimum effort for designing the controller and generating code which can be deployed on any embedded automotive control unit.

The four graphs in Figure 11.15, Figure 11.16, Figure 11.17 and Figure 11.18 below show the input signal on each of the four actuators. One can see that model predictive controller starts lifting the front right part of the vehicle body as soon as the bump is in sight of the preview sensor, i. e. at time $t = 0.3$ [s]. This is 0.5 seconds, the length of the preview horizon, before the front right wheel hits the bump at time $t = 0.8$ [s]. This causes a better absorption of the shock and therefore reduced accelerations. The input constraints are also satisfied and u never exceeds the admitted range.

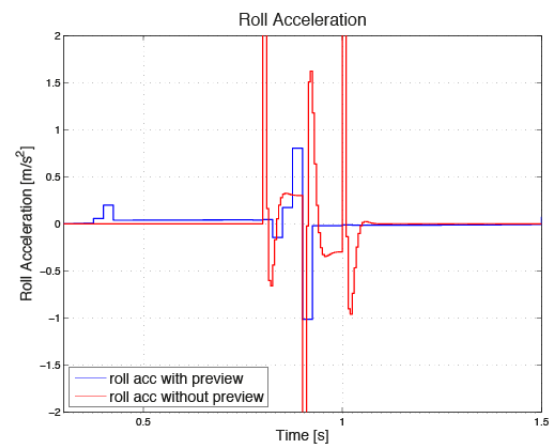


Figure 11.14: Acceleration in roll direction

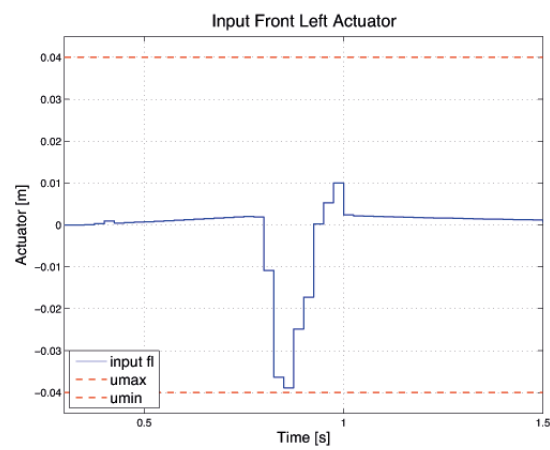


Figure 11.15: Input front left actuator

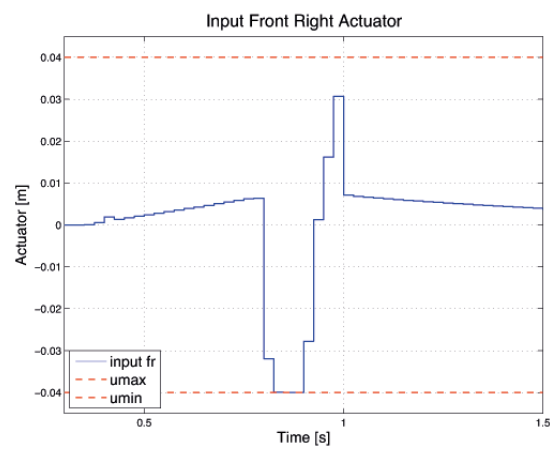


Figure 11.16: Input front right actuator

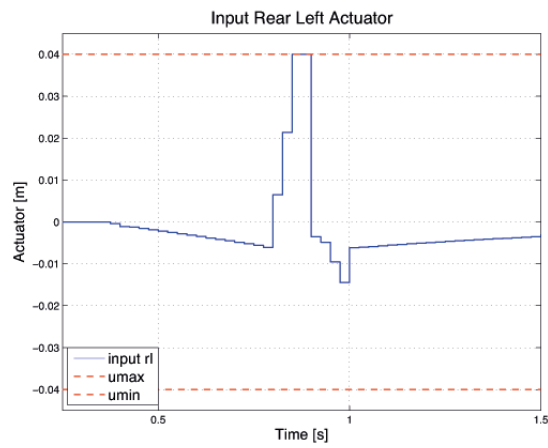


Figure 11.17: Input rear left actuator

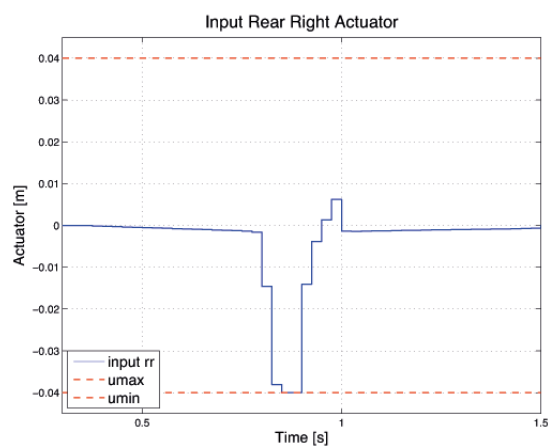


Figure 11.18: Input rear right actuator

11.5 Low-level interface: Robust estimation (Kalman filter)

- *System Description*
- *Robust Kalman filter*
- *Simulation and Comparison*

11.5.1 System Description

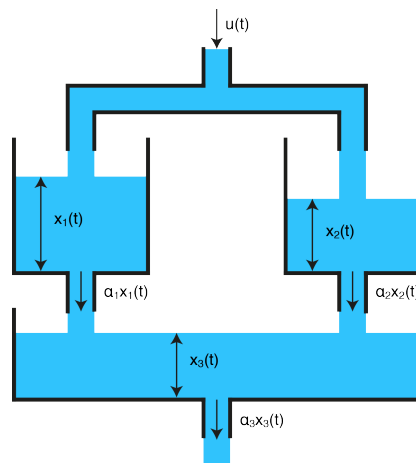
In this example we consider the water tank system depicted on the right. Tank 1 has one input flow and one output flow. Also tank 2 has one input flow and one output flow. Tank 3 has two input flows and one output flow. The system dynamics are represented via the first equation below. As an output z we have a measurement of the level of tank 1 and of the level of tank 3.

$$x^+ = Ax + Bu + v = \begin{pmatrix} 1 - \alpha_1 & 0 & 0 \\ 0 & 1 - \alpha_2 & 0 \\ \alpha_+ & \alpha_2 & 1 - \alpha_3 \end{pmatrix} x + \begin{pmatrix} 0.5 \\ 0.5 \\ 0 \end{pmatrix} u + v$$

$$z = Hx + w + y = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} x + w + y$$

The states of the system are $x = (x_1 \ x_2 \ x_3)^T$ is given. There is a process noise v and a measurement noise w , both are Gaussian Random Variables with mean 0 and variance Q and R , i. e. $v \sim \mathcal{N}(0, Q)$ and $w \sim \mathcal{N}(0, R)$. The sparse signal y , which is used to model sensor failures, distorts the measurement signal additionally.

The goal of this example is to show, that the standard Kalman Filter is not working that good anymore if sensor failures are present. There does not exist an analytic solution to the problem if the disturbance y is present. Using the robust Kalman Filter, i. e. replacing the standard measurement update step with an extended optimization problem, which is solved by FORCESPRO, the filter is robust against y and the estimated states are much more accurate compared to the standard Kalman Filter. To process the measurement data online, the optimization problem has to be solved in a sufficiently short amount of time.



11.5.2 Robust Kalman filter

Recall that the standard Kalman Filter, which would be applied if disturbance signal y were not present, consists of two steps: First a prediction step is made, where a predicted stated

$x^p(k)$ is calculated based on the estimated state $x^m(k-1)$. Additionally, the predicted variance $P_p(k)$ gets calculated in the prediction step. The measurement step returns the variance $P_m(k)$ and the state estimate $x^m(k)$. This state estimate $x^m(k)$ is basically the solution of the optimization problem

$$\begin{aligned} & \text{minimize} && w^T R^{-1} w + (x - \hat{x}_p)^T P^{-1} (x - \hat{x}_p) \\ & \text{subject to} && z = Hx + w \end{aligned}$$

In this example, we assume that out of 100 measurements the sensors of tank 1 and tank 3 gives each 5 bogus signals. In order to make the state estimator robust against the sensor failures y , we solve the following convex optimization problem at every time instance

$$\begin{aligned} & \text{minimize} && w^T R^{-1} w + (x - \hat{x}_p)^T P^{-1} (x - \hat{x}_p) + \lambda \|y\|_1 \\ & \text{subject to} && z = Hx + w + y \end{aligned}$$

In the optimization problem w , x and y are optimization variables. The cost function of the optimization problem is extended with the l_1 -penalty which is non-quadratic. The value $\lambda \geq 0$ is a tuning parameter. For λ large enough, the solution of the optimization problem has $y = 0$ and therefore the estimates of the robust Kalman Filter coincides with the standard Kalman Filter solution. This optimization problem can be transformed as described in here. We transform this problem to the form required by FORCESPRO, which reads as

$$\begin{aligned} & \text{minimize} && \frac{1}{2} \tilde{z}^T \tilde{H} \tilde{z} + f^T \tilde{z} \\ & \text{subject to} && D\tilde{z} = z \\ & && A\tilde{z} \leq b \end{aligned}$$

where the optimization variable is given by $\tilde{z} = (x^T \ w^T \ y^T \ e^T)^T$. Please find below the MATLAB code to generate the solver for the optimization problem with FORCESPRO. The covariance matrix P^{-1} is updated at every time step and therefore the problem can't be solved explicitly. In this problem three parameters need to be defined, which are H , f - containing the predicted covariance and the predicated state - and c - contains the current measurement.

```
% Create multistage struct
stages = MultistageProblem(1);

% Dimension
[ny nx] = size(H);
nw = ny;
ne = ny;
stages(1).dims.n = nx+nw+ny+ne; % number of stage variables
stages(1).dims.r = ny; % number of equality constraints
stages(1).dims.p = 2*ne; % number of polytopic constraints

% Polytopic bounds
stages(1).ineq.p.A = [zeros(ny,nx), zeros(ny,nw), lambda*eye(ny), -eye(ne); ...
                    zeros(ny,nx), zeros(ny,nw), -
                    lambda*eye(ny), -eye(ne)];
stages(1).ineq.p.b = zeros(2*ne,1);

% Equality constraints
stages(1).eq.D = [H, eye(nw), eye(ny), zeros(ne)];

% Parameters
params(1) = newParam('H_i',1,'cost.H');
params(2) = newParam('f_i',1,'cost.f');
params(3) = newParam('z_i',1,'eq.c');

% Output
outputs(1) = newOutput('x_hat_RKF',1,1:3);
```

(continues on next page)

(continued from previous page)

```
% Code Generation
codeoptions = getOptions('Robust_KF');
generateCode(stages,params,codeoptions,outputs);
```

You can find the Matlab code of this example to try it out for yourself in the `examples` folder that comes with your client.

11.5.3 Simulation and Comparison

In the simulation the optimization problem has to be solved at every time instance. In the prediction step the state x^p is calculated based on the estimation of the current state. Also the variance is updated in every prediction step. In the measurement update step the estimated state x^m is calculated based on the predicted state, its predicted variance and the current measurement z by the function `Robust_KF()` generated by FORCESPRO.

```
for i = 2:(N+1)
    % Prediction Step
    x_p_RKF = Ak(:,:,i-1)*x_hat_RKF(:,i-1)+B*u(i-1);
    P_p_RKF(:,:,i) = Ak(:,:,i-1)*P_hat_RKF(:,:,i-1)*Ak(:,:,i-1)' + Q;

    % Measurement Update Step - Optimization Problem
    problem.H_i = [2*inv(P_p_RKF(:,:,i)), zeros(nx,nw+ny+ne);...
                  zeros(ny,nx), 2*R_inv, zeros(ny,ny+ne);...
                  zeros(ny+ne,nx+nw+ny+ne)];

    problem.f_i = [-2*(inv(P_p_RKF)*x_p_RKF);...
                  zeros(nw,1);...
                  zeros(ny,1);...
                  ones(ne,1)];

    problem.z_i = z(:,i);
    [solverout,exitflag,info] = Robust_KF(problem);
    solve_time(1,i-1) = info.solvetime;
    x_hat_RKF(:,i) = solverout.x_hat_RKF;
    P_hat_RKF(:,:,i) = P_p_RKF(:,:,i);
end
```

In the plots in [Figure 11.19](#), [Figure 11.20](#) and [Figure 11.21](#) respectively, the estimated states are depicted. The estimates calculated via the robust Kalman Filter, in blue, are much more accurate than the standard approach. The peaks in the red line indicate sensor failures against which the standard Kalman Filter is not robust.

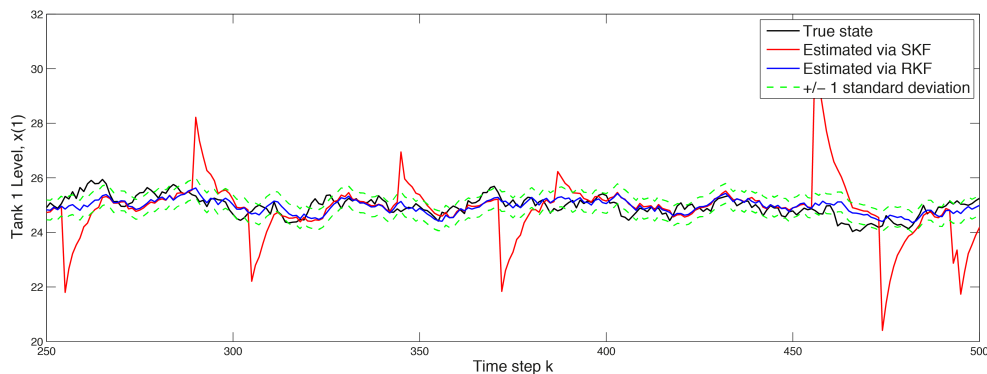
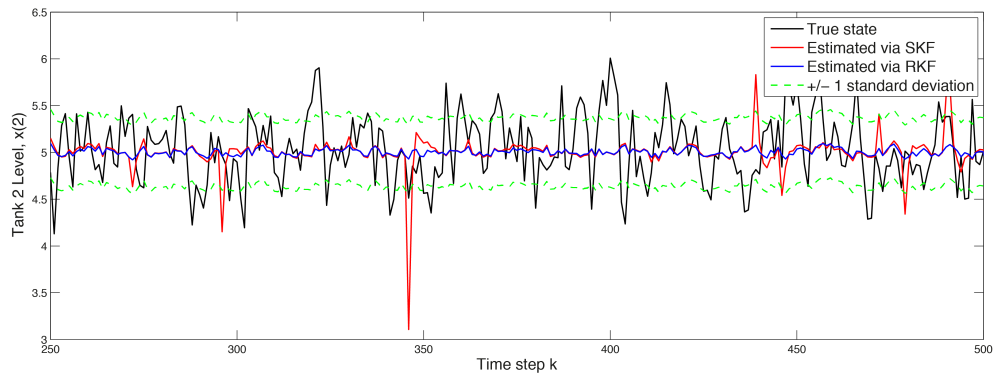
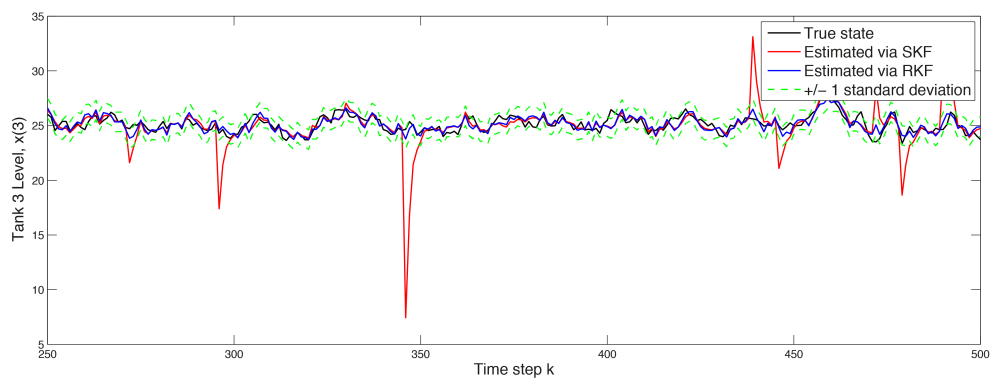


Figure 11.19: Estimated state $x(1)$

The impact on the RMS error magnitude of the robust Kalman Filter can be seen in the plots in [Figure 11.22](#), [Figure 11.23](#) and [Figure 11.24](#). The magnitude of the robust Kalman Filter depicted

Figure 11.20: Estimated state $x(2)$ Figure 11.21: Estimated state $x(3)$

in blue, is reduced by $\sim 65\%$ for state 1, $\sim 12\%$ for state 2, $\sim 61\%$ for state 3 (these values vary). Applying online optimization with FORCESPRO improves the quality of the state estimations significantly.

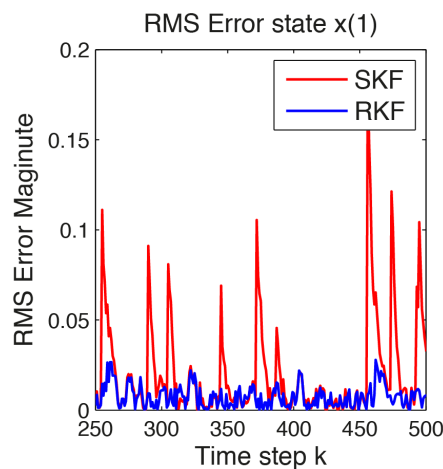


Figure 11.22: RMS error for $x(1)$

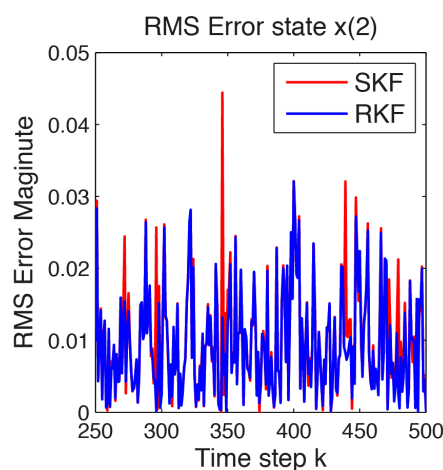
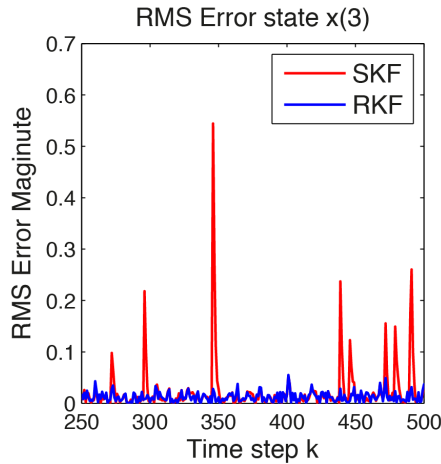


Figure 11.23: RMS error for $x(2)$

With FORCESPRO convex optimization can be embedded directly in signal processing algorithms that run online, with strict real-time deadlines, even at rates of tens of kilohertz. In this example the optimization problem is solved in $\sim 0.1ms$.

11.6 Low-level interface: Spacecraft Rendezvous

- *Introduction*
- *Model*
- *Constraints*
- *Objective*
- *Spacecraft Rendezvous Manoeuvres with and without 1-Norm Cost*

Figure 11.24: RMS error for $x(3)$

11.6.1 Introduction

This example uses the concepts described in the subsections *HOW TO: Implement an MPC Controller with a Time-Varying Model* and *How to Implement 1-Norm and Infinity-Norm Cost Functions*.

The goal is to design a controller to perform a spacecraft rendezvous operation, where a controlled chaser spacecraft is performing rendezvous with a passive target that is orbiting around Mars. Using a time-varying prediction model allows to perform spacecraft maneuvers in elliptical orbits and allows the controller to be updated when there are changes in the system parameters or control objectives. This example is based on the models described in [HarMac14] and the references therein.

11.6.2 Model

The Yamanaka-Ankersen (Y-A) equations are used to describe the dynamics, where the six states x of the system represent the relative position and velocity of the chaser with respect to the target in the three dimensions. These equations apply in elliptical orbits, but are time-varying in terms of the *true anomaly*, v , of the target, i.e. the model is given by

$$x_{k+1} = A(v)x_k + B(v)u_k$$

and the requirement is that the state at the end of the horizon is at the target. The plant input is modeled as an impulsive change in velocity, such that

$$B(v) = A(v) \begin{pmatrix} 0 \\ I_3 \end{pmatrix}$$

You can find the Matlab code of this example to try it out for yourself in the `examples` folder that comes with your client.

11.6.3 Constraints

The three impulsive control inputs can give a maximum change in velocity of 5 meters per second along each axis. In addition, the chaser spacecraft is required to remain within a cone of vision of 20 degrees from the target and must not go behind the target to facilitate the docking maneuver.

11.6.4 Objective

The goal of the controller is to balance the following objectives:

- the chaser should be always as close as possible to the target,
- use as little fuel as possible to get there.

The second objective is more important, hence it is weighed higher. We consider two types of cost functions: one where all the terms are weighed using standard quadratic penalties; and one where the inputs are penalised using the 1-norm, which better reflects the propellant consumption being directly proportional to delivered thrust and also attempts to minimise the use of the actuators. In order to implement the 1-norm cost we need to add slack variables and additional constraints as described in *How to Implement 1-Norm and Infinity-Norm Cost Functions*.

The following code shows how to generate an MPC controller for the spacecraft rendezvous problem with a time-varying model and a 1-norm penalty on the actuators.

```
%% MPC with Preview
% FORCESPRO multistage form
% assume variable ordering zi = [ui; xi+1, eui] for i=1...N-1

% Parameters: First Eq. RHS
parameter(1) = newParam('minusA_times_x0',1,'eq.c');

stages = MultistageProblem(N);
for i = 1:N

    % dimension
    stages(i).dims.n = nx+2*nu; % number of stage variables
    stages(i).dims.r = nx; % number of equality constraints
    stages(i).dims.l = nu; % number of lower bounds
    stages(i).dims.u = nu; % number of upper bounds
    stages(i).dims.p = 3+2*nu; % number of polytopic constraints

    % cost
    stages(i).cost.H = blkdiag(zeros(nu),Q,zeros(nu));
    stages(i).cost.f = [zeros(nu,1); -Q*xs; ones(nu,1)];

    % lower bounds
    stages(i).ineq.b.lidx = 1:nu; % lower bound acts on these indices
    stages(i).ineq.b.lb = umin*ones(4,1); % lower bound for the input signal

    % upper bounds
    stages(i).ineq.b.ubidx = 1:nu; % upper bound acts on these indices
    stages(i).ineq.b.ub = umax*ones(4,1); % upper bound for the input signal

    % polytopic bounds
    stages(i).ineq.p.A = [ zeros(3,nu), Hx, zeros(3,nu); ...
        R, zeros(nu,nx), -eye(nu); ...
        -R, zeros(nu,nx), -eye(nu) ];
    stages(i).ineq.p.b = [ hx; R*us; -R*us ];

    % equality constraints
    if( i < N )
        params(end+1) = newParam(['C_',num2str(i)],i,'eq.C');
    end
    params(end+1) = newParam(['D_',num2str(i)],i,'eq.D');
    if( i > 1 )
        params(end+1) = newParam(['pre',num2str(i+1),'_w'],i+1,'eq.c');
    end
end
```

(continues on next page)

(continued from previous page)

end

11.6.5 Spacecraft Rendezvous Manoeuvres with and without 1-Norm Cost

The simulation describes a rendezvous maneuver where the chaser starts 15km away from the target spacecraft and the goal is to approach the target to within 1000 meter distance, while respecting the constraints, to start the docking maneuver. The target is modeled as being in a Keplerian orbit around Mars with an orbital radius of 3,600,000 meters. The controller sampling time is 200s but the target and chaser dynamics are simulated in intervals of 1s for illustration purposes. The plots in Figure 11.25 illustrates the behaviour of the controlled spacecraft with standard quadratic cost, while the plots in Figure 11.26 shows the behaviour of the controller when the quadratic cost on the actuators is swapped with a 1-norm penalty. Notice the sparsity in the actuation commands - the thrusters are only engaged when necessary to keep the spacecraft within the cone of visibility of the target.

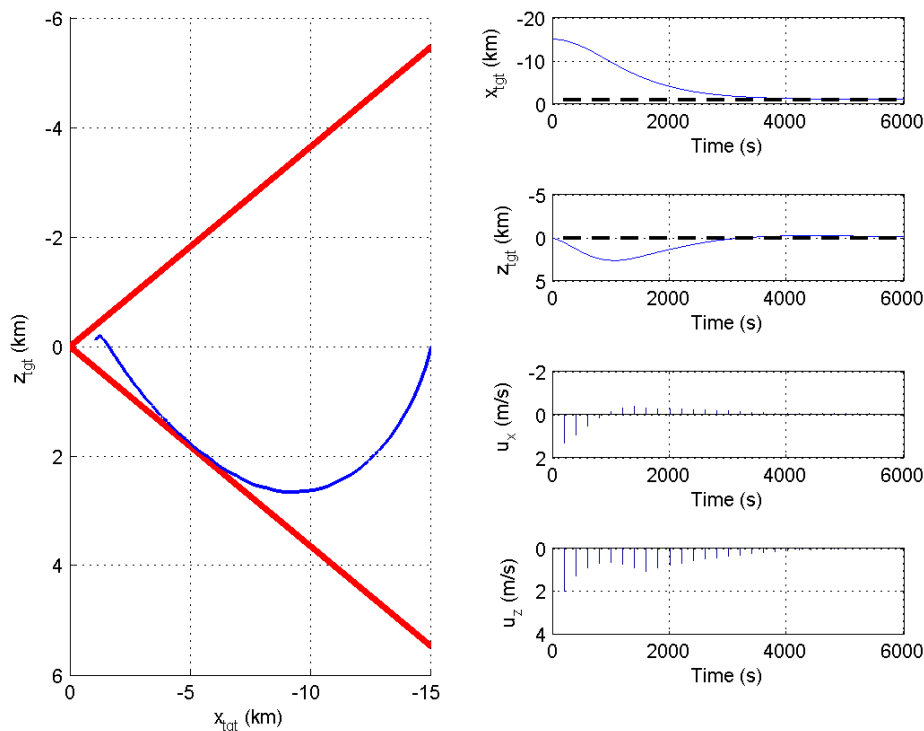


Figure 11.25: Behaviour with quadratic cost.

11.7 Low-level interface: DC/DC converter

- *Example Overview*
- *Special Requirements*
- *Introduction - Control of a DC/DC Converter*

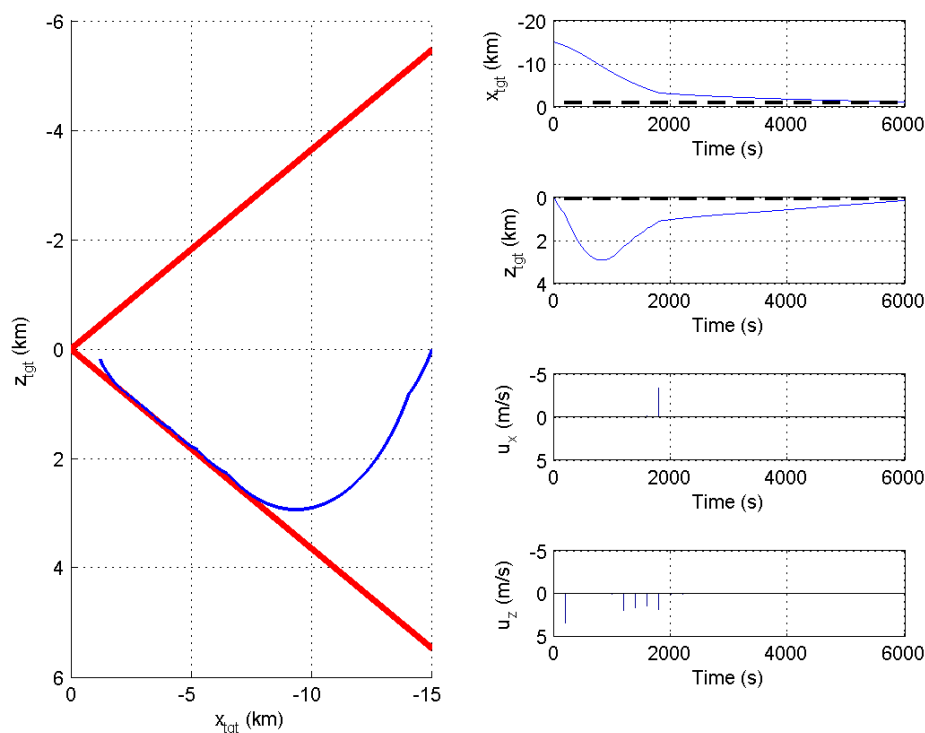


Figure 11.26: Behaviour with cost given by 1-norm.

- *Control Objective by Using Model Predictive Control*
- *Model Predictive Control Design via FORCESPRO MATLAB® Interface*
- *Simulation of the PLECS® Model with Model Predictive Control*
- *Comparison of Model Predictive Control and PI Control*

11.7.1 Example Overview

The example starts by describing the power electronics of the DC/DC converter and how the control oriented model of the system is derived. Then the potential advantages of model predictive control over a conventional PI controller are discussed. Afterwards the design of the MPC controller using FORCESPRO is presented. Finally, the simulation setup is explained and the simulation results using PI and MPC are compared.

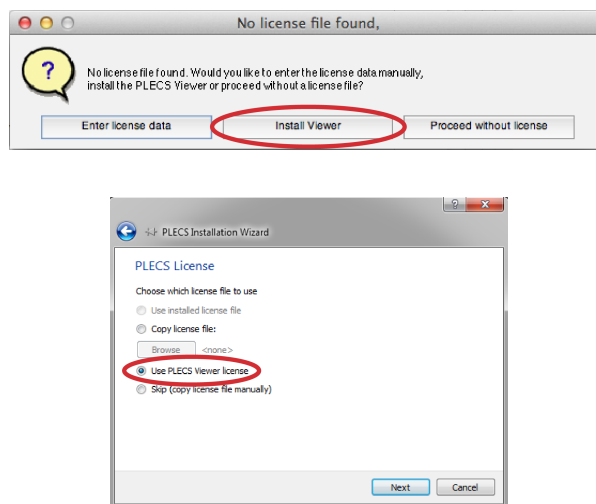
- *Introduction*: General introduction to the example.
- *Control Objective*: What can be gained by applying MPC with FORCESPRO.
- *MPC via FORCESPRO*: How to generate a solver with FORCESPRO for the power electronic converter.
- *Simulation*: Illustration on how to simulate the system with the generated controller.
- *Comparison*: Discussion of the results of the simulation.

11.7.2 Special Requirements

For the simulation of the power electronic converter in this example PLEXIM provided their software PLECS®. PLECS® is the tool for high-speed simulations of power electronic systems. To simulate this example, PLECS Blockset with a viewer licence is required. Please follow the instructions on how to install PLECS® below.

PLECS Blockset installation instructions:

- Download PLECS® Blockset installation script available from here.
- Download the required PLECS® Blockset package file here and save it in the same directory as the file installplecs.m.
- Run the file installplecs.m in MATLAB® from the command line.
- During the installation a dialog asks where to save 'PLECS'. Choose a location which is in the MATLAB® search path.
- During the installation a dialog asks for a license. Install the 'viewer license' as shown in the figures below.



Once the installation is completed you are ready to simulate the files provided with this example.

11.7.3 Introduction - Control of a DC/DC Converter

An important field of application for model predictive control are power electronic systems. In this example a typical DC/DC converter which supplies an isolated DC voltage to a telecom system is considered. Assume that the input voltage of the two-transistor forward converter, depicted below on the left, is a constant voltage U_{IN} delivered by a previous PFC rectifier stage. The load attached to the converter has an ohmic-capacitive characteristic.

This two-transistor forward converter can be modelled as a buck converter from which it is more convenient to derive a control oriented model. The buck converter has only one switch and the input voltage U_{in} is the actual input voltage scaled by the transformer turn ratio. The equivalent circuit is depicted on the right in the figure below.

The states of the control oriented model, which is used as a model for the predictive controller, are the inductor current i_L and the capacitor voltage u_C . Further there are the input signal d and the disturbances in the input voltage and the load current $w = (u_{in} \quad i_{Load})^T$. As an output signal the states i_L and u_C as well as the output voltage u_{out} are considered. The small signal

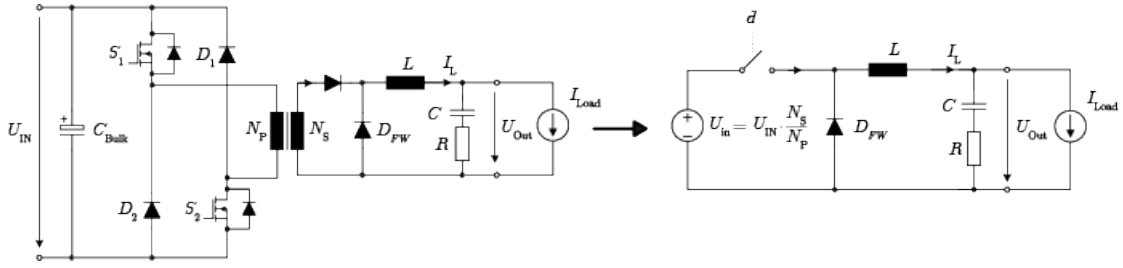


Figure 11.27: Based on the lecture material Power Electronic Systems II, Institute for Power Electronic Systems, ETH Zürich

model (small signals are marked with a hat) in state-space form reads as:

$$\frac{d}{dt}\hat{x} = \begin{pmatrix} -\frac{R}{L} & -\frac{1}{L} \\ \frac{1}{C} & 0 \end{pmatrix} \hat{x} + \begin{pmatrix} \frac{U_{in}}{L} \\ 0 \end{pmatrix} \hat{d} + \begin{pmatrix} \frac{D}{L} & -\frac{R}{L} \\ 0 & -\frac{1}{C} \end{pmatrix} \hat{w}$$

$$\hat{y} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ R & 1 \end{pmatrix} \hat{x} + \begin{pmatrix} 0 & 0 \\ 0 & 0 \\ 0 & -R \end{pmatrix} \hat{w}$$



$$\frac{d}{dt}\hat{x} = A \cdot \hat{x} + B1 \cdot u + B2 \cdot \hat{w}$$

$$\hat{y} = C \cdot \hat{x} + \begin{pmatrix} D2 \\ D4 \end{pmatrix} \cdot \hat{w}$$

11.7.4 Control Objective by Using Model Predictive Control

The converter should provide a constant output voltage U_{Out} of 60 V while delivering the power required by the load. The nominal load current I_{Load} is 22 A. The input voltage U_{in} is constant at level 144 V, while the load resistance varies in the range $[1.5, 5]\Omega$.

Conventionally the output voltage of the Buck Converter was controlled by a PI controller. In the first plot below, the current i_L in the inductor is shown, when the resistance in the load is reduced from 5Ω to 1.5Ω , i. e. from upper bound to the lower bound of the possibly required load resistance. The red curve represents the current in the inductor. Also the change in the output voltage is depicted when changing the load resistance.

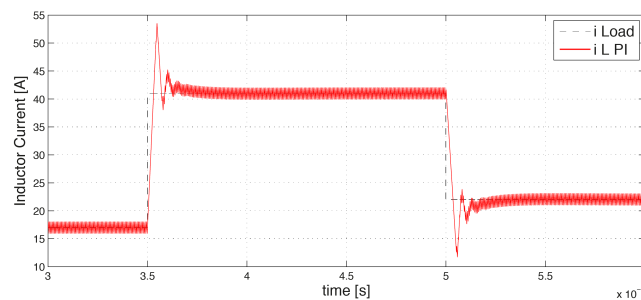


Figure 11.28: Inductor current vs. time

From Figure 11.28 and Figure 11.29 one can see that the current in the inductor has a high overshoot and the output voltage has a relatively long settling time when a change in the load resistance occurs.

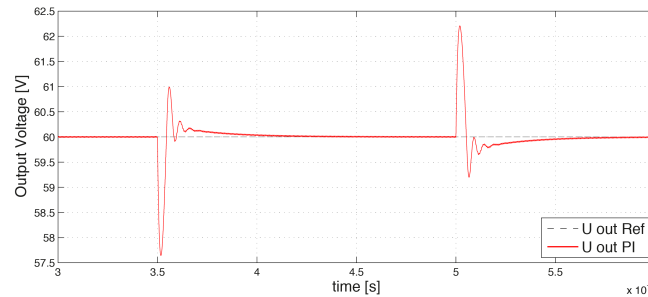


Figure 11.29: Output voltage vs. time

Important: Some of the potential benefits of model predictive control are the following

- Below it is shown that the size of the converter can be reduced by using a MPC controller designed with FORCESPRO. With the MPC controller it will be possible to limit the current in the inductor. With the warranty that the current does not exceed a certain upper bound, a smaller inductor can be built in and the costs are reduced.
- Also the controller designed with FORCESPRO will calculate the optimal input at every time step. The performance of the system is increased, i. e. less overshoot and faster settling time.

11.7.5 Model Predictive Control Design via FORCESPRO MATLAB® Interface

To design the FORCESPRO controller, the MPC setup has to be defined first. Below the requirements are shown. A prediction horizon of 25 is chosen. In the cost function R penalizes the deviation of the input signal from its reference value. The matrix Q penalizes the deviation of the states from its reference values. Notice that Q is defined such that a deviation of the inductor current to its reference value is less penalized than a deviation of the output voltage to its reference value. The input signal d to the PWM is limited to $[0, 1]$, while the inductor current should not exceed a current of 42 A. This overshoot limitation concerns the average inductor current. Below one can see, that this limit is exceeded by half of the currents peak-to-peak value. The constraints are consistently defined with the model, i. e. a current reduction by -20 A and a current enhancement by 20 A is allowed at most. This is equivalent to a current in the inductor in the range of $[2, 42]$ A.

```
% MPC Setup
N = 25;
Q = [.01, 0; 0, 10];
R = 1;
nx = 2;
nu = 1;

% Constraints
umin = 0;
umax = 1;
xmin = -20;
xmax = 20;
```

Next, the multistage problem is formulated. In this example, there exists a linear term f in the cost function due to the variable load, i. e. the steady-state inductor current changes. The cost function therefore reads as

$$(x^+ - x_{ref})^T Q (x^+ - x_{ref}) + (u - u_{ref})^T R (u - u_{ref})$$

To solve the optimization problem, the reference values need to be re-calculated at every time step. Below the parameters of the problem are marked red. The optimization variable of the multistage problem is $z_i = (u_i \quad x_{i+1})^T$, where u is the input signal given to the system.

$$\begin{aligned}
 & \text{minimize} && \sum_{i=1}^N \frac{1}{2} z_i^T H_i z_i + f_i^T z_i && \text{(separable objective)} \\
 & \text{subject to} && D_1 z_1 = c_1 && \text{(initial equality)} \\
 & && C_{i-1} z_{i-1} + D_i z_i = c_i && \text{(inter-stage equality)} \\
 & && \underline{z}_i \leq z_i \leq \bar{z}_i && \text{(bounds)}
 \end{aligned}$$

In this example three parameters have to be given to the solver.

- parameter (1): Represents the right hand side of the initial equality of the problem in standard form above.
- parameter (2): The linear term f of the cost function. This term contains the reference values of the states which are calculated based on the resistance of the load.
- parameter (3): Represents the right hand side of the inter-stage equality constraint for the stages $i = 2 : N$ of the problem.

Next to the parameters, the dimensions of the variables, the equality constraints and the bounds have to be defined. The values defined in the MPC setup are added to the multistage problem in the section 'cost'. The terms in the equality constraints which are constant over all stages are defined in the section 'equality constraints'. After defining the output of the solver and the solver settings, the code for the controller can be generated.

```

%% Multistage Problem
% get stages struct of length N
stages = MultistageProblem(N);

% RHS of first eq. constr. is a parameter: stages(1).eq.c = -A*x0 - B2*w
parameter(1) = newParam('minusAx0_minusB2w',1,'eq.c');

% Linear Term depends on x_ref and u_ref
parameter(2) = newParam('Linear_Term',1:N,'cost.f');

% RHS of equality constraints for remaining stages: stages(i).eq.c = - B2*w
parameter(3) = newParam('minusB2w',2:N,'eq.c');

for i = 1:N

    % dimension
    stages(i).dims.n = nx+nu; % number of stage variables
    stages(i).dims.r = nx; % number of equality constraints
    stages(i).dims.l = 2; % number of lower bounds
    stages(i).dims.u = 2; % number of upper bounds

    % cost
    stages(i).cost.H = blkdiag(R,Q);

    % lower bounds
    stages(i).ineq.b.lidx = 1:2; % lower bound acts on these indices
    stages(i).ineq.b.lb = [umin; xmin]; % lower bound on input u and state iL

    % upper bounds
    stages(i).ineq.b.ubidx = 1:2; % upper bound acts on these indices
    stages(i).ineq.b.ub = [umax; xmax]; % upper bound on input u and state iL

    % equality constraints

```

(continues on next page)

(continued from previous page)

```

if ( i < N )
    stages(i).eq.C = [zeros(nx,nu), Ad];
end
    stages(i).eq.D = [Bd1, -eye(nx)];
end

% define outputs of the solver
outputs(1) = newOutput('u0',1,1);

% solver settings
codeoptions = getOptions('DCDC_FORCES_Pro_Controller');

% generate code
generateCode(stages,parameter,codeoptions,outputs);

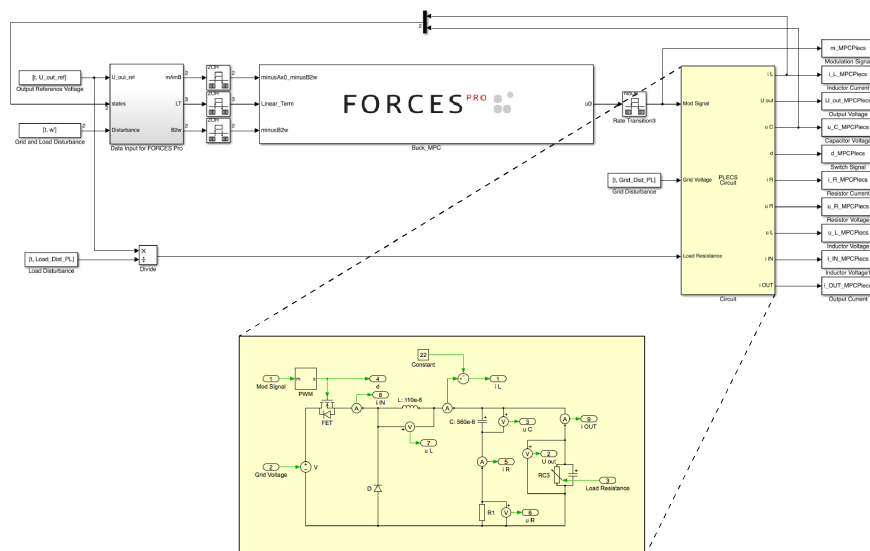
```

You can find the Matlab code of this example to try it out for yourself in the `examples` folder that comes with your client.

11.7.6 Simulation of the PLECS® Model with Model Predictive Control

After the code is generated, the FORCESPRO Simulink® block can be added to the model DCDC_FORCES_Pro_viewer.slx as shown in the figure below (copy/paste it from the file DCDC_FORCES_Pro_Controllercompact_lib.mdl in the folder DCDC_FORCES_Pro_Controller/Interface generated by FORCESPRO).

The controller has a frequency of 100 kHz. To simulate the system with a time step of $1e-7s$, rate transition blocks are used. Below the Simulink® model DC_DC_FORCES_Pro.slx with the PLECS® circuit and the FORCESPRO controller is depicted.



In the grey box in the model depicted above, the three parameters which are the input to the FORCESPRO controller, are calculated.

- `parameter (1)`: The right hand side of the initial equality constraint is $-Ad \cdot x - Bd2 \cdot w$.
- `parameter (2)`: For the linear term of the cost function the reference values for the states and the input signal need to be calculated.

The reference values are calculated by solving the linear system

$$\begin{pmatrix} Ad - I & Bd1 \\ Cd2 & Dd3 \end{pmatrix} \cdot \begin{pmatrix} x_{ref} \\ u_{ref} \end{pmatrix} = \begin{pmatrix} -Bd2 \cdot w \\ U_{out.ref} - Dd4 \cdot w \end{pmatrix}$$

which follows from the system equations in steady-state. To calculate the linear term f the reference values are plugged into the linear term $f = (-u_{ref} \cdot R - x_{ref}^T \cdot Q)^T$, which is equal to

$$f = \begin{pmatrix} Ad - I & Bd1 \\ Cd2 & Dd3 \end{pmatrix}^{-1} \cdot \begin{pmatrix} 0 & -Bd2 \\ 1 & -Dd4 \end{pmatrix} \cdot \begin{pmatrix} U_{out,ref} \\ w \end{pmatrix} \cdot \begin{pmatrix} 0 & -R \\ -Q & 0 \end{pmatrix}$$

The matrices in the derivation above are explained in more detail in the system presented in the code available for this example.

- parameter(3) is equal to $-Bd2 \cdot w$.

11.7.7 Comparison of Model Predictive Control and PI Control

In the [Figure 11.30](#) and [Figure 11.31](#) below the evolution of the inductor current and the output voltage are compared when controlling the system with PI and with the MPC controller designed using FORCESPRO. It can be seen that the MPC controller is able to keep the inductor current within the limits defined above. However, this limits the tracking speed of the output voltage in the corresponding time interval. Overall, the tracking performance of the output voltage is increased compared to the baseline PI controller.

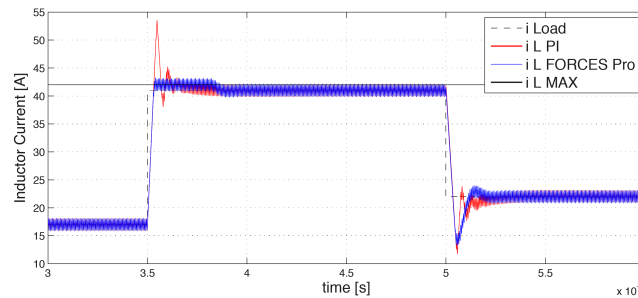


Figure 11.30: Inductor current vs. time

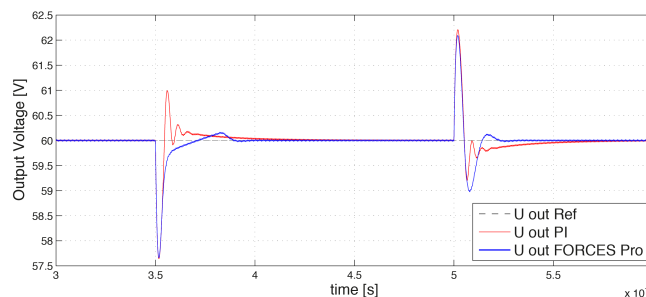


Figure 11.31: Output voltage vs. time

11.8 High-level interface: Basic example

- *Defining the problem data*
- *Defining the MPC problem*
- *Generating a solver*
- *Calling the generated solver*

- *Simulation*
- *Results*

Consider the following linear MPC problem with lower and upper bounds on state and inputs, and a terminal cost term:

$$\begin{aligned}
 &\text{minimize} && x_N^\top P x_N + \sum_{i=0}^{N-1} x_i^\top Q x_i + u_i^\top R u_i \\
 &\text{subject to} && x_0 = \mathbf{x} \\
 &&& x_{i+1} = A x_i + B u_i \\
 &&& \underline{x} \leq x_i \leq \bar{x} \\
 &&& \underline{u} \leq u_i \leq \bar{u}
 \end{aligned}$$

This problem is parametric in the initial state \mathbf{x} and the first input u_0 is typically applied to the system after a solution has been obtained.

You can find the Matlab code of this example to try it out for yourself in the `examples` folder that comes with your client.

11.8.1 Defining the problem data

Let's define the known data of the MPC problem, i.e. the system matrices A and B , the prediction horizon N , the stage cost matrices Q and R , the terminal cost matrix P , and the state and input bounds:

```

%% system
A = [1.1 1; 0 1];
B = [1; 0.5];
[nx,nu] = size(B);

%% MPC setup
N = 10;
Q = eye(nx);
R = eye(nu);
if( exist('dlqr','file') )
    [~,P] = dlqr(A,B,Q,R);
else
    P = 10*Q;
end
umin = -0.5;      umax = 0.5;
xmin = [-5, -5]; xmax = [5, 5];

```

11.8.2 Defining the MPC problem

Let's now dive in right into the problem formulation:

```

%% FORCES multistage form
% assume variable ordering zi = [ui; xi] for i=1...N

% dimensions
model.N      = 11;    % horizon length
model.nvar   = 3;     % number of variables
model.neq    = 2;     % number of equality constraints

% objective

```

(continues on next page)

(continued from previous page)

```

model.objective = @(z) z(1)*R*z(1) + [z(2);z(3)]'*Q*[z(2);z(3)];
model.objectiveN = @(z) z(1)*R*z(1) + [z(2);z(3)]'*P*[z(2);z(3)];

% equalities
model.eq = @(z) [ A(1,:) * [z(2);z(3)] + B(1)*z(1);
                  A(2,:) * [z(2);z(3)] + B(2)*z(1) ];

model.E = [zeros(2,1), eye(2)];

% initial state
model.xinitidx = 2:3;

% inequalities
model.lb = [ umin,      xmin  ];
model.ub = [ umax,      xmax  ];

```

11.8.3 Generating a solver

We have now populated `model` with the necessary fields to generate a solver for our problem. Now we use the function `FORCES_NLP` to generate a solver for the problem defined by `model` with the first state as a parameter:

```

%% Generate FORCES solver

% get options
codeoptions = getOptions('FORCESNLPsolver');
codeoptions.printlevel = 2;

% generate code
FORCES_NLP(model, codeoptions);

```

11.8.4 Calling the generated solver

Once all parameters have been populated, the MEX interface of the solver can be used to invoke it:

```

problem.x0 = zeros(model.N*model.nvar,1);
problem.xinit = xinit;
[solverout,exitflag,info] = FORCESNLPsolver(problem);

```

Tip: Type `help solvername` to get more information about how to call the solver.

11.8.5 Simulation

Let's now simulate the closed loop over the prediction horizon N :

```

%% simulate
x1 = [-4; 2];
kmax = 30;
X = zeros(2,kmax+1); X(:,1) = x1;
U = zeros(1,kmax);
problem.x0 = zeros(model.N*model.nvar,1);
for k = 1:kmax

```

(continues on next page)

(continued from previous page)

```

problem.xinit = X(:,k);

[solverout,exitflag,info] = FORCESNLPsolver(problem);

if( exitflag == 1 )
    U(:,k) = solverout.x0l(1);
    solvetime(k) = info.solvetime;
    iters(k) = info.it;
else
    error('Some problem in solver');
end

%X(:,k+1) = A*X(:,k) + B*U(:,k);
X(:,k+1) = model.eq( [U(:,k);X(:,k)] )';
end

```

11.8.6 Results

The results of the simulation are presented in [Figure 11.8](#). The plot on the top shows the system's states over time, while the plot on the bottom shows the input commands. We can see that all constraints are respected.

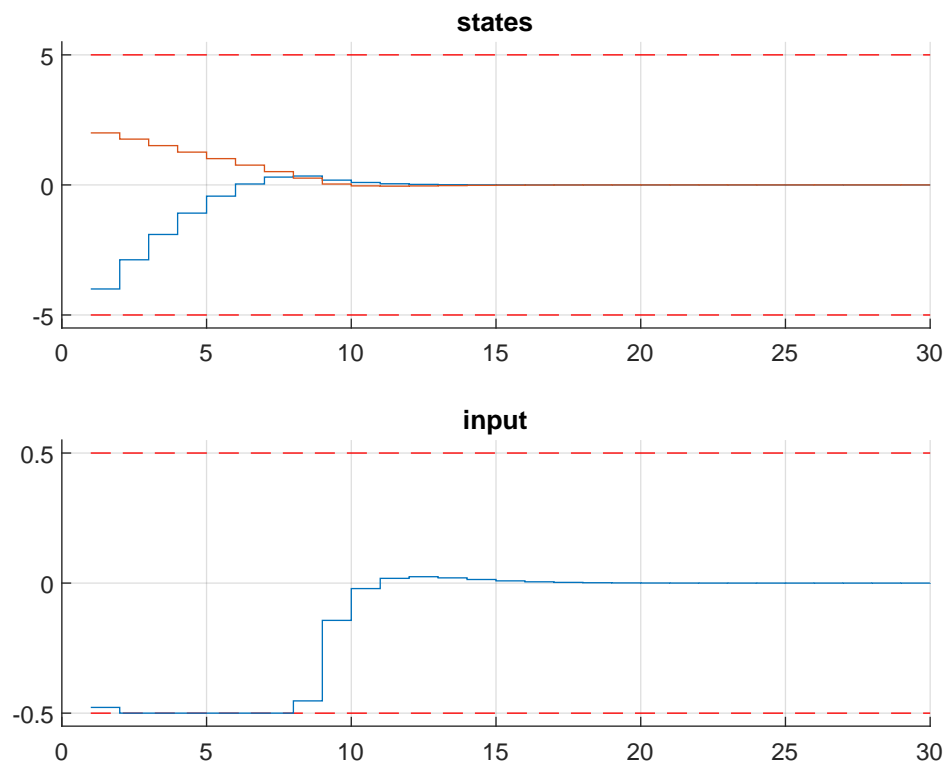


Figure 11.32: Simulation results of the states (top, in blue and red) and input (bottom, in blue) over time. The state and input constraints are plotted in red dashed lines.

11.9 High-level interface: Obstacle avoidance (MATLAB & Python)

- *Defining the MPC Problem*
 - *Objective*
 - *Matrix equality constraints*
 - *Runtime Parameters*
 - *Inequality constraints*
 - *Dimensions*
 - *Initial conditions*
- *Generating a solver*
- *Calling the generated solver*
- *Results*
- *Variation: External functions*

In this example we illustrate the simplicity of the high-level user interface on a vehicle optimal trajectory generation problem. The user can place an obstacle in front of the vehicle using an interactive window and the car trajectory is automatically adjusted.

In particular, we use a kinematic bicycle model described by a set of ordinary differential equations (ODEs):

$$\begin{aligned}
 \dot{x} &= v \cos(\theta + \beta) \\
 \dot{y} &= v \sin(\theta + \beta) \\
 \dot{v} &= \frac{F}{m} \\
 \dot{\theta} &= \frac{v}{l_r} \sin(\beta) \\
 \dot{\delta} &= \phi
 \end{aligned}$$

with:

$$\beta = \arctan\left(\frac{l_r}{l_r + l_f} \tan(\delta)\right)$$

The model consists of five differential states: x and y are the Cartesian coordinates of the car, and v is the linear velocity. The angles θ and δ denote the heading angle of the car and its steering angle. Next, there are two control inputs to the model: the acceleration force F and the steering rate ϕ . The angle β describes the direction of movement of the car's center of gravity relative to the heading angle θ . The remaining three constant parameters of the system are the car mass $m = 1\text{ kg}$, and the lengths $l_r = 0.5\text{ m}$ and $l_f = 0.5\text{ m}$ specifying the distance from the car's center of gravity to the rear wheels and the front wheels, respectively.

The trajectory of the vehicle will be defined as an NLP. First, we define stage variable z by stacking the input and differential state variables:

$$z = [F, \phi, x, y, v, \theta, \delta]^T$$

You can find the code of this example to try it out for yourself in the `examples` folder that comes with your client.

11.9.1 Defining the MPC Problem

Objective

In this example the cost function provided by `model.objective` is the same for all stages. We have a target position $(3, 0)$ and we want to minimize the distance of the car to that point. Therefore, the distance is penalized with linear costs. Plus, some small quadratic costs are added to the inputs F and s , i.e.:

$$f(z) = 100|z_3 - 0| + 100|z_4 - 3| + 0.1z_1^2 + 0.01z_2^2$$

The stage cost function is coded in MATLAB and Python as the following function:

Matlab

Python

```
model.objective = @objective

function f = objective(z)
    F = z(1);
    phi = z(2);
    x = z(3)
    y = z(4);
    f = 100*abs(x-0) + 100*abs(y-3) + 0.1*F^2 + 0.01*phi^2;
end
```

```
model = forcespro.nlp.SymbolicModel() # create empty model
model.objective = lambda z: 100 * casadi.fabs(z[2] - 0.) \
    + 100 * casadi.fabs(z[3] - 3.) \
    + 0.1 * z[0]**2 + 0.01 * z[1]**2
```

Matrix equality constraints

The matrix equality constraints `model.eq` in this example result from the vehicle's dynamics given above. First, the continuous dynamic equations are implemented as follows:

Matlab

Python

```
function [xDot] = continuousDynamics(x,u)
    % state x = [xPos,yPos,v,theta,delta], input u = [F, phi]

    % set physical constants
    l_r = 0.5; % distance rear wheels to center of gravity of the car
    l_f = 0.5; % distance front wheels to center of gravity of the car
    m = 1.0; % mass of the car

    % set parameters
    beta = atan(l_r/(l_f + l_r) * tan(x(5)));

    % calculate dx/dt
    xDot = [x(3) * cos(x(4) + beta); % dxPos/dt = v*cos(theta+beta)
            x(3) * sin(x(4) + beta); % dyPos/dt = v*cos(theta+beta)
            u(1)/m; % dv/dt = F/m
            x(3)/l_r * sin(beta); % dtheta/dt = v/l_r*sin(beta)
            u(2)]; % ddelta/dt = phi

end
```

```
def continuous_dynamics(x, u):
    """ state x = [xPos,yPos,v,theta,delta], input u = [F,phi]"""

    # set physical constants
    l_r = 0.5 # distance rear wheels to center of gravitiy of the car
    l_f = 0.5 # distance front wheels to center of gravitiy of the car
    m = 1.0   # mass of the car

    # set parameters
    beta = casadi.arctan(l_r/(l_f + l_r) * casadi.tan(x[4]))

    # calculate dx/dt
    return np.array([x[2] * casadi.cos(x[3] + beta), # dxPos/dt = v*cos(theta+beta)
                    x[2] * casadi.sin(x[3] + beta), # dyPos/dt = v*sin(theta+beta)
                    u[0] / m,                       # dv/dt = F/m
                    x[2]/l_r * casadi.sin(beta),      # dtheta/dt = v/l_r*sin(beta)
                    u[1]])                          # ddelta/dt = phi
```

Now, these continuous dynamics are discretized using an explicit Runge-Kutta integrator of order 4 as shown below. Note that the function RK4 is included in the FORCESPRO client software.

Matlab

Python

```
integrator_stepsize = 0.1;
% z(3:7) = states x, z(1:2) = inputs u
model.eq = @(z) RK4(z(3:7), z(1:2), @continuousDynamics, integrator_stepsize);
```

```
integrator_stepsize = 0.1
# z[2:7] = states x, z[0:2] = inputs u
model.eq = lambda z: forcespro.nlp.integrate(continuous_dynamics, z[2:7], z[0:2],
                                             integrator=forcespro.nlp.integrators.
↳RK4,
                                             stepsize=integrator_stepsize)
```

As a last step, the indices of the left hand side of the dynamical constraint are defined. For efficiency reasons, make sure the matrix has structure [0 I].

Matlab

Python

```
model.E = [zeros(5,2), eye(5)];
```

```
model.E = np.concatenate([np.zeros((5,2)), np.eye(5)], axis=1)
```

Runtime Parameters

The user can place an obstacle to be avoided in front of the car. The x- and y-coordinates of the position p of this obstacle are considered as runtime parameters of the system.

$$p = [p_x, p_y]^T$$

The runtime parameters are the same for all stages. Their values will be set later on at runtime.

Inequality constraints

The maneuver is subjected to a set of constraints, involving both the simple bounds:

$$\begin{aligned} -5 \text{ N} &\leq F \leq 5 \text{ N} \\ -40 \text{ deg/s} &\leq \phi \leq 40 \text{ deg/s} \\ -3 \text{ m} &\leq x \leq 0 \text{ m} \\ 0 \text{ m} &\leq y \leq 3 \text{ m} \\ 0 \text{ m/s} &\leq v \leq 2 \text{ m/s} \\ -\infty &\leq \theta \leq \infty \\ -0.48\pi \text{ rad} &\leq \delta \leq 0.48\pi \text{ rad} \end{aligned}$$

as well the nonlinear nonconvex constraints in dependence of the runtime parameters p

$$\begin{aligned} 1 \text{ m}^2 &\leq x^2 + y^2 \leq 9 \text{ m}^2 \\ 0.7^2 \text{ m}^2 &\leq (x - p_x)^2 + (y - p_y)^2 \end{aligned}$$

The implementation of the simple bounds is given here:

Matlab

Python

```
% upper/lower variable bounds lb <= z <= ub
%           inputs           |           states
%           F           phi           x           y           v           theta           delta
model.lb = [ -5.0,  deg2rad(-40),  -3.,    0.,    0.,    -inf,    -0.48*pi];
model.ub = [ +5.0,  deg2rad(+40),   0.,    3.,    2.,    +inf,    0.48*pi];
```

```
# upper/lower variable bounds lb <= z <= ub
#           inputs           |           states
#           F           phi           x           y           v           theta           delta
model.lb = np.array([-5.,  np.deg2rad(-40.),  -3.,    0.,    0,    -np.inf,  -0.48*np.
↳pi])
model.ub = np.array([+5.,  np.deg2rad(+40.),   0.,    3.,    2.,    np.inf,   0.48*np.
↳pi])
```

The nonlinear constraint function h with its bounds can be coded in MATLAB/Python as follows:

Matlab

Python

```
% General (differentiable) nonlinear inequalities h1 <= h(x,p) <= hu
model.ineq = @(z,p) [    z(3)^2 + z(4)^2;                % x^2 + y^2
                      (z(3)-p(1))^2 + (z(4)-p(2))^2 ]; % (x-p_x)^2 + (y-p_y)^2

% Upper/lower bounds for inequalities
model.hu = [9, +inf]';
model.h1 = [1, 0.7^2]';
```

```
# General (differentiable) nonlinear inequalities h1 <= h(x,p) <= hu
model.ineq = lambda z,p: np.array([z[2]**2 + z[3]**2,                # x^2 + y^2
                                   (z[2] - p[0])**2 + (z[3] - p[1])**2]) # (x-p_x)^2 +
↳ (y-p_y)^2

# Upper/lower bounds for inequalities
```

(continues on next page)

(continued from previous page)

```
model.hu = np.array([9, +np.inf])
model.hl = np.array([1, 0.7**2])
```

Dimensions

Furthermore, the number of variables, constraints and real-time parameters explained above needs to be provided as well as the length of the multistage problem. For this example, we chose to use $N = 50$ stages in the NLP:

Matlab

Python

```
model.N = 50;      % horizon length
model.nvar = 7;    % number of variables
model.neq = 5;     % number of equality constraints
model.nh = 2;      % number of inequality constraint functions
model.npar = 2;    % number of runtime parameters
```

```
model.N = 50      # horizon length
model.nvar = 7    # number of variables
model.neq = 5     # number of equality constraints
model.nh = 2      # number of inequality constraint functions
model.npar = 2    # number of runtime parameters
```

Initial conditions

The goal of the maneuver is to steer the vehicle from a set of initial conditions:

$$x_{\text{init}} = -2 \text{ m}, \quad y_{\text{init}} = 0 \text{ m}, \quad v_{\text{init}} = 0 \text{ m/s}, \quad \theta_{\text{init}} = 0.5\pi \text{ rad}, \quad \delta_{\text{init}} = 0 \text{ rad}$$

For the code generation, only the indices of the variables to which initial values will be applied are required. This is coded as follows:

Matlab

Python

```
model.xinitidx = 3:7;
```

```
model.xinitidx = range(2,7)
```

11.9.2 Generating a solver

We have now populated `model` with the necessary fields to generate a solver for our problem. Now we set some options for our solver and then use the function `FORCES_NLP` to generate a solver for the problem defined by `model`:

Matlab

Python

```
%% Define solver options
codeoptions = getOptions('FORCESNLPsolver');
codeoptions.maxit = 400;           % Maximum number of iterations
codeoptions.printlevel = 0;
```

(continues on next page)

(continued from previous page)

```

codeoptions.optlevel = 0; % 0: no optimization, 1: optimize for_
↳size, 2: optimize for speed, 3: optimize for size & speed
codeoptions.printlevel = 0;
codeoptions.nlp.bfgs_init = 3.0*eye(7); % set initialization of the hessian_
↳approximation

%% Generate forces solver
FORCES_NLP(model, codeoptions);

```

```

# Set solver options
codeoptions = forcespro.CodeOptions('FORCESNLPsolver')
codeoptions.maxit = 400 # Maximum number of iterations
codeoptions.printlevel = 0
codeoptions.optlevel = 0 # 0 no optimization, 1 optimize for_
↳size, 2 optimize for speed, 3 optimize for size & speed
codeoptions.nlp.bfgs_init = 3.0*np.identity(7) # initialization of the hessian_
↳approximation
codeoptions.noVariableElimination = 1.

# Creates code for symbolic model formulation given above, then contacts server to_
↳generate new solver
solver = model.generate_solver(codeoptions)

```

11.9.3 Calling the generated solver

Once all parameters of the problem instance to be solved have been populated, the MEX interface of the solver can be used to invoke it.

Matlab

Python

```

% Set initial guess to start solver from (here, middle of upper and lower bound)
x0i=[0.0,0.0,-1.5,1.5,1.,pi/4.,0.];
x0=repmat(x0i,model.N,1);
problem.x0=x0;

% Set initial condition
problem.xinit = [-2., 0., 0., deg2rad(90), 0.];

% Set runtime parameters
params = [-1.5; 1.0]; # In this example, the user can change these parameters by_
↳clicking into an interactive window
problem.all_parameters = repmat(params,model.N,1);

% Time to solve the NLP!
[output,exitflag,info] = FORCESNLPsolver(problem);

% Make sure the solver has exited properly.
assert(exitflag == 1,'Some problem in FORCES solver');
fprintf('\nFORCES took %d iterations and %f seconds to solve the problem.\n',info.
↳it,info.solvetime);

```

```

# Set initial guess to start solver from (here, middle of upper and lower bound)
x0i = np.array([0.,0.,-1.5,1.5,1.,np.pi/4.,0.])
x0 = np.transpose(np.tile(x0i, (1, model.N)))

# set initial condition
xinit = np.transpose(np.array([-2.,0.,0.,np.deg2rad(90),0.]))

```

(continues on next page)

(continued from previous page)

```

problem = {"x0": x0,
          "xinit": xinit,
          "xfinal": xfinal}

# Set runtime parameters
params = np.array([-1.5, 1.]) # In this example, the user can change these_
↪parameters by clicking into an interactive window
problem["all_parameters"] = np.transpose(np.tile(params, (1, model.N)))

# Time to solve the NLP!
output, exitflag, info = solver.solve(problem)

# Make sure the solver has exited properly.
assert exitflag == 1, "bad exitflag"
print("FORCES took {} iterations and {} seconds to solve the problem.".format(info.
↪it, info.solvetime))

```

11.9.4 Results

The goal is to find a trajectory that steers the vehicle from point A as close as possible to point B while avoiding obstacles. The trajectory should also be feasible with respect to the vehicle dynamics and its safety and physical limitations. The calculated vehicle's trajectory in 2D space is presented in Figure 11.33. The progress of the other states and the inputs over time is shown in Figure 11.34. One can see that all constraints are respected. To try out other obstacle positions you can run the example file on your own machine and click into the interactive window.

You can find the code of this example in the examples folder that comes with your client.

11.9.5 Variation: External functions

In this variation, we want to supply the required functions through external functions in C. To do so we have to provide the directory that contains said source files in the MATLAB code:

```

%% Define source file containing function evaluation code
model.extfuncs = 'C/myfevals.c';

```

We also need to include the two extern functions `car_dynamics` and `car_dynamics_jacobian`, both contained in the `car_dynamics.c` file, through the `other_srcs` options field:

```

% add additional source files required - separate by spaces if more than 1
codeoptions.nlp.other_srcs = 'C/car_dynamics.c';

```

In Python, we need to switch to an `ExternalFunctionModel` if we intend to use external callbacks. We give the main callback evaluating the objective function, equality constraints and inequality constraints, using the `set_main_function()`, and supply any additional files required by this callback using `add_auxiliary()`.

```

model = forcespro.nlp.ExternalFunctionModel()

# Define source file containing function evaluation code
model.set_main_callback("C/myfevals.c", function="myfevals")
model.add_auxiliary("C/car_dynamics.c")
# One can also add a 'relative_to' argument specifying the paths to be understood

```

(continues on next page)

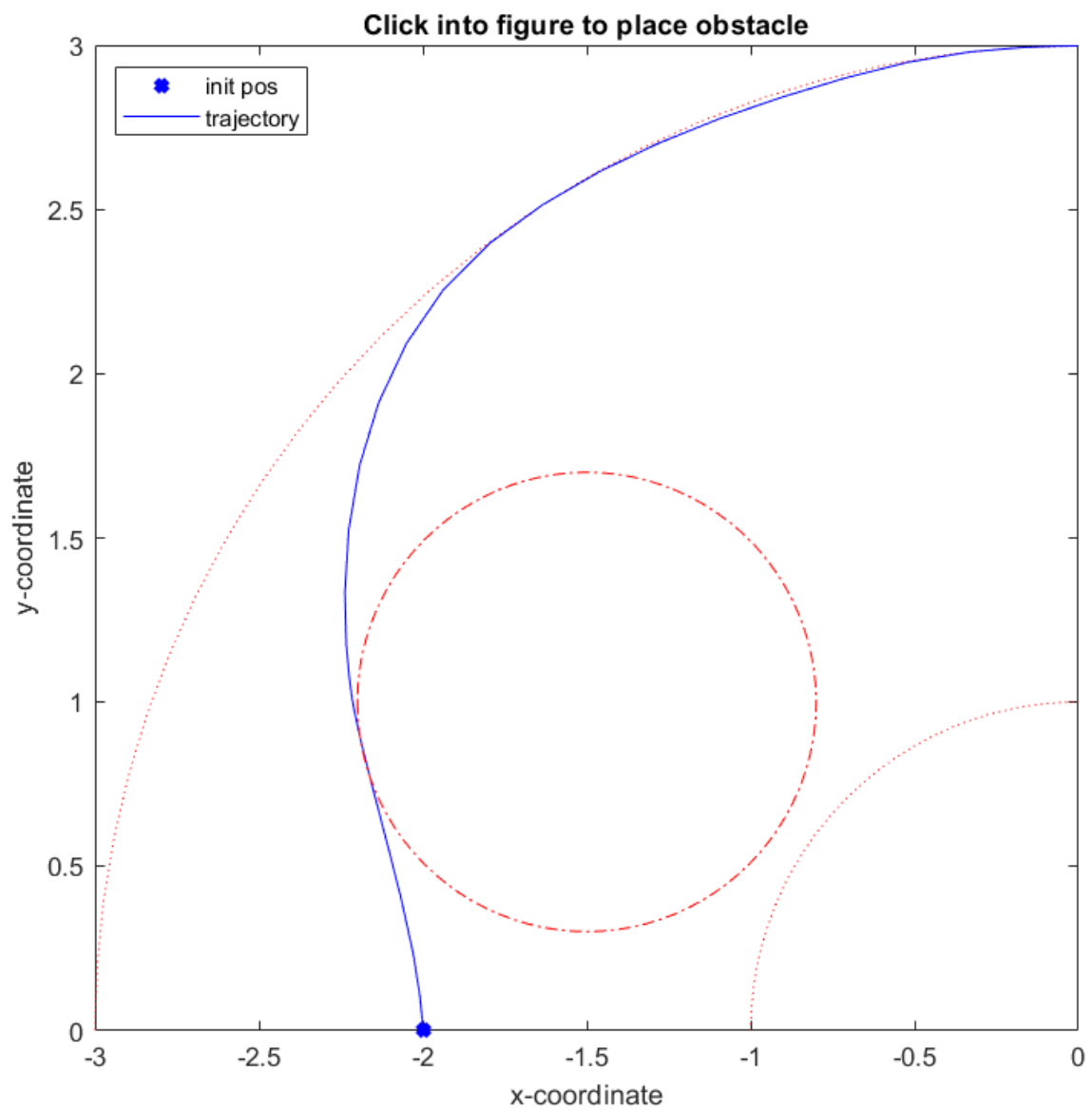


Figure 11.33: The calculated trajectory of the car

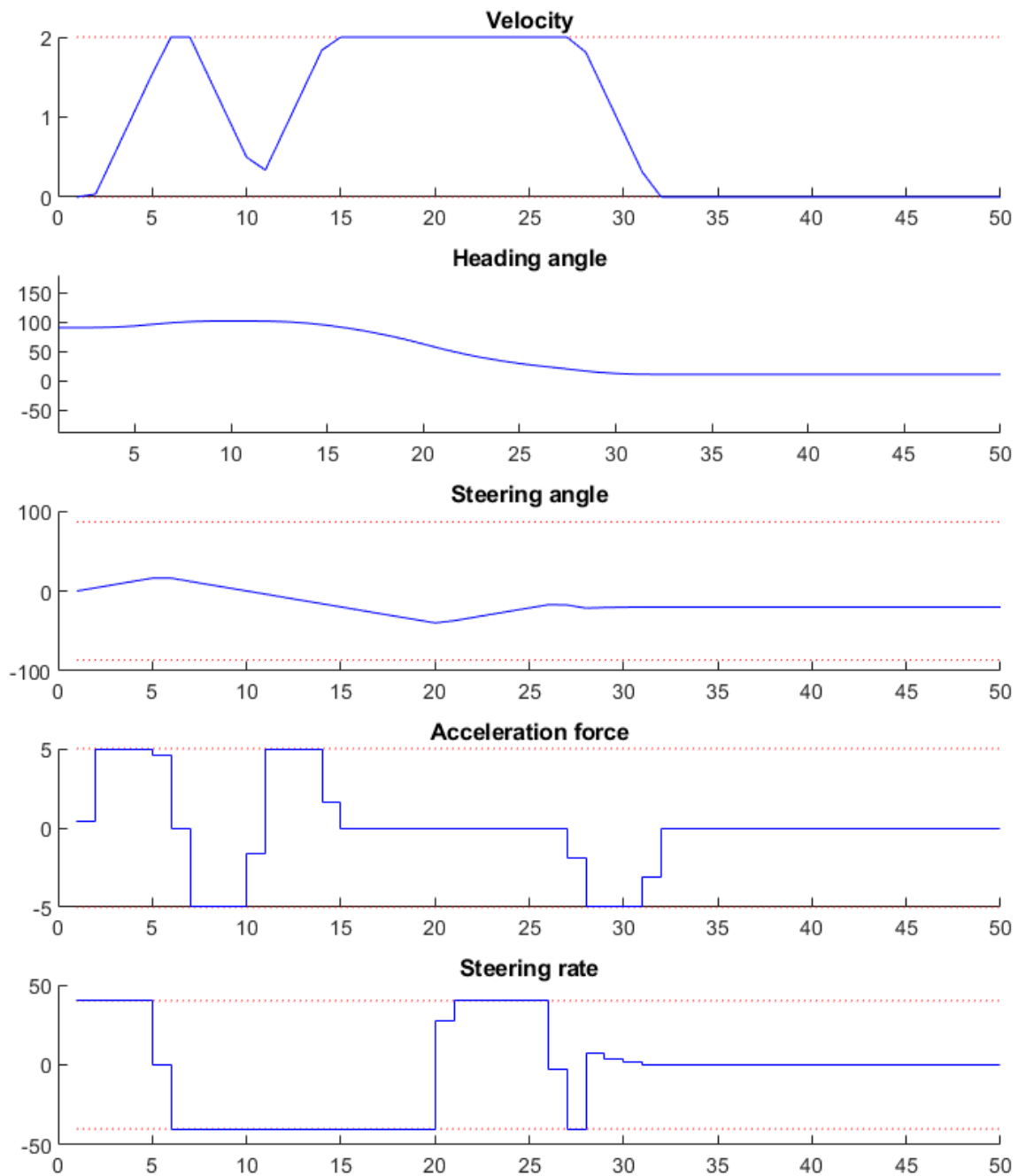


Figure 11.34: Development of the vehicle's states and the system's inputs over time

(continued from previous page)

```
# relative to this file's location. if not supplied, paths are relative to the
# current working directory in which this script is executed:
# model.set_main_callback('c/myfevals.c', function="myfevals" relative_to=os.path.
↪dirname(__file__))
# model.add_auxiliary('c/car_dynamics.c', relative_to=os.path.dirname(__file__))
```

You can find the code of this example to try it out for yourself in the `examples` folder that comes with your client.

11.10 High-level interface: Indoor localization (MATLAB & Python)

- *Time of flight measurements*
- *Estimation error*
- *Minimize the error*
- *Implementation*

The indoor localization problem is to estimate the position of a target by measurements from various anchors with known location. Outdoors, this well known as GPS, while indoors other frequency bands (and less accurate clocks) are usually used. In this example, we show how to generate code for a position estimator that relies on time-of-flight (TOF) measurements (GPS uses time-difference-of-arrival, TDOA). The latter can be easily implemented with FORCESPRO as well with only minor changes to the code below.

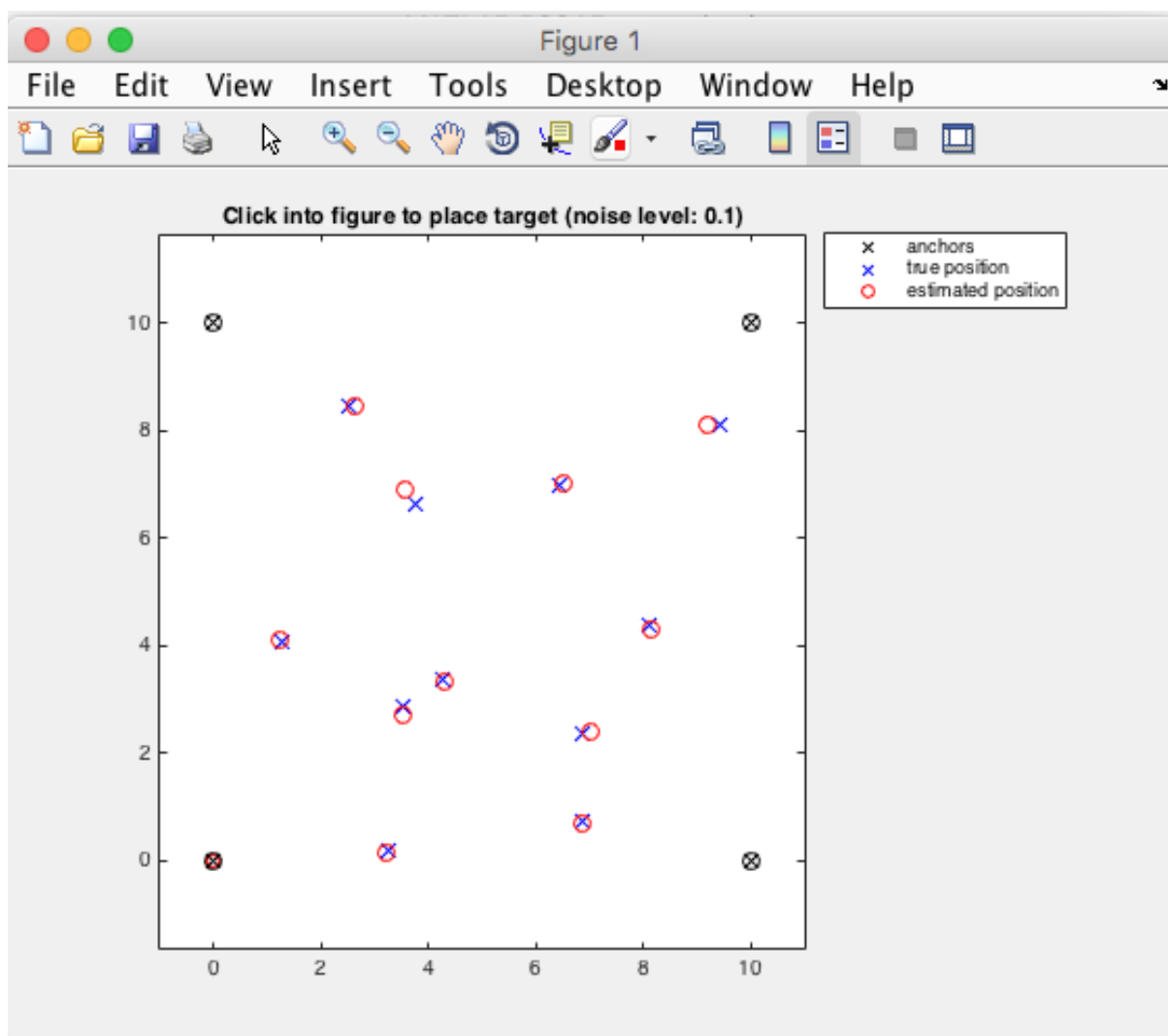


Figure 11.35: Indoor localization example GUI.

You can find the code of this example to try it out for yourself in the `examples` folder that comes with your client.

Running the code will produce an interactive window like in [Figure 11.35](#).

11.10.1 Time of flight measurements

Given N anchors with known positions (x_i^a, y_i^a) , $i = 1, \dots, N$, the distance to the target with unknown position (x, y) is given by:

$$d_i = ct_i = \sqrt{(x - x_i^a)^2 + (y - y_i^a)^2}$$

where t_i is the time the signal from anchor i travels at the speed $c = 299\,792\,458$ m/s

11.10.2 Estimation error

Instead of the real distance, we work with squared distances to define the estimation error:

$$e_i = (x - x_i^a)^2 + (y - y_i^a)^2 - d_i^2$$

11.10.3 Minimize the error

The objective is a least-squares error function:

$$\min_{x,y} \sum_{i=1}^N e_i^2$$

11.10.4 Implementation

The following Matlab/Python code generates C-code for implementing an optimizer for minimizing the least-squares error function from above. It takes the anchor positions and the distance measurements, and returns the estimated position of the target.

Matlab

Python

```
%% This function generates the estimator
function generateEstimator(numberOfAnchors,xlimits,ylimits)
% Generates 2D decoding code for localization using FORCES NLP
% na: number of anchors
global na
na = numberOfAnchors;

%% NLP problem definition
% no need to change anything below
model.N = 1;          % number of distance measurements
model.nvar = 2;        % number of variables (use 3 if 3D)
model.npar = numberOfAnchors*3; % number of parameters: coordinates of anchors_
% in 2D, plus measurements
model.objective = @objective;
model.lb = [xlimits(1) ylimits(1)]; % lower bounds on (x,y)
model.ub = [xlimits(2) ylimits(2)]; % upper bounds on (x,y)

%% codesettings
codesettings = getOptions('localizationDecoder');
codesettings.printlevel = 0; % set to 2 to see some prints
% codesettings.server = 'http://winner10:2470';
```

(continues on next page)

(continued from previous page)

```

codesettings.maxit = 50; % maximum number of iterations

%% generate code
FORCES_NLP(model, codesettings);
end

%% This function implements the objective
% We assume that the parameter vector p is ordered as follows:
% p(1:na)          - x-coordinates of the anchors
% p(na+1:na))      - y-coordinates of the anchors
% p(2*na+1:na))    - distance measurements of the anchors
function obj = objective( z,p )
    global na
    obj=0;
    for i = 1:na
        obj = obj + ( (p(i)-z(1))^2 + (p(i+na)-z(2))^2 - p(i+2*na)^2 )^2;
    end
end

def generate_estimator(number_of_anchors, xlimits, ylimits):
    """
    Generates and returns a FORCESPRO solver that estimates a position based on
    noisy measurement inputs.
    """

    # NLP problem definition
    # -----

    model = forcespro.nlp.SymbolicModel(1) # number of distance measurements
    model.nvar = 2 # number of variables (use 3 if 3D)
    model.npar = number_of_anchors * 3 # number of parameters: coordinates of_
    ↪anchors in 2D, plus measurements
    model.objective = objective # objective is defined as it's own function below
    model.lb = np.array([xlimits[0], ylimits[0]]) # lower bounds on (x,y)
    model.ub = np.array([xlimits[1], ylimits[1]]) # upper bounds on (x,y)

    # FORCESPRO solver settings
    # -----

    codesettings = forcespro.CodeOptions()
    codesettings.printlevel = 0 # set to 2 to see some prints
    codesettings.maxit = 50 # maximum number of iterations

    # Generate a solver
    # -----
    solver = model.generate_solver(codesettings)

    return solver

def objective(z, p):
    """
    This function implements the objective to be minimized.

    We assume that the parameter vector p is ordered as follows:

    - p[0:(na-1)]          - x-coordinates of the anchors
    - p[na:(2*na-1)]       - y-coordinates of the anchors
    - p[(2*na):(3*na-1)]   - distance measurements of the anchors
    """
    obj = 0

```

(continues on next page)

(continued from previous page)

```
for i in range(n):
    obj += ((p[i] - z[0])**2 + (p[i + n] - z[1])**2 - p[i + 2*n]**2)**2
return obj

def distance(xa, xtrue, ya, ytrue):
    return np.sqrt((xa - xtrue)**2 + (ya - ytrue)**2)
```

11.11 High-level interface: Path tracking example (MATLAB)

- *Defining the MPC Problem*
 - *Objective*
 - *Equality constraints*
 - *Bounds*
 - *Dimensions*
- *Generating a solver*
- *Calling the generated solver*
 - *Choosing the Path*
- *Results*

In this example we illustrate the simplicity of the SQP_NLP API on a path-tracking problem. In every simulation step, the predicted trajectory of the car is optimized to follow a set of path points, either an ellipse or a artificial racetrack. The example visualizes how the predicted trajectory changes while the car moves along the path.

We use a kinematic bicycle model described by a set of ordinary differential equations (ODEs):

$$\begin{aligned}\dot{x} &= v \cos(\theta + \beta) \\ \dot{y} &= v \sin(\theta + \beta) \\ \dot{v} &= \frac{F}{m} \\ \dot{\theta} &= \frac{v}{l_r} \sin(\beta) \\ \dot{\delta} &= \phi\end{aligned}$$

with:

$$\beta = \arctan\left(\frac{l_r}{l_r + l_f} \tan(\delta)\right)$$

The model consists of five differential states: x and y are the Cartesian coordinates of the car, and v is the linear velocity. The angles θ and δ denote the heading angle of the car and its steering angle, respectively. Next, there are two control inputs to the model: the longitudinal acceleration force F and the steering rate ϕ . The angle β describes the direction of movement of the car's center of gravity relative to the heading angle θ . The remaining three constant parameters of the system are the car mass $m = 1$ kg, and the lengths $l_r = 0.5$ m and $l_f = 0.5$ m specifying the distance from the car's center of gravity to the rear wheels and the front wheels, respectively.

The trajectory of the vehicle will be defined as an NLP. First, we define stage variable z by stacking the input and differential state variables:

$$z = [F, \phi, x, y, v, \theta, \delta]^T$$

You can find the code of this example to try it out for yourself in the `examples` folder that comes with your client.

11.11.1 Defining the MPC Problem

Objective

In this example the cost function is the same for all stages except for the last stage N. The objective of this example is to follow a set of path points. At runtime, a target position p_i for each stage i is provided. Each point consists of a x- and a y-coordinate:

$$p_i = [p_{i,x}, p_{i,y}]^T$$

The goal is to minimize the distance of the car to these target points. The distance is penalized with quadratic costs. Plus, some small quadratic costs are added to the inputs F and s , i.e.:

$$f(z, p_i) = 200(z_3 - p_{i,x})^2 + 200(z_4 - p_{i,y})^2 + 0.2z_1^2 + 10z_2^2$$

Since all cost terms are quadratic and summed up, we can formulate the objective as a least squares problem:

$$f(z, p_i) = \frac{1}{2} \|r(z, p_i)\|_2^2$$

$$r(z, p_i) = [\sqrt{200}(z_3 - p_{i,x}), \sqrt{200}(z_4 - p_{i,y}), \sqrt{0.2}z_1, \sqrt{10.0}z_2]^T$$

The stage cost function is coded in MATLAB as the following function:

Matlab

```
model.LSobjective = @(z,p) LSobj(z,p,I);

function [r] = LSobj(z,currentTarget, I)
% Least square costs on deviating from the path and on the inputs
% currentTarget = point on path that is tracked in this stage

r = [sqrt(200.0)*(z(I.xPos)-currentTarget(1));           % costs for deviating from the
    path in x-direction
    sqrt(200.0)*(z(I.yPos)-currentTarget(2));           % costs for deviating from the
    path in y-direction
    sqrt(0.2)*z(I.FLon);                                 % penalty on input FLon
    sqrt(10.0)*z(I.steeringRate)];                      % penalty on input steeringRate
end
```

Note that using the `model.LSobjective` option instead of `model.objective` allows you to try out the gauss-newton method for the hessian approximation.

For the last stage, the terminal costs are slightly increased by adapting the weighting factors:

$$f(z, p_i) = 400(z_3 - p_{i,x})^2 + 400(z_4 - p_{i,y})^2 + 0.2z_1^2 + 10.0z_2^2$$

The code looks a follows:

Matlab

```
model.LSobjectiveN = @(z,p) LSobjN(z,p,I);

function [r] = LSobjN(z,currentTarget, I)
% Increased least square costs for last stage on deviating from the path and on
the inputs
% currentTarget = point on path that is tracked in this stage

r = [sqrt(400.0)*(z(I.xPos)-currentTarget(1));           % costs for deviating from the
    path in x-direction
    sqrt(400.0)*(z(I.yPos)-currentTarget(2));           % costs for deviating from the
    path in y-direction
    sqrt(0.2)*z(I.FLon);                                 % penalty on input FLon
    sqrt(10.0)*z(I.steeringRate)];                      % penalty on input steeringRate
end
```

Equality constraints

The equality constraints `model.eq` in this example result from the vehicle's dynamics given above. First, the continuous dynamic equations are implemented as follows:

Matlab

```
function [xDot] = continuousDynamics(x,u,I)

% Number of inputs is needed for indexing
nu = numel(I.inputs);

% Set physical constants
l_r = 0.5; % Distance rear wheels to center of gravity of the car
l_f = 0.5; % Distance front wheels to center of gravity of the car
m = 1.0;   % Mass of the car

% Set parameters
beta = atan(l_r/(l_r + l_f) * tan(x(I.steeringAngle-nu)));

% Calculate dx/dt
xDot = [x(I.velocity-nu) * cos(x(I.heading-nu) + beta); % dxPos/dt = v*cos(theta+beta)
        x(I.velocity-nu) * sin(x(I.heading-nu) + beta); % dyPos/dt = v*sin(theta+beta)
        u(I.FLon)/m; % dv/dt = F/m
        x(I.velocity-nu)/l_r * sin(beta); % dtheta/dt = v/l_r*sin(beta)
        u(I.steeringRate)]; % ddelta/dt = phi

end
```

Now, these continuous dynamics are discretized using an explicit Runge-Kutta integrator of order 4 as shown below. Note that the function `RK4` is included in the FORCESPRO client software.

Matlab

```
timeStep = 0.1;
model.eq = @(z) RK4( z(I.states), z(I.inputs), @(x,u)continuousDynamics(x,u,I), ...
    timeStep);
```

As a last step, the indices of the left hand side of the dynamical constraint are defined. For efficiency reasons, make sure the matrix has structure `[0 I]`.

Matlab

```
model.E = [zeros(nStates,nInputs), eye(nStates)];
```

Bounds

All variables except the heading angle θ are bounded:

$$\begin{aligned} -5 \text{ N} &\leq F \leq 5 \text{ N} \\ -90 \text{ deg/s} &\leq \dot{\phi} \leq 90 \text{ deg/s} \\ -100 \text{ m} &\leq x \leq 100 \text{ m} \\ -100 \text{ m} &\leq y \leq 100 \text{ m} \\ 0 \text{ m/s} &\leq v \leq 5 \text{ m/s} \\ -\infty &\leq \theta \leq \infty \\ -50 \text{ deg} &\leq \delta \leq 50 \text{ deg} \end{aligned}$$

The implementation of the simple bounds is given here:

Matlab

```
% Upper/lower variable bounds lb <= z <= ub
%           inputs | states
%           FLon   steeringRate   xPos   yPos   velocity   heading   steeringAngle
model.lb = [ -5.,   deg2rad(-90),   -100., -100.,   0.,       -inf,   deg2rad(-
↪50)];
model.ub = [ +5.,   deg2rad(90),    100.,  100.,   5.,       +inf,   deg2rad(50)];
```

Dimensions

Furthermore, the number of variables, constraints and real-time parameters explained above needs to be provided as well as the length of the multistage problem. For this example, we chose to use $N = 10$ stages in the NLP:

Matlab

```
horizonLength = 10;
nInputs = numel(I.inputs);
nStates = numel(I.states);

model.N = horizonLength;           % Horizon length
model.nvar = nInputs+nStates;      % Number of variables
model.neq = nStates;               % Number of equality constraints
model.npar = 2;                    % Number of runtime parameters (waypoint_
↪coordinates)
```

11.11.2 Generating a solver

The actual solver generation happens inside the function `generatePathTrackingSolver`:

Matlab

```
%% Define solver options
codeoptions = getOptions('PathTrackingSolver');
codeoptions.maxit = 200;           % Maximum number of iterations
codeoptions.optlevel = 3;          % 0: No optimization, good for prototyping
codeoptions.timing = 1;
codeoptions.printlevel = 0;
codeoptions.nohash = 1;            % Enforce solver regeneration
codeoptions.override = 1;          % Overwrite existing solver
codeoptions.BuildSimulinkBlock = 0;
```

(continues on next page)

(continued from previous page)

```
% SQP options
codeoptions.solvermethod = 'SQP_NLP';
codeoptions.nlp.hessian_approximation = 'gauss-newton';
codeoptions.sqp_nlp.maxqps = 1;      % Maximum number of quadratic problems to be_
↳solved in one solver call
codeoptions.sqp_nlp.use_line_search = 0;

%% Generate FORCESPRO solver
cd(solverDir);
FORCES_NLP(model, codeoptions);
```

First, appropriate codeoptions are set. In particular, we chose to use an SQP algorithm with Gauss-Newton approximation for the Hessian matrix and perform only a single QP solve per solver call. Finally, we use the function `FORCES_NLP` to generate a solver called `PathTrackingSolver`.

11.11.3 Calling the generated solver

The goal of this example is to optimize the predicted car trajectory for the next N time steps and then apply the calculated input for the current time step. The procedure is repeated for the entire simulation period.

Choosing the Path

The path to follow can either be an ellipse or a racetrack profile.

Matlab

```
mapName = 'racetrack';      % Current options: 'ellipse' and 'racetrack'
```

The initial conditions for the dynamic states are chose as the first waypoint of the path and the real-time parameters are initialized with the waypoint coordinates:

Matlab

```
% Set initial condition
problem.xinit = simulatedZ(I.states,k);

% Set runtime parameters (here, the next N points on the map)
nextPathPoints = resamplePathForTracker(simulatedZ(:,k), I, map, timeStep,↳
↳horizonLength);
problem.all_parameters = reshape(nextPathPoints,2*model.N,1);
```

Note: The racetrack map used for this example originates from the repository <https://github.com/alexliniger/MPCC>. See `PathTracking.m` inside the example folder/archive for more details.

The simulation itself is performed using the following loop, which makes use of several auxiliary functions:

Matlab

```
for k = 1:simLength

    % Set initial condition
```

(continues on next page)

(continued from previous page)

```

problem.xinit = simulatedZ(I.states,k);

% Set runtime parameters (here, the next N points on the map)
nextPathPoints = resamplePathForTracker(simulatedZ(:,k), I, map, timeStep,
↳horizonLength);
problem.all_parameters = reshape(nextPathPoints,2*model.N,1);

% Solve optimization problem
[output,exitflag,info] = PathTrackingSolver(problem);

% Make sure the solver has exited properly
if (exitflag == 1)
    fprintf('FORCESPRO took %d iterations and ',info.it);
    fprintf('%.3f milliseconds to solve the problem.\n\n',info.solvetime*1000);
elseif (exitflag == -8)
    warning('FORCESPRO finished with exitflag=-8. The underlying QP might be
↳infeasible.');
```

```

    fprintf('FORCESPRO took %d iterations and ',info.it);
    fprintf('%.3f milliseconds to solve the problem.\n\n',info.solvetime*1000);
else
    error('Some problem in solver!');
end

% Apply optimized input u to system and save simulation data
simulatedZ(I.inputs,k) = output.x01(I.inputs);
simulatedZ(I.states,k+1) = model.eq( simulatedZ(:,k) );

% Extract output for prediction plots
cwidth = floor(log10(model.N))+1;
for i = 1:model.N
    predictedZ(:,i) = output.(sprintf(sprintf('x%0%i',cwidth), i));
end
% Plot
handles = plotPathTrackerData(k,simulatedZ,predictedZ,model,I,simLength,map,
↳nextPathPoints,handles);

if k == 1
    % From now on, the solver should be initialized with the solution of its
↳last call
    problem.reinitialize = 0;
end

% Pause to slow down plotting
pause(0.05);

end

```

11.11.4 Results

The goal is to find a trajectory that steers the vehicle as close to the provided racetrack waypoints as possible. The trajectory should also be feasible with respect to the vehicle dynamics and its safety and physical limitations. The 2D calculated vehicle's trajectory at timestep $k = 100$ is presented in blue in [Figure 11.36](#). Here, you can see the current predictions for the trajectory marked green. The progress of the other states and inputs over time as well as their predictions is shown in [Figure 11.37](#).

The trajectory and the progress of the system variables over the entire simulation period of 360 steps are presented in [Figure 11.38](#) and [Figure 11.39](#). One can see that all constraints are respected.

To see how the predictions of the system variables develop over all timesteps you can run the example file on your own machine.

You can find the code of this example in the `examples` folder that comes with your client.

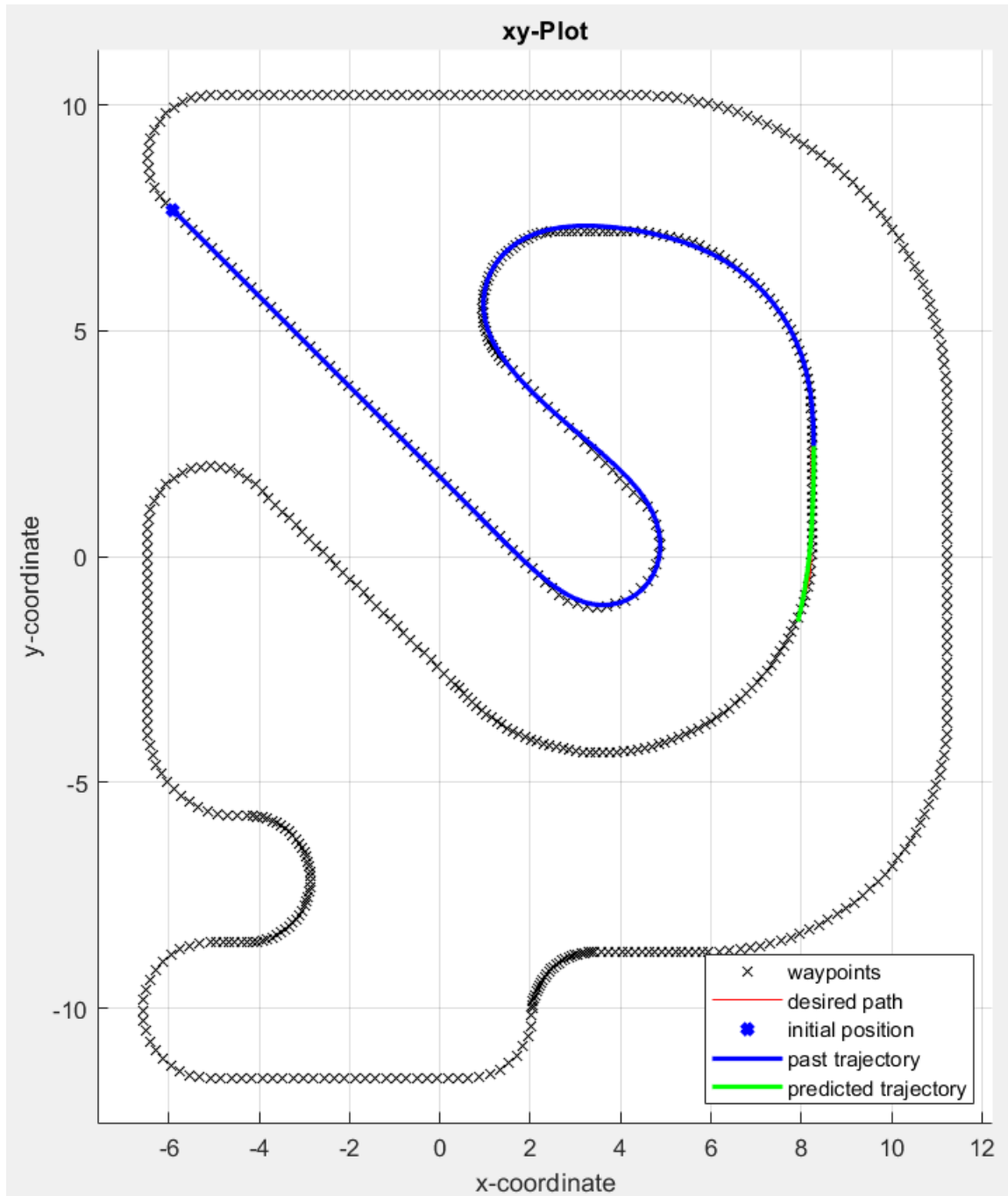


Figure 11.36: The calculated trajectory of the car (blue) and its predictions (green) at timestep $k = 100$ (racetrack map from repository <https://github.com/alexliniger/MPCC>)

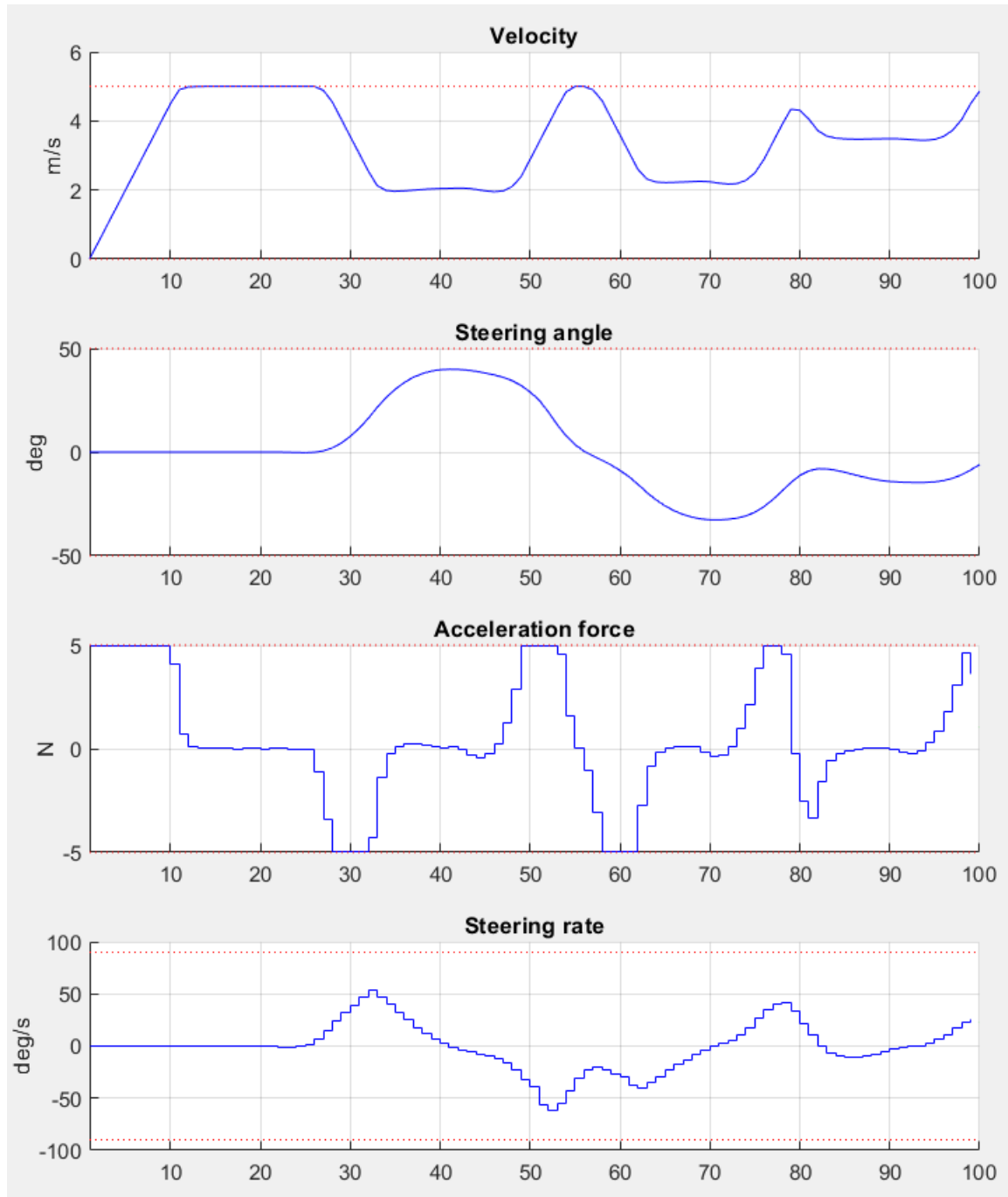


Figure 11.37: Development of the vehicle's states and the system's inputs over time at timestep $k = 100$

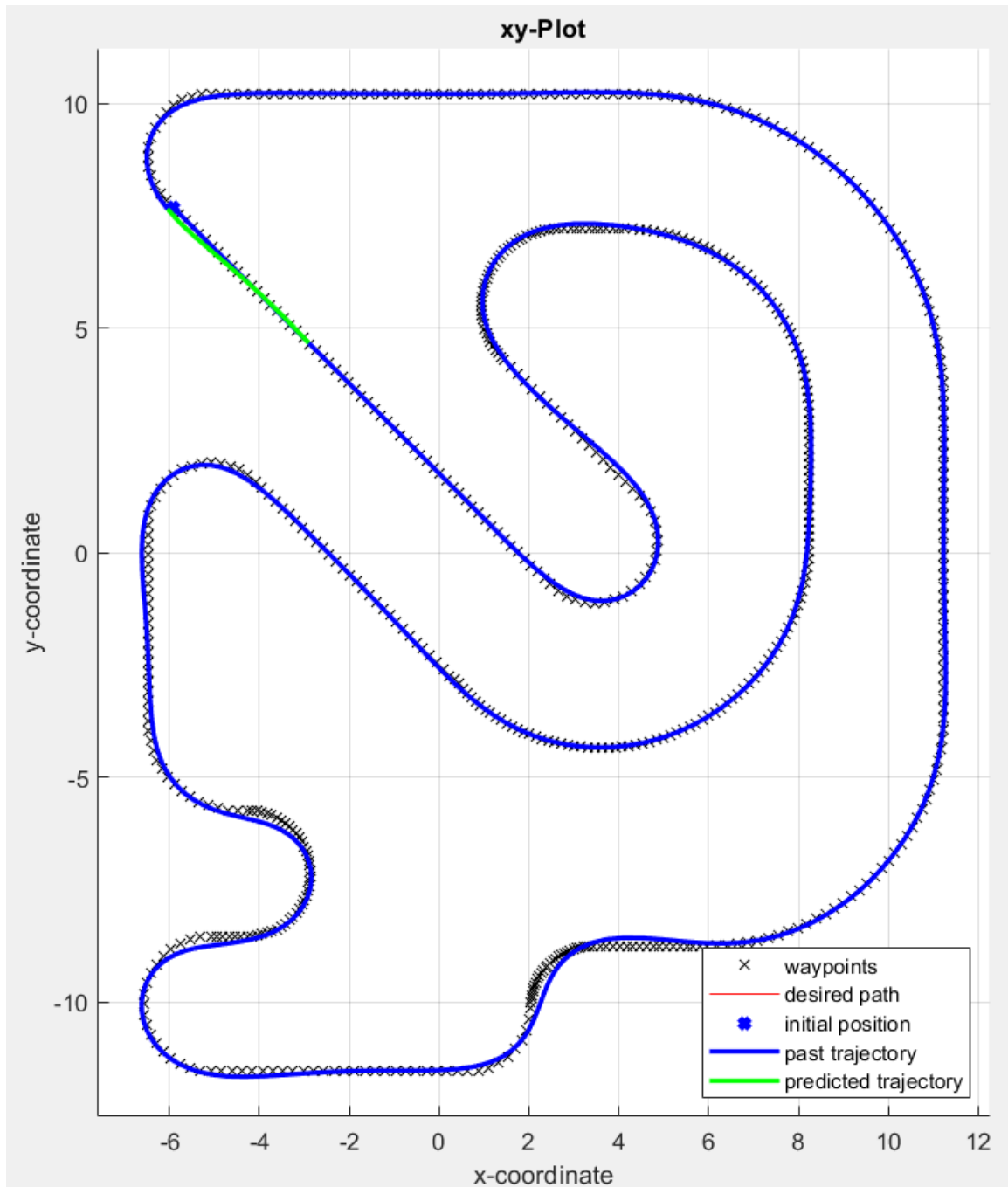


Figure 11.38: The calculated trajectory of the car (racetrack map from repository <https://github.com/alexliniger/MPCC>)

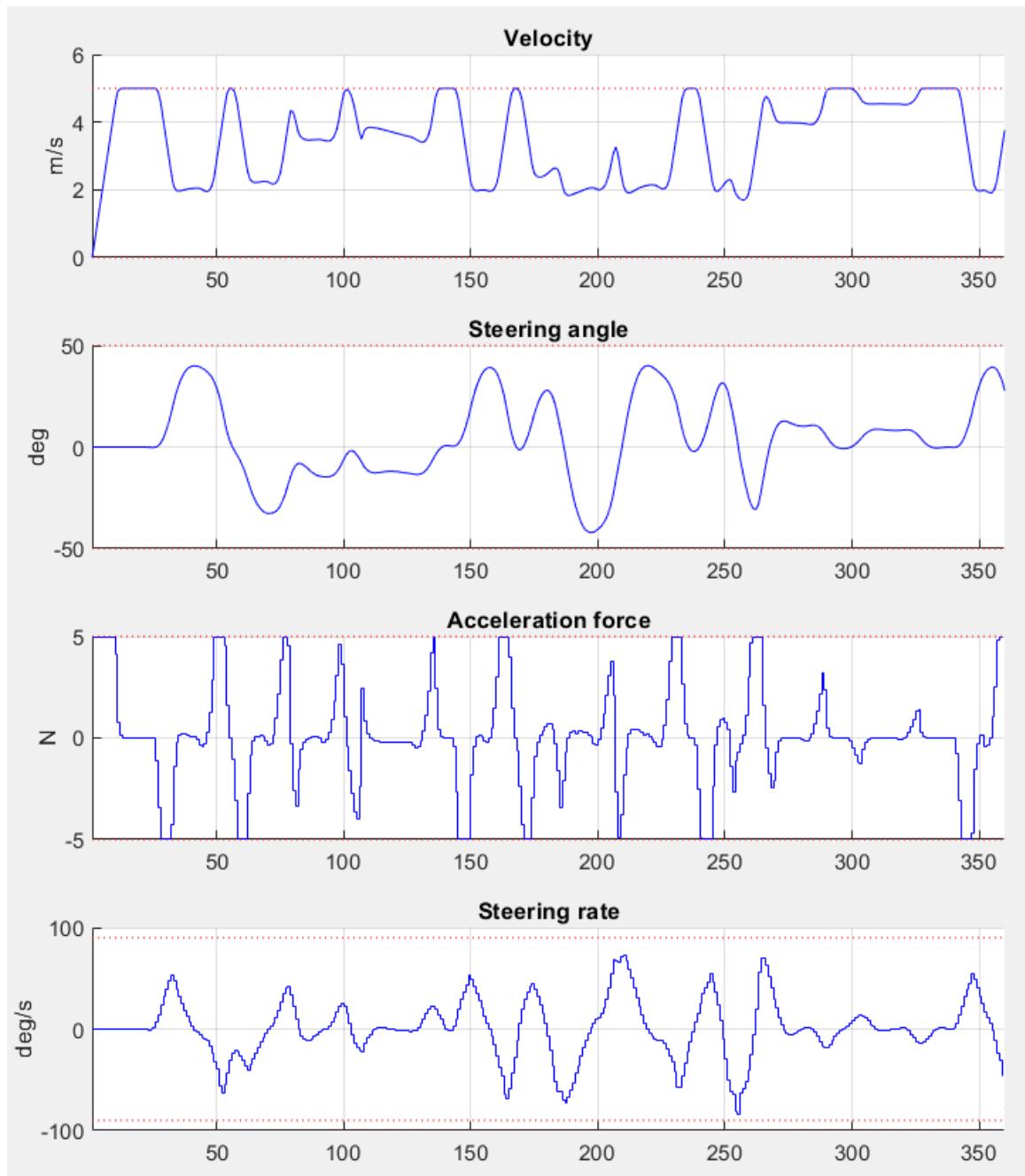


Figure 11.39: Development of the vehicle's states and the system's inputs over time

11.12 High-level interface: Legacy path tracking example (MATLAB & Python)

- *Defining the MPC Problem*
 - *Objective*
 - *Matrix equality constraints*
 - *Bounds*
 - *Dimensions*
 - *Initial conditions*
- *Generating a solver*
- *Calling the generated solver*
- *Results*

In this example we illustrate the simplicity of the SQP_NLP API on a path-tracking problem. In every simulation step, the predicted trajectory of the car is optimized to follow a set of path points. The example also visualizes how the predicted trajectory changes while the car moves forward.

Note that an improved version of this example is available for MATLAB, see [High-level interface: Path tracking example \(MATLAB\)](#).

We use a kinematic bicycle model described by a set of ordinary differential equations (ODEs):

$$\begin{aligned}\dot{x} &= v \cos(\theta + \beta) \\ \dot{y} &= v \sin(\theta + \beta) \\ \dot{v} &= \frac{F}{m} \\ \dot{\theta} &= \frac{v}{l_r} \sin(\beta) \\ \dot{\delta} &= \phi\end{aligned}$$

with:

$$\beta = \arctan\left(\frac{l_r}{l_r + l_f} \tan(\delta)\right)$$

The model consists of five differential states: x and y are the Cartesian coordinates of the car, and v is the linear velocity. The angles θ and δ denote the heading angle of the car and its steering angle. Next, there are two control inputs to the model: the acceleration force F and the steering rate ϕ . The angle β describes the direction of movement of the car's center of gravity relative to the heading angle θ . The remaining three constant parameters of the system are the car mass $m = 1\text{ kg}$, and the lengths $l_r = 0.5\text{ m}$ and $l_f = 0.5\text{ m}$ specifying the distance from the car's center of gravity to the rear wheels and the front wheels, respectively.

The trajectory of the vehicle will be defined as an NLP. First, we define stage variable z by stacking the input and differential state variables:

$$z = [F, \phi, x, y, v, \theta, \delta]^\top$$

You can find the code of this example to try it out for yourself in the `examples` folder that comes with your client.

11.12.1 Defining the MPC Problem

Objective

In this example the cost function is the same for all stages except for the last stage N . The objective of this example is to follow a set of path points. At runtime, a target position p_i for each stage i is provided. Each point consists of a x - and a y -coordinate:

$$p_i = [p_{i,x}, p_{i,y}]^T$$

The goal is to minimize the distance of the car to these target points. The distance is penalized with quadratic costs. Plus, some small quadratic costs are added to the inputs F and s , i.e.:

$$f(z, p_i) = 200(z_3 - p_{i,x})^2 + 200(z_4 - p_{i,y})^2 + 0.2z_1^2 + 0.2z_2^2$$

Since all cost terms are quadratic and summed up, we can formulate the objective as a least squares problem:

$$f(z, p_i) = \frac{1}{2} \|r(z, p_i)\|_2^2$$

$$r(z, p_i) = [\sqrt{200}(z_3 - p_{i,x}), \sqrt{200}(z_4 - p_{i,y}), \sqrt{0.2}z_1, \sqrt{0.2}z_2]^T$$

The stage cost function is coded in MATLAB and Python as the following function:

Matlab

Python

```
model.LSObjective = @LSobj;

function [r] = LSobj(z,currentTarget)
    % z = [F,phi,xPos,yPos,v,theta,delta]
    % currentTarget = point on path that is to be headed for

    r = [sqrt(200.0)*(z(3)-currentTarget(1)); % costs for deviating from the path_
    ↪in x-direction
        sqrt(200.0)*(z(4)-currentTarget(2)); % costs for deviating from the path_
    ↪in y-direction
        sqrt(0.2)*z(1); % penalty on input F
        sqrt(0.2)*z(2)]; % penalty on input phi
end
```

```
model = forcespro.nlp.SymbolicModel() # create empty model
model.objective = obj

def obj(z,current_target):
    """z = [F,phi,xPos,yPos,v,theta,delta]
    current_target = point on path that is to be headed for
    """
    return (100.0*(z[2]-current_target[0])**2 # costs on deviating on the path_
    ↪in x-direction
        + 100.0*(z[3]-current_target[1])**2 # costs on deviating on the path_
    ↪in y-direction
        + 0.1*z[0]**2 # penalty on input F
        + 0.1*z[1]**2) # penalty on input phi
```

Note that using the `model.LSObjective` option instead of `model.objective` allows you to try out the `gauss-newton` method for the hessian approximation.

For the last stage, the terminal costs are slightly increased by adapting the weighting factors:

$$f(z, p_i) = 400(z_3 - p_{i,x})^2 + 400(z_4 - p_{i,y})^2 + 0.4z_1^2 + 0.4z_2^2$$

The code looks a follows:

Matlab

Python

```
model.LSobjectiveN = @LSobjN;

function [r] = LSobjN(z,currentTarget)
    % z = [F,phi,xPos,yPos,v,theta,delta]
    % currentTarget = point on path that is to be headed for

    r = [sqrt(400.0)*(z(3)-currentTarget(1)); % costs for deviating from the path_
    ↪in x-direction
        sqrt(400.0)*(z(4)-currentTarget(2)); % costs for deviating from the path_
    ↪in y-direction
        sqrt(0.4)*z(1); % penalty on input F
        sqrt(0.4)*z(2)]; % penalty on input phi
end
```

```
model.objectiveN = objN

def objN(z,current_target):
    """z = [F,phi,xPos,yPos,v,theta,delta]
    current_target = point on path that is to be headed for
    """
    return (200.0*(z[2]-current_target[0])**2 # costs on deviating on the path_
    ↪in x-direction
        + 200.0*(z[3]-current_target[1])**2 # costs on deviating on the path_
    ↪in y-direction
        + 0.2*z[0]**2 # penalty on input F
        + 0.2*z[1]**2) # penalty on input phi
```

Matrix equality constraints

The matrix equality constraints `model.eq` in this example result from the vehicle's dynamics given above. First, the continuous dynamic equations are implemented as follows:

Matlab

Python

```
function [xDot] = continuousDynamics(x,u)
    % state x = [xPos,yPos,v,theta,delta], input u = [F, phi]

    % set physical constants
    l_r = 0.5; % distance rear wheels to center of gravity of the car
    l_f = 0.5; % distance front wheels to center of gravity of the car
    m = 1.0; % mass of the car

    % set parameters
    beta = atan(l_r/(l_f + l_r) * tan(x(5)));

    % calculate dx/dt
    xDot = [x(3) * cos(x(4) + beta); % dxPos/dt = v*cos(theta+beta)
            x(3) * sin(x(4) + beta); % dyPos/dt = v*cos(theta+beta)
            u(1)/m; % dv/dt = F/m
            x(3)/l_r * sin(beta); % dtheta/dt = v/l_r*sin(beta)
            u(2)]; % ddelta/dt = phi
end
```

```
def continuous_dynamics(x, u):
    """ state x = [xPos,yPos,v,theta,delta], input u = [F,phi]"""

    # set physical constants
    l_r = 0.5 # distance rear wheels to center of gravitiy of the car
    l_f = 0.5 # distance front wheels to center of gravitiy of the car
    m = 1.0   # mass of the car

    # set parameters
    beta = casadi.atan(l_r/(l_f + l_r) * casadi.tan(x[4]))

    # calculate dx/dt
    return np.array([x[2] * casadi.cos(x[3] + beta), # dxPos/dt = v*cos(theta+beta)
                    x[2] * casadi.sin(x[3] + beta), # dyPos/dt = v*sin(theta+beta)
                    u[0] / m,                       # dv/dt = F/m
                    x[2]/l_r * casadi.sin(beta),     # dtheta/dt = v/l_r*sin(beta)
                    u[1]])                          # ddelta/dt = phi
```

Now, these continuous dynamics are discretized using an explicit Runge-Kutta integrator of order 4 as shown below. Note that the function RK4 is included in the FORCESPRO client software.

Matlab

Python

```
integrator_stepsize = 0.1;
% z(3:7) = states x, z(1:2) = inputs u
model.eq = @(z) RK4(z(3:7), z(1:2), @continuousDynamics, integrator_stepsize);
```

```
integrator_stepsize = 0.1
# z[2:7] = states x, z[0:2] = inputs u
model.eq = lambda z: forcespro.nlp.integrate(continuous_dynamics, z[2:7], z[0:2],
                                             integrator=forcespro.nlp.integrators.
↳RK4,
                                             stepsize=integrator_stepsize)
```

As a last step, the indices of the left hand side of the dynamical constraint are defined. For efficiency reasons, make sure the matrix has structure [0 I].

Matlab

Python

```
model.E = [zeros(5,2), eye(5)];
```

```
model.E = np.concatenate([np.zeros((5,2)), np.eye(5)], axis=1)
```


Bounds

All variables except the heading angle θ are bounded:

$$\begin{aligned} -5 \text{ N} &\leq F \leq 5 \text{ N} \\ -90 \text{ deg/s} &\leq \dot{\phi} \leq 90 \text{ deg/s} \\ -2 \text{ m} &\leq x \leq 2 \text{ m} \\ -2 \text{ m} &\leq y \leq 2 \text{ m} \\ 0 \text{ m/s} &\leq v \leq 4 \text{ m/s} \\ -\infty &\leq \theta \leq \infty \\ -0.48\pi \text{ rad} &\leq \delta \leq 0.48\pi \text{ rad} \end{aligned}$$

The implementation of the simple bounds is given here:

Matlab

Python

```
% upper/lower variable bounds lb <= z <= ub
%           inputs           |           states
%           F           phi           x           y           v           theta           delta
model.lb = [ -5.,   deg2rad(-90),   -2.,   -2.,   0.,   -inf,   -0.48*pi];
model.ub = [ +5.,   deg2rad(90),    2.,    2.,   4.,   +inf,   0.48*pi];
```

```
# upper/lower variable bounds lb <= z <= ub
#           inputs           |           states
#           F           phi           x           y           v           theta           delta
model.lb = np.array([-5.,   np.deg2rad(-90.),   -2.,   -2.,   0.,   -np.inf,   -0.48*np.
    ↪pi])
model.ub = np.array([+5.,   np.deg2rad(+90.),    2.,    2.,   4.,   np.inf,   0.48*np.
    ↪pi])
```

Dimensions

Furthermore, the number of variables, constraints and real-time parameters explained above needs to be provided as well as the length of the multistage problem. For this example, we chose to use $N = 10$ stages in the NLP:

Matlab

Python

```
model.N = 10;           % horizon length
model.nvar = 7;         % number of variables
model.neq = 5;          % number of equality constraints
model.npar = 2;         % number of runtime parameters
```

```
model.N = 10           # horizon length
model.nvar = 7          # number of variables
model.neq = 5           # number of equality constraints
model.npar = 2          # number of runtime parameters
```

Initial conditions

The goal of the maneuver is to steer the vehicle from a set of initial conditions:

$$x_{\text{init}} = 0.8 \text{ m}, \quad y_{\text{init}} = 0 \text{ m}, \quad v_{\text{init}} = 0 \text{ m/s}, \quad \theta_{\text{init}} = 0.5\pi \text{ rad}, \quad \delta_{\text{init}} = 0 \text{ rad}$$

For the code generation, only the indices of the variables to which initial values will be applied are required. This is coded as follows:

Matlab

Python

```
model.xinitidx = 3:7;
```

```
model.xinitidx = range(2,7)
```

11.12.2 Generating a solver

We have now populated `model` with the necessary fields to generate a solver for our problem. We choose the SQP solve method and set some further options for our solver. Then, we use the function `FORCES_NLP` to generate a solver for the problem defined by `model`:

Matlab

Python

```
%% Set solver options
codeoptions = getOptions('FORCESNLPsolver');
codeoptions.maxit = 200; % Maximum number of iterations
codeoptions.printlevel = 2; % Use printlevel = 2 to print
↳progress (but not for timings)
codeoptions.optlevel = 0; % 0: no optimization, 1: optimize
↳for size, 2: optimize for speed, 3: optimize for size & speed
codeoptions.cleanup = false;
codeoptions.timing = 1;
codeoptions.printlevel = 0;
codeoptions.nlp.hessian_approximation = 'bfgs'; % set initialization of the
↳hessian approximation
codeoptions.solvemethod = 'SQP_NLP'; % choose the solver method
↳Sequential Quadratic Programming
codeoptions.sqp_nlp.maxqps = 5; % maximum number of quadratic
↳problems to be solved during one solver call
codeoptions.sqp_nlp.reg_hessian = 5e-9; % increase this parameter if
↳exitflag=-8
```

```
# Set solver options
codeoptions = forcespro.CodeOptions('FORCESNLPsolver')
codeoptions.maxit = 200 # Maximum number of iterations
codeoptions.printlevel = 0
codeoptions.optlevel = 0 # 0 no optimization, 1 optimize
↳for size, 2 optimize for speed, 3 optimize for size & speed
codeoptions.cleanup = False
codeoptions.timing = 1
codeoptions.nlp.hessian_approximation = 'bfgs' # when using solvemethod = 'SQP_NLP
↳' and LSObjective, try out 'gauss-newton' here
codeoptions.solvemethod = 'SQP_NLP' # choose the solver method
↳Sequential Quadratic Programming
codeoptions.nlp.bfgs_init = 2.5*np.identity(7) # set initialization of the
↳hessian approximation
codeoptions.sqp_nlp.maxqps = 1 # maximum number of quadratic
↳problems to be solved
codeoptions.sqp_nlp.reg_hessian = 5e-9 # increase this if exitflag=-8

# Creates code for symbolic model formulation given above, then contacts
# server to generate new solver
solver = model.generate_solver(options=codeoptions)
```

11.12.3 Calling the generated solver

The goal of this example is to optimize the predicted car trajectory for the next N time steps and then apply the calculated input for the current time step. The procedure is repeated for the entire simulation period.

This means, after setting up the initial problem instance, the solver is called in a loop for every simulation time step. The MEX interface of the solver is used to invoke it.

Matlab

Python

```
%% Simulation
simLength = 80; % simulate 8sec

% Variables for storing simulation data
x = zeros(5,simLength+1); % states
u = zeros(2,simLength);    % inputs

% Set initial guess to start solver from
x0i = zeros(model.nvar,1);
problem.x0 = repmat(x0i,model.N,1);

% Set initial condition
xinit = [0.8, 0., 0., deg2rad(90), 0.];
x(:,1) = xinit;

for k = 1:simLength

    % Set initial condition
    problem.xinit = x(:,k);

    % Set runtime parameters (here, the next N points on the path)
    nextPathPoints = extractNextPathPoints(pathPoints, x(1:2,k), model.N);
    problem.all_parameters = reshape(nextPathPoints,2*model.N,1);

    % Solve optimization problem
    [output,exitflag,info] = FORCESNLPsolver(problem);

    % Make sure the solver has exited properly
    if( exitflag == 1 )
        fprintf('\nFORCES took %d iterations and ',info.it);
        fprintf('%f seconds to solve the problem.\n',info.solvetime);
    else
        error('Some problem in solver');
    end

    % Apply optimized input u to system and save simulation data
    u(:,k) = output.x01(1:2);
    x(:,k+1) = model.eq( [u(:,k);x(:,k)] )';

end
```

```
# Simulation
# -----
sim_length = 80 # simulate 8sec

# Variables for storing simulation data
x = np.zeros((5,sim_length+1)) # states
u = np.zeros((2,sim_length)) # inputs

# Set initial guess to start solver from
```

(continues on next page)

(continued from previous page)

```

x0i = np.zeros((model.nvar,1))
x0 = np.transpose(np.tile(x0i, (1, model.N)))

# Set initial condition
xinit = np.transpose(np.array([0.8, 0., 0., np.deg2rad(90), 0.]))
x[:,0] = xinit

problem = {"x0": x0,
           "xinit": xinit}

for k in range(sim_length):

    # Set initial condition
    problem["xinit"] = x[:,k]

    # Set runtime parameters (here, the next N points on the path)
    next_path_points = extract_next_path_points(path_points, x[0:2,k], model.N)
    problem["all_parameters"] = np.reshape(np.transpose(next_path_points), \
        (2*model.N,1))

    # Time to solve the NLP!
    output, exitflag, info = solver.solve(problem)

    # Make sure the solver has exited properly.
    assert exitflag == 1, "bad exitflag"
    sys.stderr.write("FORCES took {} iterations and {} seconds to solve the_
↪problem.\n"
        .format(info.it, info.solvetime))

    # Extract output
    temp = np.zeros((np.max(model.nvar), model.N))
    for i in range(0, model.N):
        temp[:, i] = output['x{0:02d}'.format(i+1)]
    pred_u = temp[0:2, :] # predicted inputs
    pred_x = temp[2:7, :] # predicted states

    # Apply optimized input u of first stage to system and save simulation data
    u[:,k] = pred_u[:,0]
    x[:,k+1] = np.transpose(model.eq(np.concatenate((u[:,k], x[:,k]))))

```

11.12.4 Results

The goal is to find a trajectory that steers the vehicle as close to the provided path points as possible. The trajectory should also be feasible with respect to the vehicle dynamics and its safety and physical limitations. The 2D calculated vehicle's trajectory at timestep $k = 40$ is presented in blue in [Figure 11.40](#). Here, you can see the current predictions for the trajectory marked green. The progress of the other states and inputs over time as well as their predictions is shown in [Figure 11.41](#).

The trajectory and the progress of the system variables over the entire simulation period are presented in [Figure 11.42](#) and [Figure 11.43](#). One can see that all constraints are respected.

To see how the predictions of the system variables develop over all timesteps you can run the example file on your own machine.

You can find the code of this example in the `examples` folder that comes with your client.

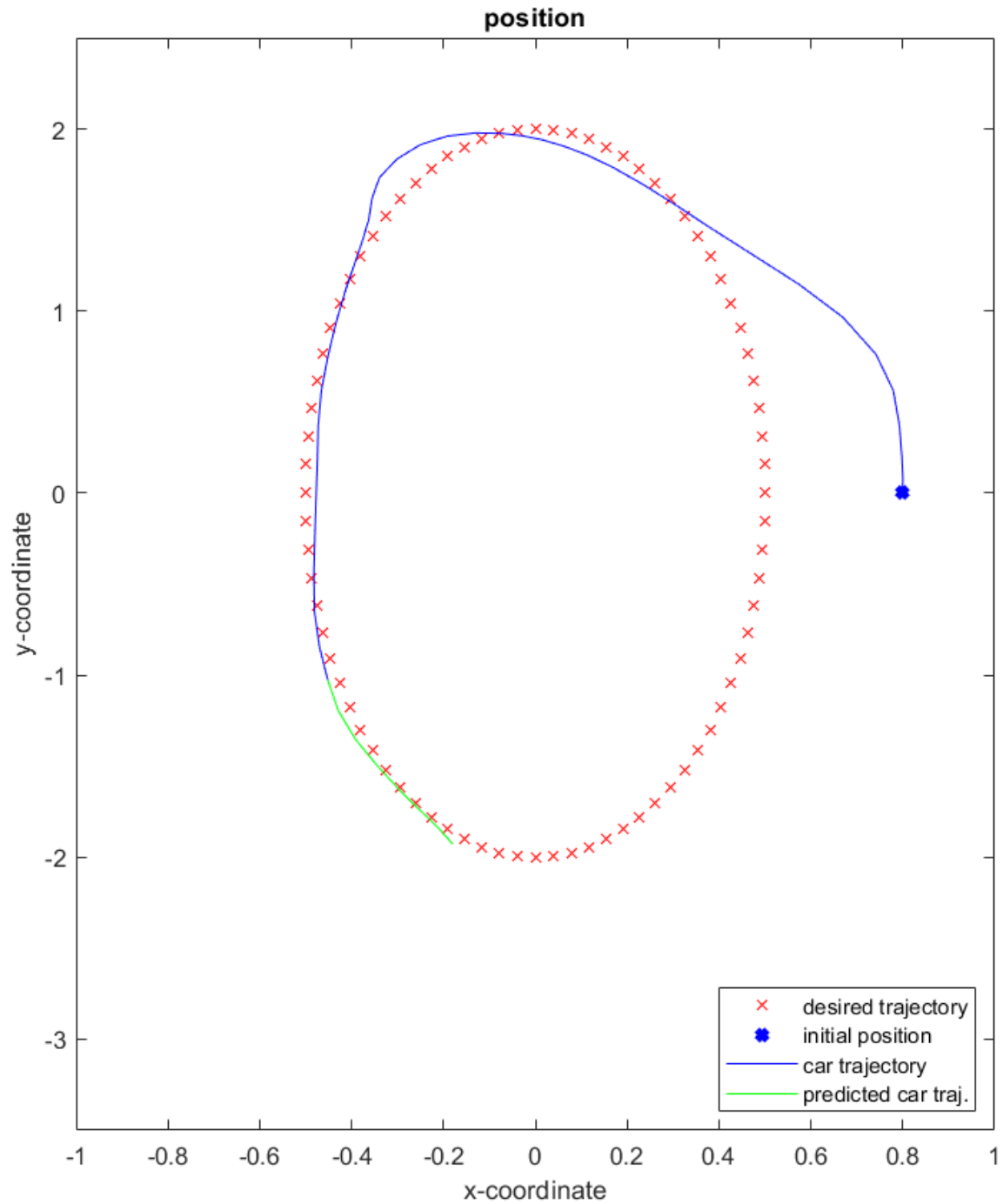


Figure 11.40: The calculated trajectory of the car (blue) and its predictions (green) at timestep $k = 40$

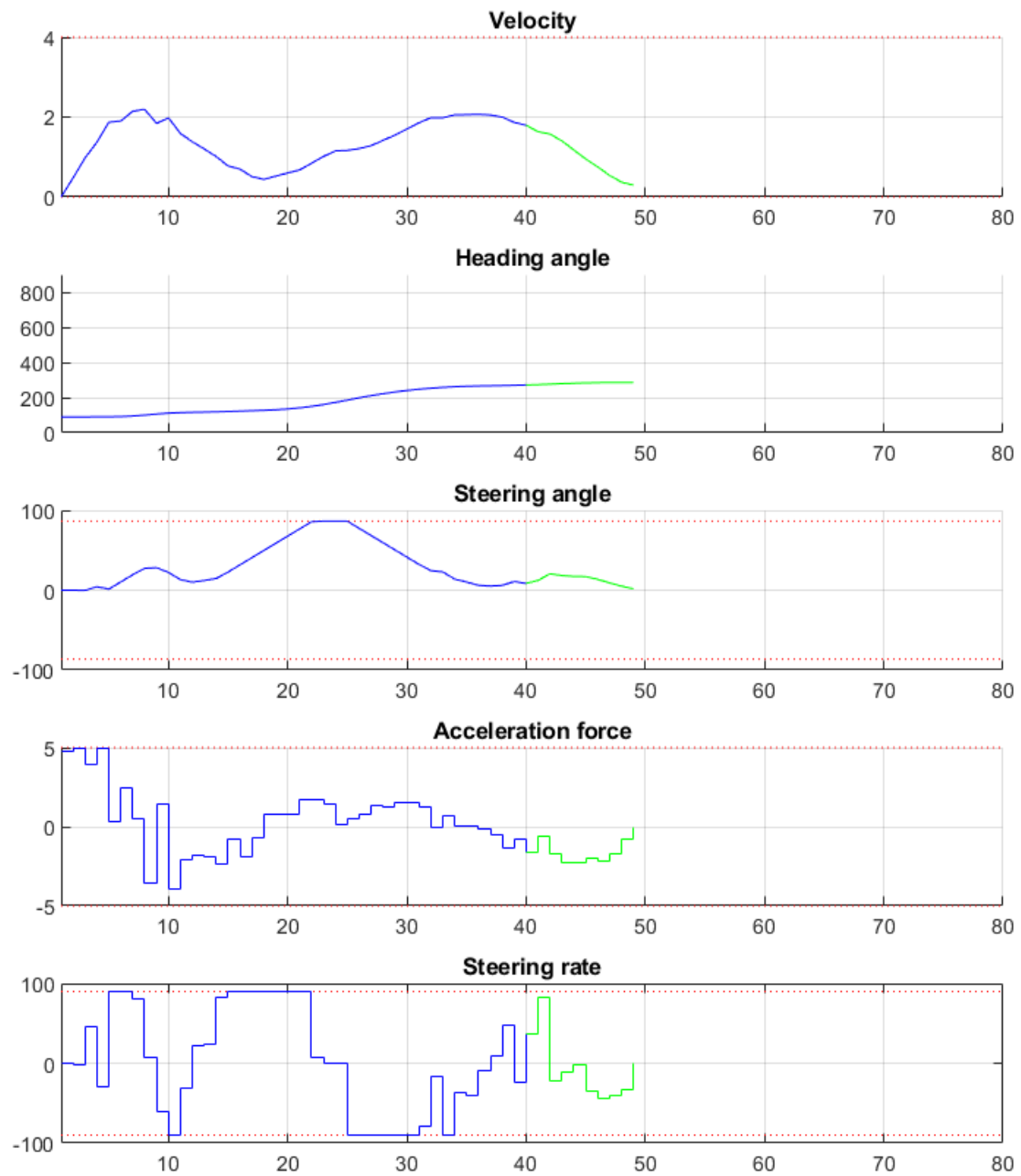


Figure 11.41: Development of the vehicle's states and the system's inputs over time (timestep $k = 40$)

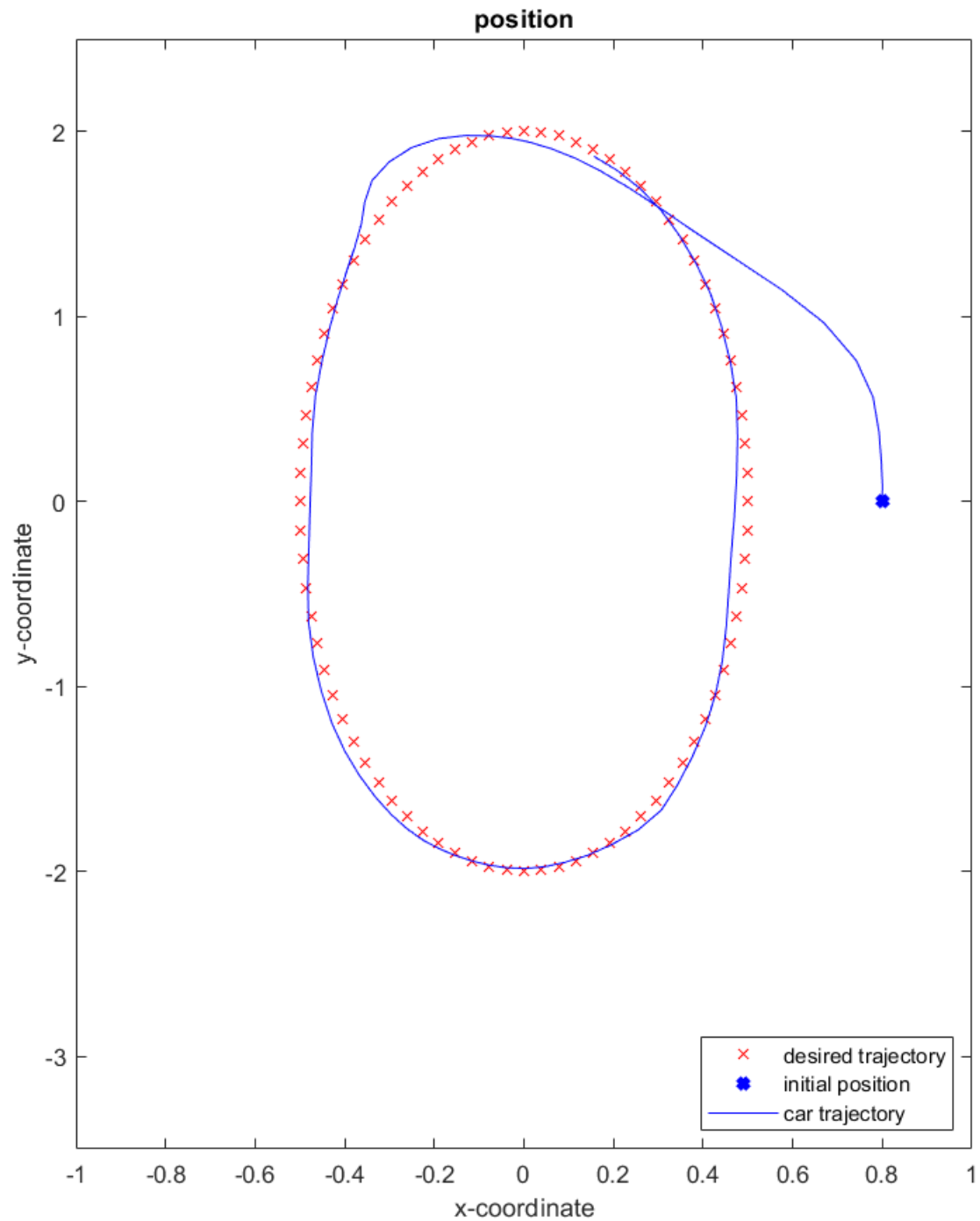


Figure 11.42: The calculated trajectory of the car

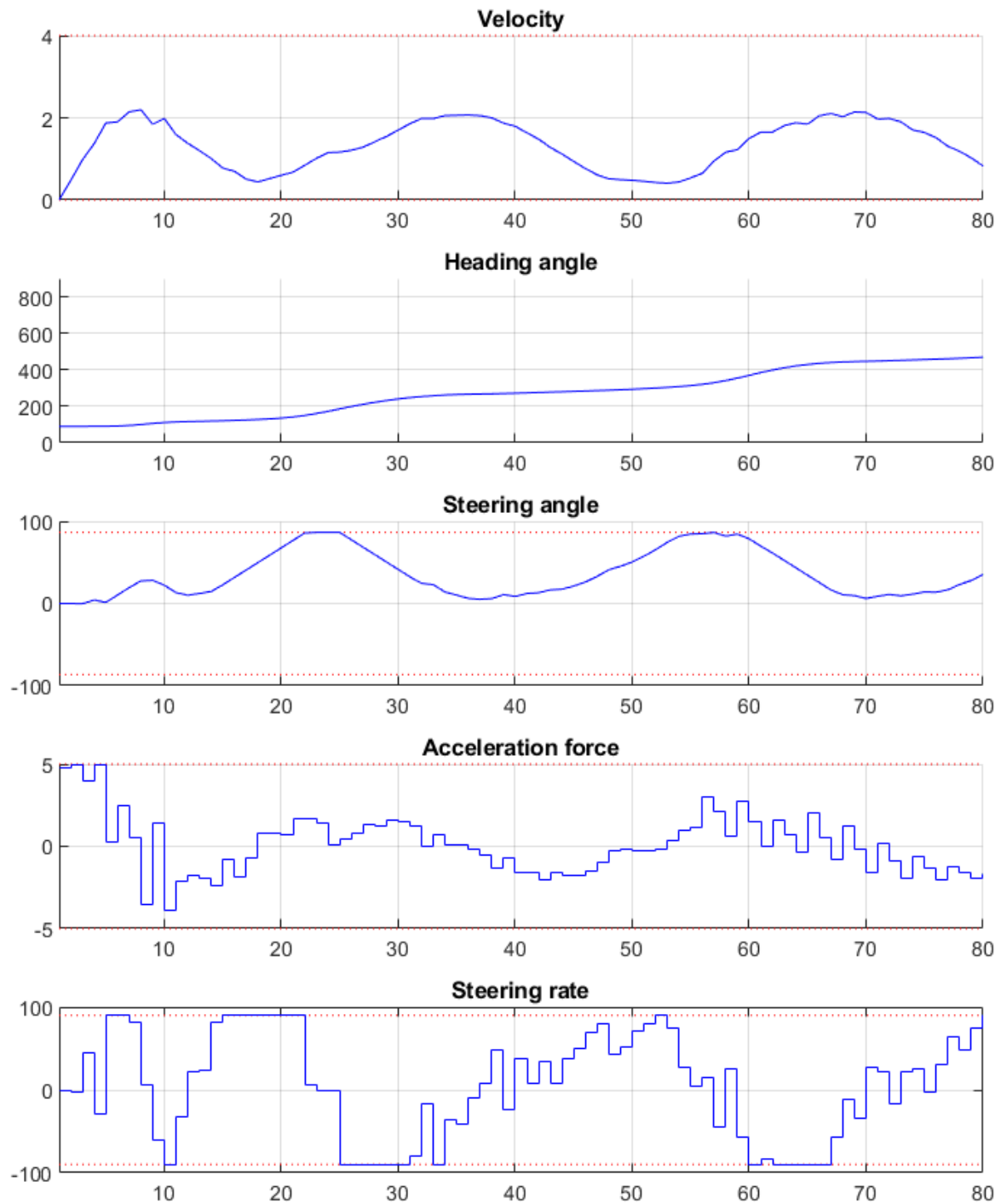


Figure 11.43: Development of the vehicle's states and the system's inputs over time

11.13 High-level interface: Rate Constraints

- *Implementation in MATLAB*
- *Results*

As in Section *High-level interface: Basic example* we consider the following linear MPC problem with lower and upper bounds on state and inputs, and a terminal cost term:

$$\begin{aligned} & \text{minimize} && x_N^\top P x_N + \sum_{i=0}^{N-1} (x_i^\top Q x_i + u_i^\top R u_i) \\ & \text{subject to} && x_0 = \mathbf{x} \\ & && x_{i+1} = A x_i + B u_i \\ & && \underline{x} \leq x_i \leq \bar{x} \\ & && \underline{u} \leq u_i \leq \bar{u} \end{aligned}$$

This problem is parametric in the initial state \mathbf{x} and the first input u_0 is typically applied to the system after a solution has been obtained. For the sake of this example, we assume $u_i \in \mathbb{R}$ and $x_i \in \mathbb{R}^2$ and write

$$A = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix}, \quad B = \begin{pmatrix} B_1 \\ B_2 \end{pmatrix}.$$

In addition, we impose constraints on the input rate change $\Delta u_i = u_{i+1} - u_i$:

$$\underline{\Delta u} \leq \Delta u_i \leq \overline{\Delta u}.$$

The constraints can be included by defining states

$$z_i = \begin{pmatrix} \Delta u_i \\ u_i \\ x_i \end{pmatrix} \in \mathbb{R}^4.$$

The MPC problem now reads

$$\begin{aligned} & \text{minimize} && x_N^\top P x_N + \sum_{i=0}^{N-1} (x_i^\top Q x_i + u_i^\top R u_i), \\ & \text{subject to} && x_0 = \mathbf{x}, \\ & && E z_{i+1} = \hat{A} z_i, \\ & && \underline{z} \leq z_i \leq \bar{z}. \end{aligned}$$

with

$$\begin{aligned} E &= \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}, \quad \hat{A} = \begin{pmatrix} 1 & 1 & 0 & 0 \\ 0 & B_1 & A_{11} & A_{12} \\ 0 & B_2 & A_{21} & A_{22} \end{pmatrix}, \\ \underline{z} &= (\underline{\Delta u}, \underline{u}, \underline{x})^\top, \quad \bar{z} = (\overline{\Delta u}, \bar{u}, \bar{x})^\top. \end{aligned}$$

11.13.1 Implementation in MATLAB

The Matlab code is based on the Matlab code in *High-level interface: Basic example*. We define a variable `absrate` which limits the absolute value of Δu .

Matlab

Python

```

%% system
A = [1.1 1; 0 1];
B = [1; 0.5];
[nx,nu] = size(B);

%% MPC setup
N = 10;
Q = eye(nx);
R = eye(nu);
if( exist('dlqr','file') )
[~,P] = dlqr(A,B,Q,R);
else
P = 10*Q;
end

absrate = 0.5;
umin = -0.5;      umax = 0.5;
dumin = -absrate; dumax = absrate;
xmin = [-5, -5]; xmax = [5, 5];

%% FORCESPRO multistage form
% assume variable ordering zi = [u{i+1}-u{i}; u{i}; x{i}] for i=1...N

% dimensions
model.N      = 11;    % horizon length
model.nvar   = nu+nu+nx; % number of variables
model.neq    = nu+nx; % number of equality constraints

% objective
model.objective = @(z) z(2)*R*z(2) + [z(3);z(4)]'*Q*[z(3);z(4)];
model.objectiveN = @(z) z(2)*R*z(2) + [z(3);z(4)]'*P*[z(3);z(4)];

% equalities
model.eq = @(z) [ z(1) + z(2);
                  A(1,:)*[z(3);z(4)] + B(1)*z(2);
                  A(2,:)*[z(3);z(4)] + B(2)*z(2)];

model.E = [zeros(3,1), eye(3)];

% initial state
model.xinitidx = 3:4;

% inequalities
model.lb = [ dumin, umin,      xmin ];
model.ub = [ dumax, umax,      xmax ];

```

```

# system
A = np.array([[1.1, 1], [0, 1]])
B = np.array([[1], [0.5]])
nx, nu = np.shape(B)

# MPC setup
N = 10
Q = np.eye(nx)
R = np.eye(nu)
P = 10*Q
umin = -0.5
umax = 0.5
absrate = 0.05
dumin = -absrate
dumax = absrate

```

(continues on next page)

(continued from previous page)

```

xmin = np.array([-5, -5])
xmax = np.array([5, 5])

# FORCESPRO multistage form
# assume variable ordering zi = [u{i+1}-ui; ui; xi] for i=1...N

# dimensions
model = forcespro.nlp.ConvexSymbolicModel(11)    # horizon length
model.nvar = 4    # number of variables
model.neq = 3    # number of equality constraints

# objective
model.objective = (lambda z: z[1]*R*z[1] +
                   casadi.horzcat(z[2], z[3]) @ Q @ casadi.vertcat(z[2], z[3]))
model.objectiveN = (lambda z: z[0]*R*z[0] +
                   casadi.horzcat(z[2], z[3]) @ P @ casadi.vertcat(z[2], z[3]))

# equalities
model.eq = lambda z: casadi.vertcat( z[0] + z[1],
                                     casadi.dot(A[0, :], casadi.vertcat(z[2], z[3])) +
                                     ↪B[0, :]*z[1],
                                     casadi.dot(A[1, :], casadi.vertcat(z[2], z[3])) +
                                     ↪B[1, :]*z[1])

model.E = np.concatenate([np.zeros((3, 1)), np.eye(3)], axis=1)

# initial state
model.xinitidx = [2, 3]

# inequalities
model.lb = np.concatenate([[dumin, umin], xmin])
model.ub = np.concatenate([[dumax, umax], xmax])

```

You can find the Matlab code of this example to try it out for yourself in the `examples` folder that comes with your client.

11.13.2 Results

We run the simulation for different values of `absrate`. The results of the simulation are presented below. The plot on the top shows the system's states over time, the plot in the middle shows the input commands, the plot on the bottom shows the input rate change. We can see that all constraints are respected. We observe that compared to *High-level interface: Basic example* the behaviour does not change for `absrate` ≥ 0.1 (see [Figure 11.44](#)). If `absrate` = 0.05, it takes more time to steer the state to its setpoint (see [Figure 11.45](#)).

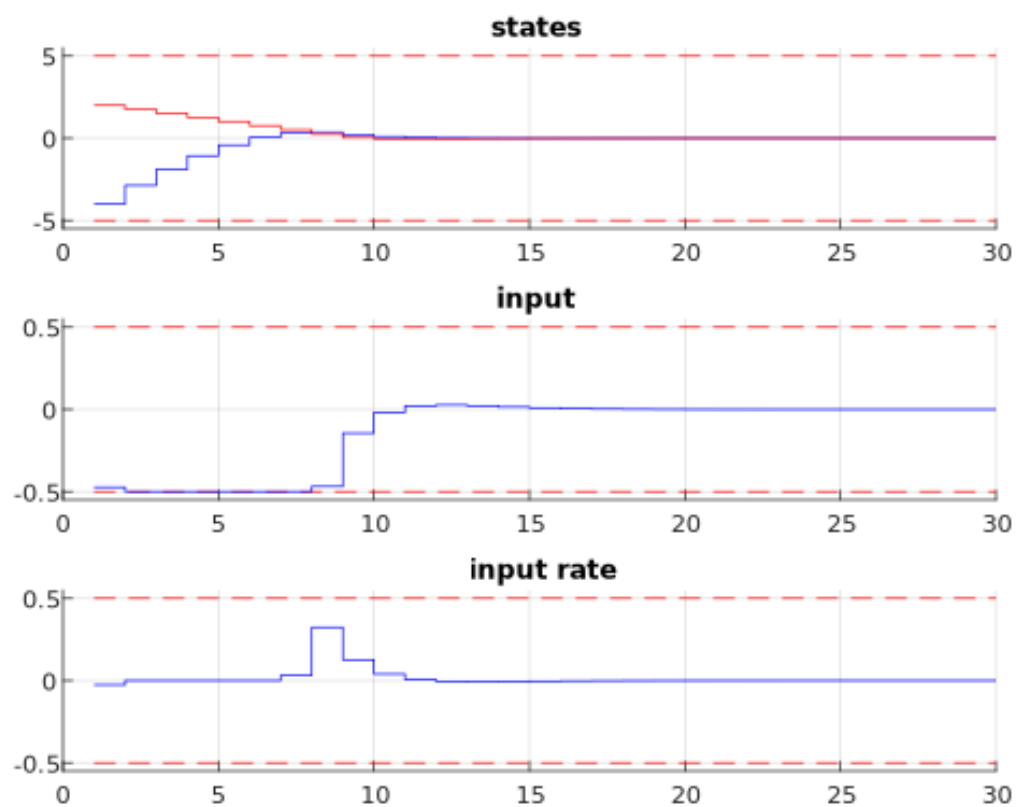


Figure 11.44: Simulation results of the states (top, in blue and red), input (middle, in blue), and input rate change (bottom, in blue) over time. The constraints are plotted in red dashed lines. The rate constraint is set to 0.5 and is not active at any moment.

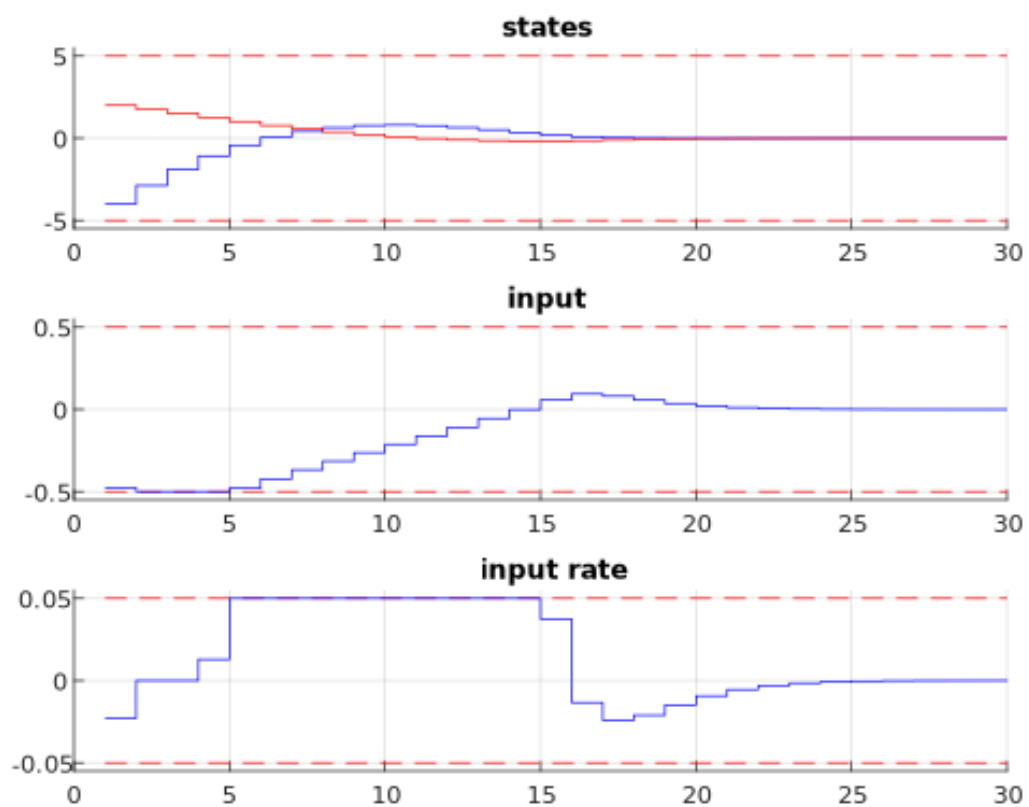


Figure 11.45: Simulation results of the states (top, in blue and red), input (middle, in blue), and input rate change (bottom, in blue) over time. The constraints are plotted in red dashed lines. The rate constraint is set to 0.05 and is active at some points.

11.14 High-level interface: Soft Constraints

- *Implementation in MATLAB*
- *Results*

As in Section *High-level interface: Basic example* we consider the following linear MPC problem with lower and upper bounds on state and inputs, and a terminal cost term:

$$\begin{aligned} & \text{minimize} && x_N^\top P x_N + \sum_{i=0}^{N-1} (x_i^\top Q x_i + u_i^\top R u_i) \\ & \text{subject to} && x_0 = \mathbf{x} \\ & && x_{i+1} = A x_i + B u_i \\ & && \underline{x} \leq x_i \leq \bar{x} \\ & && \underline{u} \leq u_i \leq \bar{u} \end{aligned}$$

This problem is parametric in the initial state \mathbf{x} and the first input u_0 is typically applied to the system after a solution has been obtained. For the sake of this example, we assume $u_i \in \mathbb{R}$ and $x_i \in \mathbb{R}^2$ and write

$$A = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix}, \quad B = \begin{pmatrix} B_1 \\ B_2 \end{pmatrix}.$$

Suppose we want to allow the inequality constraints for u_i to be slightly violated. In this case, we introduce a slack variable $s_i \geq 0$ and write

$$\underline{u} - s_i \leq u_i \leq \bar{u} + s_i.$$

We want to punish positive values of s_i by adding a penalty term to the objective function. We use a hyperparameter $\lambda \geq 0$ and write

$$x_N^\top P x_N + \sum_{i=0}^{N-1} (x_i^\top Q x_i + u_i^\top R u_i + \lambda s_i).$$

Here, we use a penalty term linear in s_i . For λ large enough, the slack variables s_i are only chosen positive if the problem is infeasible with a hard constraint. For small λ , it may be optimal to slightly violate the constraints even though the original problem is feasible. It is also common to choose a penalty term quadratic in s_i . In order to use the FORCESPRO framework, we need to recast the new inequality constraints:

$$\begin{aligned} & \text{minimize} && x_N^\top P x_N + \sum_{i=0}^{N-1} (x_i^\top Q x_i + u_i^\top R u_i + \lambda s_i), \\ & \text{subject to} && x_0 = \mathbf{x}, \\ & && x_{i+1} = A x_i + B u_i, \\ & && \underline{x} \leq x_i \leq \bar{x}, \\ & && h_1(u_i, s_i) \leq \bar{u}, \\ & && \underline{u} \leq h_2(u_i, s_i), \end{aligned}$$

with $h_1(u_i, s_i) = u_i - s_i$ and $h_2(u_i, s_i) = u_i + s_i$.

11.14.1 Implementation in MATLAB

The Matlab code is based on the Matlab code in *High-level interface: Basic example*. The modified inequality constraints can be implemented as follows:

Matlab

Python

```
%% relaxed inequality constraints
% assume variable ordering zi = [si, ui, xi]

model.nh      = 2;                % number of inequality constraints
model.ineq     = @(z) [ z(2) - z(1);    % h_1
                       z(2) + z(1)];    % h_2
model.hu       = [umax, +inf];      % upper bound on inequality constraints
model.hl       = [-inf, umin];      % lower bound on inequality constraints
```

```
# relaxed inequalities constraints
# assume variable ordering zi = [si, ui, xi]

model.ineq = lambda z: casadi.vertcat( z[1] - z[0],
                                       z[1] + z[0])
model.hu = np.array([umax, +float('inf')])
model.hl = np.array([-float('inf'), umin])
```

The resulting code is depicted below.

Matlab

Python

```
%% system
A = [1.1 1; 0 1];
B = [1; 0.5];
[nx,nu] = size(B);
lambda = 8; % measure for penalty term

%% MPC setup
N = 10;
Q = eye(nx);
R = eye(nu);
if( exist('dlqr','file') )
    [~,P] = dlqr(A,B,Q,R);
else
    P = 10*Q;
end
umin = -0.5;      umax = 0.5;
xmin = [-5, -5]; xmax = [5, 5];

%% FORCESPRO multistage form
% assume variable ordering zi = [si; ui; xi] for i=1...N

% dimensions
model.N      = 11;    % horizon length
model.nvar   = 4;     % number of variables
model.neq    = 2;     % number of equality constraints
model.nh     = 2;     % number of inequality constraints

% objective with penalty term
model.objective = @(z) z(2)*R*z(2) + [z(3);z(4)]'*Q*[z(3);z(4)] + lambda*z(1);
model.objectiveN = @(z) z(2)*R*z(2) + [z(3);z(4)]'*P*[z(3);z(4)] + lambda*z(1);

% equalities
model.eq = @(z) [ A(1,:)*[z(3);z(4)] + B(1)*z(2);
                  A(2,:)*[z(3);z(4)] + B(2)*z(2)];

model.E = [zeros(2,2), eye(2)];
```

(continues on next page)

(continued from previous page)

```
% initial state
model.xinitidx = 3:4;

% relaxed inequalities
model.ineq = @(z) [ z(2) - z(1);
                  z(2) + z(1)];
model.hu    = [umax, +inf];
model.hl    = [-inf, umin];

model.lb = [0,      -inf, xmin ];
model.ub = [+inf,   +inf, xmax  ];
```

```
# system
A = np.array([[1.1, 1], [0, 1]])
B = np.array([[1], [0.5]])
nx, nu = np.shape(B)
lam = 8 # measure for penalty term

# MPC setup
N = 10
Q = np.eye(nx)
R = np.eye(nu)
P = 10*Q
umin = -0.5
umax = 0.5
xmin = np.array([-5, -5])
xmax = np.array([5, 5])

# FORCESPRO multistage form
# assume variable ordering zi = [si; ui; xi] for i=1...N

# dimensions
model = forcespro.nlp.SymbolicModel(11) # horizon length
model.nvar = 4 # number of variables
model.neq = 2 # number of equality constraints
model.nh = 2

# objective with penalty term
model.objective = (lambda z: z[1]*R*z[1] + lam*z[0] +
                  casadi.horzcat(z[2], z[3]) @ Q @ casadi.vertcat(z[2], z[3]))
model.objectiveN = (lambda z: z[1]*R*z[1] + lam*z[0] *
                  casadi.horzcat(z[2], z[3]) @ P @ casadi.vertcat(z[2], z[3]))

# equalities
model.eq = lambda z: casadi.vertcat(casadi.dot(A[0, :], casadi.vertcat(z[2],
↪ z[3])) + B[0, :]*z[1],
                                   casadi.dot(A[1, :], casadi.vertcat(z[2], z[3])) +
↪ B[1, :]*z[1])

model.E = np.concatenate([np.zeros((2, 2)), np.eye(2)], axis=1)

# initial state
model.xinitidx = [2, 3]

# relaxed inequalities
model.ineq = lambda z: casadi.vertcat( z[1] - z[0],
                                       z[1] + z[0])
model.hu = np.array([umax, +float('inf')])
model.hl = np.array([-float('inf'), umin])
```

(continues on next page)

(continued from previous page)

```
# inequalities
model.lb = np.concatenate([[0, -float('inf')], xmin])
model.ub = np.concatenate([[float('inf'), float('inf')], xmax])
```

You can find the Matlab code of this example to try it out for yourself in the `examples` folder that comes with your client.

11.14.2 Results

We run the simulation for $\lambda = 2, 8$. The results of the simulation are presented in Figure 11.46 below. The plot on the top shows the system's states over time, the plot on the bottom shows the input commands. For $\lambda = 2$, the constraints on u are clearly violated, for $\lambda = 8$, these constraints are only slightly violated.

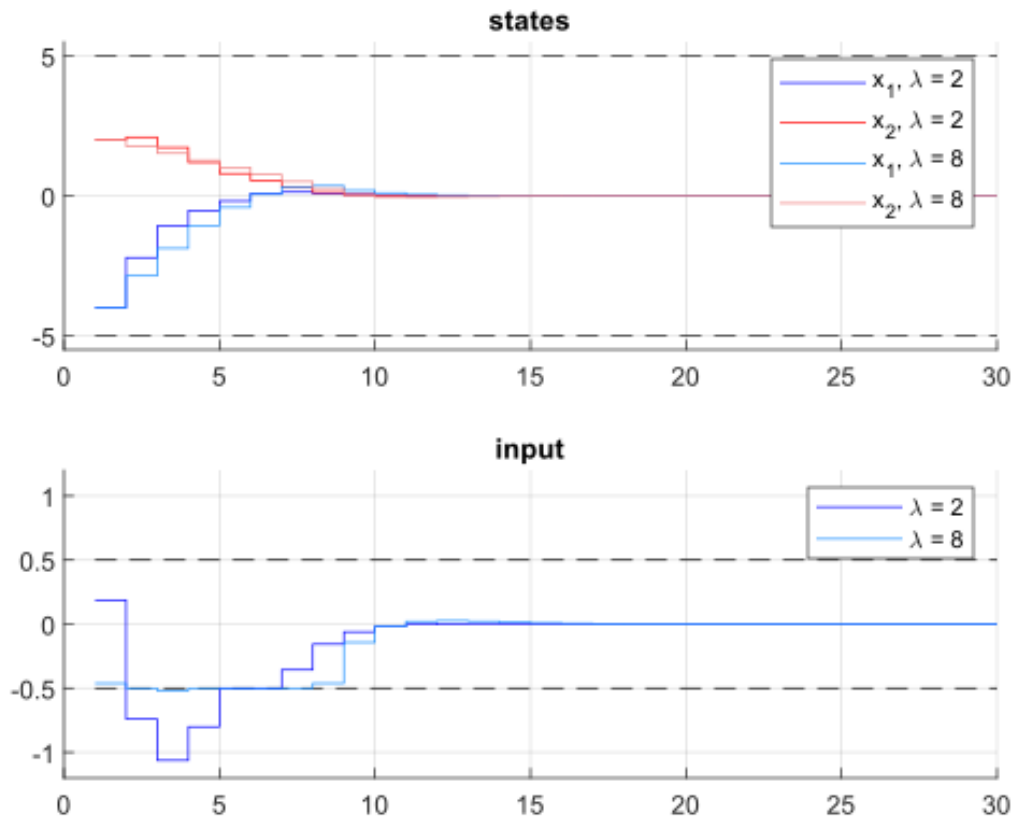


Figure 11.46: Simulation results of the states (top), input (middle) over time. The constraints are plotted in black dashed lines.

11.15 Controlling a crane using a FORCESPRO NLP solver

- *Defining the MPC problem*
 - *Model dimensions and dynamics*
 - *System constraints*
 - *Objective function*
- *Generating a FORCESPRO interior point NLP solver*
- *Calling the crane solver*
- *Results*

In this example we will see how to control a crane using the FORCESPRO interior point NLP solver. One interesting feature of this system is that it has a rather large linear subsystem which FORCESPRO can exploit for performance (see *Linear subsystem exploitation*). The crane is described by the following states:

x_C : cart position
 v_C : cart velocity
 x_L : cable length
 v_L : rate of change of cable length
 θ : angle of pendulum
 ω : rate of change of angle
 u_C : voltage for horizontal actuator
 u_L : voltage for rotating actuator

and the control inputs are given by the voltage rate for the horizontal actuator u_{CR} and the voltage rate of the rotating actuator u_{LR} . The system dynamics are described by the following ODE:

$$\begin{aligned}
 \dot{x}_C &= v_C \\
 \dot{v}_C &= a_C \\
 \dot{x}_L &= v_L \\
 \dot{v}_L &= a_L \\
 \dot{\theta} &= \omega \\
 \dot{\omega} &= -\frac{a_C \cos(\theta) + g \sin(\theta) + 2v_L \omega}{x_L} \\
 \dot{u}_C &= u_{CR} \\
 \dot{u}_L &= u_{LR}
 \end{aligned}$$

where $a_C = \frac{-v_C}{\tau} + \frac{A_C u_C}{\tau}$ and $a_L = \frac{-v_L}{\tau} + \frac{A_L u_L}{\tau}$ and the constants are given by

$g = 9.81$ (gravitational constant)
 $A_C = 0.0474$ (gain of GC(s) in m/s/V)
 $A_L = 0.0341$ (gain of GL(s) m/s/V)
 $\tau = 0.0247$ (time constant of winch dynamics in seconds)

For further details on these models we refer to [VukLook] and [QuirDiehl].

You can find the Matlab code below for this example to try it out for yourself in the `examples` folder that comes with your client.

11.15.1 Defining the MPC problem

Model dimensions and dynamics

The following code-snippet shows how to define the MPC problem associated with controlling the crane in FORCESPRO. The primal variable of our optimization problem is

$$z = \begin{pmatrix} u \\ x \end{pmatrix}$$

```
%% Define crane model
% Dimensions
model.N      = 20;          % horizon length
model.nvar   = 10;          % number of variables
model.neq    = 8;           % number of equality constraints
model.nh     = 0;           % number of inequality constraint functions
model.npar   = 2;           % number of parameters (these will be the reference values,
    ↳to track)
nx = 8;
nu = 2;

% Dynamics
model.E = [zeros(nx,nu), eye(nx)];
model.continuous_dynamics = @(x,u,p) ode(x,u,p);
```

Here the right-hand-side of the differential equation ode is defined by the following Matlab function

```
function dx = ode(x,u,p)

g = 9.81; % gravitational constant
AC = 0.0474; % gain of GC(s) in m/s/V
AL = 0.0341; % gain of GL(s) m/s/V
tau = 0.0247; % time constant of winch dynamics in seconds

uCR = u(1); % voltage rate for horizontal actuator
uLR = u(2); % voltage rate for rotating actuator

xC = x(1); % cart position
vC = x(2); % cart velocity
xL = x(3); % cable length
vL = x(4); % rate of change of cable length
theta = x(5); % angle of pendulum
omega = x(6); % rate of change of angle
uC = x(7); % voltage for horizontal actuator
uL = x(8); % voltage for rotating actuator

aT = -(1/tau)*vC + (AC/tau)*uC;
aL = -(1/tau)*vL + (AL/tau)*uL;

dx = [ vC; ...
       aT; ...
       vL; ...
       aL; ...
       omega; ...
       -(1/xL)*(aT*cos(theta) + g*sin(theta) + 2*vL*omega); ...
       uCR; ...
       uLR ];

end
```

System constraints

We put simple constraints on both of the control inputs as well as the voltage for horizontal actuator and the voltage for rotating actuator. We also specify that we have an initial condition for all the states.

```
% Bounds
model.lb = [ -100, -100, -inf, -inf, -inf, -inf, -inf, -inf, -10, -10 ];
model.ub = [ +100, +100, +inf, +inf, +inf, +inf, +inf, +inf, +10, +10 ];

% Initial state
xinitidx = 3:10;
model.xinitidx = xinitidx;
```

Objective function

The goal of the control will be to track reference values for the cart position and cable length of the crane. Hence, it makes sense to use a Gauss-Newton hessian approximation in our optimization problem. Hence, in FORCESPRO we specify a least squares objective function

```
% Least squares objective function
model.LSobjective = @(z, p) LScost(z, p);
```

where the LScost function is defined as follows

```
function [ r ] = LScost(z,p)
ep = 1e-5;
cst = 50;
sep = sqrt(ep);
scst = sqrt(cst);
r = [ sep*z(1); sep*z(2); scst*(z(3)-p(1)); sep*z(4); scst*(z(5)-p(2)); sep*z(6);
    ↪sep*z(7); sep*z(8); sep*z(9); sep*z(10)];
end
```

11.15.2 Generating a FORCESPRO interior point NLP solver

In order to generate a solver we first need to choose options to specify the algorithmic specifications (see *Solver Options*) we want implemented in our solver. The two most important options to mention here is that we specify to use a Gauss-Newton hessian approximation and we want to allow FORCESPRO to exploit linear subsystems of our dynamics.

```
%% Set codeoptions to specify solver settings
codeoptions = getOptions('CraneSolver');
Ts = 1/100; % sampling time
codeoptions.nlp.integrator.Ts = Ts;
nodes = 4;
codeoptions.nlp.integrator.nodes = nodes;
codeoptions.nlp.integrator.type = 'ERK4';
codeoptions.nlp.integrator.attempt_subsystem_exploitation = 1; % Enable subsystem_
    ↪exploitation for performance
codeoptions.printlevel = 0;
codeoptions.nlp.hessian_approximation = 'gauss-newton';
codeoptions.server = 'https://forces.embotech.com/';

% Generate solver
FORCES_NLP(model, codeoptions);
```

The last command will generate a FORCESPRO solver which can now be called from Matlab via the name `CraneSolver`.

11.15.3 Calling the crane solver

With our FORCESPRO controller at hand we can easily simulate our system in Matlab as the following code-snippet shows.

```
%% Simulation
totalTime = 100; % number of seconds
nSamples = totalTime / Ts;

x = [ 0.15; 0; 0.7; 0; 0; 0; 0; 0];
for ii = 1:nSamples

    % get current reference
    ref = getRef(t, totalTime);

    % set up problem data
    problem.xinit = x;
    problem.x0 = repmat([0;0;x],model.N,1);
    problem.all_parameters = repmat(ref,model.N,1);

    % call FORCESPRO solver and check exit status
    [solution, exitflag, info] = CraneSolver(problem);
    if exitflag ~= 1
        error('Encountered solver failure.');
```

11.15.4 Results

As can be seen from figures [Figure 11.47](#) and [Figure 11.48](#) below the FORCESPRO controller achieves tracking the reference values almost perfectly. A benchmark running the `CraneSolver` with and without linear subsystem exploitation on a Raspberry Pi 3 showed an overall reduction of computation time by 22% when exploiting linear subsystems.

11.16 Real-time SQP Solver: Robotic Arm Manipulator (MATLAB & Python)

- *Defining the MPC problem*
 - *Tracking objective*
 - *State and input constraints*
 - *Initial condition and horizon length*
- *Generating a real-time SQP solver*
- *Calling the generated SQP solver*

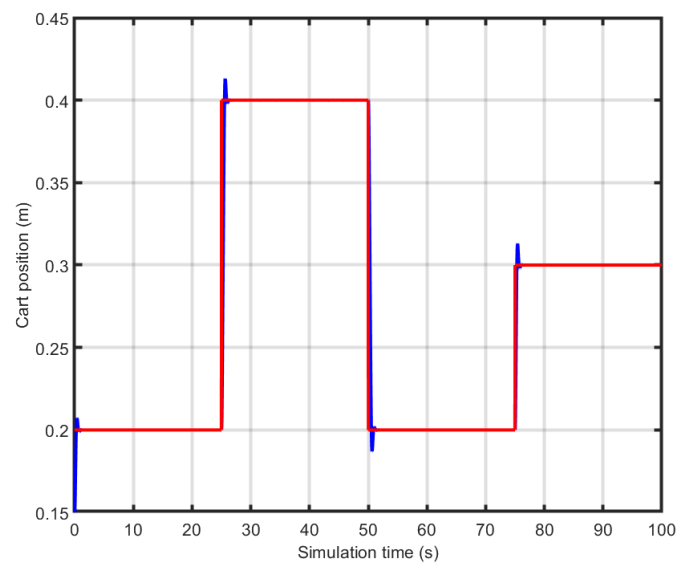


Figure 11.47: The reference values for the cart position (x_C) seen in red and the simulated cart position seen in blue.

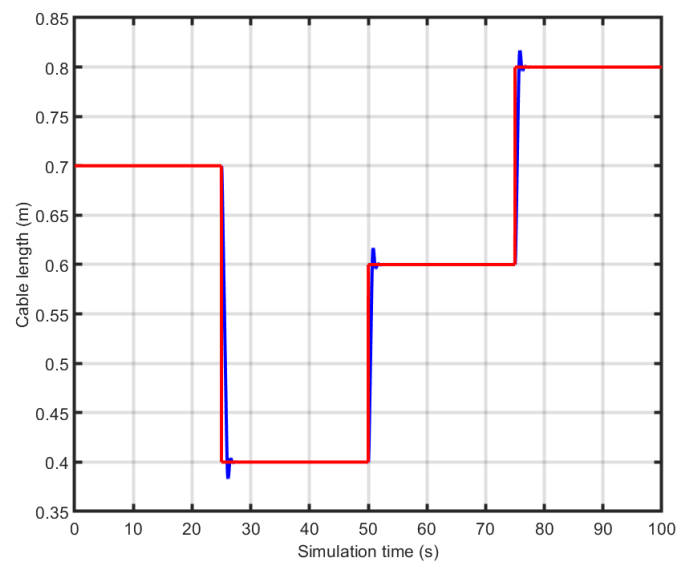


Figure 11.48: The reference values for the cable length (x_L) seen in red and the simulated cable length seen in blue.

- *Calling the dynamics used in the model directly in MATLAB/Python*
- *Results*

In this example we illustrate the use of the real-time Sequential Quadratic Programming (SQP) solver and how to generate and call the dynamics used in the formulation of the optimization problem directly in MATLAB/Python. In particular, we use a robotic arm manipulator described by a set of ordinary differential equations (ODEs):

$$\begin{aligned}\ddot{\theta}_1 &= \gamma \\ \ddot{\theta}_2 &= \frac{1}{\beta_2}(\tau_2 - \beta_1\gamma - \beta_3\dot{\theta}_1^2 - \beta_4) \\ \dot{\tau}_1 &= u_1 \\ \dot{\tau}_2 &= u_2\end{aligned}$$

where θ_1, θ_2 are joint angles modelling the manipulator configuration, u_1, u_2 are the rates (inputs) of the torques τ_1, τ_2 applied to the joints and

$$\gamma \triangleq \frac{1}{\alpha_1 - \alpha_2 \frac{\beta_1}{\beta_2}} \left(\frac{\alpha_2}{\beta_2} (\beta_4 + \beta_3 \dot{\theta}_1^2 - \tau_2) - \alpha_3 \dot{\theta}_1 \dot{\theta}_2 - \alpha_4 \dot{\theta}_2 - \alpha_5 + \tau_1 \right).$$

The coefficients $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$ and $\beta_1, \beta_2, \beta_3, \beta_4$ depend on the inertia and mass of the robot arm components. Their expressions can be found in [SicSci09]. The optimal control problem is formalized from the state x defined by

$$x \triangleq (\theta_1, \dot{\theta}_1, \theta_2, \dot{\theta}_2, \tau_1, \tau_2)^\top$$

and the input u defined as

$$u \triangleq (\dot{\tau}_1, \dot{\tau}_2)^\top.$$

The control objective is to make the first joint angle θ_1 follow a reference of 1.2rad from 0 to 10s and -1.2 rad from 10 to 20s. Similarly, the second joint angle θ_2 should follow a reference of -1.2 rad from 0 to 10s and 1.2rad from 10 to 20s. The stage variable z is defined by stacking the input and differential state variables:

$$z = (\dot{\tau}_1, \dot{\tau}_2, \theta_1, \dot{\theta}_1, \theta_2, \dot{\theta}_2, \tau_1, \tau_2)^\top$$

You can find the code of this example to try it out for yourself in the `examples` folder that comes with your client.

11.16.1 Defining the MPC problem

Tracking objective

Our goal is to minimize the distance of the joint angles to the reference, which can be translated in the following stage cost function:

$$f(z, p) = 1000(z_3 - 1.2p)^2 + 0.1z_4^2 + 1000(z_5 + 1.2p)^2 + 0.1z_6^2 + 0.01z_7^2 + 0.01z_8^2 + 0.01z_1^2 + 0.01z_2^2,$$

where p is a run-time parameter taking value 1 from 0 to 10s and -1 from 10 to 20s.

The stage cost function is coded in MATLAB as the least-squares vector:

Matlab

Python

```

model.LSobjective = @(z,p)[sqrt(1000) * (z(3)-p(1)*1.2);...
    sqrt(0.1) * z(4);...
    sqrt(1000) * (z(5)+p(1)*1.2);...
    sqrt(0.1) * z(6);...
    sqrt(0.01) * z(7);...
    sqrt(0.01) * z(8);...
    sqrt(0.01) * z(1);...
    sqrt(0.01) * z(2)];

```

```

model.objective = lambda z, p: ( 1000 * (z[2] - p[0]*1.2)**2
    + 0.1 * z[3]**2
    + 1000 * (z[4] + p[0]*1.2)**2
    + 0.10 * z[5]**2
    + 0.01 * z[6]**2
    + 0.01 * z[7]**2
    + 0.01 * z[0]**2
    + 0.01 * z[1]**2)

```

In the MATLAB example, this is needed to compute a Gauss-Newton approximation from the Jacobian of the least-squares vector. In the Python example, where Gauss-Newton approximations are not yet available, we use the *objective* field to supply the target function.

State and input constraints

The following constraints are imposed on the torques and torque rates:

$$\begin{aligned}
 -100 \text{ Nm} &\leq \tau_1 \leq 70 \text{ Nm} \\
 -100 \text{ Nm} &\leq \tau_2 \leq 70 \text{ Nm} \\
 -200 \text{ Nm/s} &\leq \dot{\tau}_1 \leq 200 \text{ Nm/s} \\
 -200 \text{ Nm/s} &\leq \dot{\tau}_2 \leq 200 \text{ Nm/s}
 \end{aligned}$$

This corresponds to the code below.

Matlab

Python

```

% upper/lower variable bounds lb <= x <= ub
model.lb = [ -200, -200, -pi, -100, -pi, -100, -100, -100 ];
model.ub = [ 200, 200, pi, 100, pi, 100, 70, 70 ];

```

```

# Upper/lower variable bounds lb <= x <= ub
#                               Inputs |           States
#                               dtau1 dtau2 ttheta1 dtheta1 theta2 dtheta2 tau1 tau2
model.lb = np.array([ -200, -200, -np.pi, -100, -np.pi, -100, -100, -100])
model.ub = np.array([ 200, 200, np.pi, 100, np.pi, 100, 70, 70])

```

Initial condition and horizon length

The prediction horizon is set to 21 and the following initial condition is set

Matlab

Python

```

model.xinit = [-0.4 0 0.4 0 0 0]';
model.xinitidx = 3:8;

```



```
xinit = np.array([-0.4, 0, 0.4, 0, 0, 0])
model.xinitidx = range(2, 8)
```

11.16.2 Generating a real-time SQP solver

We have now populated `model` with the necessary fields to generate an SQP solver, which requires settings a few options, as follows:

Matlab

Python

```
%% Define solver options
codeoptions = getOptions('RobotArmSolver');
codeoptions.maxit = 200; % Maximum number of
↳ iterations of inner QP solver
codeoptions.printlevel = 0; % Use printlevel = 2
↳ to print progress (but not for timing)
codeoptions.optlevel = 3;
% Explicit Runge-Kutta 4 integrator
codeoptions.nlp.integrator.Ts = integrator_stepsize;
codeoptions.nlp.integrator.nodes = 5;
codeoptions.nlp.integrator.type = 'ERK4';
% Options for SQP solver
codeoptions.solvemethod = 'SQP_NLP'; % SQP algorithm
codeoptions.nlp.hessian_approximation = 'gauss-newton'; % Gauss-Newton hessian
↳ approximation of nonlinear least-squares objective
codeoptions.sqp_nlp.use_line_search = 0; % Disable line-search
↳ for efficiency (only doable with Gauss-Newton approximation)
codeoptions.MEXinterface.dynamics = 1; % generate MEX entry
↳ point for the dynamics used in the model

%% Generate real-time SQP solver
FORCES_NLP(model, codeoptions);
```

```
# Define solver options
codeoptions = forcespro.CodeOptions()
codeoptions.maxit = 200 # Maximum number of
↳ iterations
codeoptions.printlevel = 0 # Use printlevel = 2 to
↳ print progress (but not for timings)
codeoptions.optlevel = 3 # 0 no optimization, 1
↳ optimize for size, 2 optimize for speed, 3 optimize for size & speed
codeoptions.nlp.integrator.Ts = integrator_stepsize
codeoptions.nlp.integrator.nodes = 5
codeoptions.nlp.integrator.type = 'ERK4'
codeoptions.solvemethod = 'SQP_NLP'
codeoptions.sqp_nlp.rti = 1
codeoptions.sqp_nlp.maxSQPit = 1

# Generate real-time SQP solver
solver = model.generate_solver(codeoptions)
```

The number of solved QPs in every iteration is set via `sqp_nlp.maxSQPit`. It is important to note that disabling the line search in the SQP algorithm does not guarantee global convergence and hence may result in less robust performance, but produces much faster solve times. Turning off the line search via `sqp_nlp.use_line_search` is only allowed when the Gauss-Newton approximation is on.

11.16.3 Calling the generated SQP solver

Once all parameters have been populated, the MEX interface of the solver can be used to invoke it from MATLAB, or the Python *Solver* class can be used to use it from within Python:

Matlab

Python

```
% Set primal initial guess
x0i = model.lb+(model.ub-model.lb)/2;
x0 = repmat(x0i',model.N,1);
problem.x0 = x0;

% Set reference as run-time parameter
problem.all_parameters = ones(model.N,1);

% Set initial condition
problem.xinit = X(:,i);

% Call SQP solver
[output, exitflag, info] = RobotArmSolver(problem);
```

```
# Set solver parameters
x0i = (model.ub + model.lb) / 2
x0 = np.tile(x0i, (1, model.N))
problem = {"x0": x0, # Primal initial guess to start solver from
          "xinit": xinit, # Initial condition
          "all_parameters": np.ones((model.N, 1))} # Reference as a real-time_
↪parameter

# Call SQP solver
output, exitflag, info = solver.solve(problem)
```

The *RobotArmSolver* is expected to return an *exitflag* equal to 1, which corresponds to a successful solver. However, note that the QP could become infeasible in some cases. In this case, one should expect an *exitflag* of -8 .

11.16.4 Calling the dynamics used in the model directly in MATLAB/Python

The MEX interface for the dynamics used in the formulation of the optimization problem can also be called directly in MATLAB and in Python, the *Solver* class has a method which can compute the dynamics along with its derivative (see section *Calling the nonlinear functions from Matlab or Python*). This is convenient for debugging a solver formulation or simulating the system dynamics. This can be done as follows:

Matlab

Python

```
% Set data at first stage
z = problem.x0(1:model.nvar);
p = problem.all_parameters(1:model.npar);

[c, jacc] = RobotArmSolver_dynamics(z, p);
```

```
# Set data at first stage
z = problem['x0'][0:model.nvar]
p = problem['all_parameters'][0:model.npar]
c, jacc = solver.dynamics(z,p)
```

This stores the integrated stage in c and its jacobian with respect to z in j_{acc} .

11.16.5 Results

The control objective is to track the joint references of -1.2 rad and 1.2 rad respectively, while keeping the input torque rates below 200 Nm/s in magnitude and the torque states between -100 N and 70 Nm .

The joint angle and torques trajectories are shown in Figure [Figure 11.49](#) and Figure [Figure 11.50](#) respectively, while the input torque rates are plotted in Figure [Figure 11.51](#). The closed-loop objective, which is a measure of the control performance is shown in Figure [Figure 11.52](#).

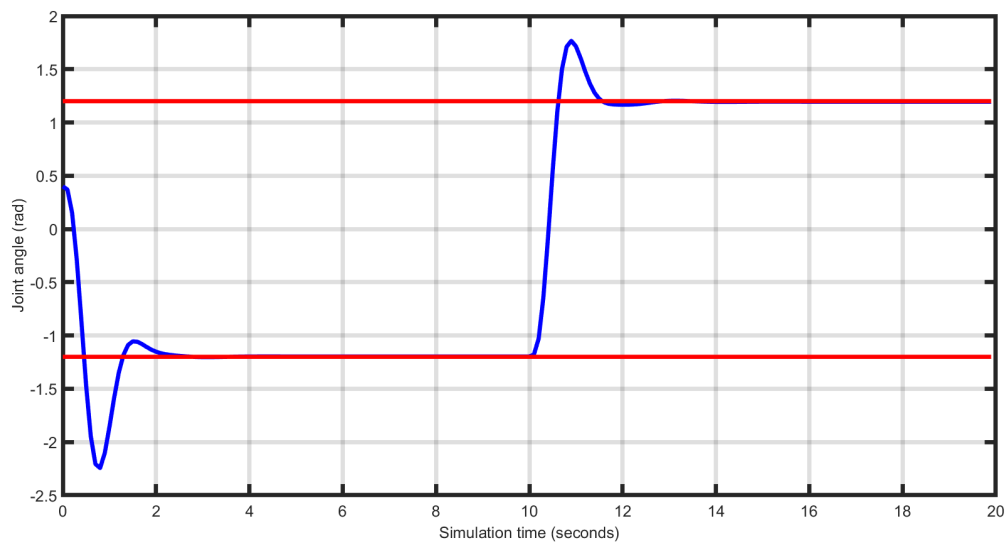


Figure 11.49: Manipulator's joint angle.

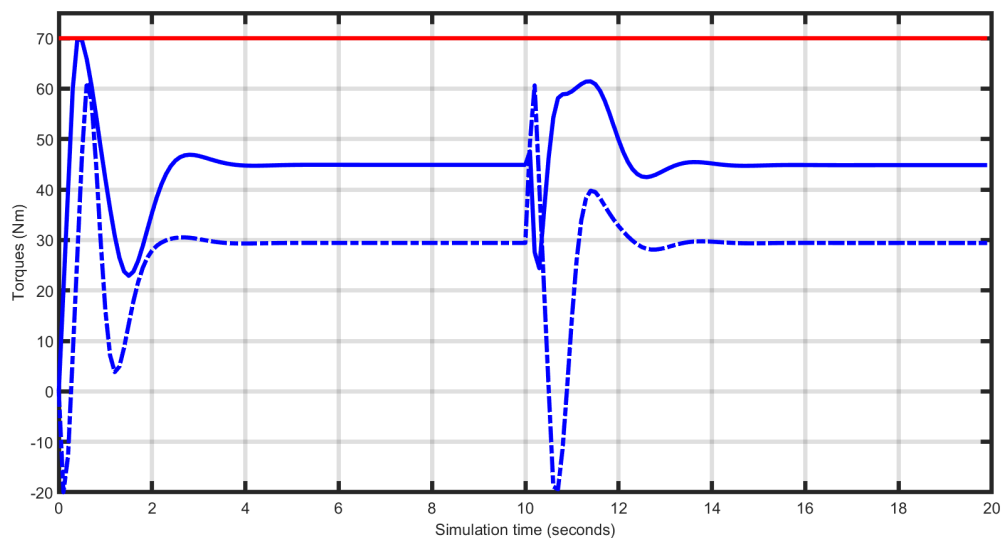


Figure 11.50: Manipulator's torques at joints.

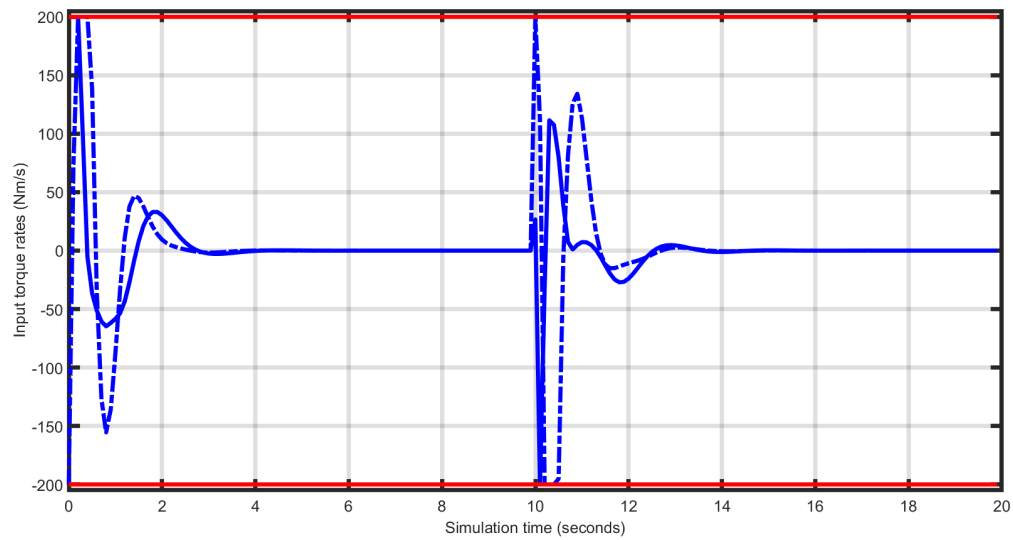


Figure 11.51: Manipulator's torque rates.

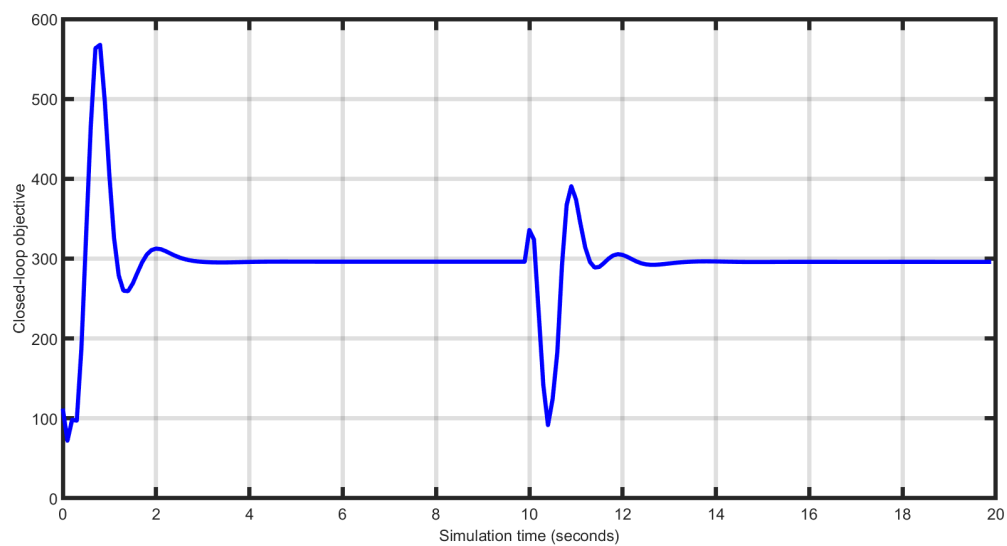


Figure 11.52: Manipulator's closed loop objective.

11.17 Controlling a DC motor using a FORCESPRO SQP solver

- *Defining the MPC problem*
 - *The tracking objective function*
 - *The dynamics*
 - *Input and state constraints*
 - *Generating the FORCESPRO SQP solver*
 - *Calling the solver*
 - *Results*

In this example our aim is to control a DC-motor using a FORCESPRO SQP solver. The model for the DC motor which we consider is borrowed from [BerUnb], to which we refer for further details. The dynamics of our model is described by the following set of ordinary differential equations:

$$\begin{aligned}\dot{x}_1(t) &= -\frac{R_a}{L_a}x_1(t) - \frac{k_m}{L_a}u(t)x_2(t) + \frac{u_a}{L_a} \\ \dot{x}_2(t) &= -\frac{B}{J}x_2(t) + \frac{k_m}{J}u(t)x_1(t) - \frac{\tau_l}{J}.\end{aligned}$$

The states x_1 and x_2 model the armature current and motor angular speed of our DC motor respectively and the control u models the input field current. The following values are chosen for our model constants

$R_a = 12.548\Omega$	(armature resistance)
$L_a = 0.307\text{H}$	(armature inductance)
$k_m = 0.23576\text{Nm/A}^2$	(motor constant)
$u_a = 60\text{V}$	(armature voltage)
$B = 0.00783\text{Nmsec}$	(total viscous damping)
$\tau_L = 1.47\text{Nmsec}$	(Load torque)
$J = 0.00385\text{Nmsec}^2$	(total moment of inertia)

The control objective is to track a piecewise constant angular speed. To test the robustness of our resulting controller we switch reference half way through our simulation. In the first half of the simulation we will track a constant angular speed $x_2^{ref1} = 2$ and then switch to tracking a constant angular speed $x_2^{ref2} = -2$. We collect the 2-dimensional state vector $x = (x_1, x_2)^T$ and the 1-dimensional control u in the vector

$$z = \begin{pmatrix} u \\ x_1 \\ x_2 \end{pmatrix}$$

You can find the Matlab code below for this example to try it out for yourself in the `examples` folder that comes with your client.

11.17.1 Defining the MPC problem

The tracking objective function

Since we want to track a reference value it is natural to consider a least squared cost $f(z, p) = \frac{\|r(z, p)\|^2}{2}$ for

$$r(z, p) = z_3 - p$$

Recall that $z_3 = x_2$ models the motor angular speed which is made to track a piecewise constant reference. The parameter p will be equal to x_2^{ref1} during the first half of the simulation and equal to x_2^{ref2} during the second.

The following code snippet reads in the least squared objective

```
model.LSobjective = @(z,p) sqrt(100) * (z(3) - p);
model.LSobjectiveN = @(z,p) sqrt(100) * (z(3) - p);
```

The dynamics

The following code snippet reads in the dynamics (11.17) of our model:

```
%% model parameters
% Armature inductance (H)
La = 0.307;
% Armature resistance (Ohms)
Ra = 12.548;
% Motor constant (Nm/A^2)
km = 0.23576;
% Total moment of inertia (Nm.sec^2)
J = 0.00385;
% Total viscous damping (Nm.sec)
B = 0.00783;
% Load torque (Nm)
tauL = 1.47;
% Armature voltage (V)
ua = 60;

model.E = [zeros(2,1), eye(2)];
model.continuous_dynamics = @(x,u) [(-1/La)*(Ra*x(1) + x(2)*u(1) - ua);...
                                     (-1/J)*(B*x(2) - km*x(1)*u(1) + tauL)];
```

Input and state constraints

The following constraints are to be met by our control and state vectors:

$$\begin{aligned} 1A &\leq u \leq 1.6A \\ -5A &\leq x_1 \leq 5A \\ -10\frac{\text{rad}}{\text{sec}} &\leq x_2 \leq 10\frac{\text{rad}}{\text{sec}} \end{aligned}$$

This can be read into the FORCESPRO model as follows

```
model.lb = [1, -5, -10];
model.ub = [1.6, 5, 10];
```

Generating the FORCESPRO SQP solver

To generate a suitable SQP solver for our MPC problem one needs a model struct as well as a codeoptions struct. Our model struct has been populated above and we now specify the codeoptions we want and generate the solver by calling FORCES_NLP. The following code snippet shows how this can be done:

```
%% set codeoptions
codeoptions = getOptions('FORCESPROSolver');
codeoptions.solvermethod = 'SQP_NLP'; % generate SQP solver
```

(continues on next page)

(continued from previous page)

```
codeoptions.nlp.integrator.type = 'ERK4';
codeoptions.nlp.integrator.Ts = 0.01;
codeoptions.nlp.integrator.nodes = 1;
codeoptions.nlp.hessian_approximation = 'gauss-newton';
codeoptions.server = 'https://forces.embotech.com';

%% generate FORCESPRO solver
FORCES_NLP(model, codeoptions);
```

Calling the solver

Once the solver has been generated it needs a struct containing an initial guess, initial condition of the ODE, the run-time parameters and the `reinitialize` field as explained in [Sequential quadratic programming algorithm](#). The following code-snippet shows how this can be done:

```
% populate run time parameters struct
params.all_parameters = repmat(2, model.N, 1);
params.xinit = zeros(model.neq, 1); % initial condition to ODE
params.x0 = repmat([1.2; zeros(2,1)], model.N, 1); % initial guess
params.reinitialize = 0;

% Solve optimization problem
[output, exitflag, info] = FORCESPROSolver(params);
```

The `FORCESPROSolver` is expected to return an `exitflag` equal to 1, which corresponds to a successful solve. However, note that the QP could become infeasible in some cases. In this case, one should expect an `exitflag` equal to -8.

Results

The control objective is to track an angular speed of 2 and -2 respectively. As can be seen in [Figure 11.57](#) the controller completes this task. The control (u) is plotted in [Figure 11.53](#), the first state (x_1) is plotted in [Figure 11.54](#) and second state (x_2) in [Figure 11.55](#). As a measure of control quality, the closed loop objective value is plotted in [Figure 11.56](#).

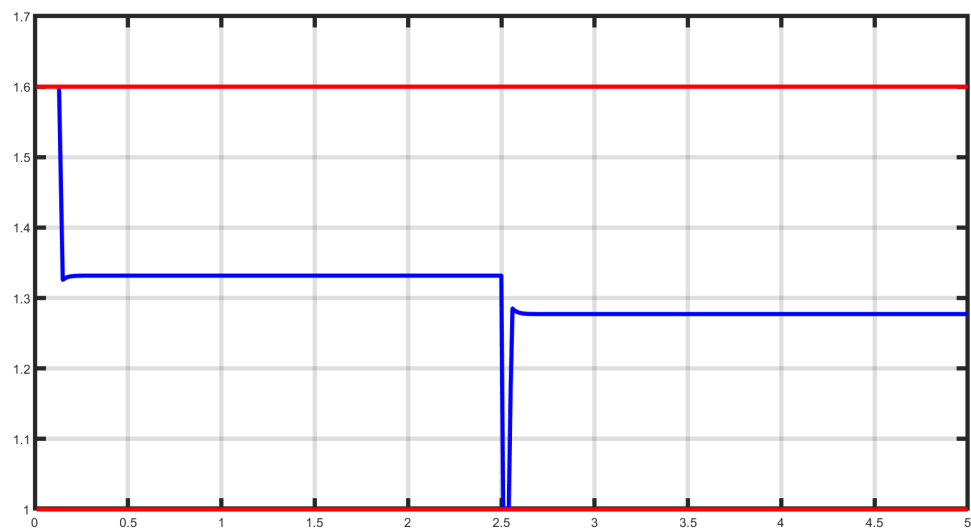


Figure 11.53: The control (u , in blue) as a function of simulation time (s). The control obeys its constraints (red) throughout the simulation.

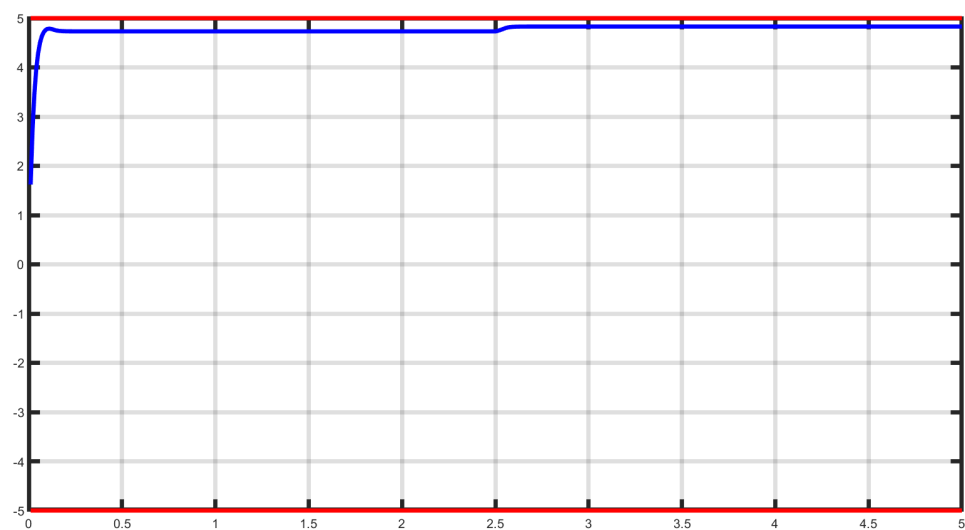


Figure 11.54: The first state (x_1 , in blue) as a function of simulation time. It obeys its constraints (red) throughout the simulation.

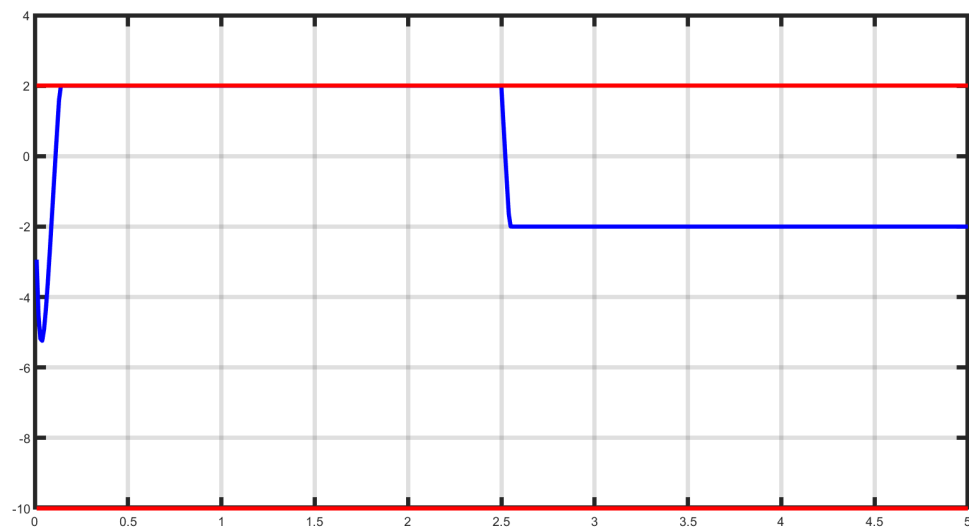


Figure 11.55: The second state (x_2 , in blue) as a function of simulation time. It obeys its constraints (red) throughout the simulation.

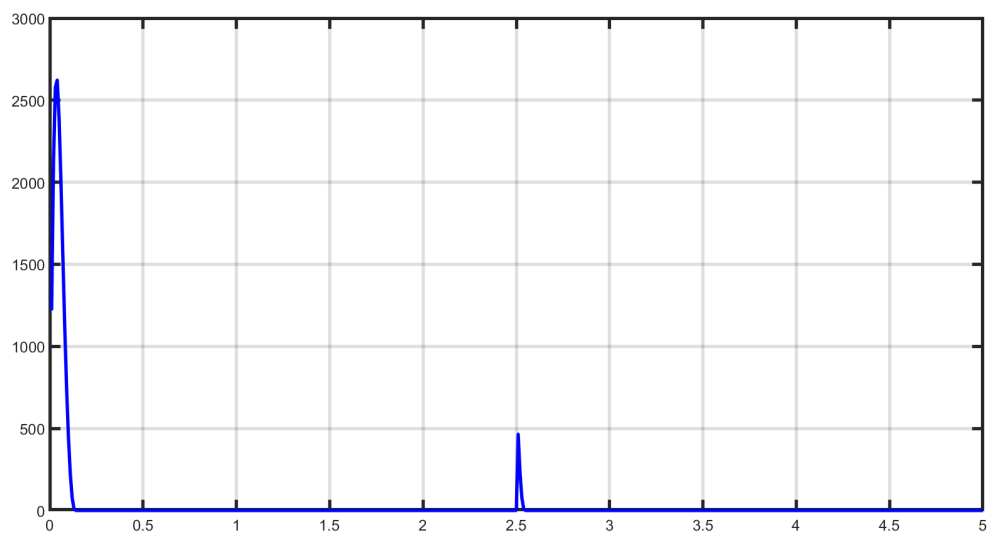


Figure 11.56: Closed-loop objective value as a function of time

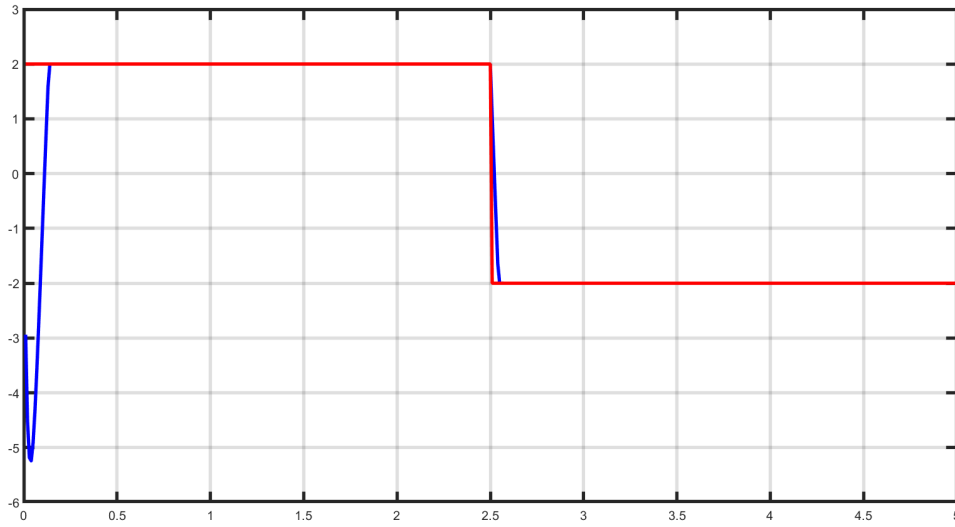


Figure 11.57: Angular speed (blue) and tracked reference (red) value as a function of time.

11.18 Mixed-integer nonlinear solver: F8 Crusader aircraft

- *Defining the problem data*
 - *Objective*
 - *Equality constraints*
 - *Inequality constraints*
 - *Initial and final conditions*
- *Defining the MPC problem*
- *Generating an MINLP solver*
- *Calling the generated MINLP solver*
- *Providing an initial guess at run-time*
- *Changing the parallelization strategy at run-time*
- *Results*

In this example we illustrate the simplicity of the high-level user interface on a mixed-integer nonlinear program. In particular, we use an F8 Crusader aircraft model described by a set of ordinary differential equations (ODEs):

$$\begin{aligned}\dot{x}_0 &= -0.877x_0 + x_2 - 0.088x_0x_2 + 0.47x_0^2 - 0.019x_1^2 - x_0^2x_2 + 3.846x_0^3 \\ &\quad - 0.215w + 0.28x_0^2w + 0.47x_0w^2 + 0.63w^3 \\ \dot{x}_1 &= x_2 \\ \dot{x}_2 &= -0.4208x_0 - 0.396x_2 - 0.47x_0^2 - 3.564x_0^3 - 20.967w \\ &\quad + 6.265x_0^2w + 46x_0w^2 + 61.4w^3\end{aligned}$$

The model is taken from [GarJor77] and consists of three differential states: x_0 the angle of attack in radians, x_1 the pitch angle in radians and x_2 the pitch angle rate in radians per second. There is one control input w , the tail deflection angle in radians. The input is the discrete component of the model, since it can take values within the discrete set $\{-0.05236, 0.05236\}$.

This makes the solution process more complicated in comparison to a nonlinear program, as the different combinations of inputs have to be checked over the control horizon.

The trajectory of the aircraft is to be computed by solving a mixed-integer nonlinear program (MINLP). First, we define the stage variable z by stacking the input and differential state variables:

$$z = [w, x_0, x_1, x_2]^T$$

You can find the Matlab code of this example to try it out for yourself in the `examples` folder that comes with your client.

11.18.1 Defining the problem data

Objective

Our goal is to minimize the distance of the final state to the origin, which can be translated in the following cost function on the final stage variable:

$$f(z) = 150x_0^2 + 5x_1^2 + 5x_2^2$$

The terminal cost function is coded in MATLAB as the following function:

```
model.objectiveN = @(z) 150 * z(2)^2 + 5 * z(3)^2 + 5 * z(4)^2;
```

Moreover, control inputs are penalized at every stage via the following stage cost function:

```
model.objective = @(z) 0.1 * z(1)^2;
```

Equality constraints

In this example, the only equality constraints are related to the dynamics. They are provided to FORCESPRO in continuous form. The discretization is then computed internally by the FORCESPRO integrators.

In the code snippet below, it is important to notice that the control input w is replaced with u such that

$$w \triangleq 0.05236 \cdot (2u - 1)$$

If w has values within $\{-0.05236, 0.05236\}$, then u lies within the binary set $\{0, 1\}$.

```
wa = 0.05236;
wa2 = wa^2;
wa3 = wa^3;
continuous_dynamics = @(x, u) [-0.877 * x(1) + x(3) - 0.088 * x(1) * x(3) ...
    + 0.47 * x(1) * x(1) - 0.019 * x(2) * x(2) ...
    - x(1) * x(1) * x(3) ...
    + 3.846 * x(1) * x(1) * x(1) ...
    - 0.215 * wa * (2 * u(1) - 1) ...
    + 0.28 * x(1) * x(1) * wa * (2 * u(1) - 1) ...
    + 0.47 * x(1) * wa2 * (2 * u(1) - 1) * (2 * u(1) - 1) ...
    + 0.63 * wa3 * (2 * u(1) - 1) * (2 * u(1) - 1) * (2 * u(1) - 1);
    x(3);
    -4.208 * x(1) - 0.396 * x(3) - 0.47 * x(1) * x(1) ...
    - 3.564 * x(1) * x(1) * x(1) ...
    - 20.967 * wa * (2 * u(1) - 1) ...
    + 6.265 * x(1) * x(1) * wa * (2 * u(1) - 1) ...
```

(continues on next page)

(continued from previous page)

```

+ 46.0 * x(1)*wa2*(2*u(1)-1)*(2*u(1)-1)...
+ 61.4*wa3*(2*u(1)-1)*(2*u(1)-1)*(2*u(1)-1)];
model.continuous_dynamics = continuous_dynamics;
model.E = [zeros(3, 1), eye(3)];

```

Inequality constraints

The maneuver is subjected to a set of constraints, involving only the simple bounds:

$$\begin{aligned}
 0 \text{ rad} &\leq u \leq 1 \text{ rad} \\
 -10 \text{ rad} &\leq x_0 \leq 10 \text{ rad} \\
 -10 \text{ rad} &\leq x_1 \leq 10 \text{ rad} \\
 -10 \text{ rad/sec} &\leq x_2 \leq 10 \text{ rad/sec}
 \end{aligned}$$

Initial and final conditions

The goal of the maneuver is to steer the aircraft from an initial condition with nose pointing upwards

$$(0.4655, 0, 0)^T$$

to the origin.

11.18.2 Defining the MPC problem

With the above defined MATLAB functions for objective and equality constraints, we can completely define the MINLP formulation in the next code snippet. For this example, the number of stages has been set to $N = 100$.

In the code snippet below, it is important to notice that the lower and upper bounds are declared as parametric before generating the solver. This needs to be done for generating mixed-integer NLP solvers. Lower and upper bounds are meant to be provided at run-time.

```

%% Problem dimension
nx = 3;
nu = 1;
nz = nx + nu;
model.N = 100;
model.nvar = nz;
model.neq = nx;

%% Indices of initial state in stage variable
model.xinitidx = nu+1:model.nvar;

%% Lower and upper bound need to be set as parametric for generating an MINLP_
↪solver
model.lb = [];
model.ub = [];
model.lbidx{1} = 1 : nu;
model.ubidx{1} = 1 : nu;
for i = 2 : model.N
    model.lbidx{i} = 1 : model.nvar;
    model.ubidx{i} = 1 : model.nvar;

```

(continues on next page)

(continued from previous page)

```

end

%% Dynamics
wa = 0.05236;
wa2 = wa^2;
wa3 = wa^3;
continuous_dynamics = @(x, u) [-0.877 * x(1) + x(3) - 0.088 * x(1) * x(3)...
    + 0.47 * x(1) * x(1) - 0.019 * x(2) * x(2)...
    - x(1) * x(1) * x(3)...
    + 3.846 * x(1) * x(1) * x(1)...
    - 0.215 * wa * (2 * u(1) - 1)...
    + 0.28 * x(1) * x(1) * wa * (2 * u(1) - 1)...
    + 0.47 * x(1) * wa2 * (2 * u(1) - 1) * (2 * u(1) - 1)...
    + 0.63 * wa3 * (2 * u(1) - 1) * (2 * u(1) - 1) * (2 * u(1) - 1);
    x(3);
    -4.208 * x(1) - 0.396 * x(3)...
    - 0.47 * x(1) * x(1)...
    - 3.564 * x(1) * x(1) * x(1)...
    - 20.967 * wa * (2 * u(1) - 1)...
    + 6.265 * x(1) * x(1) * wa * (2 * u(1) - 1)...
    + 46.0 * x(1) * wa2 * (2 * u(1) - 1) * (2 * u(1) - 1)...
    + 61.4 * wa3 * (2 * u(1) - 1) * (2 * u(1) - 1) * (2 * u(1) - 1)];
model.continuous_dynamics = continuous_dynamics;
model.E = [zeros(nx, nu), eye(nx)];

%% Objective
mode.objective = @(z) 0.1 * z(nu)^2;
model.objectiveN = @(z) 150 * z(nu+1)^2...
    + 5 * z(nu+2)^2...
    + 5 * z(nu+3)^2;

%% Indices of integer variables within every stage
for s = 1:model.N
    model.intidx{s} = [1];
end

```

11.18.3 Generating an MINLP solver

We have now populated `model` with the necessary fields to generate a mixed-integer solver for our problem. Now we set some options for our solver and then use the function `FORCES_NLP` to generate a solver for the problem defined by `model` with the initial state and the lower and upper bounds as a parameters:

```

%% Set code-generation options
codeoptions = getOptions('F8aircraft');
codeoptions.printlevel = 1;
codeoptions.misra2012_check = 1;
codeoptions.maxit = 2000;
codeoptions.timing = 0;
codeoptions.nlp.integrator.type = 'IRK2';
codeoptions.nlp.integrator.Ts = 0.05;
codeoptions.nlp.integrator.nodes = 20;

%% Generate MINLP solver
FORCES_NLP(model, codeoptions);

```

In the code snippet above, we have set some integrator options, since the continuous-time dynamics has been provided in the model. The branch-and-bound search can be run on several threads in parallel by setting the run-time parameter `numThreadsBnB` equal to the

number of threads to be used. The default value is 1. Moreover, the maximum number of threads for the branch-and-bound search can be set via the option `max_num_threads`. By default, `max_num_threads = 4`.

11.18.4 Calling the generated MINLP solver

Once all parameters have been populated, the MEX interface of the solver can be used to invoke it:

```
%% Set run-time parameters
problem.(sprintf('lb%02d', 1)) = 0;
problem.(sprintf('ub%02d', 1)) = 1;
for s = 2:99
    problem.(sprintf('lb%02d', s)) = [0, -1e1 * ones(1, 3)];
    problem.(sprintf('ub%02d', s)) = [1, 1e1 * ones(1, 3)];
end
problem.(sprintf('lb%02d', 100)) = [0, -1e1 * ones(1, 3)];
problem.(sprintf('ub%02d', Nstages)) = [1, 1e1 * ones(1, 3)];

problem.x0 = repmat([0; zeros(3, 1)], 100, 1);
problem.xinit = zeros(3, 1);
problem.xinit(1) = 0.4655;

%% Call MINLP solver
[sol, exitflag, info] = F8aircraft(problem);
```

11.18.5 Providing an initial guess at run-time

In order to provide an guess for the incumbent, the following code-generation options need to be enabled:

```
codeoptions.minlp.int_guess = 1;
codeoptions.minlp.round_root = 0; % Default value is 1
codeoptions.minlp.int_guess_stage_vars = [1]; % An integer guess is provided for_
↪variable 1 at every stage
```

Then the incumbent guess can be set at run-time via

```
for s = 1:Nstages
    problem.(sprintf('int_guess%03d', s)) = [0];
end
for s = 1:2
    problem.(sprintf('int_guess%03d', s)) = [1];
end
problem.(sprintf('int_guess%03d', 39)) = [1];
for s = 41:42
    problem.(sprintf('int_guess%03d', s)) = [1];
end
for s = 85:90
    problem.(sprintf('int_guess%03d', s)) = [1];
end
```

11.18.6 Changing the parallelization strategy at run-time

When running the MINLP solver on several threads with `numThreadsBnB >= 1`, the parallelization strategy can be changed via

```
problem.parallelStrategy = 0; % 0 (one shared priority queue, default), 1 (one_
↳priority queue per thread)
```

11.18.7 Results

The control objective is to drive the angle of attack as close as possible to zero within a five seconds time frame. The control input is the tail deflection angle, which can take values with the set $\{-0.05236, 0.05236\}$ and the initial state is $(0.4655, 0, 0)^T$, where the first component is the angle of attack, the second component is the pitch angle and the third component is the pitch angle rate.

The angle of attack computed by FORCESPRO MINLP solver running on one thread is shown in Figure Figure 11.58 and the input sequence is in Figure Figure 11.59. One can notice the bang-bang behaviour of the solution. When running on three threads the FORCESPRO MINLP solver provides a solution with lower final primal objective. Results are shown on Figures Figure 11.60 and Figure 11.61.

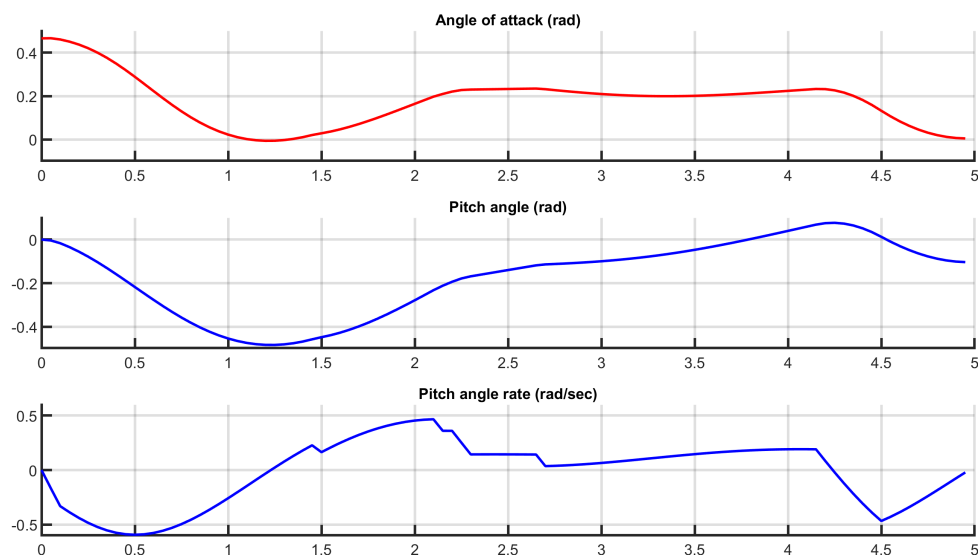


Figure 11.58: Aircraft's angle of attack over time computed with one thread.

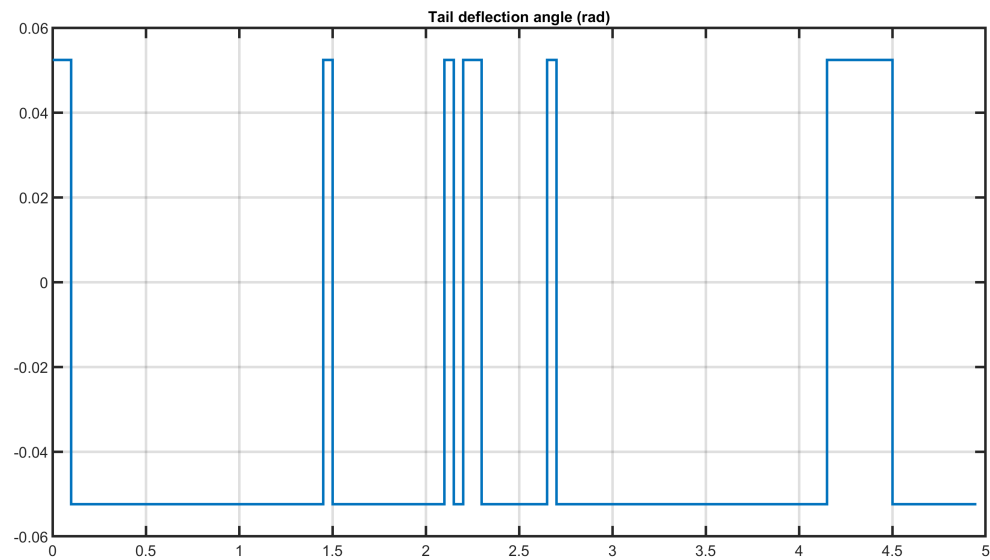


Figure 11.59: Aircraft's tail deflection angle over time with one thread.

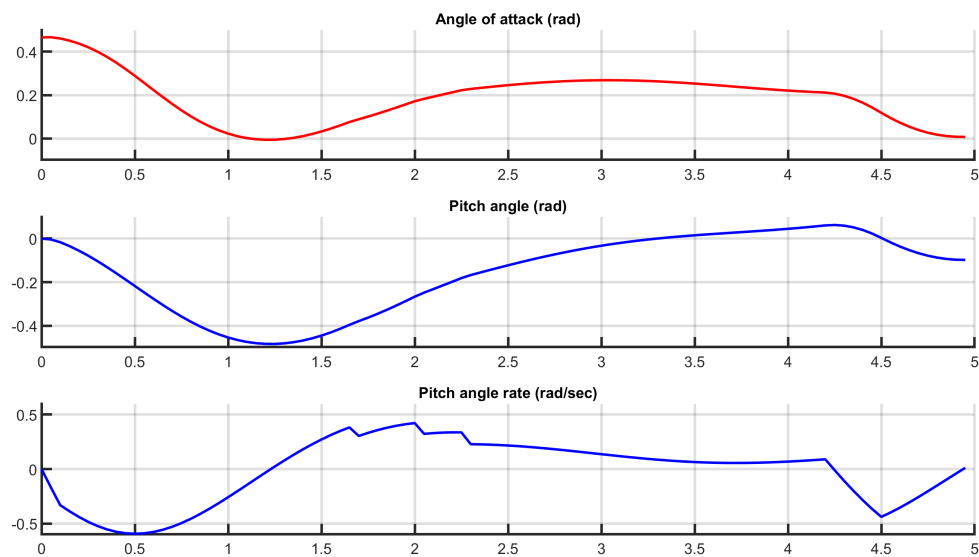


Figure 11.60: Aircraft's angle of attack over time computed with three threads.

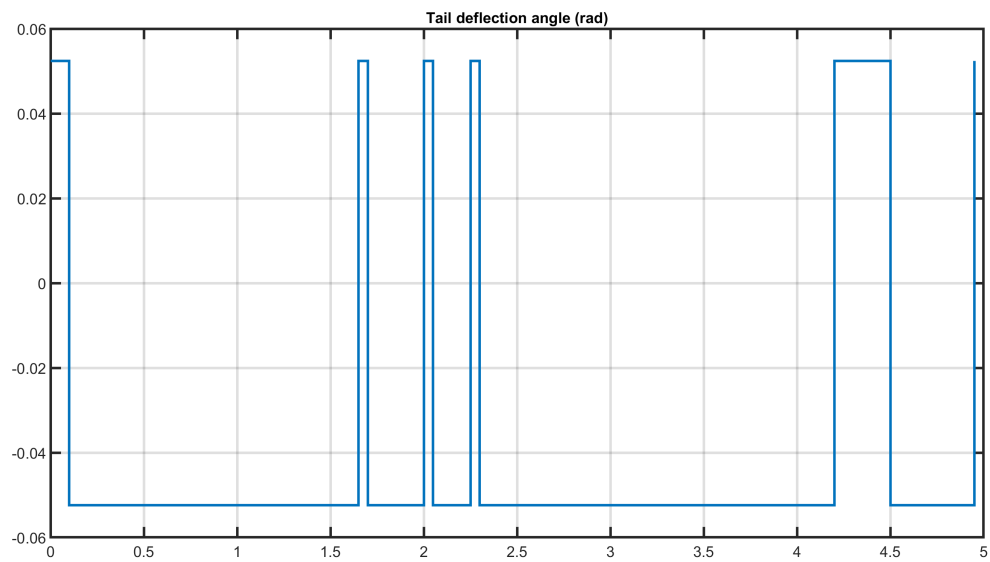


Figure 11.61: Aircraft's tail deflection angle over time with three threads.

Chapter 12

Parametric problems

- *Defining parameters*
- *Example*
- *Parametric Quadratic Constraints*
- *Diagonal Hessians*
- *Sparse Parameters*
- *Special Parameters*
- *Python: Column vs Row Major Storage Format*

Parameters (or real-time data) are a key concept in FORCESPRO. Usually at least one vector in an embedded optimization problem will change between two calls to the solver. In MPC, the initial state changes usually between two sampling times. But other data can change too, for example because you are working with linearizations of non-linear dynamics, or because the cost matrices of a quadratic objective function are tuned online. The following API is available when using the low-level interface only and cannot be used with the high-level interface.

12.1 Defining parameters

FORCESPRO gives you full control over the parametrization of the optimization problem: You can define all data matrices and vectors to be parametric. To define a parameter in MATLAB, use the function

```
parameter = newParam(name, maps2stage, maps2data);
```

and in Python, use

```
stages.newParam(name, maps2stage, maps2data)
```

where `name` is the parameter name, which you need to be set before calling the solver. The vector of indices `maps2stage` defines to which stages the parameters maps. The last argument `maps2data` has to be one of the following strings

Table 12.1: Possible string values for argument maps2data

Cost function	Equality constraints	Inequality constraints
'cost.H'	'eq.c'	'ineq.b.lb'
'cost.f'	'eq.C'	'ineq.b.ub'
	'eq.D'	'ineq.p.A'
		'ineq.p.b'
		'ineq.q.Q'
		'ineq.q.l'
		'ineq.q.r'

From FORCESPRO 1.8.0, the user is allowed to provide a parameter for all problem stages at once. All stage parameters are then stacked into one vector or matrix before getting passed to the solver at runtime. FORCESPRO is notified about this by having

```
maps2stage = [];
```

For instance, in order to provide a parametric linear cost across all stages, one should use the following code at codegen.

```
parameter = newParam('linear_stage_cost', [], 'cost.f');
```

At runtime, the user is expected to provide the linear stage cost as follows.

```
problem.linear_stage_cost = repmat(rand(problem.nvar, 1), problem.horzLength, 1);
```

where `problem.horzLength` is the horizon length and `problem.nvar` is the number of stage variables.

Note: The stacked parameters feature is only available in MATLAB from FORCESPRO '1.8.0'.

12.2 Example

To define the linear term of the cost of stages 1 to 5 as a parameter, use the following command in MATLAB

```
parameter1 = newParam('linear_cost', 1:5, 'cost.f');
```

and in Python, use

```
stages.newParam('linear_cost', range(1, 6), 'cost.f')
```

Note that this will generate only one parameter and the same runtime data will be mapped to stages 1 to 5. If the runtime data should be different for each stage one would have to generate five different in this case.

We can also have a second parameter. For instance, the right handside of the first equality constraints, which is a very common case in MPC. In MATLAB

```
parameter2 = newParam('RHS_first_equality_constraint', 1, 'eq.c');
```

In Python

```
stages.newParam('RHS_first_equality_constraint', [1], 'eq.c')
```

12.3 Parametric Quadratic Constraints

As there may be multiple quadratic constraints for every stage, one needs to specify which ones are to be parametric. One can use a fourth argument in the `newParam` call, as shown below. In MATLAB

```
parameter = newParam(name, maps2stage, maps2data, idxWithinStage);
```

In Python

```
stages.newParam(name, maps2stage, maps2data, idxWithinStage)
```

where `idxWithinStage` denotes the index of the quadratic constraints to which this parameter applies.

12.4 Diagonal Hessians

In case your parametric Hessian is diagonal, you should use the fourth argument of `newParam` as shown below. In MATLAB

```
parameter1 = newParam('Hessians', 1:5, 'cost.H', 'diag');
```

In Python

```
stages.newParam('Hessians', range(1,6), 'cost.H', 'diag')
```

The FORCESPRO solver will then only expect a vector as a parameter. The `'diag'` keyword is currently only valid for hessian matrices related to the objective function.

12.5 Sparse Parameters

If your parameters are not diagonal but they have a sparse structure that can be exploited for performance, you can use the fourth and fifth arguments of `newParam` to let FORCESPRO know about the sparsity pattern. In MATLAB

```
parameter2 = newParam('Ai', 1:5, 'ineq.p.A', 'sparse', [zeros(5, 6) rand(5, 2)]);
```

In Python

```
stages.newParam('Ai', range(1,6), 'ineq.p.A', 'sparse', numpy.hstack((numpy.zeros(5,6),
↪ random.random((5,2))))))
```

The fifth argument is used to let FORCESPRO know about the location of the non-zero elements. When a solver is generated using sparse parameters it is the responsibility of the user to pass on parameters with the correct sparsity pattern to the solver. There will be no warnings thrown at runtime.

Sparse parameter values have to be passed as a column vector of nonzero elements, i.e. to assign the values of matrix `B` to sparse parameter `Ci` one should use the following: In MATLAB

```
problem.Ci = nonzeros(sparse(B));
```

In Python

```
problem.Ci = B[numpy.nonzeros(B)]
```

Note that parameters with a general sparsity structure defined by the fifth argument are currently only supported for polytopic constraints. For the equality constraint matrices, only the structure $[0 \ A]$, where A is assumed to be dense, is currently supported.

12.6 Special Parameters

To prevent having to transfer entire matrices for parameters with few changing elements at runtime, one can specify a sixth argument to let FORCESPRO know about the location of the elements that will be supplied at runtime. In MATLAB

```
parameter2 = newParam('Ci', 1:5, 'eq.C', 'sparse', Cstruc, Cvar)
```

In Python

```
stages.newParam('Ci', range(1,6), 'eq.C', 'sparse', Cstruc, Cvar)
```

Note that in this case the constant values will be taken from the data supplied in the field `Cstruc`. At runtime the user only has to supply a column vector including the time-varying elements marked in the field `Cvar`. The ordering should be column major.

12.7 Python: Column vs Row Major Storage Format

Unlike Matlab, numpy stores arrays by default in row-major format internally. Since FORCESPRO expects the parameters in column major storage format, a conversion is necessary. This conversion is automatically performed by the Python interface when the solver is called. To avoid the conversion every time the solver is called, you should use the following way of creating the arrays storing parameters:

```
a = array([1, 2, 3, 4, 5, 6])
b = a.reshape(2,3,order='F')
```

The above code reshapes the array into a (2,3) Matrix stored in column major (Fortran) format.

Chapter 13

Code Deployment

13.1 Main Targets

- *High-level interface*
- *Y2F interface*

Important: When deploying to a target hardware platform, the library included in the **lib_target** directory of the generated solver should be used instead of the library in the **lib** directory.

Main targets include:

- x86 platforms
- x86_64 platforms
- 32bit ARM-Cortex-A platforms
- 32bit ARM-Cortex-M platforms (no shared libraries)
- 64bit ARM-Cortex-A platforms (AARCH64 toolchain)
- 64bit ARM-Cortex-A platforms (Integrity toolchain)
- NVIDIA platforms with ARM-Cortex-A processors
- PowerPC platforms with GCC compiler
- National Instruments compactRIO platforms with NILRT GCC compiler (Linux RTOS)

You can check [here](#) to find the correct naming option for each platform.

13.1.1 High-level interface

The steps to deploy and simulate a FORCESPRO controller on most targets are detailed below.

1. In the High-level interface example BasicExample.m set the code generation options:

```
codeoptions.platform = '<platform_name>'; % to specify the platform
codeoptions.printlevel = 0; % optional, on some platforms printing is not supported
codeoptions.cleanup = 0; % to keep necessary files for target compile
```

and then generate the code for your solver (henceforth referred to as “FORCESNLPsolver”, placed in the folder “BasicExample”) using the high-level interface.

2. Additionally to your solver you will receive the following files generated by CasADi:

- FORCESNLPsolver_casadi2forces.c
- FORCESNLPsolver_casadi.c
- FORCESNLPsolver_casadi.h

3. For most target platforms you will receive the following compiled files:

- For MinGW/Linux/MacOS:
 - a static library file `libFORCESNLPsolver.a` inside the folder `lib_target`
 - a shared library file `libFORCESNLPsolver.so` inside the folder `lib_target`
- For Windows:
 - a static library file `FORCESNLPsolver_static.lib` inside the folder `lib_target`
 - a dynamic library file `FORCESNLPsolver.dll` with its definition file for compilation `FORCESNLPsolver.lib` inside the folder `lib_target`

You need only one of those to build the solver.

Important: The shared library and the dynamic library if used for building need to be present during runtime as well.

4. Create an interface to call the solver and perform a simulation/test.

You can find a C interface for this example to try it out for yourself in the `examples` folder that comes with your client.

5. Copy in the target platform:

- The `FORCESNLPsolver` folder
- The source files from step 2
- The interface from step 4

6. Compile the solver. The compilation command would be (supposing you are in the directory which contains the `FORCESNLPsolver` folder):

```
<Compiler_exec> HighLevel_BasicExample.c <compiled_solver> FORCESNLPsolver_
↪casadi2forces.c FORCESNLPsolver_casadi.c <additional_libs>
```

Where:

- `<Compiler_exec>` would be the compiler used in the target
- `<compiled_solver>` would be one of the compiled files of step 3
- `<additional_libs>` would be possible libraries that need to be linked to resolve existing dependencies.
 - For Linux/MacOS it's usually necessary to link the math library (`-lm`)
 - For Windows you usually need to link the `iphlpapi.lib` library (it's distributed with the Intel Compiler, MinGW as well as Matlab) and sometimes some additional intel libraries (those are included in the FORCESPRO client under the folder `libs_Intel` – if missing they are downloaded after code generation)

13.1.2 Y2F interface

The steps to deploy and simulate a FORCESPRO controller on most targets are detailed below.

1. In the Y2F interface example `mpc_basic_example.m` set the code generation options:

```
codeoptions.platform = '<platform_name>'; % to specify the platform
codeoptions.printlevel = 0; % optional, on some platforms printing is not supported
```

and then generate the code for your solver (henceforth referred to as “simpleMPC_solver”, placed in the folder “Y2F”) using the Y2F interface.

2. The Y2F solver is composed of a main solver which calls multiple internal solvers. The file describing the main solver is:

- `simpleMPC_solver.c` inside the folder `interface`

3. The internal solvers are provided as compiled files. For most target platforms you will receive the following compiled files:

- For MinGW/Linux/macOS:
 - a static library file `libinternal_simpleMPC_solver_1.a` inside the folder `lib_target`
 - a shared library file `libinternal_simpleMPC_solver_1.so` inside the folder `lib_target`
- For Windows:
 - a static library file `internal_simpleMPC_solver_1_static.lib` inside the folder `lib_target`
 - a dynamic library file `internal_simpleMPC_solver_1.dll` with its definition file for compilation `internal_simpleMPC_solver_1.lib` inside the folder `lib_target`

You need only one of those to build the solver.

Important: The shared library and the dynamic library if used for building need to be present during runtime as well.

4. Create an interface to call the solver and perform a simulation/test.

You can find a C interface for this example to try it out for yourself in the `examples` folder that comes with your client.

5. Copy in the target platform:

- The `simpleMPC_solver` folder
- The interface from step 4

6. Compile the solver. The compilation command would be (supposing you are in the directory which contains the `simpleMPC_solver` folder):

```
<Compiler_exec> Y2F_mpc_basic_example.c simpleMPC_solver/interface/simpleMPC_
↪solver.c <compiled_solver> <additional_libs>
```

Where:

- `<Compiler_exec>` would be the compiler used in the target
- `<compiled_solver>` would be one of the compiled files of step 3
- `<additional_libs>` would be possible libraries that need to be linked to resolve existing dependencies.

- For Linux/MacOS it's usually necessary to link the math library (`-lm`)
- For Windows you usually need to link the `iphlpapi.lib` library (it's distributed with the Intel Compiler, MinGW as well as Matlab) and sometimes some additional intel libraries (those are included in the FORCESPRO client under `libs_Intel` – if missing they are downloaded after code generation)

13.2 dSPACE deployment through Simulink Coder

- *Platform Specific Configurations*
 - *Platform name codeoption*
 - *Simulink Model HW Target Configuration*
- *High-level interface*
- *Y2F interface*
 - *Instructions*

This process applies to the following dSPACE platforms

- **dSPACE MicroAutoBox II**
- **dSPACE AutoBox**
- **dSPACE MicroLabBox**

Important: When deploying to a target hardware platform, the library included in the **lib_target** directory of the generated solver should be used instead of the library in the **lib** directory.

13.2.1 Platform Specific Configurations

Platform name codeoption

When generating code for HW target platforms, `codeoptions.platform` needs to be set.

- **dSPACE MicroAutoBox II:** 'dSPACE-MABII'
- **dSPACE AutoBox:** 'dSPACE-AutoBox'
- **dSPACE MicroLabBox:** 'dSPACE-MicroLabBox'

Simulink Model HW Target Configuration

When creating a Simulink Model for HW target platforms, certain hardware options need to be set.

- Simulink Model Template:
 - **dSPACE MicroAutoBox II:** RTI1401
 - **dSPACE AutoBox:** RTI1007
 - **dSPACE MicroLabBox:** RTI1202
- System target file:
 - **dSPACE MicroAutoBox II:** rti1401.tlc
 - **dSPACE AutoBox:** rti1007.tlc
 - **dSPACE MicroLabBox:** rti1202.tlc
- Template makefile:
 - **dSPACE MicroAutoBox II:** rti1401.tmf

- **dSPACE AutoBox**: rti1007.tmf
- **dSPACE MicroLabBox**: rti1202.tmf

13.2.2 High-level interface

The steps to deploy and simulate a FORCESPRO controller on a dSPACE platform are detailed below.

1. (Figure 13.1) Set the code generation options (for <platform_name> see *Platform name codeoption*):

```
codeoptions.platform = '<platform_name>'; % to specify the platform
codeoptions.printlevel = 0; % on some platforms printing is not supported
codeoptions.cleanup = 0; % to keep necessary files for target compile
```

and then generate the code for your solver (henceforth referred to as “FORCESNLPsolver”, placed in the folder “BasicExample”) using the high-level interface.

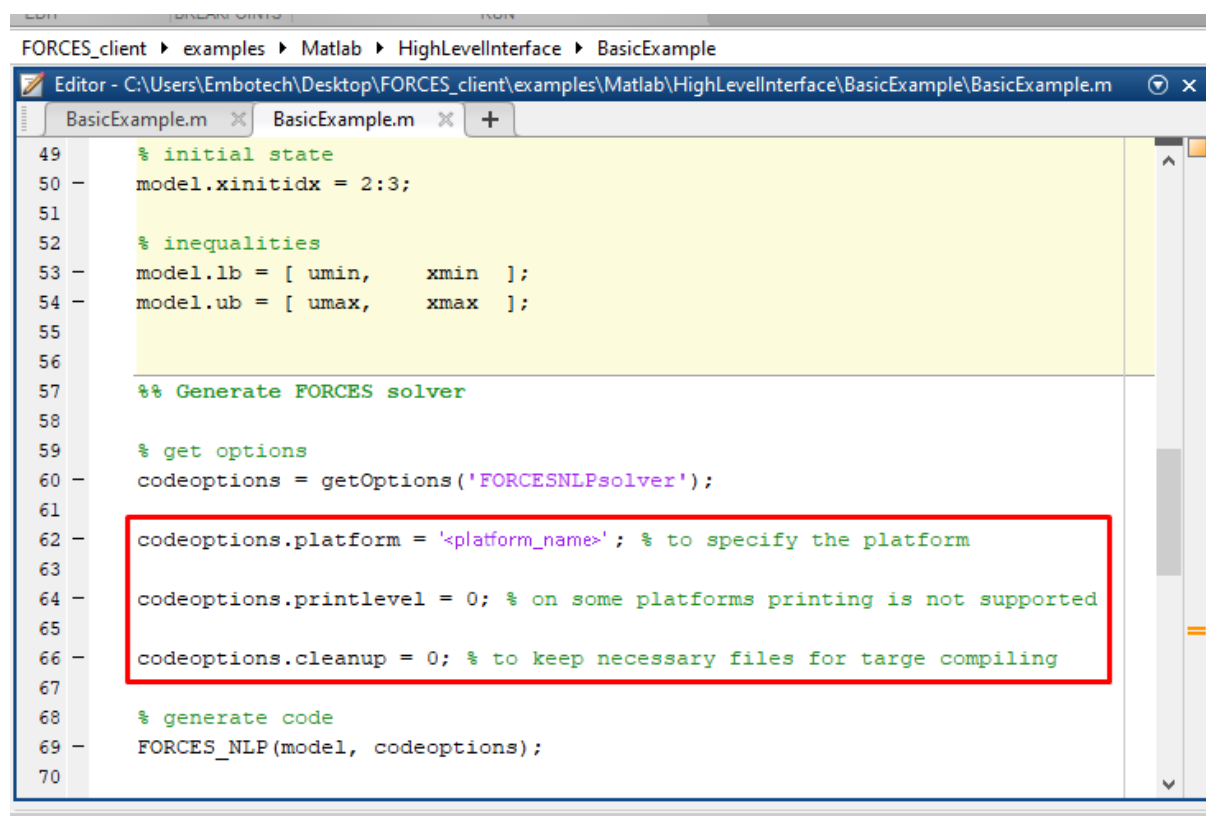


Figure 13.1: Set the appropriate code generation options.

2. (Figure 13.2) Create a new Simulink model using the Simulink model template provided by dSPACE (for <simulink_model_template> see *Simulink Model HW Target Configuration*).
3. (Figure 13.3) Populate the Simulink model with the system you want to control.
4. (Figure 13.4) Make sure the FORCESNLPsolver_simulinkBlock.mexw64 file (created during code generation) is on the Matlab path.
5. (Figure 13.5) Open the FORCESNLPsolver_lib.mdl Simulink model file, contained in the interface folder of the FORCESNLPsolver folder created during code generation.

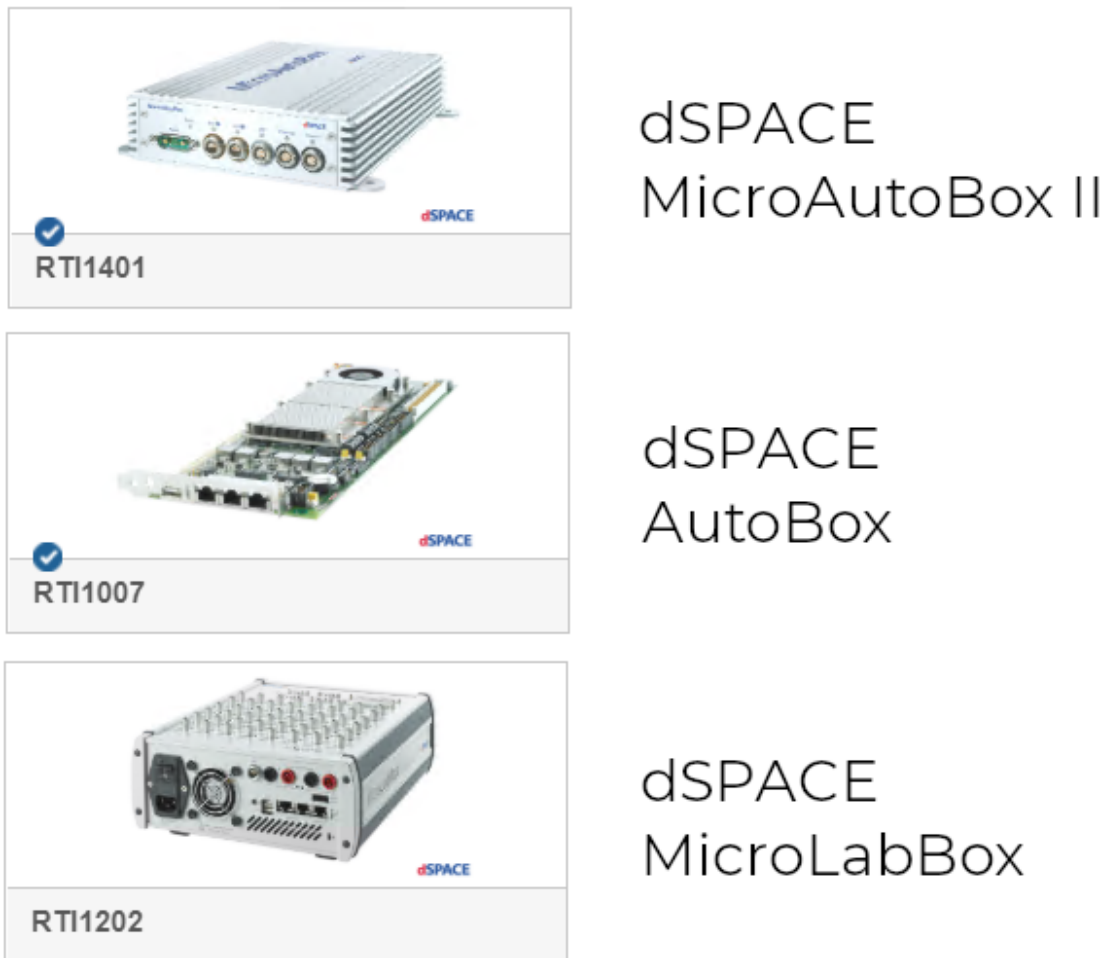


Figure 13.2: Create a Simulink model.

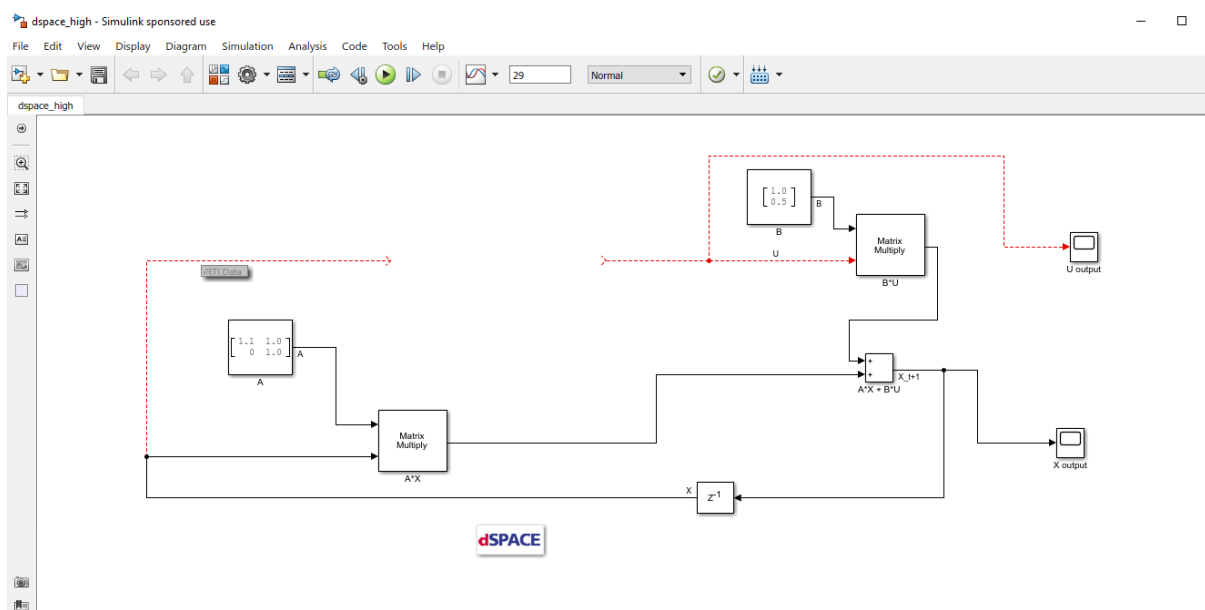


Figure 13.3: Populate the Simulink model.

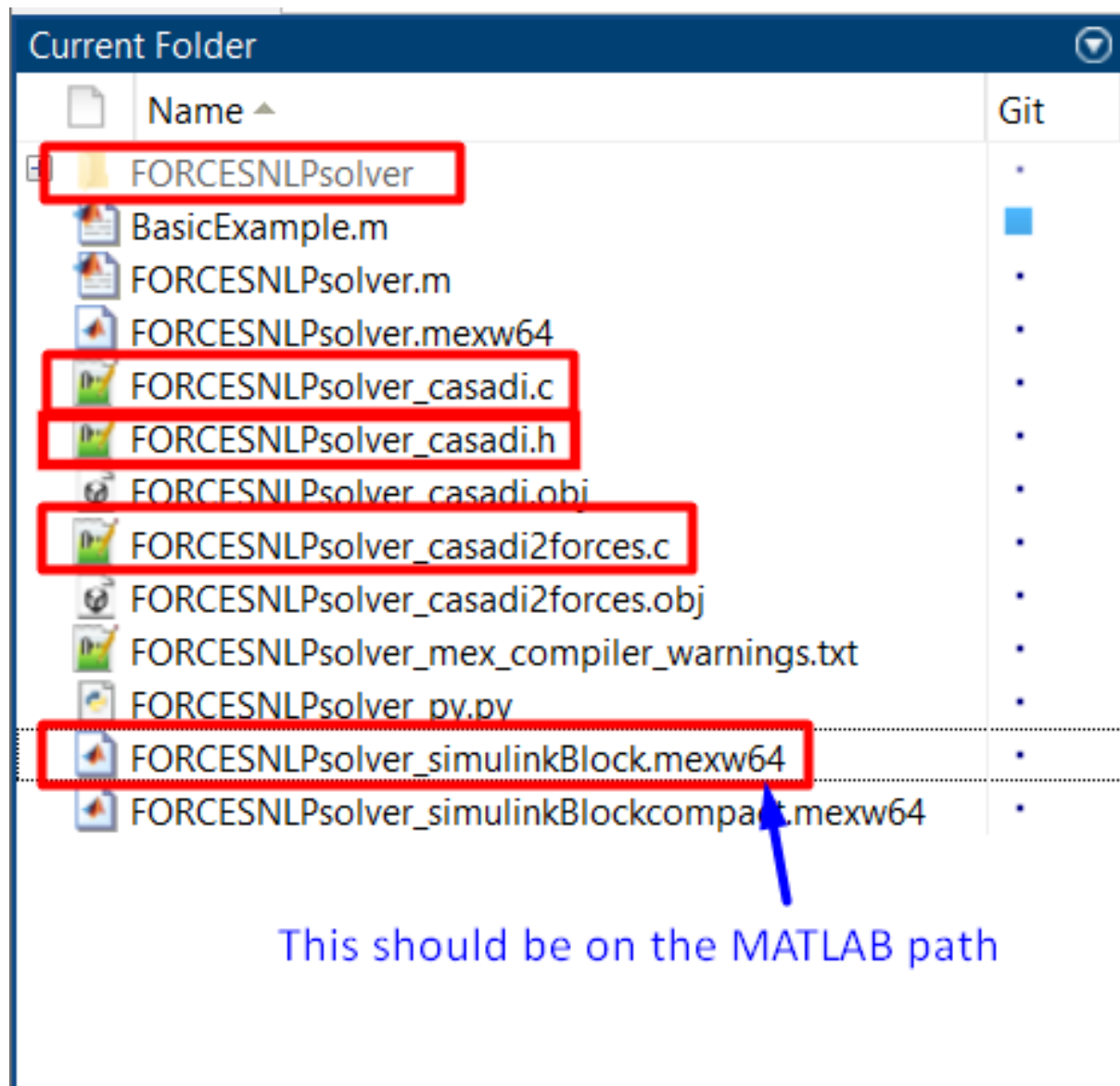


Figure 13.4: Add the folder containing the .mexw64 solver file to the Matlab path.

6. (Figure 13.6) Copy-paste the FORCESPRO Simulink block into your simulation model and connect its inputs and outputs appropriately.

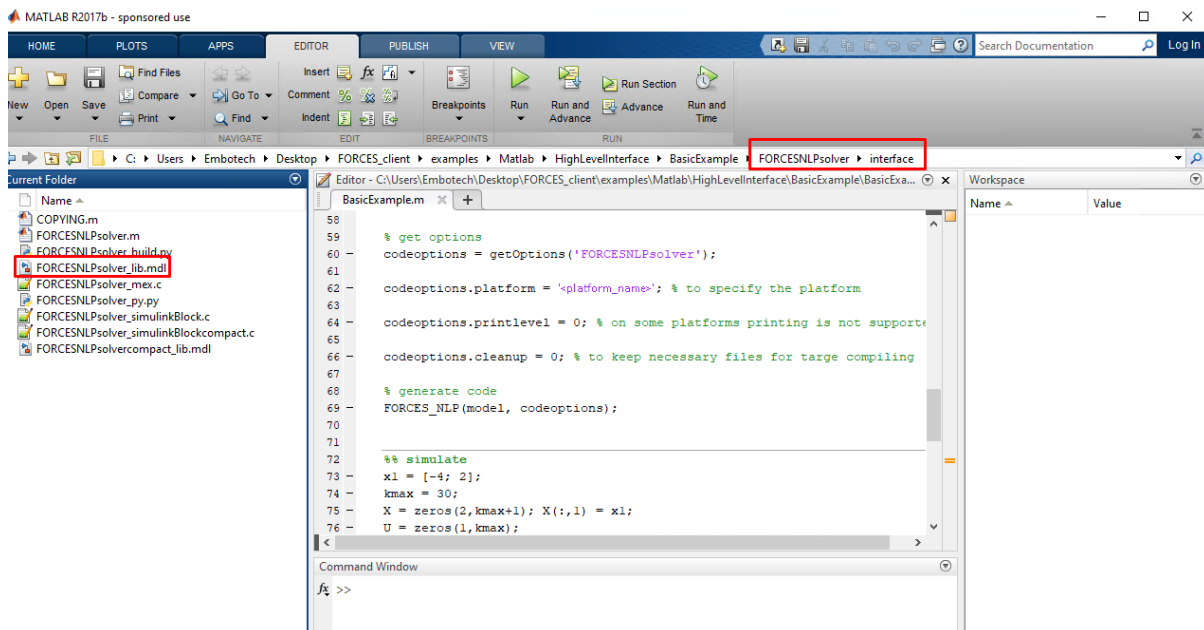


Figure 13.5: Open the generated Simulink solver model.

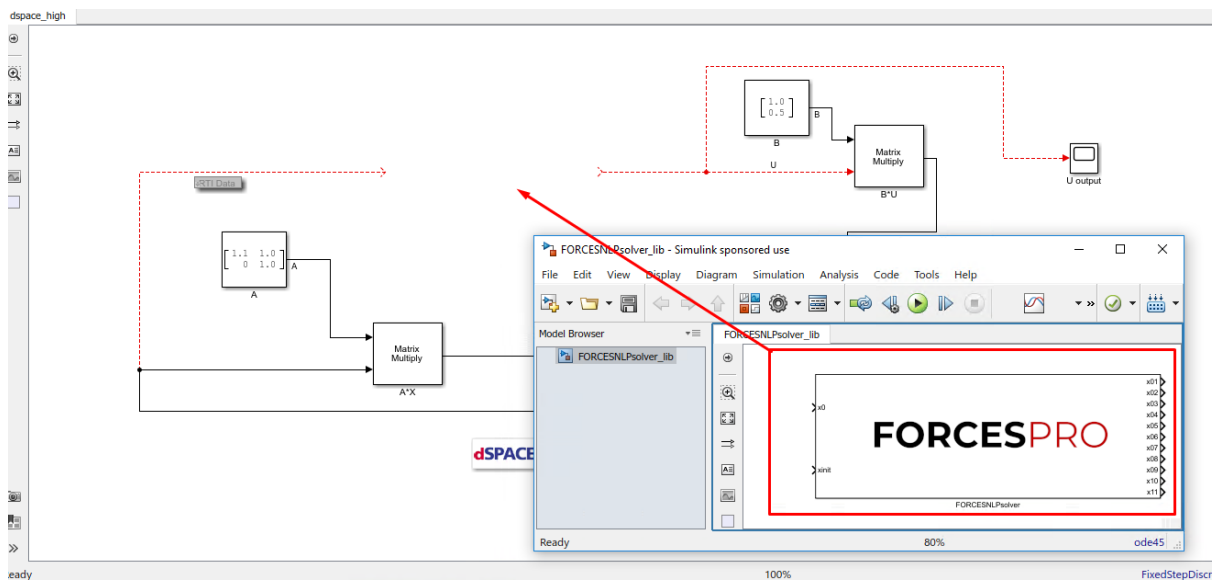


Figure 13.6: Copy-paste and connect the FORCESPRO block.

7. (Figure 13.7) Access the Simulink model's options.
8. (Figure 13.8) In the "Solver" tab, set the options:
 - Simulation start/stop time: Depending on the simulation wanted.
 - Solver type: Discrete or fixed-step.
 - Fixed-step size: Needs to be higher than the execution time of the solver.
9. (Figure 13.9) In the "Code Generation" tab, set the options (for <tlc_file> and <makefile_template> see *Simulink Model HW Target Configuration*):
 - System target file: <tlc_file>

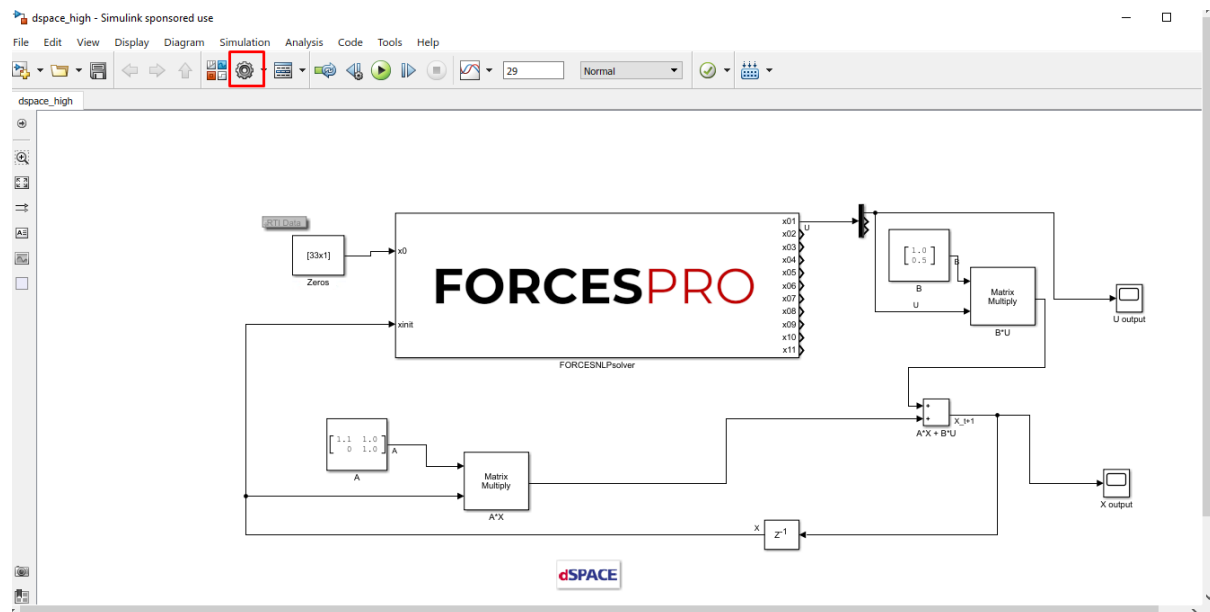


Figure 13.7: Open the Simulink model options.

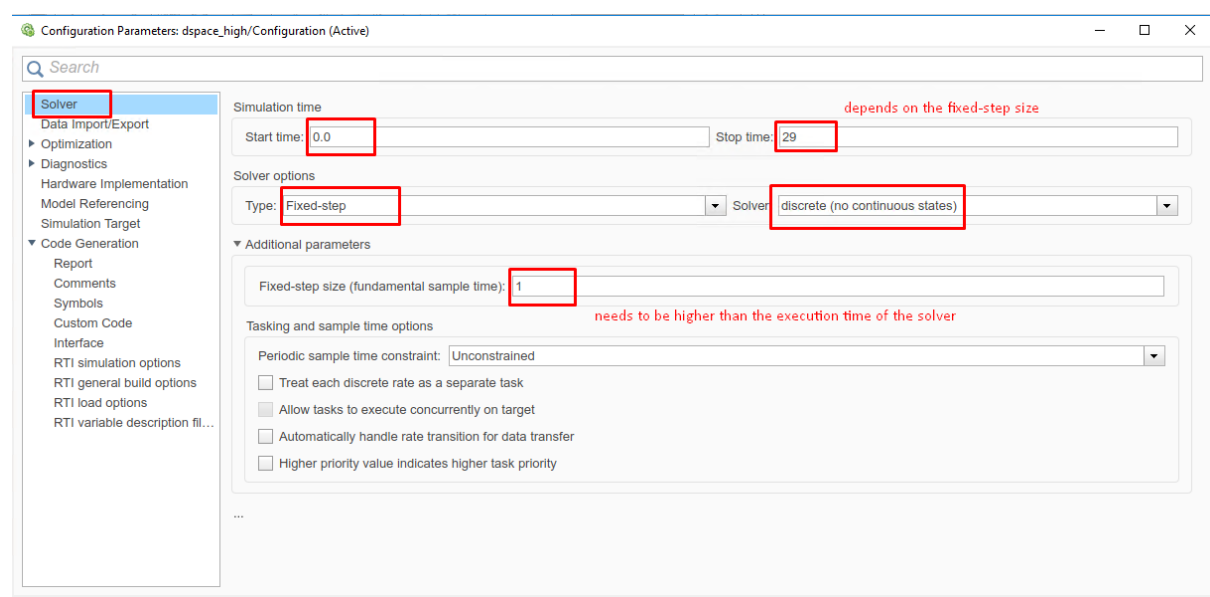


Figure 13.8: Set the Simulink solver options.

- Language: C
 - Generate makefile: On
 - Template makefile: <makefile_template>
 - Make command: make_rti
10. (Figure 13.10) In the “Code Generation/Custom Code” tab, include the directories:
 - BasicExample
 - BasicExample\FORCESNLPsolver\interface
 - BasicExample\FORCESNLPsolver\lib_target
 11. (Figure 13.11) In the “Code Generation/Custom Code” tab, add the source files:
 - FORCESNLPsolver_simulinkBlock.c
 - FORCESNLPsolver_casadi2forces.c
 - FORCESNLPsolver_casadi.c
 12. (Figure 13.12) In the “Code Generation/Custom Code” tab, add the library file:
 - FORCESNLPsolver.lib

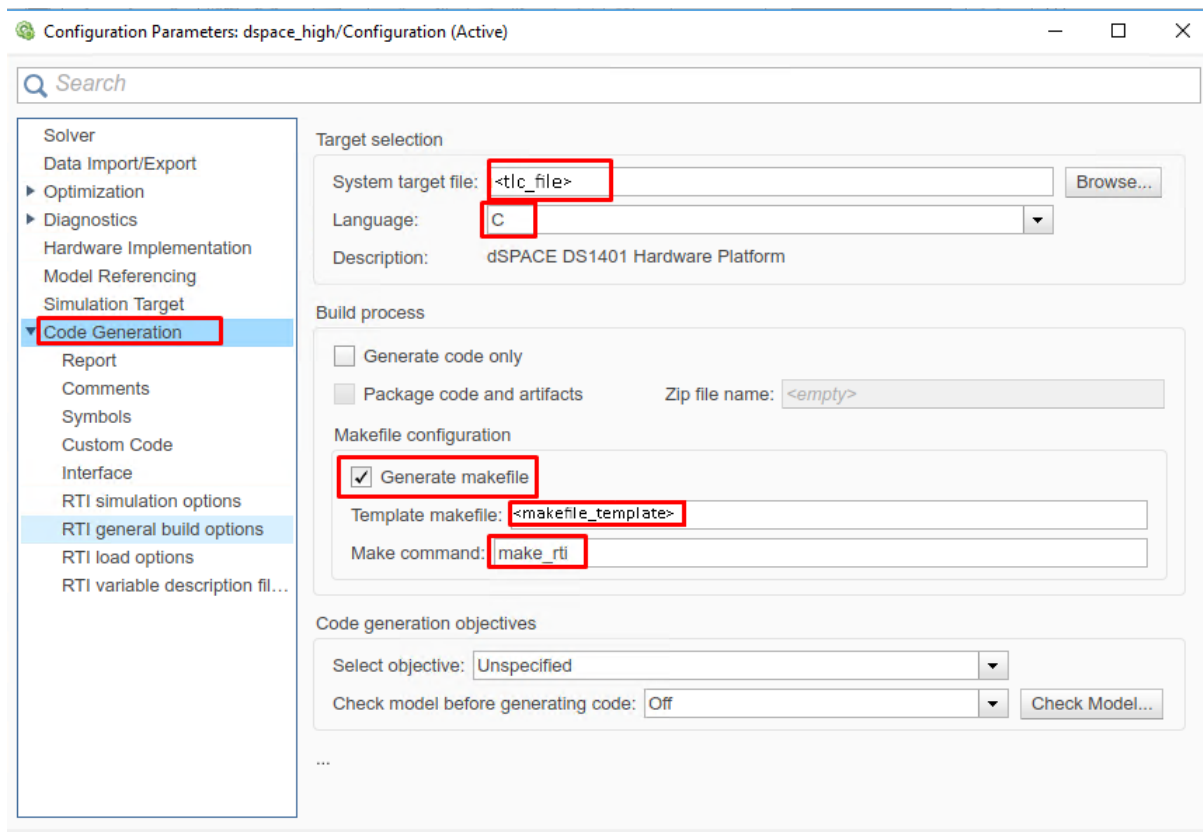


Figure 13.9: Set the Simulink code generation options.

13. (Figure 13.13) Access the FORCESPRO block’s parameters.
14. (Figure 13.14) Remove the “FORCESNLPsolver” prefix from the S-function module.
15. (Figure 13.15) Compile the code of the Simulink model. This will also automatically load the model to the connected dSPACE platform.
16. Deployment is complete and simulations can now be run on the dSPACE platform.

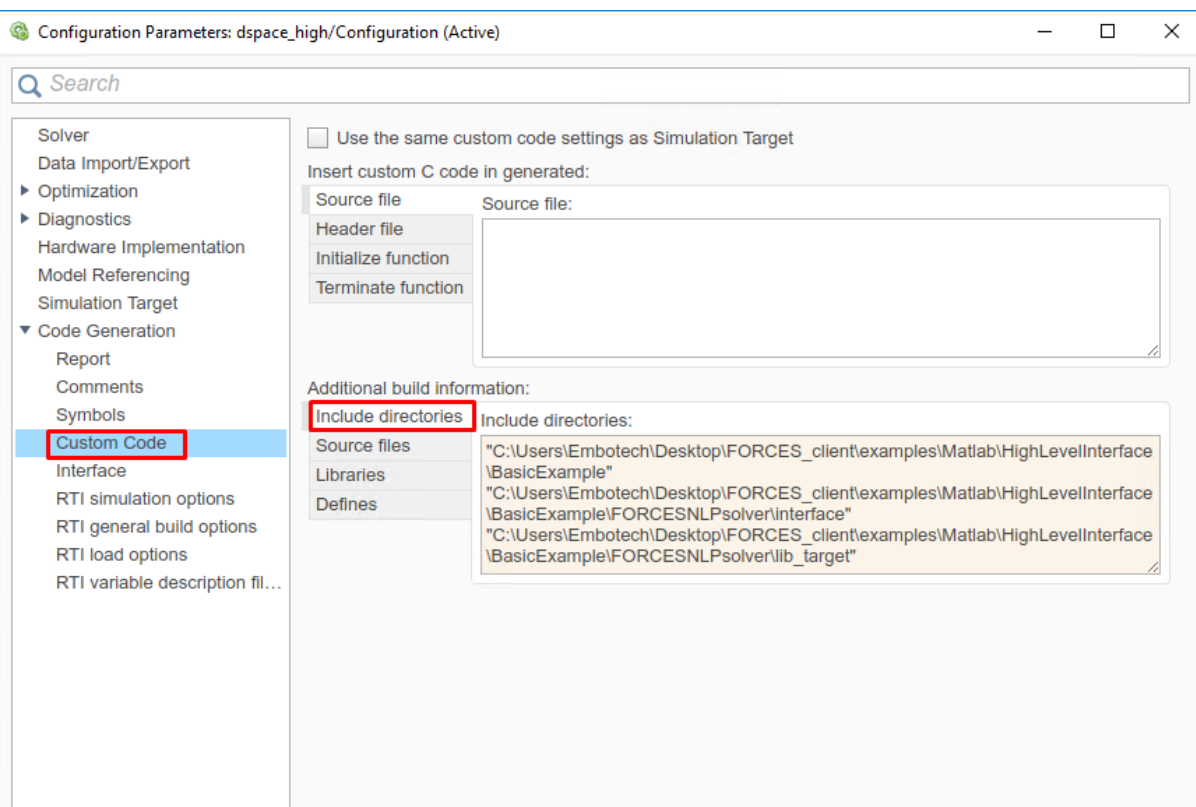


Figure 13.10: Add the directories included for the code generation.

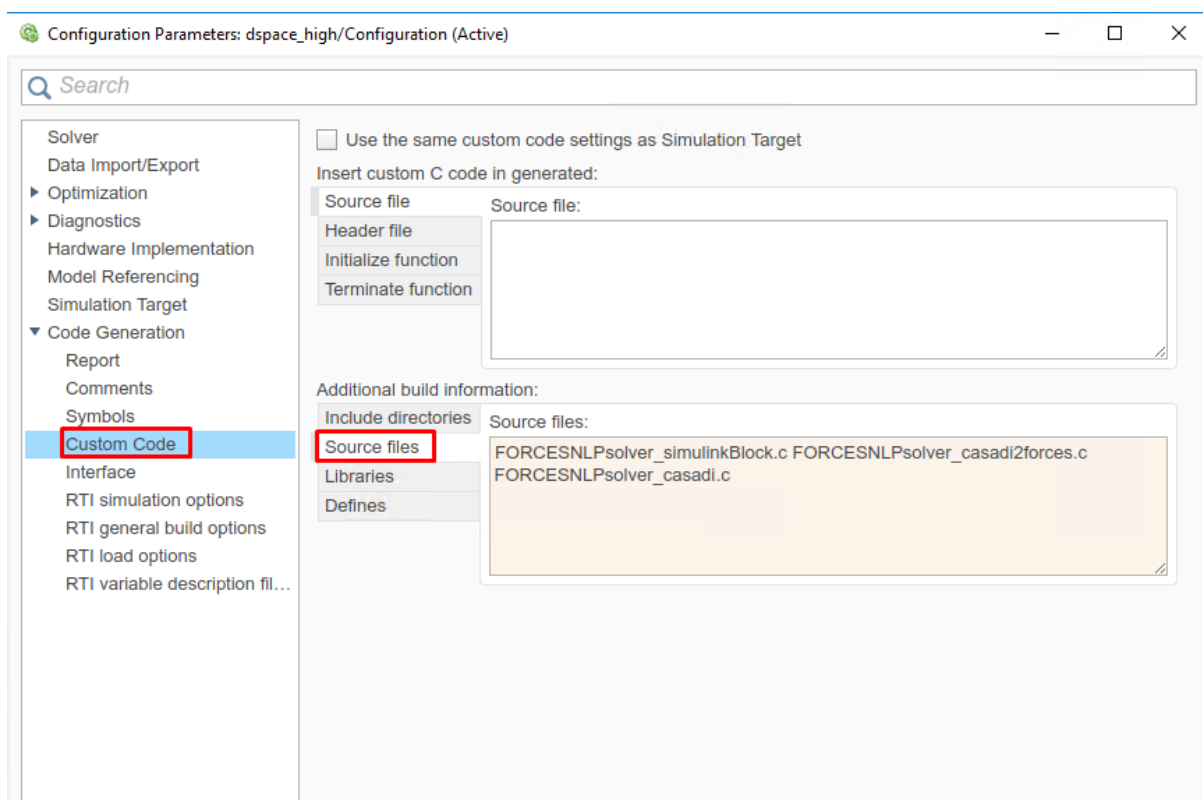


Figure 13.11: Add the source files used for the code generation.

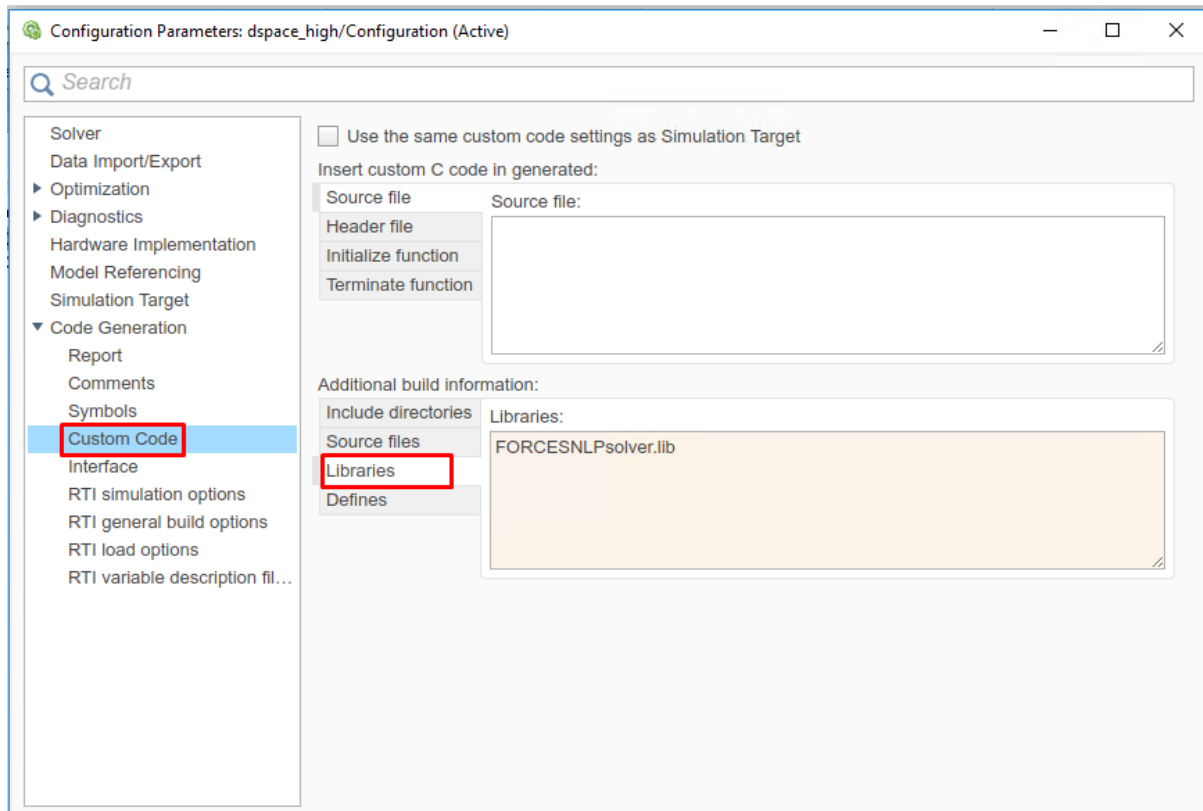


Figure 13.12: Add the libraries used for the code generation.

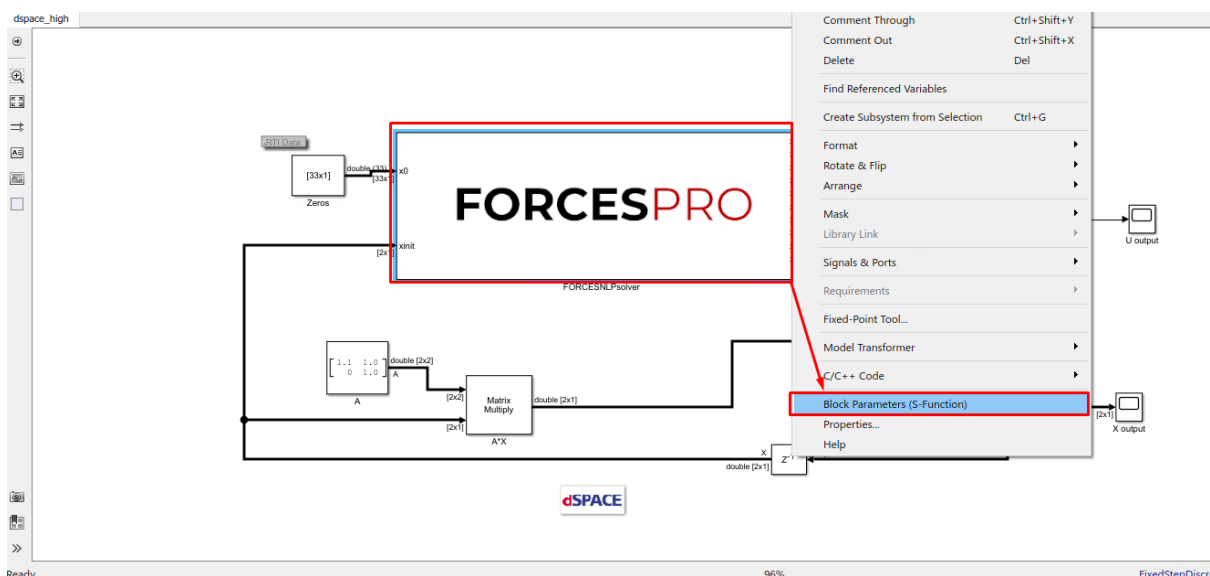


Figure 13.13: Open the FORCESPRO block's parameters.

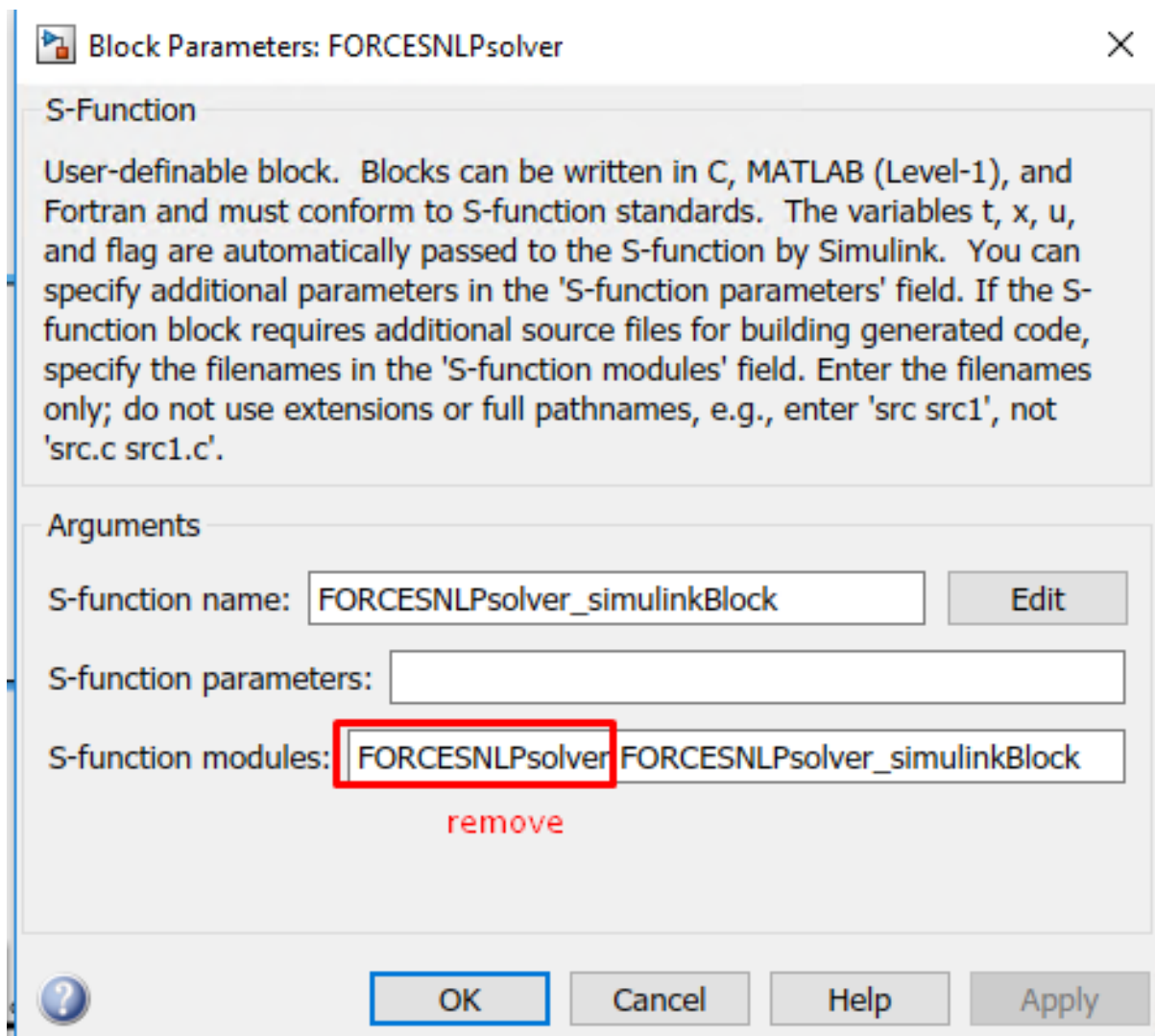


Figure 13.14: Remove the leading solver name from the S-function module.

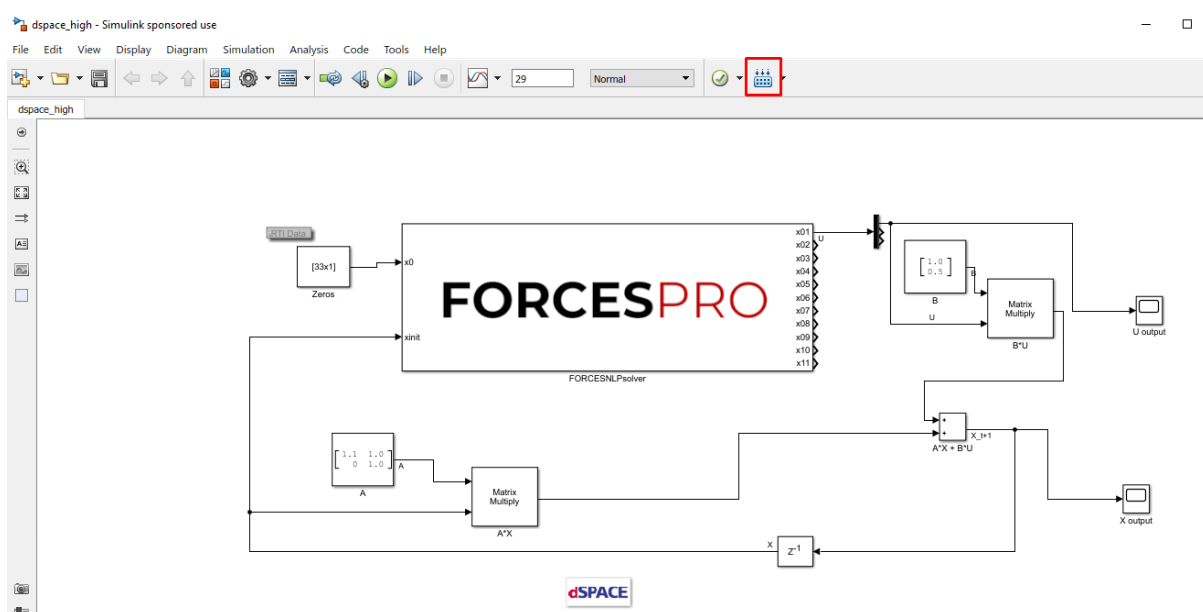


Figure 13.15: Compile the code of the Simulink model.

13.2.3 Y2F interface

Instructions

The steps to deploy and simulate a FORCESPRO controller on a dSPACE platform are detailed below.

1. (Figure 13.16) Set the code generation options (for <platform_name> see *Platform name codeoption*):

```
codeoptions.platform = '<platform_name>'; % to specify the platform
codeoptions.printlevel = 0; % on some platforms printing is not supported
```

and then generate the code for your solver (henceforth referred to as “simplempc_solver”, placed in the folder “Y2F”) using the Y2F interface.

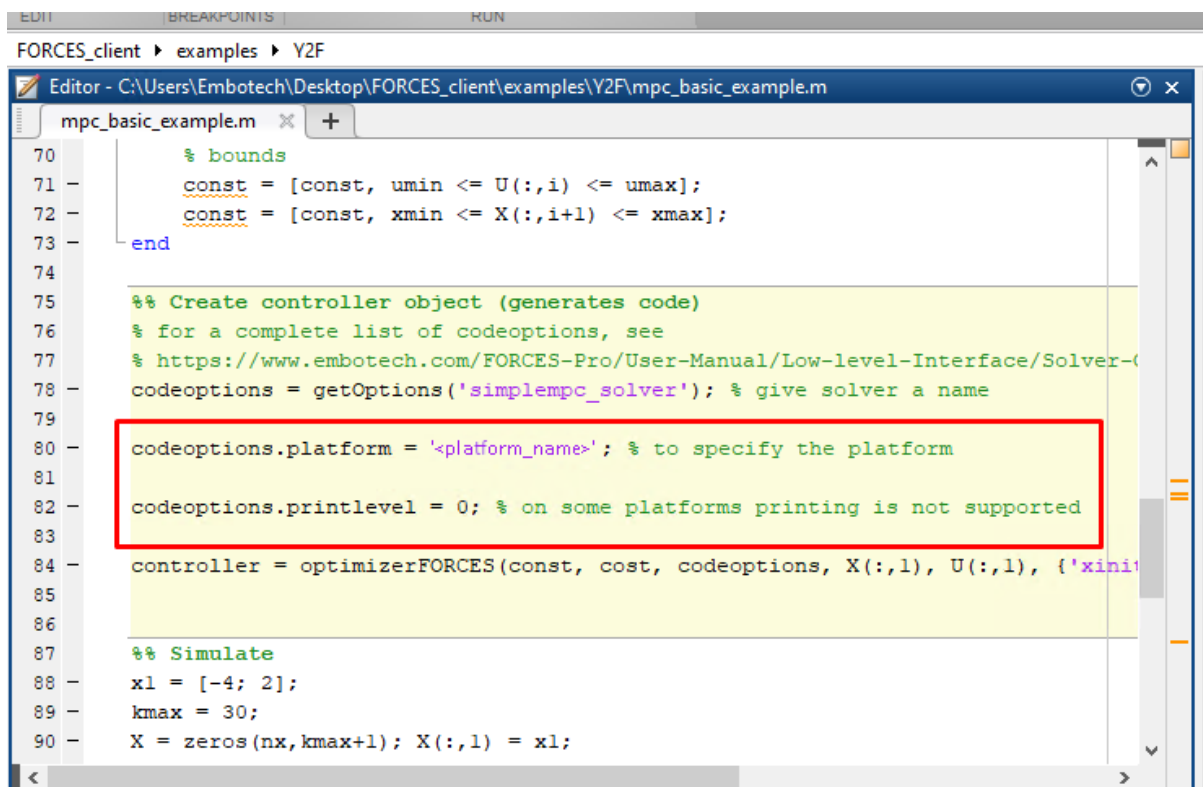


Figure 13.16: Set the appropriate code generation options.

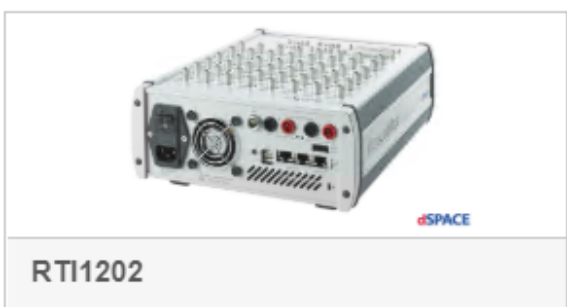
2. (Figure 13.17) Create a new Simulink model using the Simulink model template provided by dSPACE (for <simulink_model_template> see *Simulink Model HW Target Configuration*).
3. (Figure 13.18) Populate the Simulink model with the system you want to control.
4. (Figure 13.19) Make sure the simplempc_solver_simulinkBlock.mexw64 file (created during code generation) is on the Matlab path.
5. (Figure 13.20) Copy-paste the FORCESPRO Simulink block, contained in the created y2f_simulink_lib.slx Simulink model file, into your simulation model and connect its inputs and outputs appropriately.
6. (Figure 13.21) Access the Simulink model's options.
7. (Figure 13.22) In the “Solver” tab, set the options:
 - Simulation start/stop time: Depending on the simulation wanted.



dSPACE
MicroAutoBox II



dSPACE
AutoBox



dSPACE
MicroLabBox

Figure 13.17: Create a Simulink model.

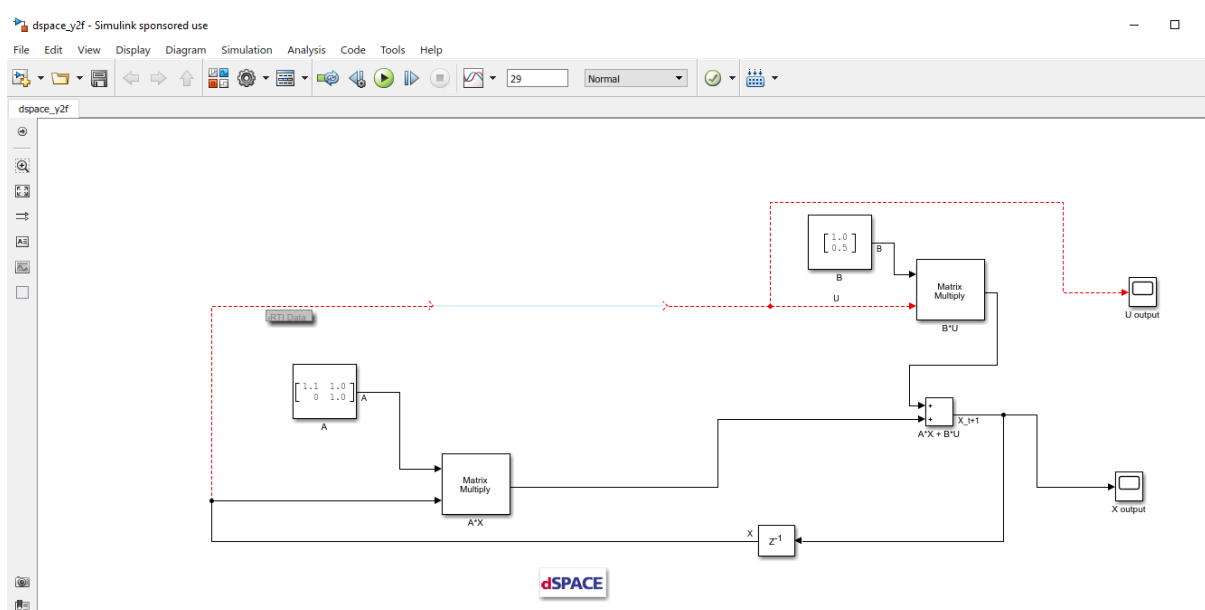


Figure 13.18: Populate the Simulink model.

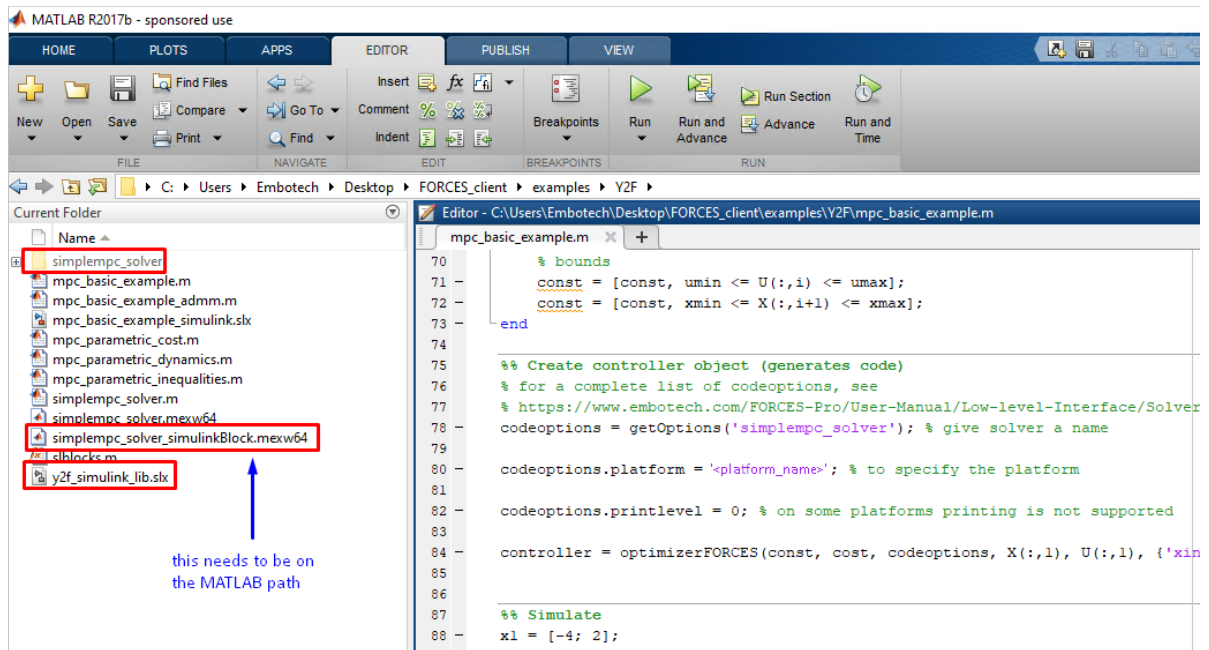


Figure 13.19: Add the folder containing the .mexw64 solver file to the Matlab path.

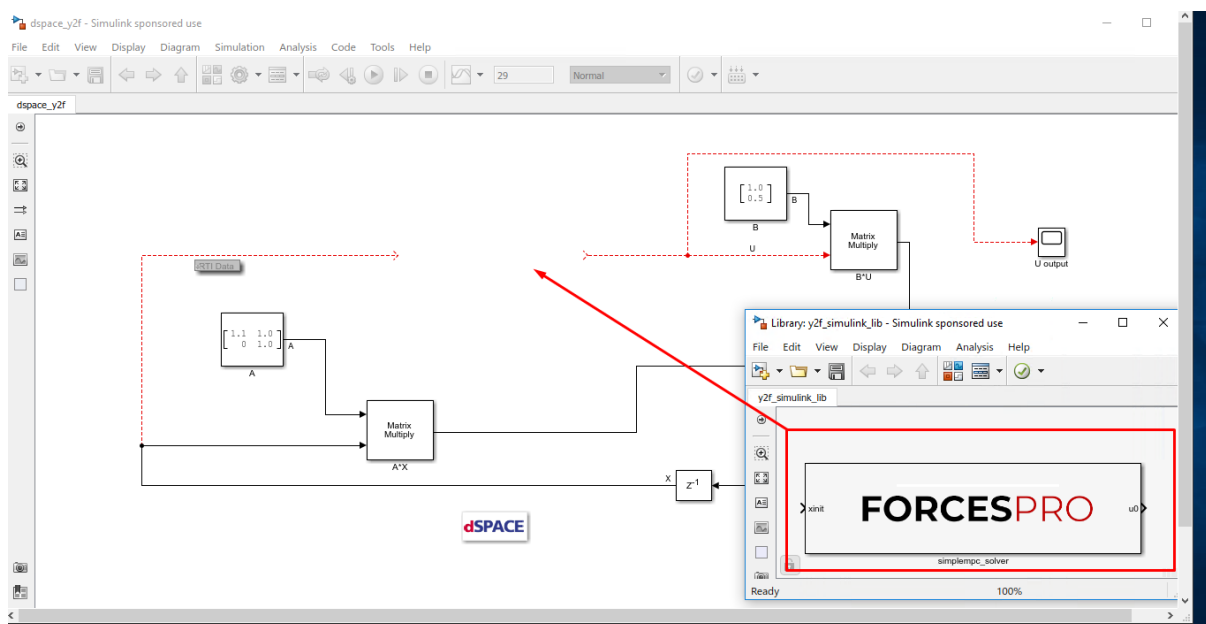


Figure 13.20: Copy-paste and connect the FORCESPRO block.

- Solver type: Discrete or fixed-step.
- Fixed-step size: Needs to be higher than the execution time of the solver.

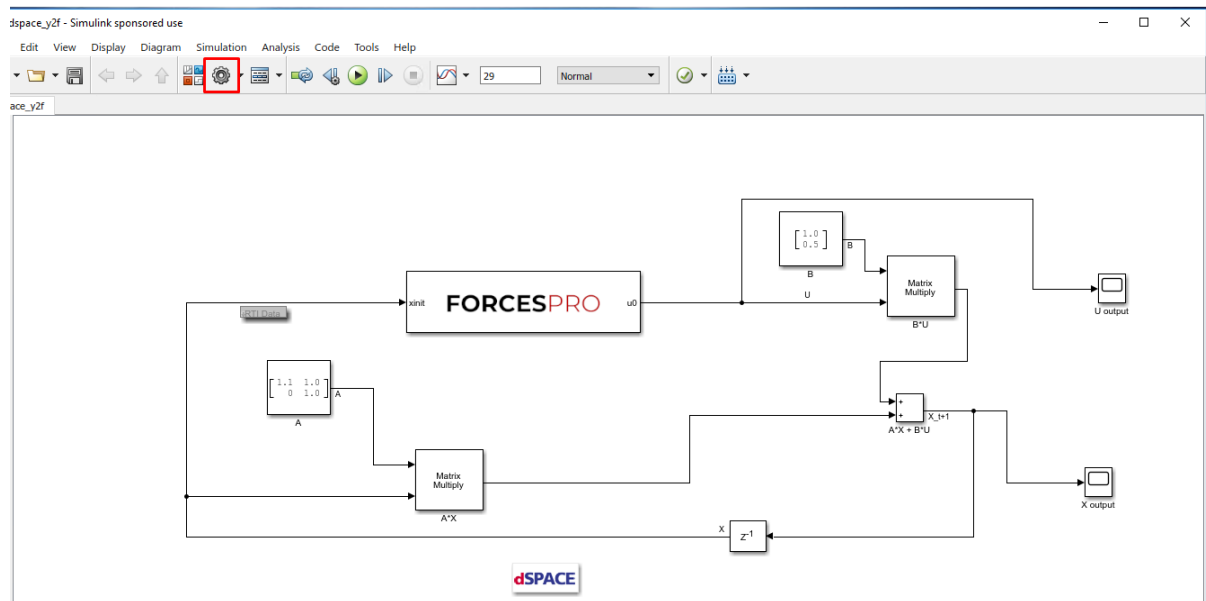


Figure 13.21: Open the Simulink model options.

- (Figure 13.23) In the “Code Generation/RTI general build options” tab, set the options (for `<tlc_file>` and `<makefile_template>` see *Simulink Model HW Target Configuration*):
 - System target file: `<tlc_file>`
 - Language: C
 - Generate makefile: On
 - Template makefile: `<makefile_template>`
 - Make command: `make_rti`
- (Figure 13.24) In the “Code Generation/Custom Code” tab, include the directories:
 - Y2F
 - Y2F\simplempc_solver\interface
 - Y2F\simplempc_solver\lib_target
- (Figure 13.25) In the “Code Generation/Custom Code” tab, add the source files:
 - `simplempc_solver_simulinkBlock.c`
 - `simplempc_solver.c`
- (Figure 13.26) In the “Code Generation/Custom Code” tab, add the library files:
 - `internal_simplempc_solver_1.lib`
- (Figure 13.27) Compile the code of the Simulink model. This will also automatically load the model to the connected dSPACE platform.
- Deployment is complete and simulations can now be run on the dSPACE platform.

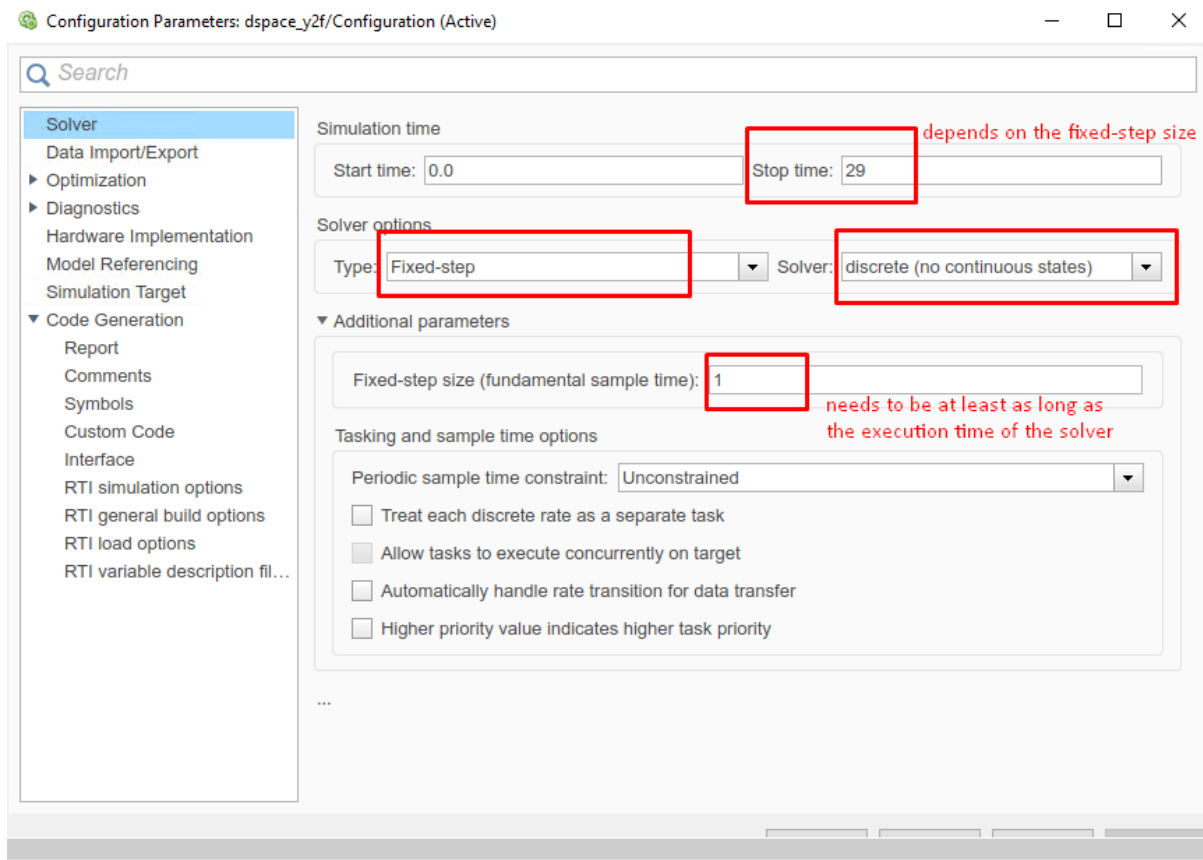


Figure 13.22: Set the Simulink solver options.

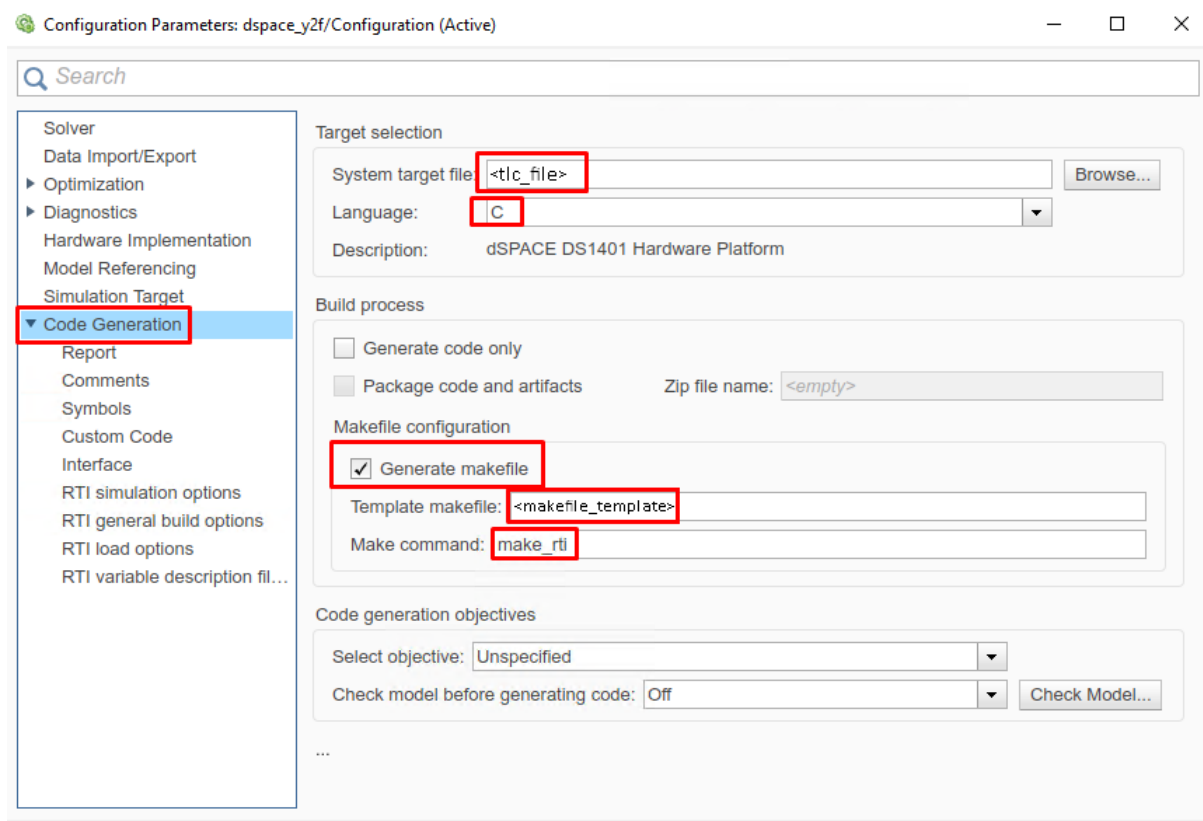


Figure 13.23: Set the Simulink code generation options.

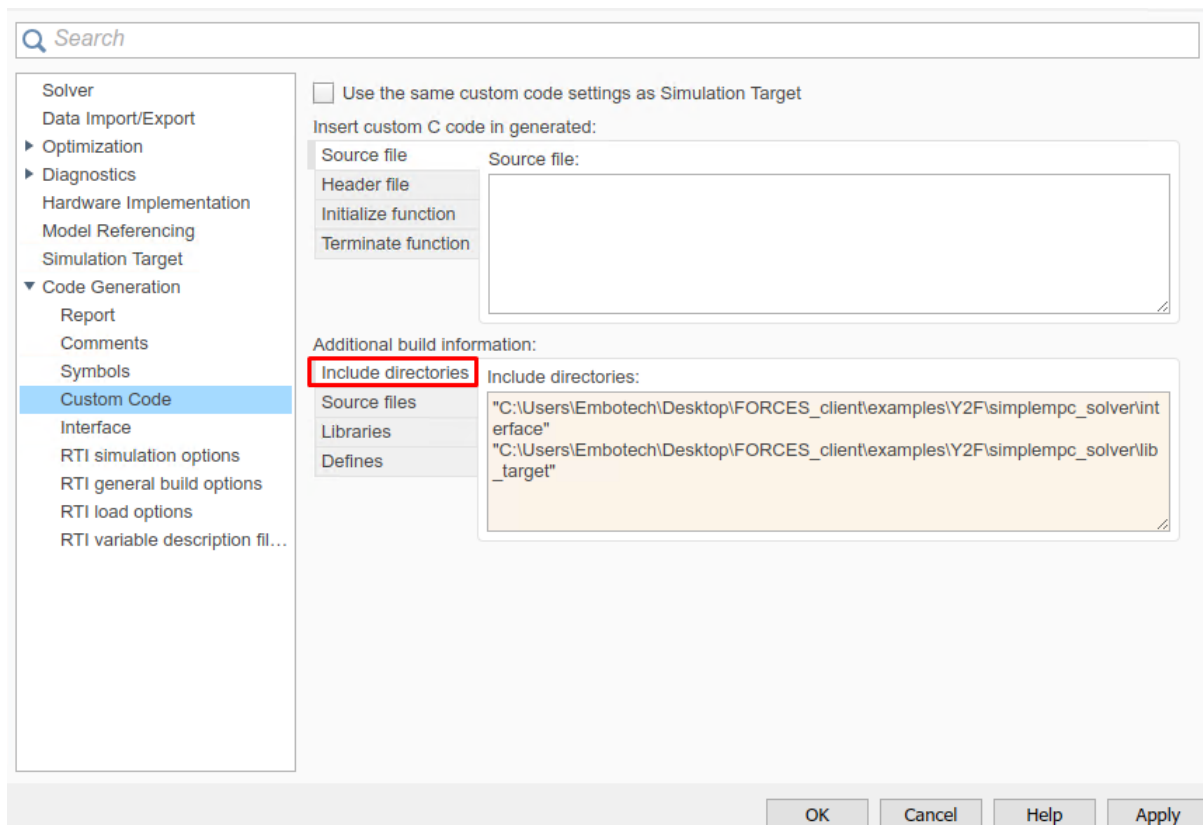


Figure 13.24: Add the directories included for the code generation.

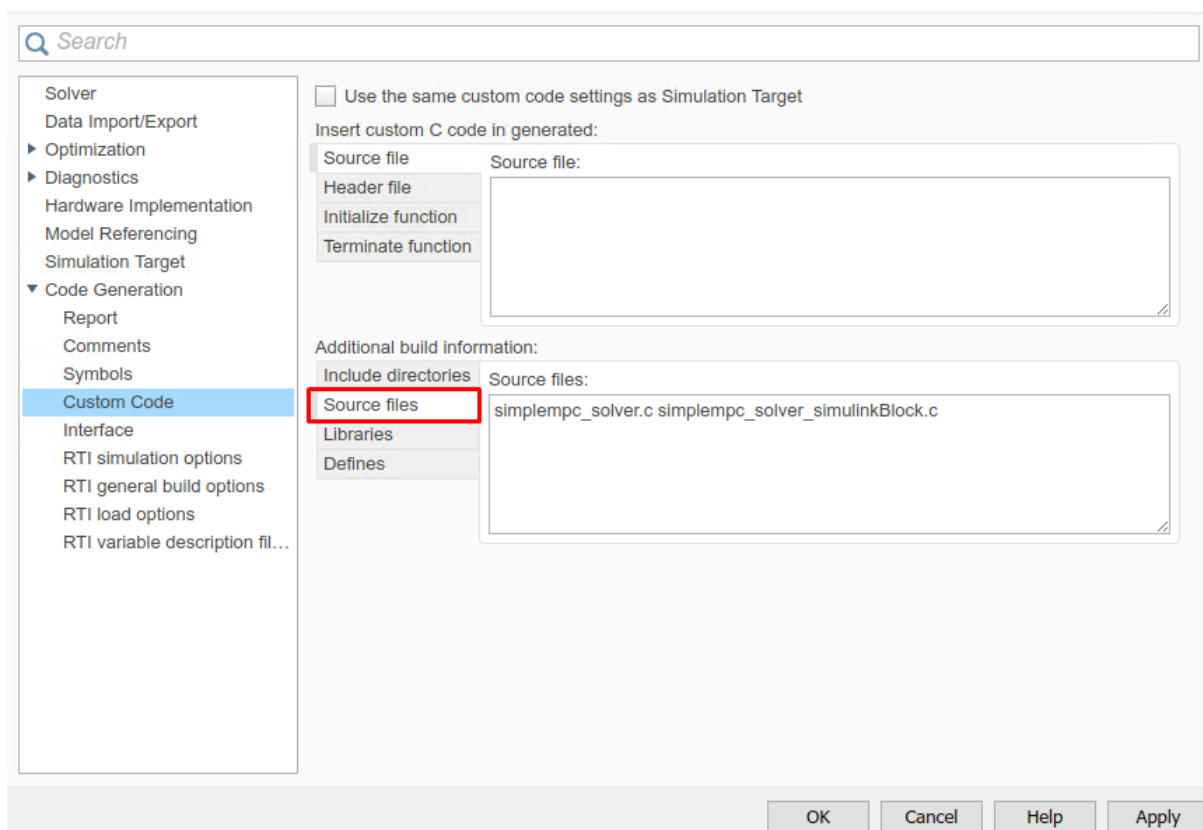


Figure 13.25: Add the source files used for the code generation.

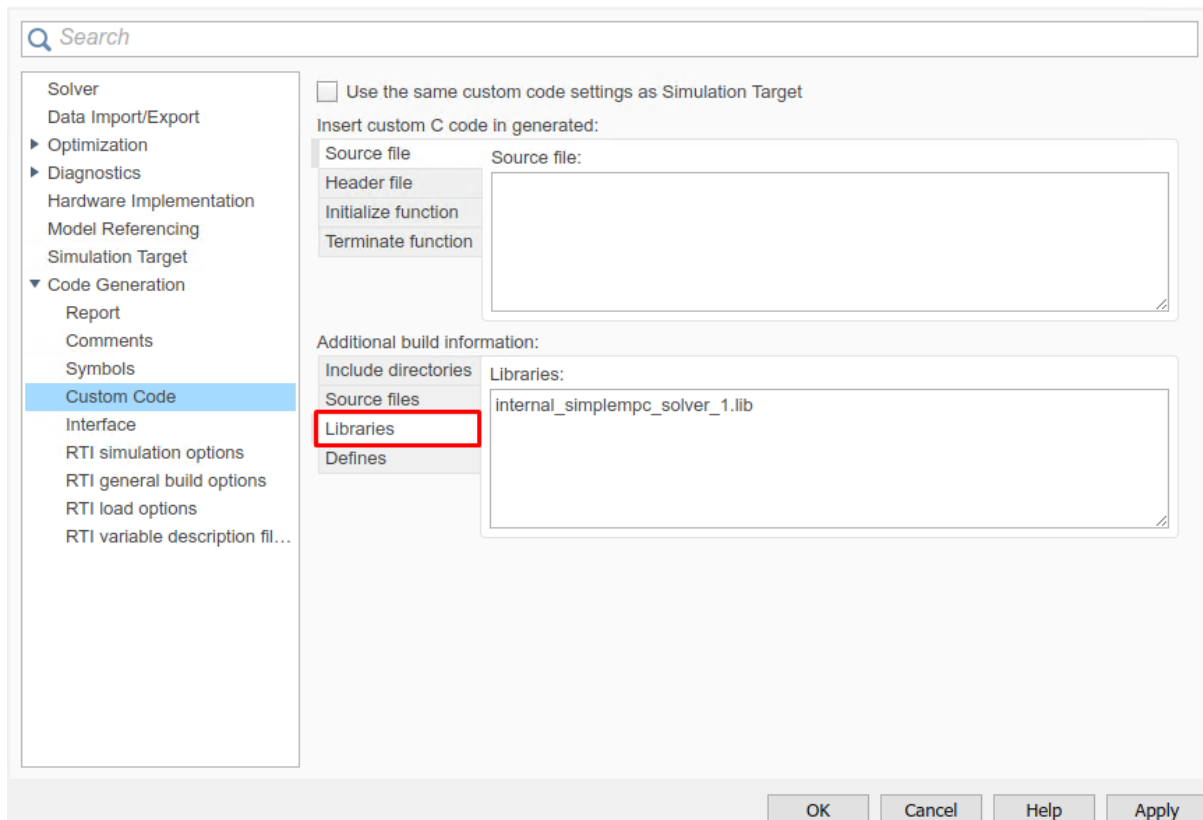


Figure 13.26: Add the libraries used for the code generation.

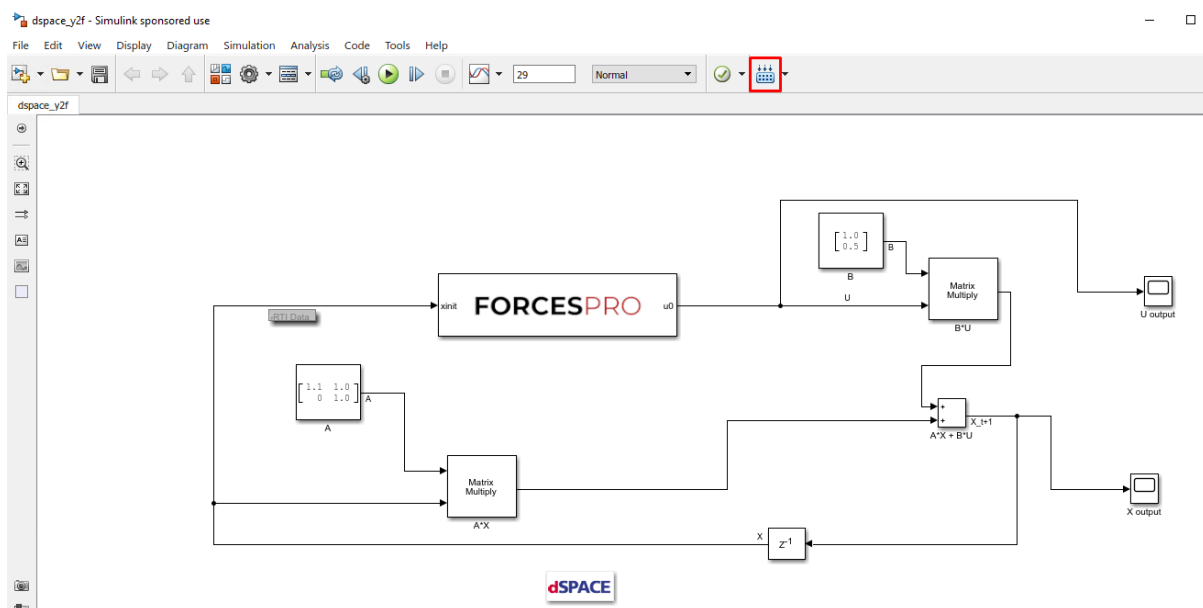


Figure 13.27: Compile the code of the Simulink model.

13.3 dSPACE deployment through ConfigurationDesk

- *Code Generation*
- *Solver Execution*

This process applies to the following dSPACE platforms

- **dSPACE MicroAutoBox III**
- **dSPACE SCALEXIO**

Important: When deploying to a target hardware platform, the library included in the **lib_target** directory of the generated solver should be used instead of the library in the **lib** directory.

13.3.1 Code Generation

The steps to deploy a FORCESPRO controller on a dSPACE platform are detailed below.

- 1) (Figure 13.28) Set the code generation options:

When generating code for HW target platforms, `codeoptions.platform` needs to be set.

- **dSPACE MicroAutoBox III:** 'dSPACE-MABXIII'
- **dSPACE SCALEXIO:** 'dSPACE-SCALEXIO'

```
codeoptions.platform = '<platform_name>'; % to generate code for the dSPACE_
↳platform
codeoptions.printlevel = 0; % printing should be disabled on target HW
codeoptions.cleanup = 0; % to keep necessary files for target compile
```

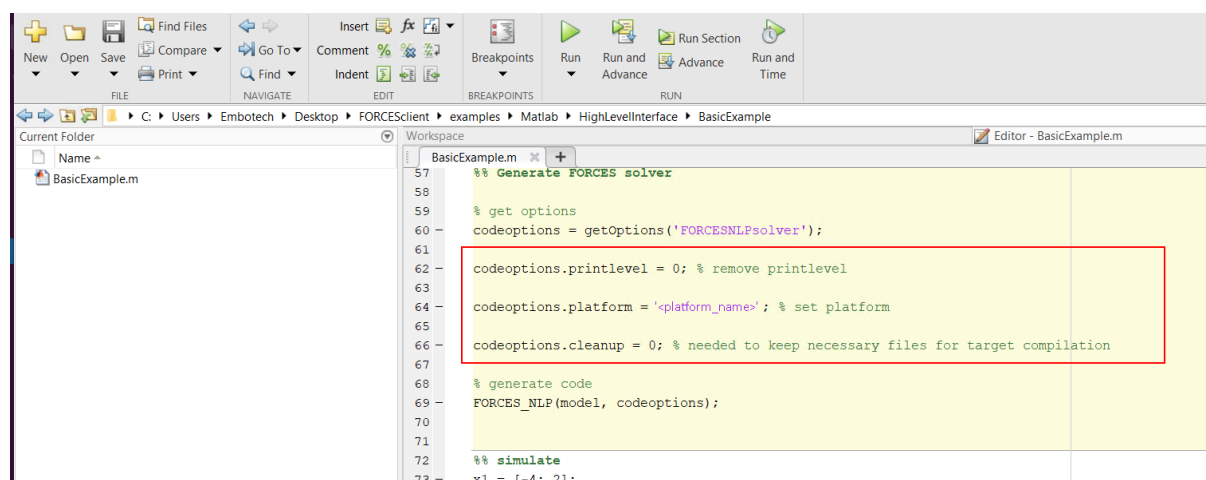


Figure 13.28: Set the appropriate code generation options.

- 1) Create a new Simulink model (henceforth referred to as `dSPACE.slx`) using the dSPACE Run-Time Target template provided by dSPACE and save it in the BasicExample folder (see Figure 13.29).
- 2) Populate the Simulink model with the system you want to control (see Figure 13.30).

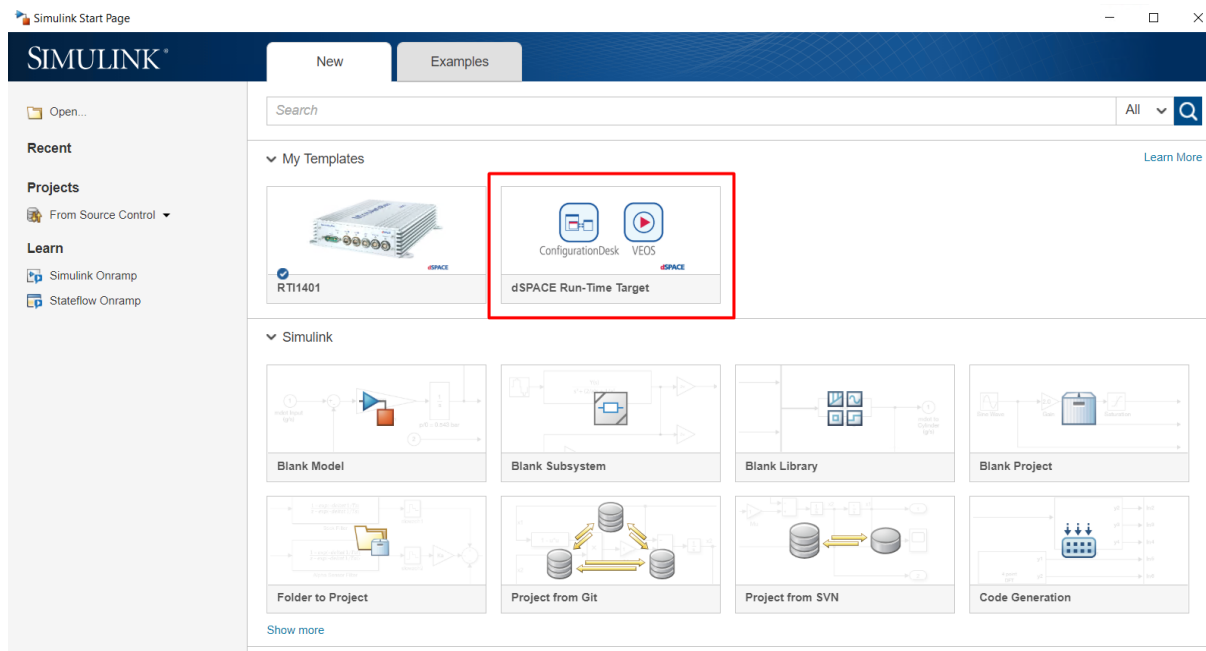


Figure 13.29: Create a Simulink model.

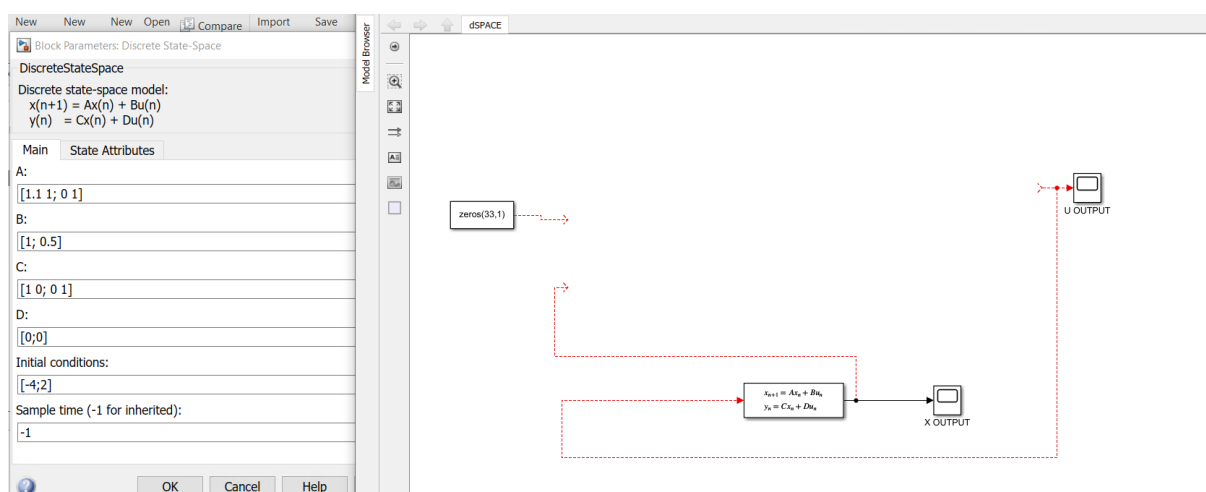


Figure 13.30: Populate the Simulink model.

- 4) Run the BasicExample.m script to perform code generation for your solver (henceforth referred to as FORCESNLPsolver, placed in the folder "BasicExample"). This will create the necessary files for your building (see [Figure 13.31](#), [Figure 13.32](#) and [Figure 13.33](#)).
- 5) The FORCESNLPsolver_simulinkBlock.<mex_extension> file (created during code generation) needs to be in the same path as your model (see [Figure 13.34](#)).
- 6) Open the FORCESNLPsolver_lib.mdl Simulink model file, contained in the interface folder of the FORCESNLPsolver folder created during code generation (see [Figure 13.35](#)).
- 7) Copy-paste the FORCESPRO Simulink block into your simulation model and connect its inputs and outputs appropriately (see [Figure 13.36](#)).
- 8) Access the Simulink model's options. In the "Solver" tab, set the options (see [Figure 13.37](#)):
 - Simulation start/stop time: Depending on the simulation wanted.
 - Solver type: Discrete or fixed-step.
 - Fixed-step size: Needs to be higher than the execution time of the solver.
- 9) In the "Code Generation" tab, set the options (see [Figure 13.38](#)):
 - System target file: dsrt.tlc
 - Language: c / c++
 - Generate makefile: Checked
 - Template makefile: dsrt_default_tmf
 - Make command: make_dsrt
- 10) In the "Code Generation/Custom Code" tab, include the directories (see [Figure 13.39](#)):
 - .\FORCESNLPsolver\include
 - .\FORCESNLPsolver\interface
 - .\FORCESNLPsolver\lib_target
- 11) In the "Code Generation/Custom Code" tab, add the source files (see [Figure 13.40](#)):
 - FORCESNLPsolver_simulinkBlock.c
 - FORCESNLPsolver_casadi2forces.c
 - FORCESNLPsolver_casadi.c
- 12) In the "Code Generation/Custom Code" tab, add the library file (see [Figure 13.41](#)):
 - libFORCESNLPsolver.a
- 13) Access the FORCESPRO block's parameters (see [Figure 13.42](#)).
- 14) Remove the "FORCESNLPsolver" prefix from the S-function module (see [Figure 13.43](#)).
- 15) Create a new Project and Application in ConfigurationDesk. Select directory of project, name of project and application, the model dSPACE.slx as the application process and connected dSPACE platform to deploy to (see [Figure 13.44](#)).
- 16) Go to the tasks tab and make sure the period of the Periodic Task matches the fixed step size selected in the Simulink model options (see [Figure 13.45](#)).
- 17) Go to the build tab and start the building process. After building is complete the application will be loaded automatically in the dSPACE platform (see [Figure 13.46](#)).

Current Folder		
	Name ▲	Git
	FORCESNLPsolver	•
	BasicExample.m	■
	dSPACE.slx	○
	FORCESNLPsolver.m	•
	FORCESNLPsolver.mexw64	•
	FORCESNLPsolver_casadi.c	•
	FORCESNLPsolver_casadi.h	•
	FORCESNLPsolver_casadi.obj	•
	FORCESNLPsolver_casadi2forces.c	•
	FORCESNLPsolver_casadi2forces.obj	•
	FORCESNLPsolver_mex_compiler_warnings.txt	•
	FORCESNLPsolver.py.py	•
	FORCESNLPsolver_simulinkBlock.mexw64	•
	FORCESNLPsolver_simulinkBlockcompact.mexw64	•

Figure 13.31: Generated files.

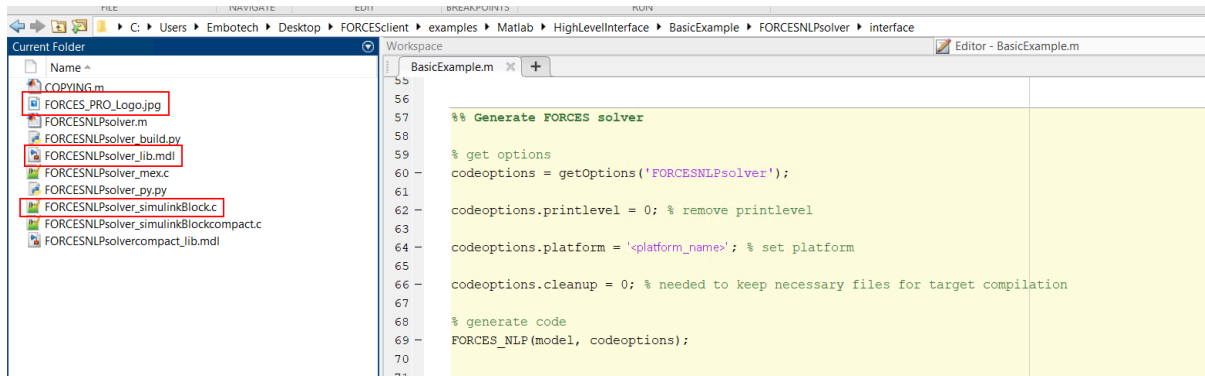


Figure 13.32: Solver interface files.

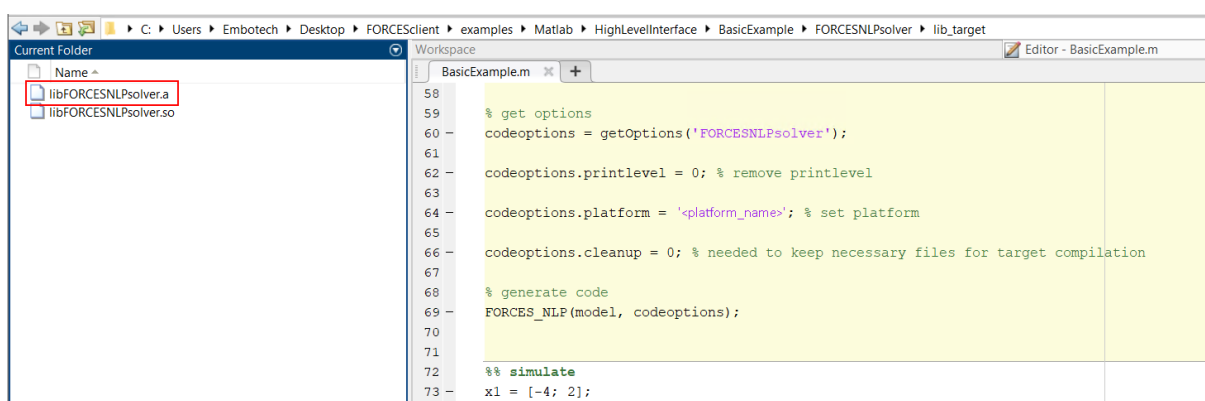


Figure 13.33: Solver libraries.

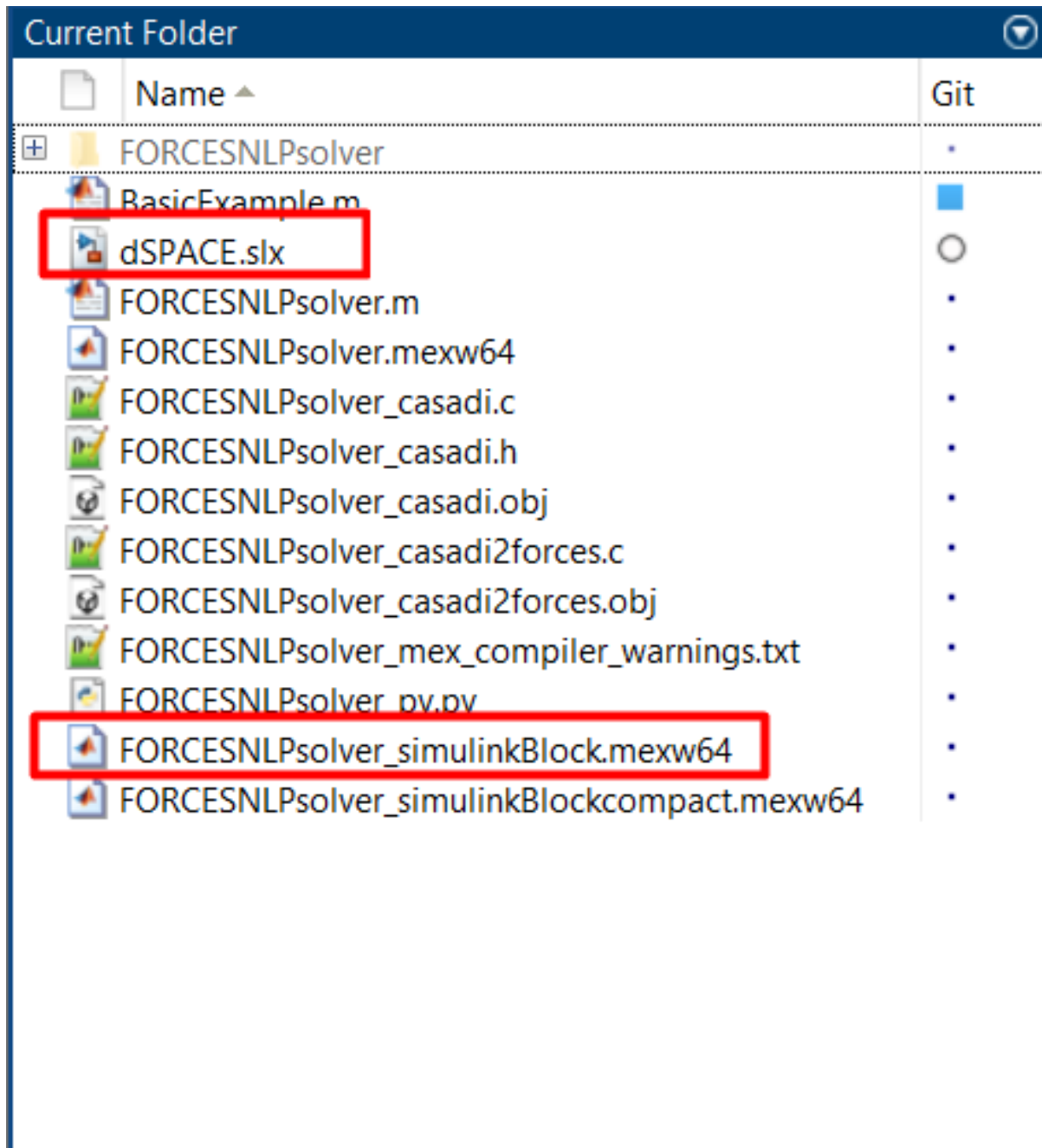


Figure 13.34: The `.<mex_extension>` solver file is in the same path as the model.

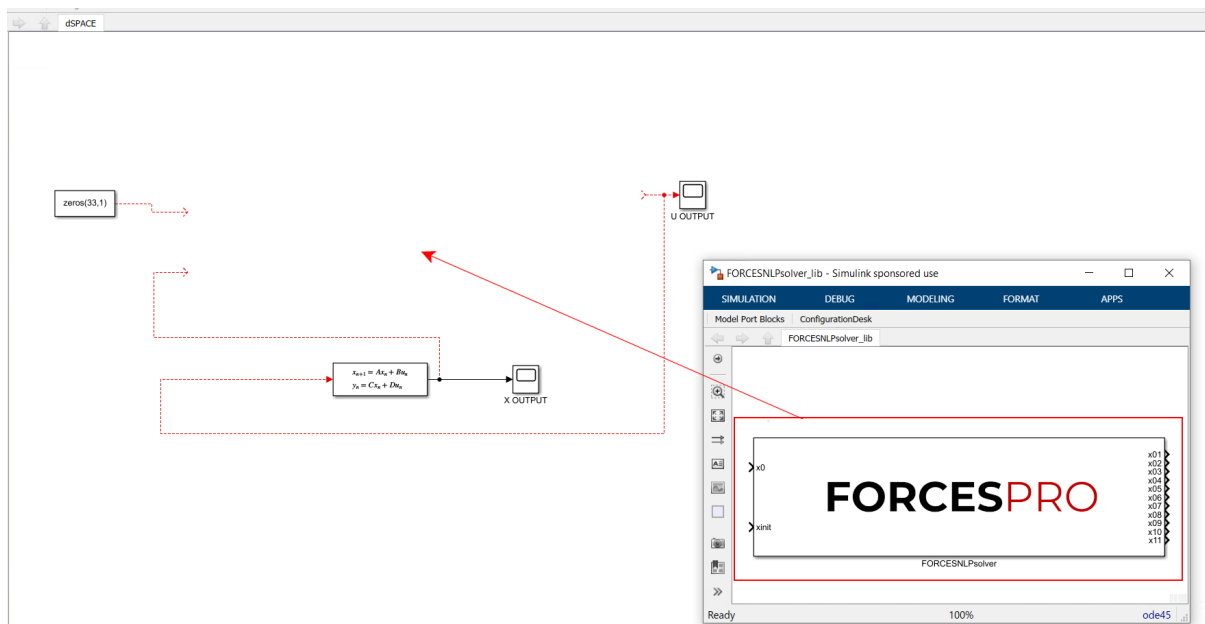


Figure 13.35: Open the generated Simulink solver model.

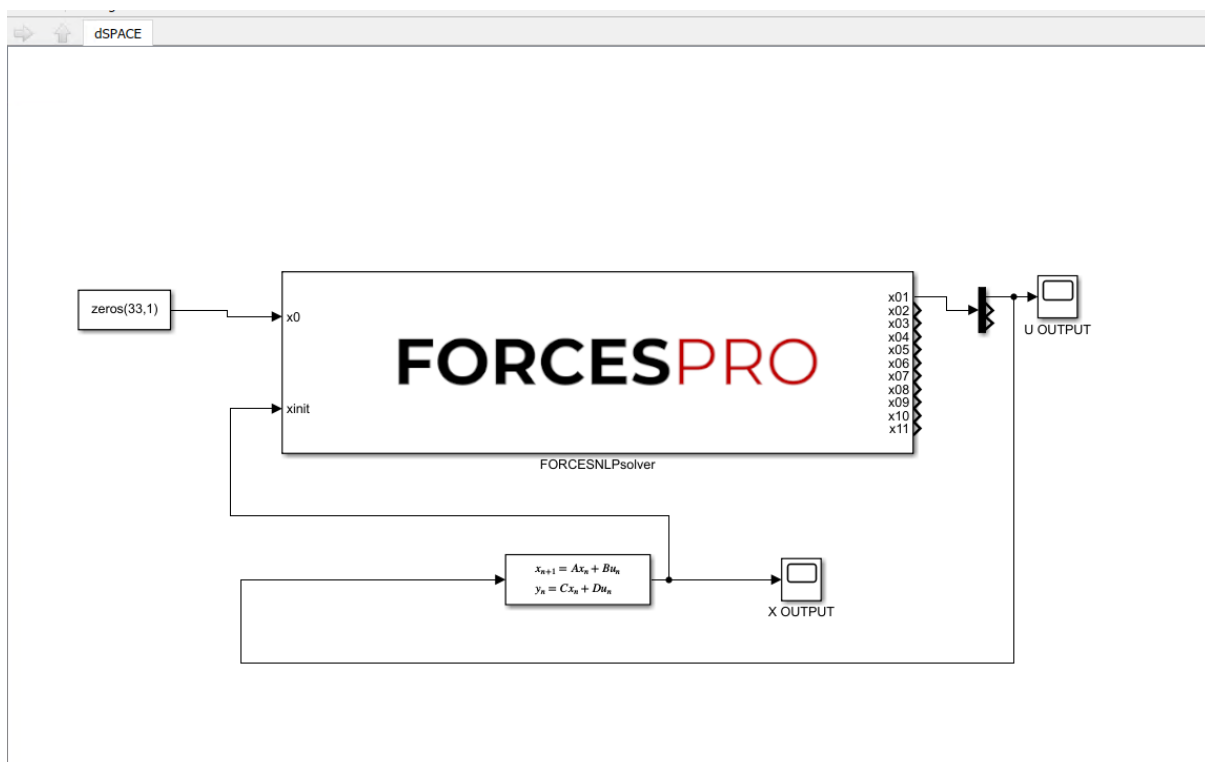


Figure 13.36: Copy-paste and connect the FORCESPRO block.

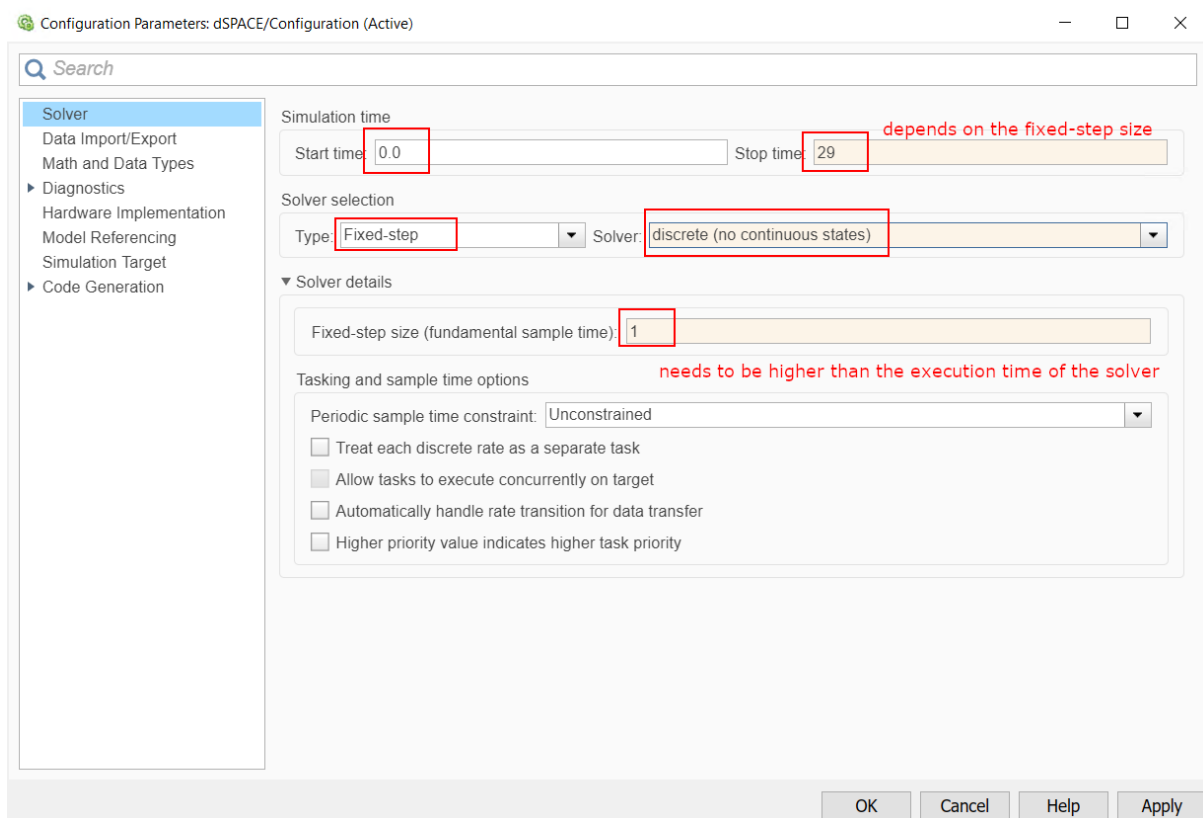


Figure 13.37: Set the Simulink solver options.

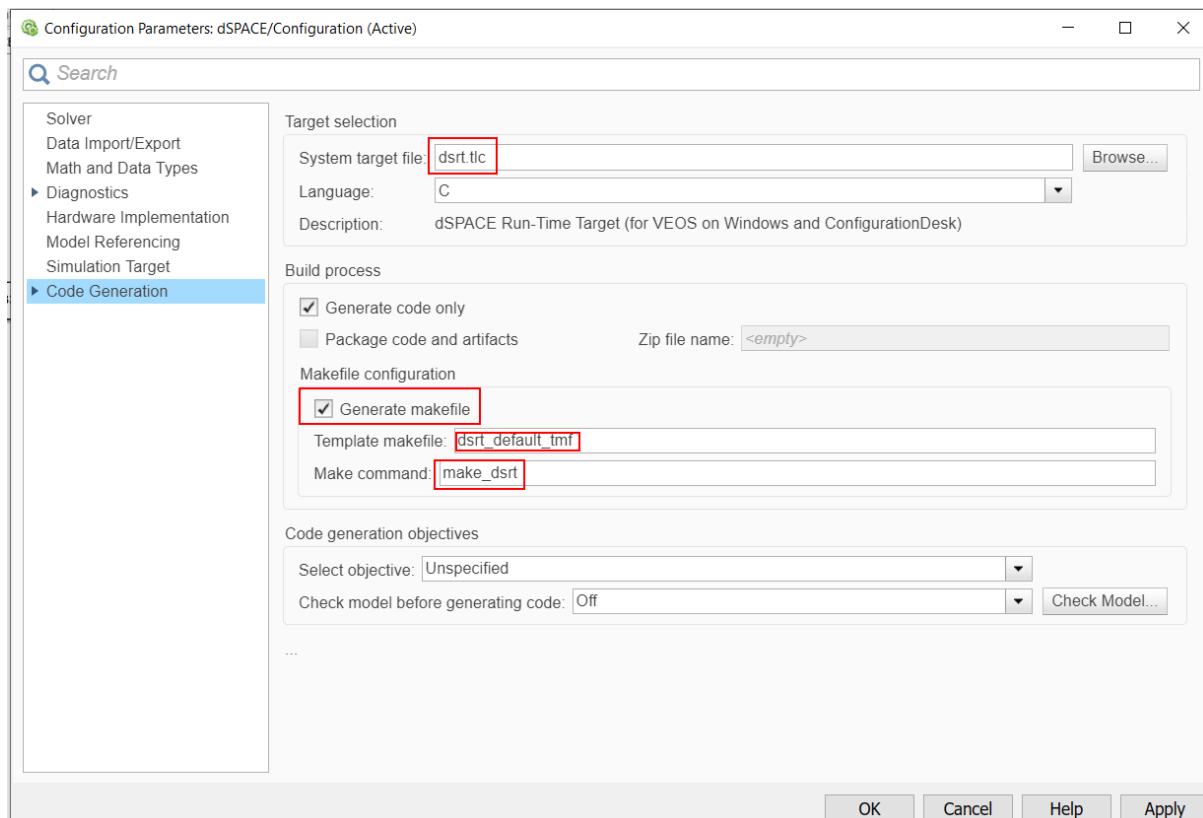


Figure 13.38: Set the Simulink code generation options.

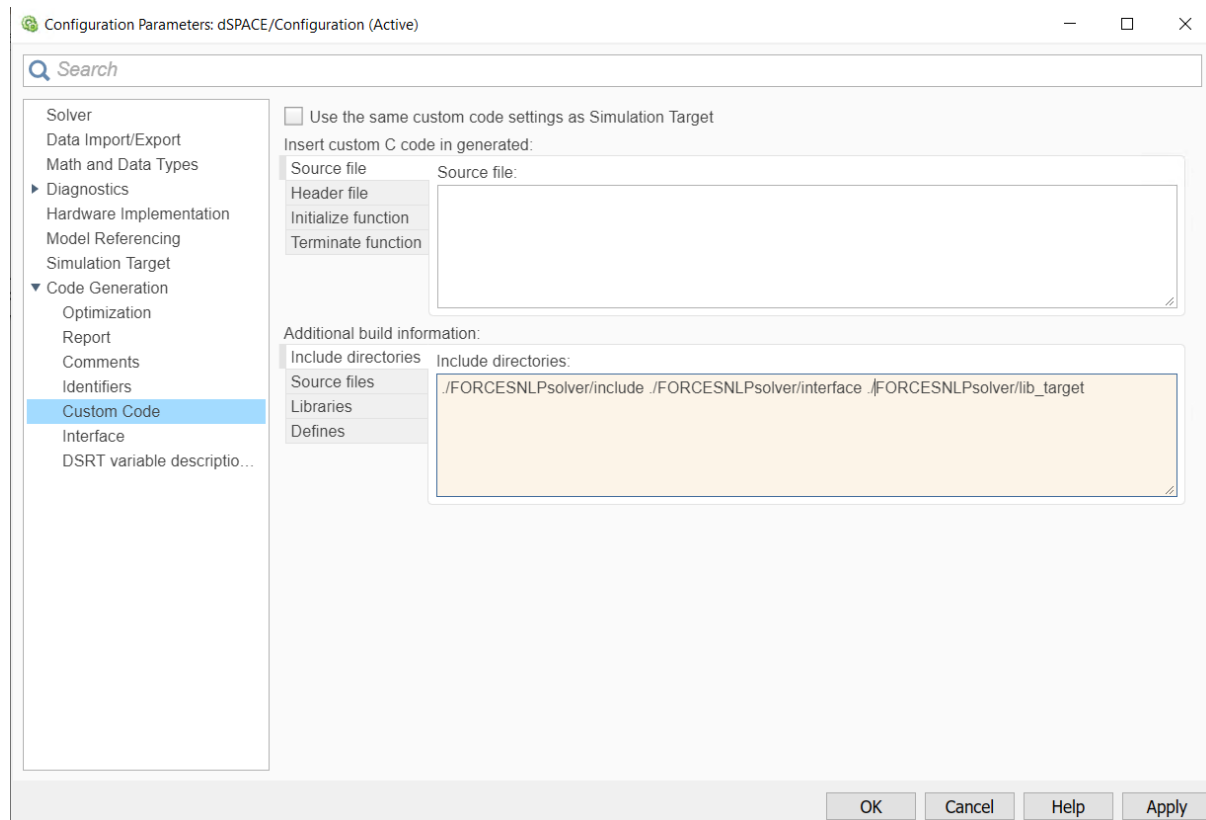


Figure 13.39: Add the directories included for the code generation.

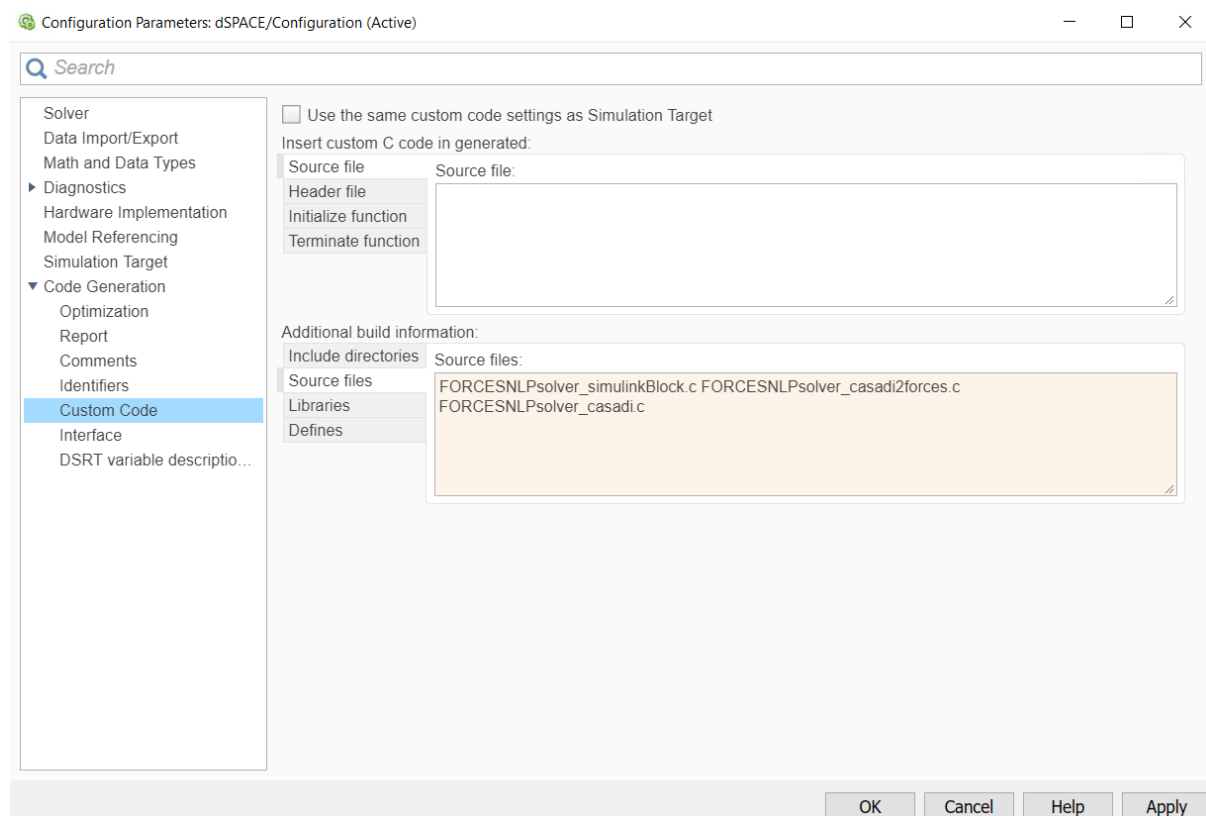


Figure 13.40: Add the source files used for the code generation.

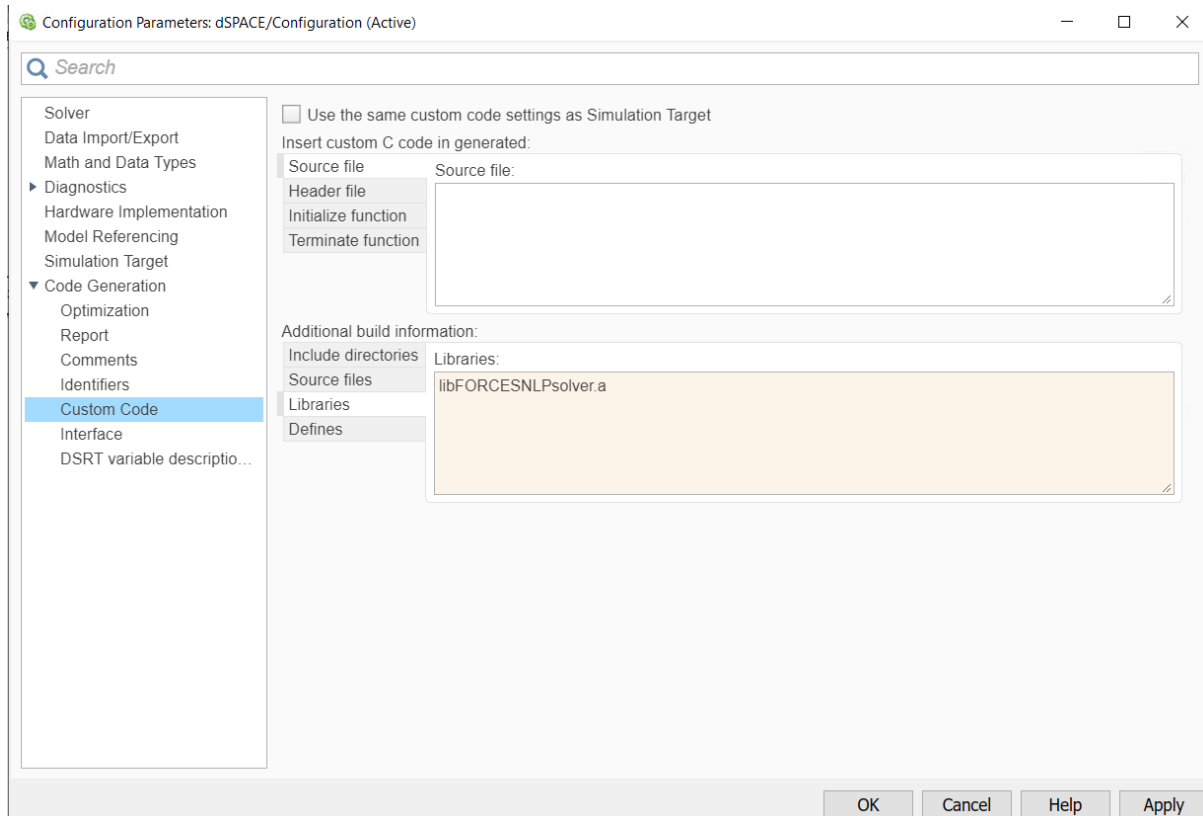


Figure 13.41: Add the libraries used for the code generation.

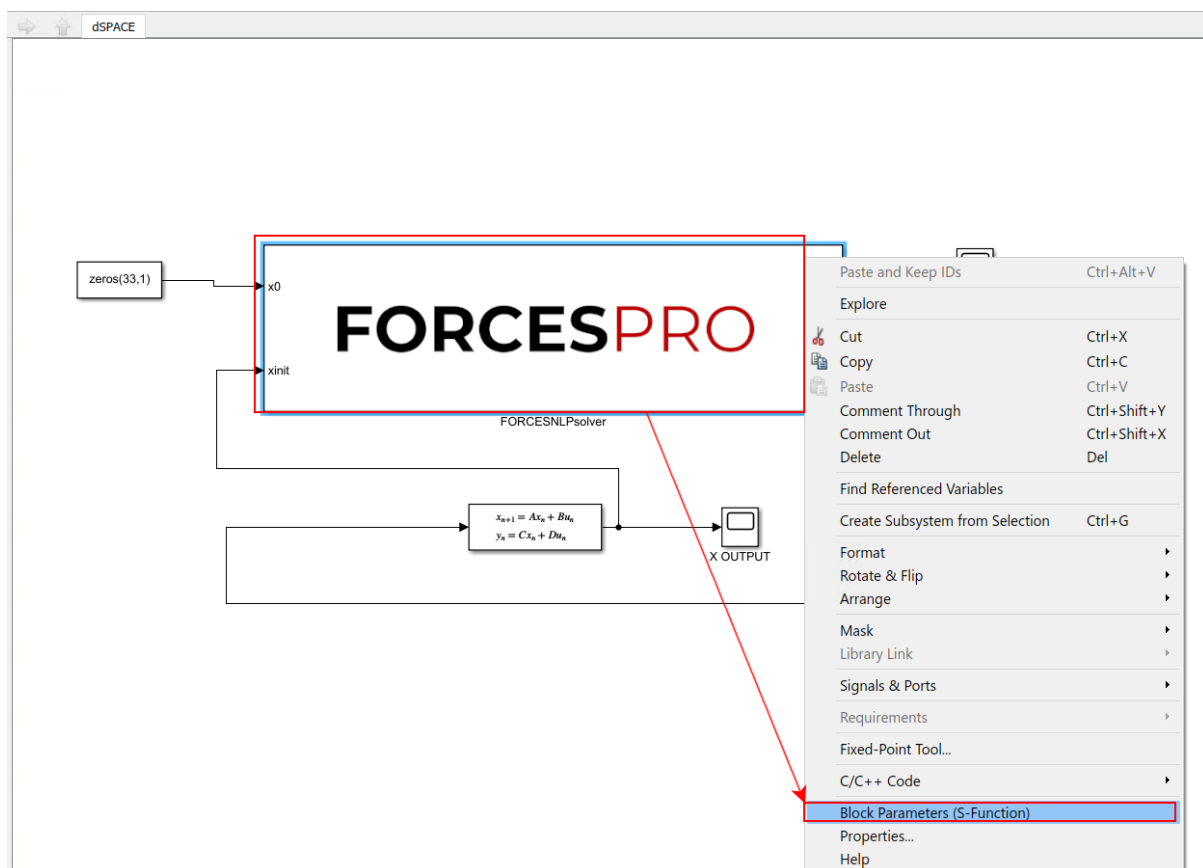


Figure 13.42: Open the FORCESPRO block's parameters.

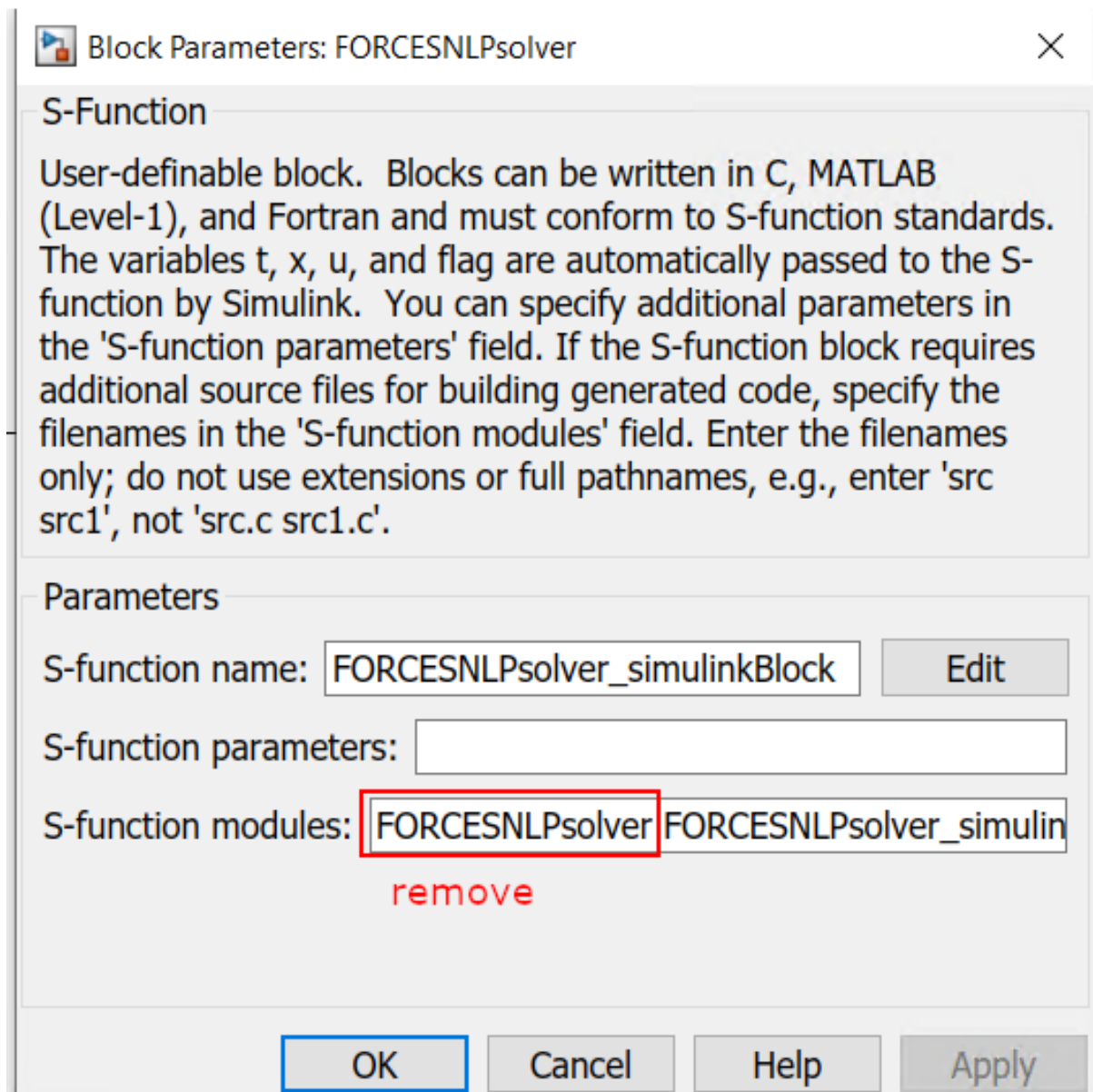


Figure 13.43: Remove the leading solver name from the S-function module.

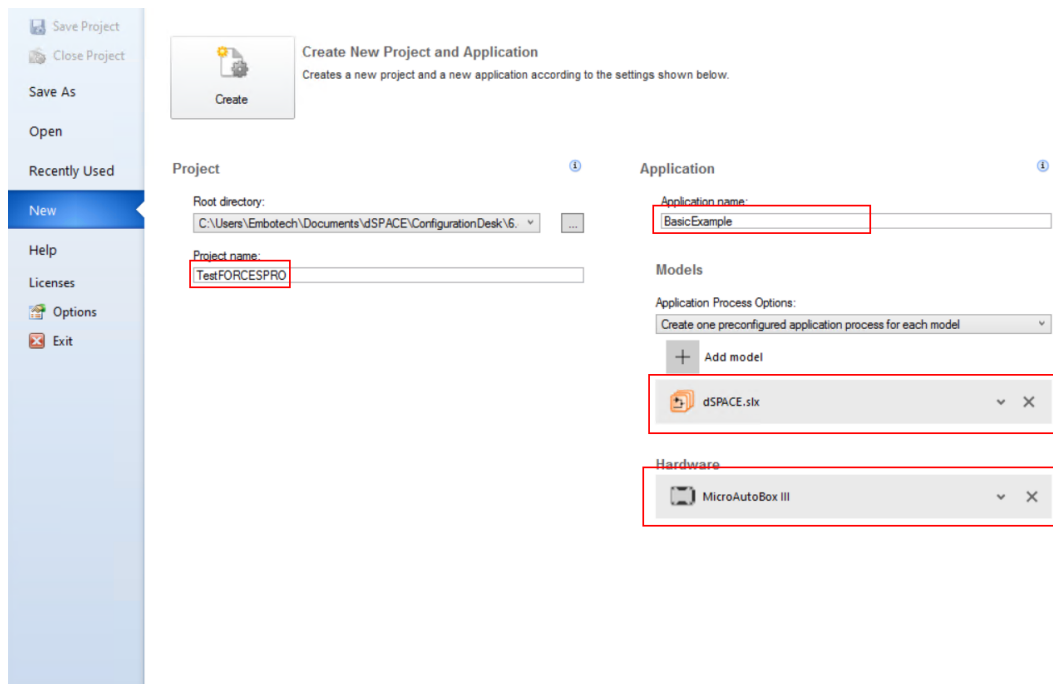


Figure 13.44: Create project and application in ConfigurationDesk.

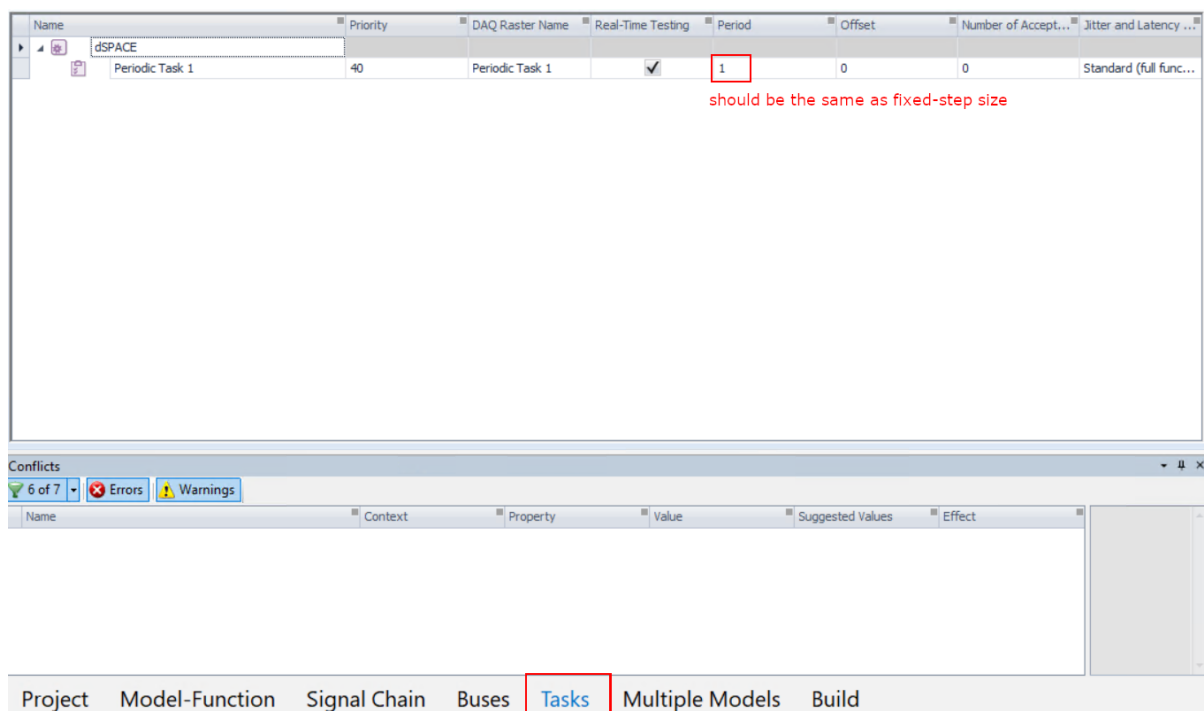


Figure 13.45: Set period of Periodic Task.

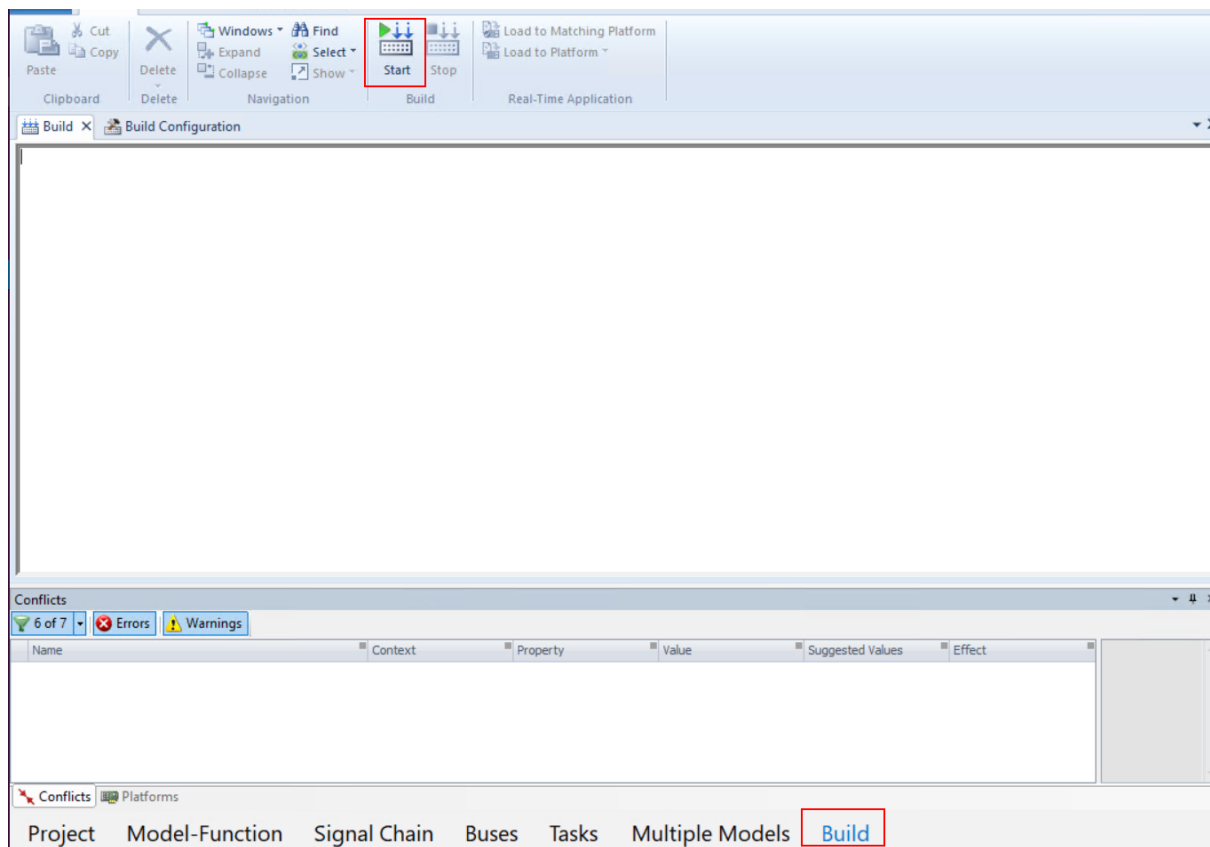


Figure 13.46: Build the project.

13.3.2 Solver Execution

The steps to simulate a FORCESPRO controller on a dSPACE platform are detailed below.

- 1) After code generation with FORCESPRO and building with the ConfigurationDesk, the ConfigurationDesk project will have generated files to use to run your model on the dSPACE platform (see [Figure 13.47](#) and [Figure 13.48](#)).

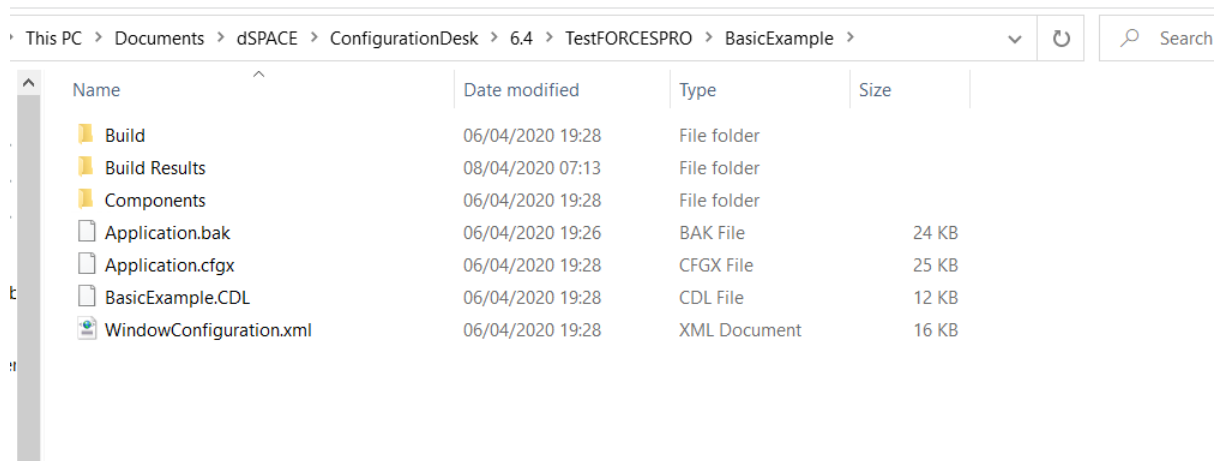


Figure 13.47: The generated files from the ConfigurationDesk building.

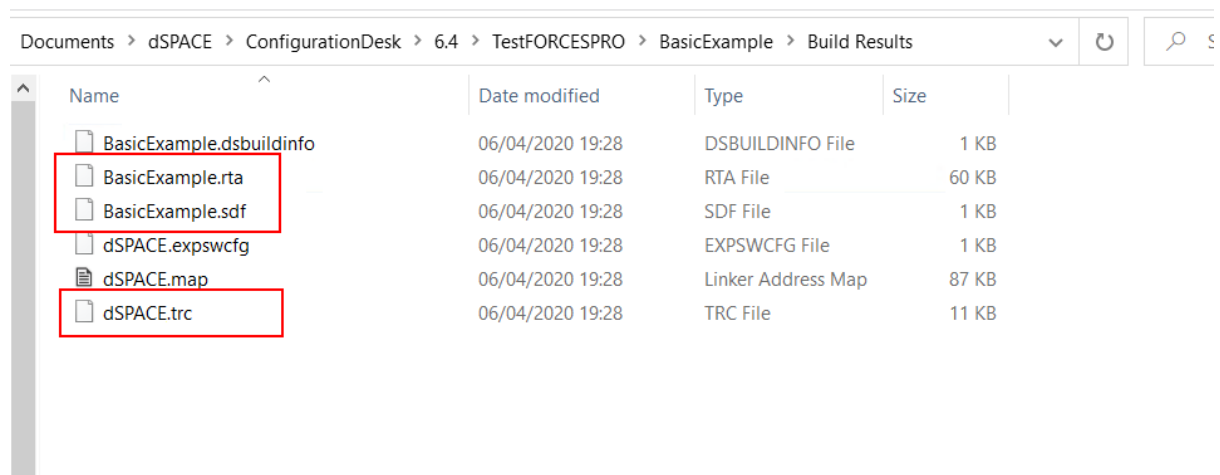


Figure 13.48: The files necessary for the simulation of the FORCESPRO controller.

- 2) Open dSpace Control Desk and select create new project and name it (see [Figure 13.49](#)).
- 3) Name the experiment to execute (see [Figure 13.50](#)).
- 4) Select the platform to which you will deploy the generated executable (see [Figure 13.51](#)).
- 5) Import the variable description file `BasicExample.sdf` in order to have access to the model variables and see the results of the execution (see [Figure 13.52](#)).
- 6) On the project layout select the tab `Variables` and on the `BasicExample.sdf` category expand `Model Root`.
- 7) Select `u OUTPUT` and `x OUTPUT` and Drag & Drop all the input variables together to the Layout. In the opened menu select `Time Plotter` (see [Figure 13.53](#) and [Figure 13.54](#)).
- 8) To see all the plots concurrently right-click on the left of the Y-axis and select `YAxes-view> Horizontal stacked` (see [Figure 13.55](#)).

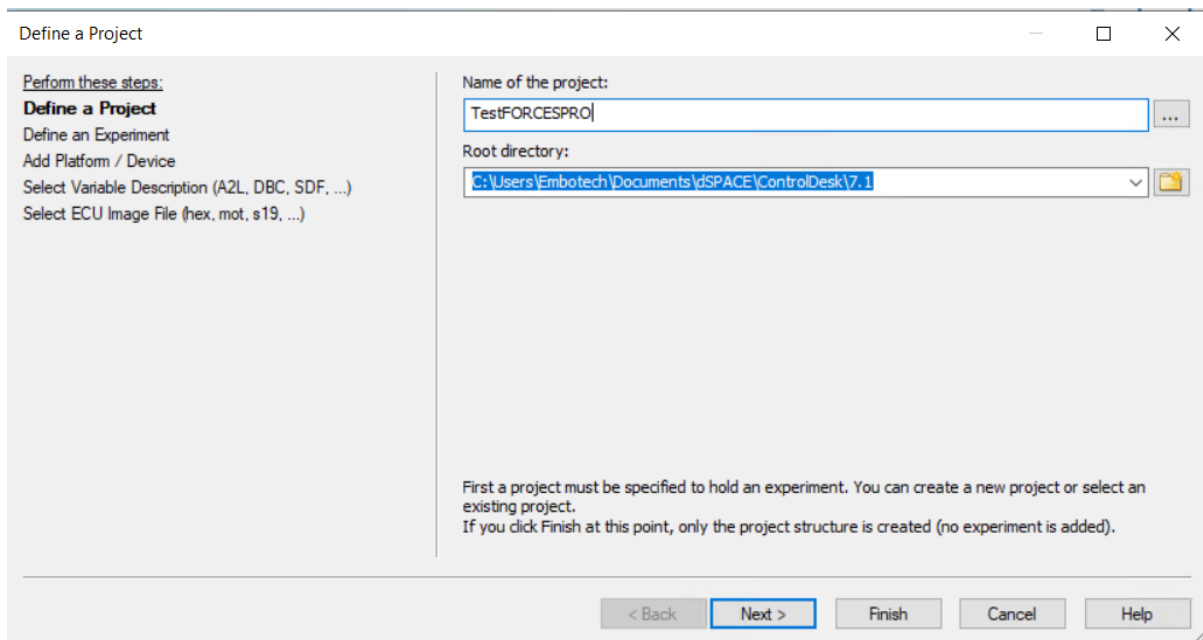


Figure 13.49: Start a new project and name it.

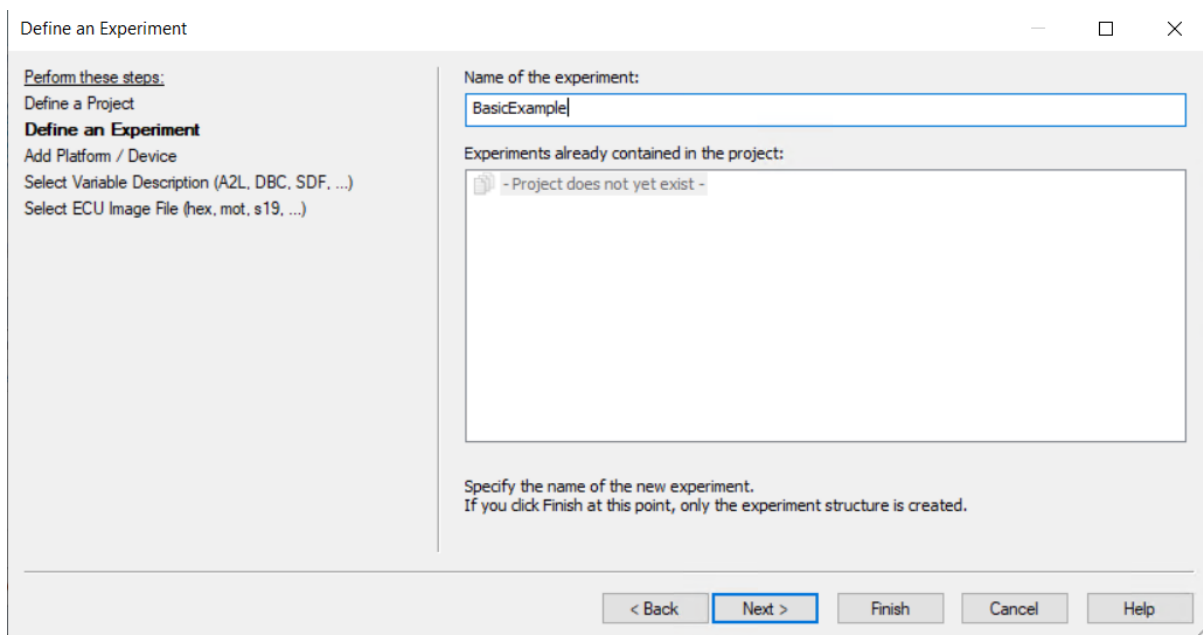


Figure 13.50: Name your experiment.

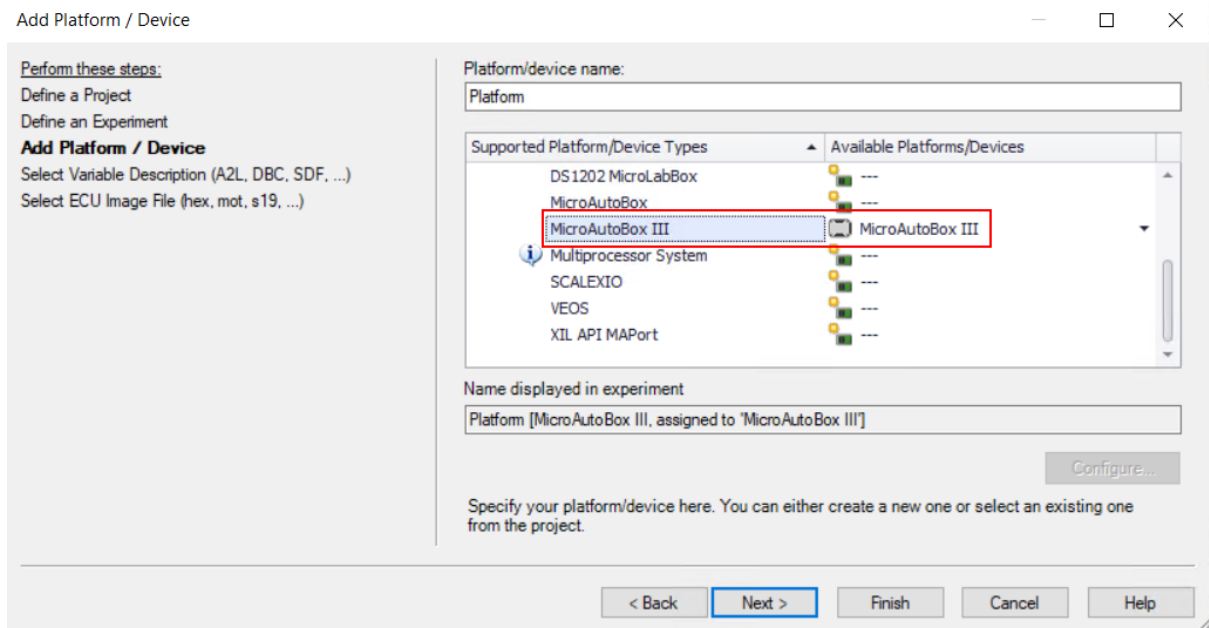


Figure 13.51: Select the dSPACE platform.

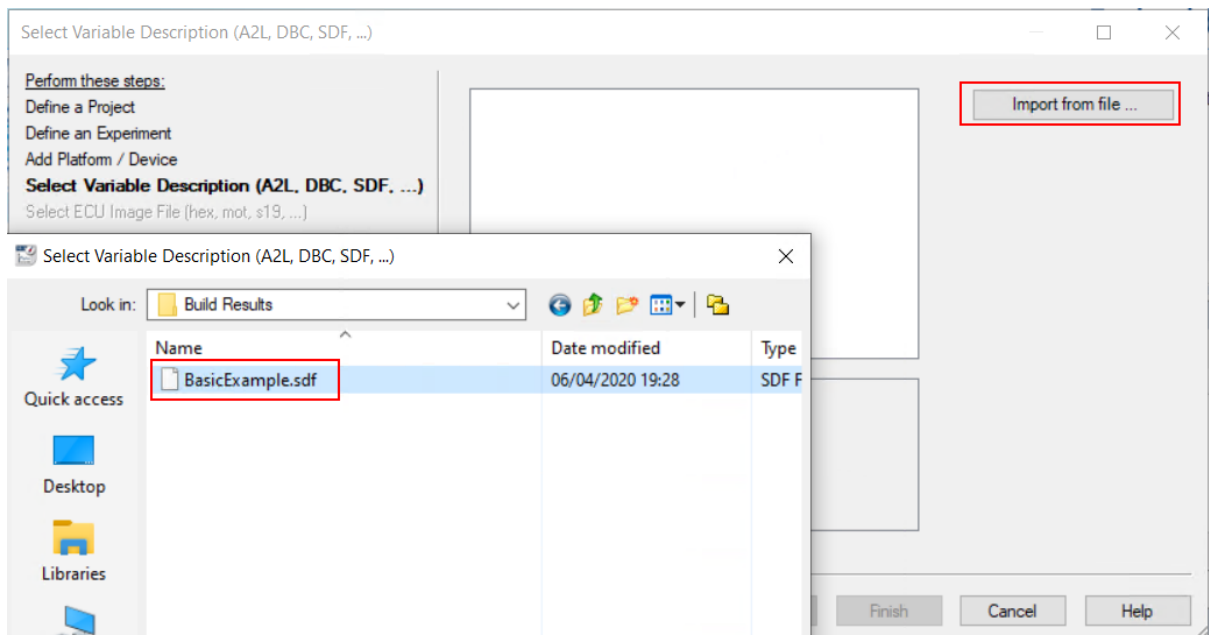


Figure 13.52: Import the variable description file.

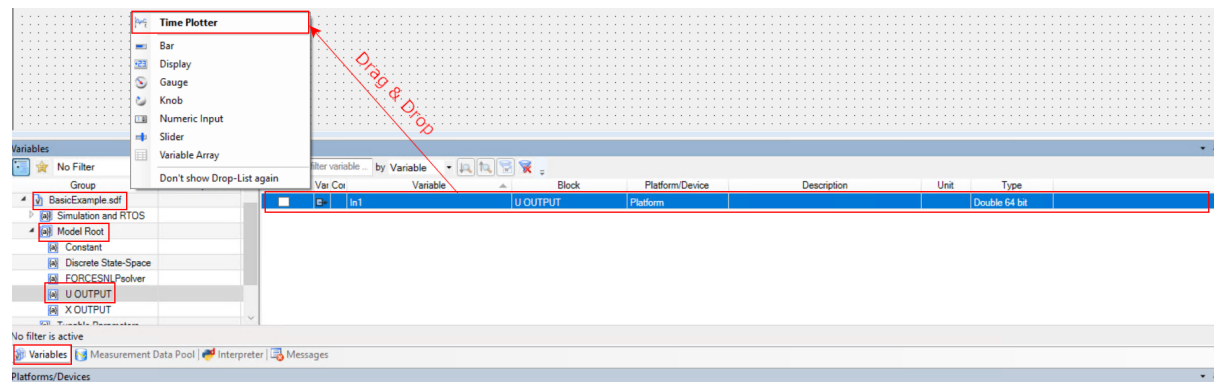


Figure 13.53: Add the inputs of U OUTPUT in a Time Plotter.

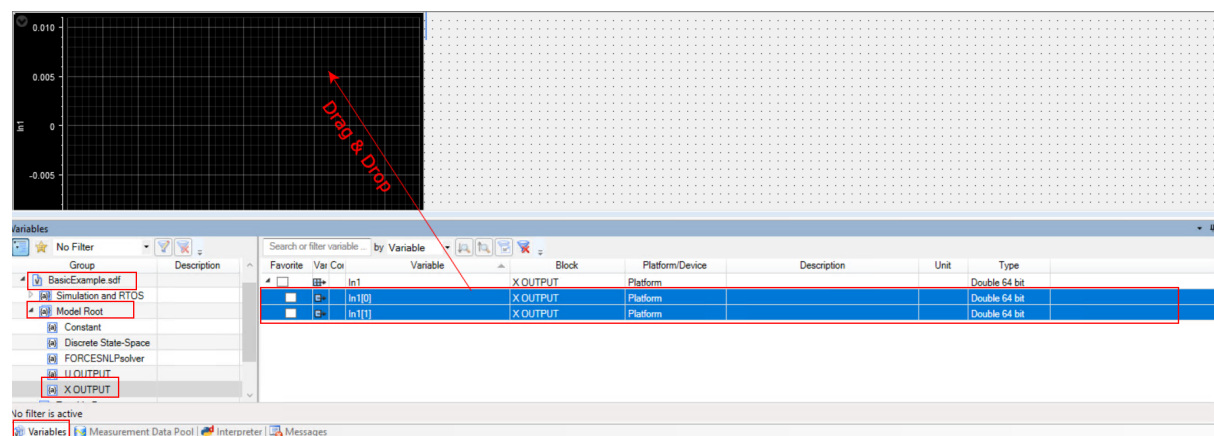


Figure 13.54: Add the inputs of X OUTPUT in the same Time Plotter.

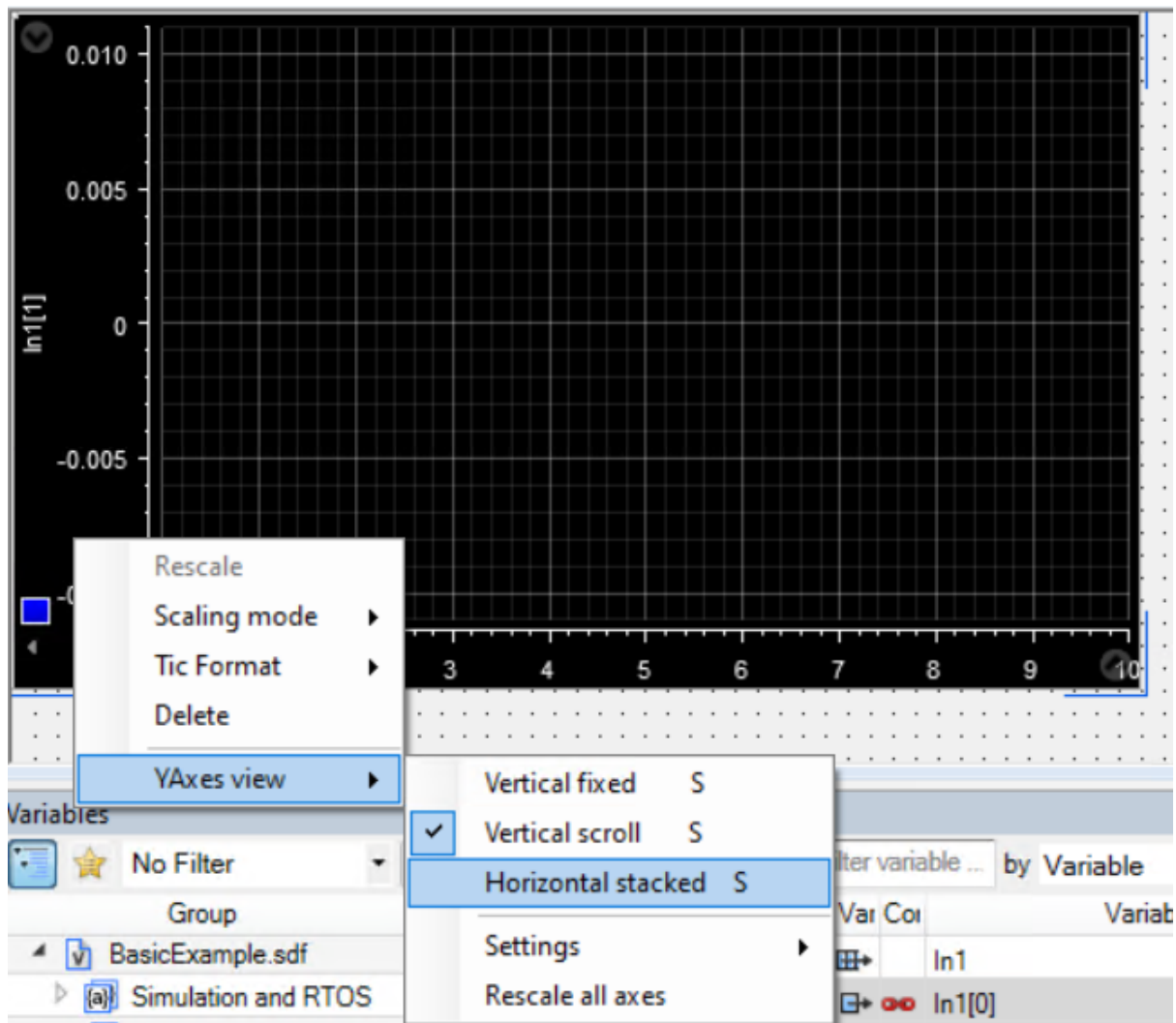


Figure 13.55: Select to show all the signals on the same plot with their own Y-axes

- 9) Application should have already been loaded from the building of ConfigurationDesk. Otherwise, select the Platforms/Devices tab. Right-Click on your platform and select Real-Time Application> Load. Choose the executable file BasicExample.rta (see Figure 13.56 and Figure 13.57).
- 10) Select Go Online and Start Measuring to see the results. (see Figure 13.58 and Figure 13.59).

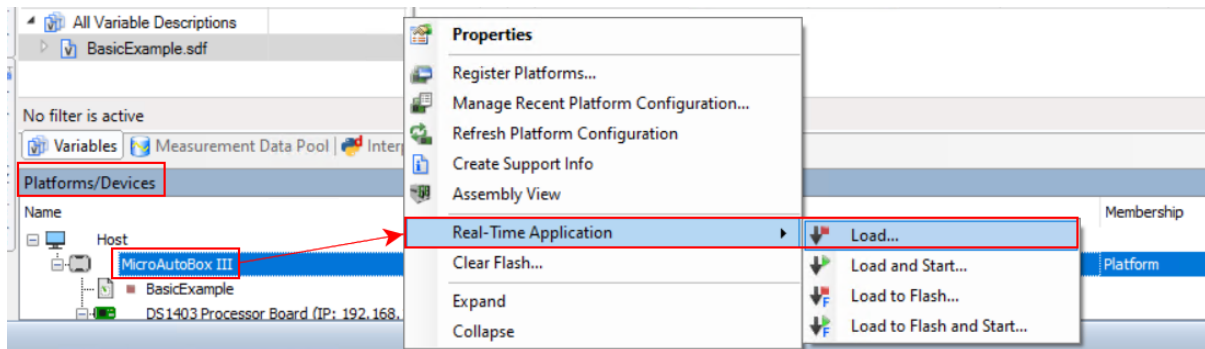


Figure 13.56: Load the application on the dSPACE platform.

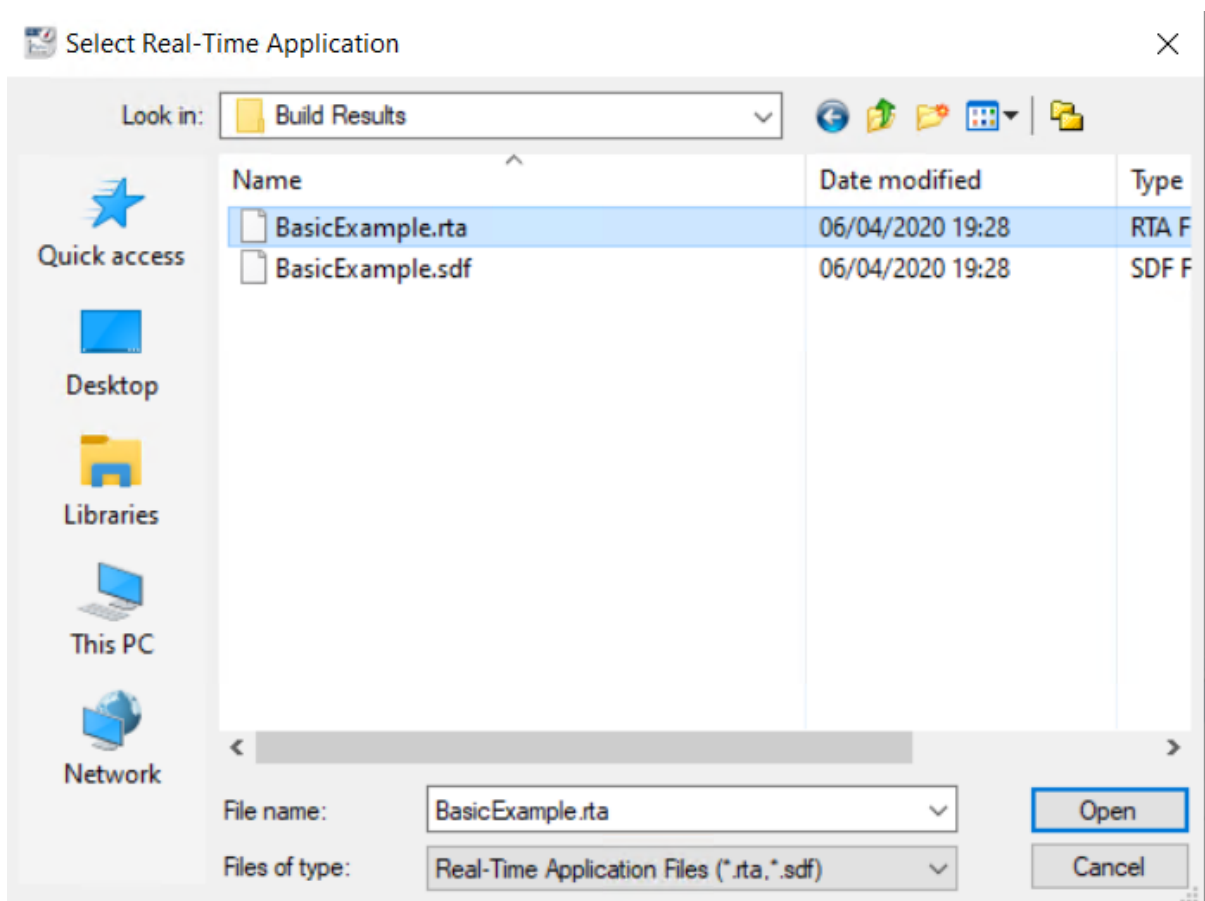


Figure 13.57: Select BasicExample.rta from the ConfigurationDesk project folder.

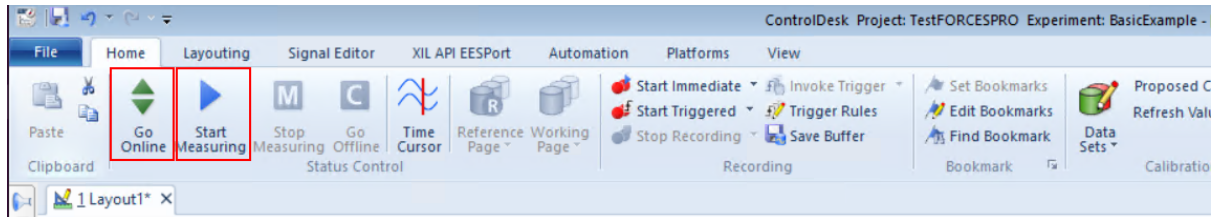


Figure 13.58: Buttons Go Online and Start Measuring to receive execution results.

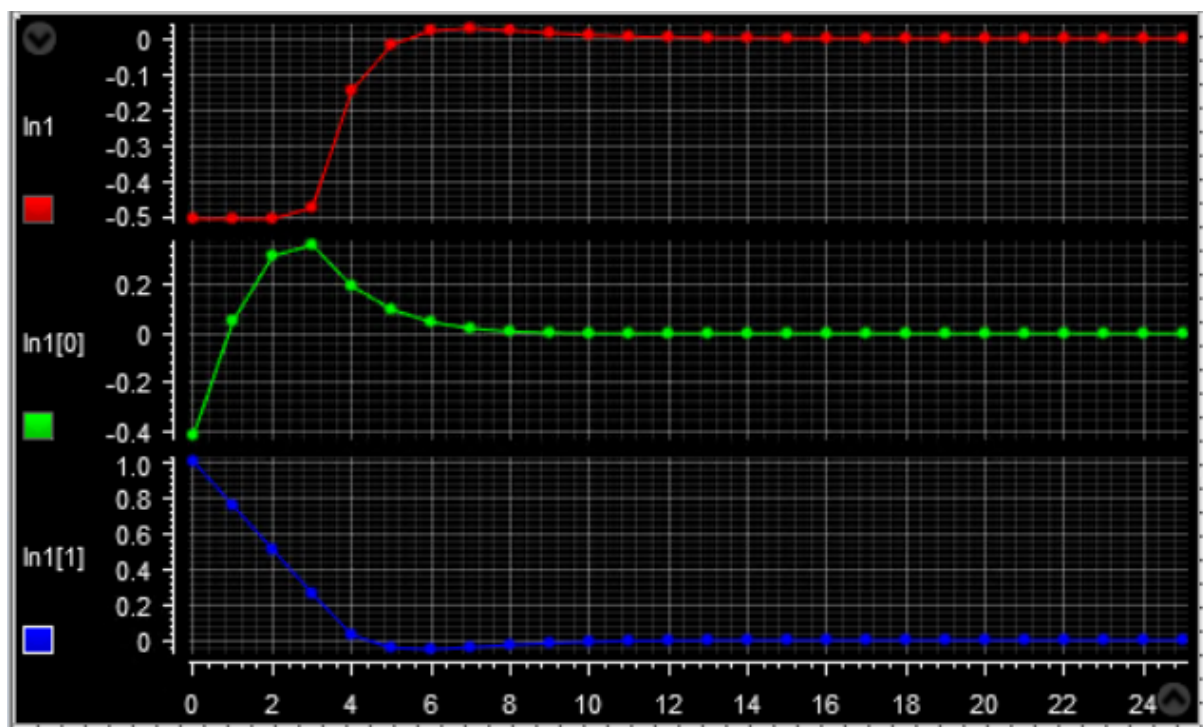


Figure 13.59: Plots and results from experiment on a dSPACE platform.

13.4 Speedgoat

- *High-level interface*
 - *Instructions*
 - *Figures*
- *Y2F interface*
 - *Instructions*
 - *Figures*

Important: When deploying to a target hardware platform, the library included in the **lib_target** directory of the generated solver should be used instead of the library in the **lib** directory.

13.4.1 High-level interface

Instructions

The steps to deploy and simulate a FORCESPRO controller on a Speedgoat platform are detailed below.

1. (Figure 13.60) Set the code generation options:

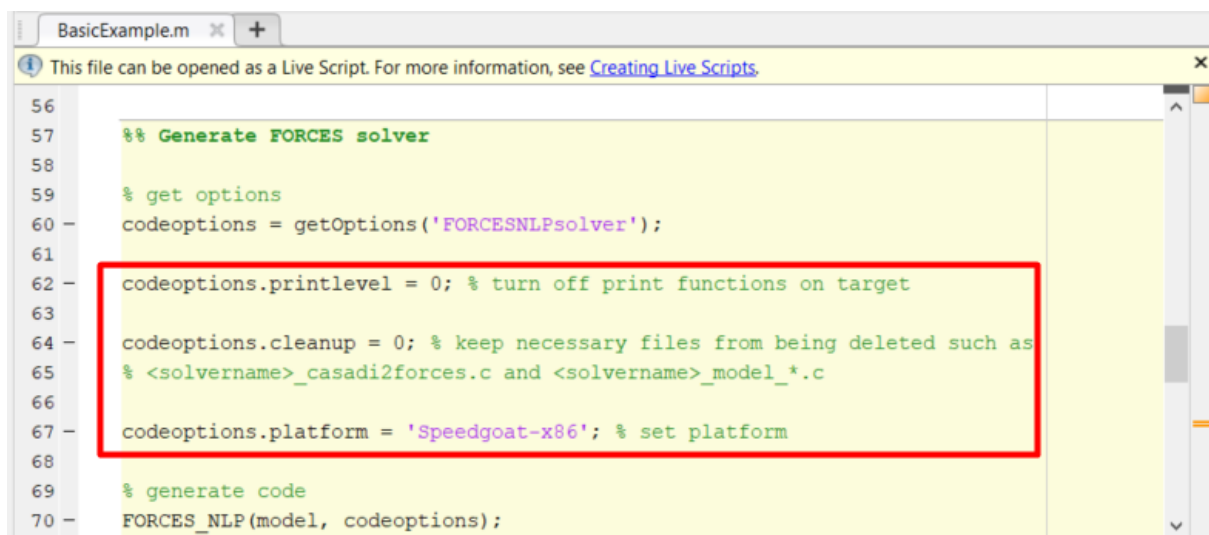
```
codeoptions.platform = 'Speedgoat-x86'; % to specify the platform
codeoptions.printlevel = 0; % on some platforms printing is not supported
codeoptions.cleanup = 0; % to keep necessary files for target compile
```

and then generate the code for your solver (henceforth referred to as “FORCESNLPsolver”, placed in the folder “BasicExample”) using the high-level interface.

2. (Figure 13.61) Create a new Simulink model using the blank model template.
3. (Figure 13.62) Populate the Simulink model with the system you want to control.
4. (Figure 13.63) Make sure the FORCESNLPsolver_simulinkBlock.mexw64 file (created during code generation) is on the Matlab path.
5. (Figure 13.64) Open the FORCESNLPsolver_lib.mdl Simulink model file, contained in the interface folder of the FORCESNLPsolver folder created during code generation.
6. (Figure 13.65) Copy-paste the FORCESPRO Simulink block into your simulation model and connect its inputs and outputs appropriately.
7. (Figure 13.66) Access the Simulink model's options.
8. (Figure 13.67) In the “Solver” tab, set the options:
 - Simulation start/stop time: Depending on the simulation wanted.
 - Solver type: Discrete or fixed-step.
 - Fixed-step size: Needs to be higher than the execution time of the solver.
9. (Figure 13.68) In the “Code Generation” tab, set the options:
 - System target file: slrt.tlc
 - Language: C

- Generate makefile: On
 - Template makefile: slrt_default_tmf
 - Make command: make_rtw
10. (Figure 13.69) In the “Code Generation/Custom Code” tab, include the directories:
 - BasicExample
 - BasicExample\FORCESNLPsolver\interface
 - BasicExample\FORCESNLPsolver\lib_target
 11. (Figure 13.70) In the “Code Generation/Custom Code” tab, add the source files:
 - FORCESNLPsolver_simulinkBlock.c
 - FORCESNLPsolver_casadi2forces.c
 - FORCESNLPsolver_casadi.c
 12. (Figure 13.71) In the “Code Generation/Custom Code” tab, add the library file:
 - FORCESNLPsolver.lib
 13. (Figure 13.72) Access the FORCESPRO block’s parameters.
 14. (Figure 13.73) Remove “FORCESNLPsolver” and “FORCESNLPsolver_simulinkBlock” from the S-function module.
 15. (Figure 13.74) Compile the code of the Simulink model. This will also automatically load the model to the connected Speedgoat platform.
 16. Deployment is complete and simulations can now be run on the Speedgoat platform.
 17. Run the simulation on the Speedgoat platform.
- You can find the Matlab code of this simulation to try it out for yourself in the examples folder that comes with your client.

Figures



```
56
57 %% Generate FORCES solver
58
59 % get options
60 codeoptions = getOptions('FORCESNLPsolver');
61
62 codeoptions.printlevel = 0; % turn off print functions on target
63
64 codeoptions.cleanup = 0; % keep necessary files from being deleted such as
65 % <solvername>_casadi2forces.c and <solvername>_model_*.c
66
67 codeoptions.platform = 'Speedgoat-x86'; % set platform
68
69 % generate code
70 FORCES_NLP(model, codeoptions);
```

Figure 13.60: Set the appropriate code generation options.

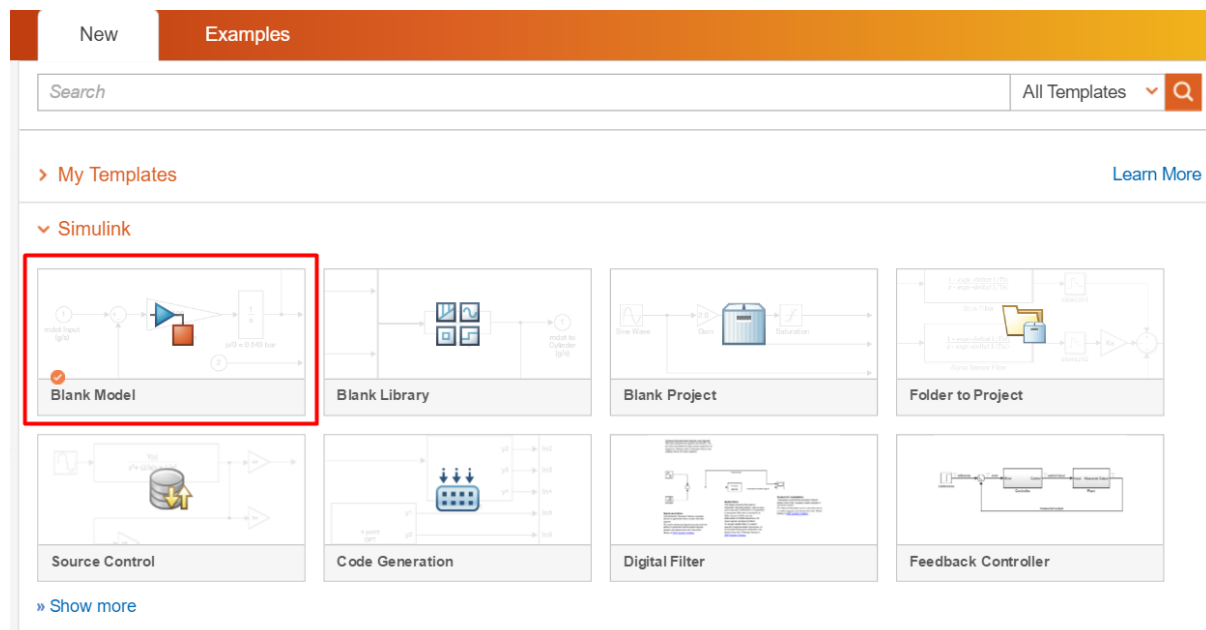


Figure 13.61: Create a Simulink model.

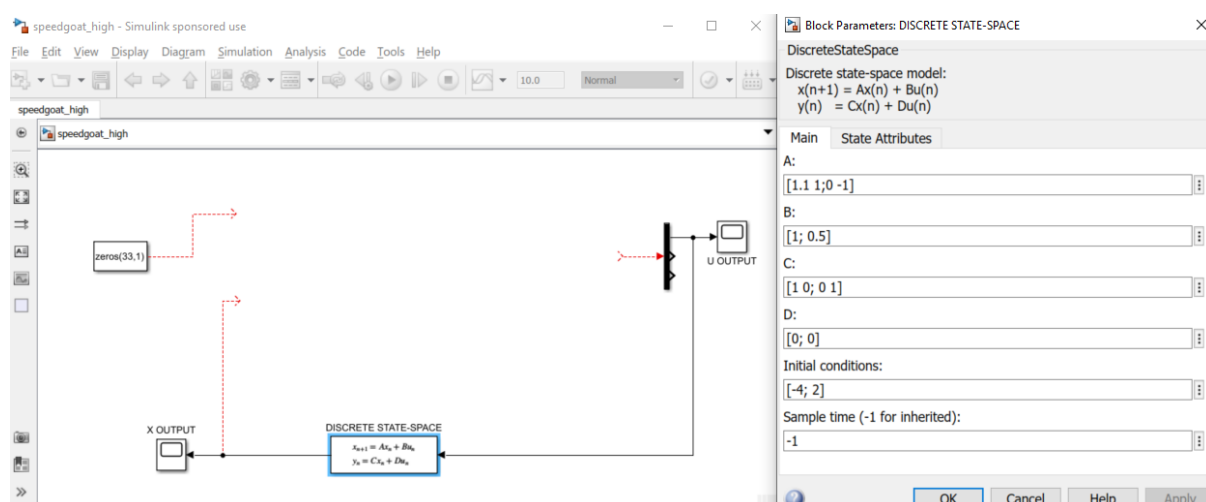


Figure 13.62: Populate the Simulink model.

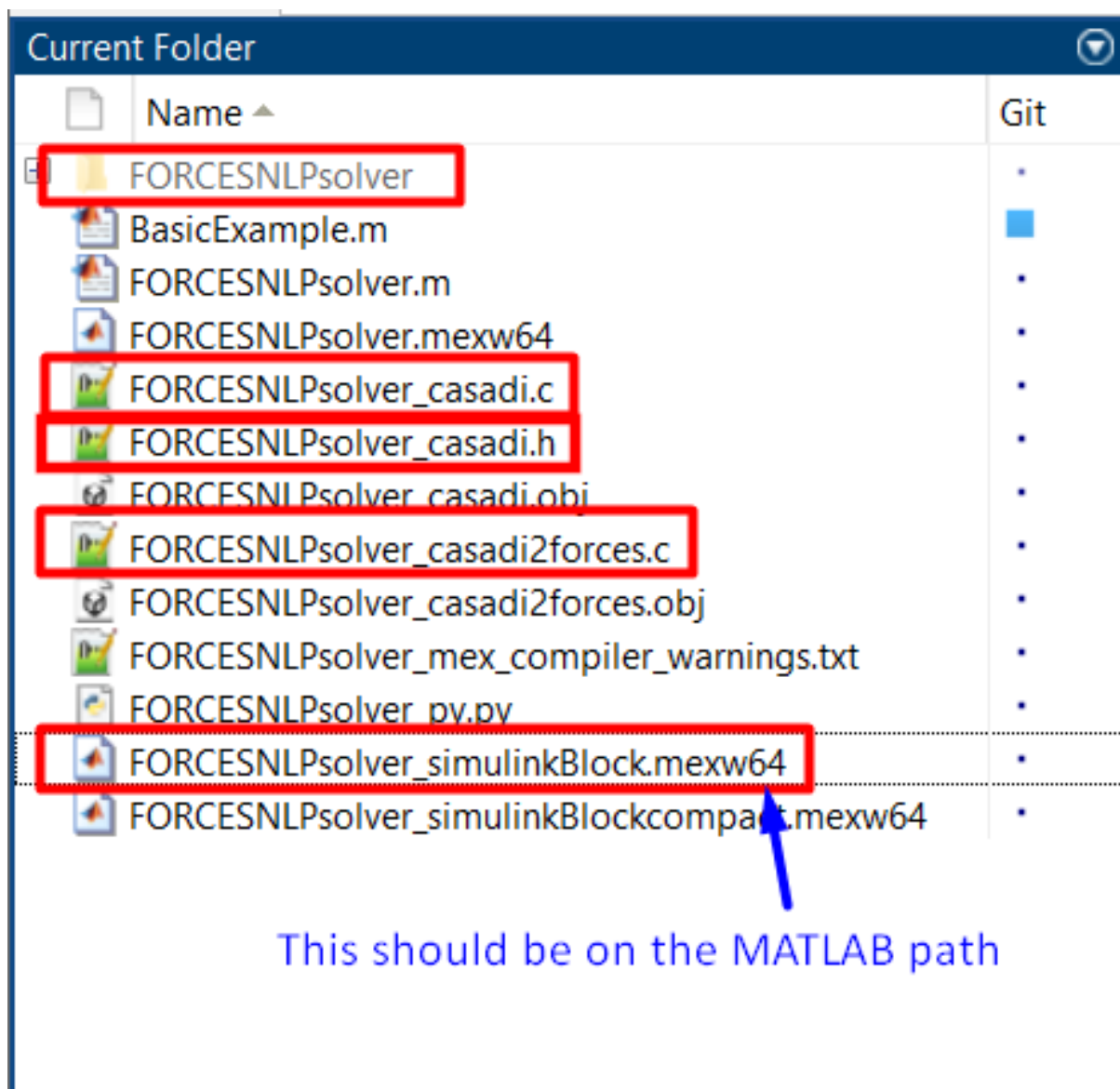


Figure 13.63: Add the folder containing the .mexw64 solver file to the Matlab path.

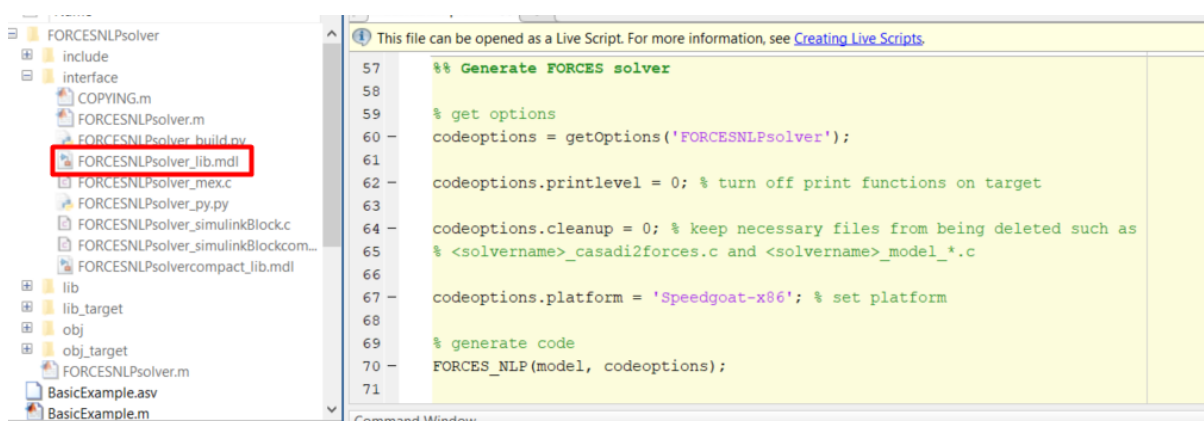


Figure 13.64: Open the generated Simulink solver model.

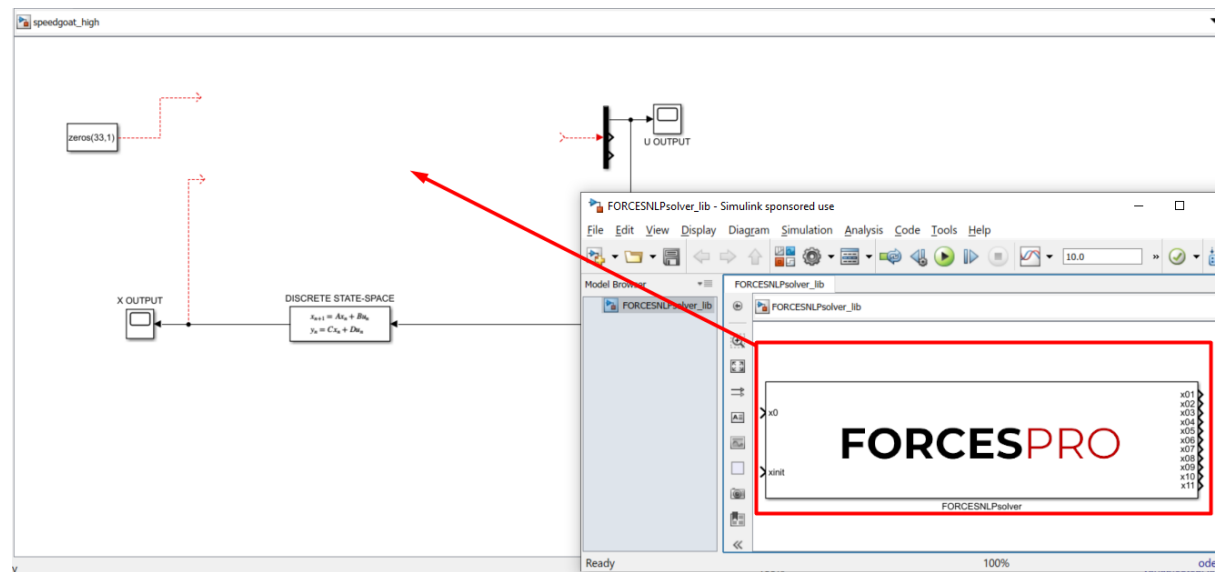


Figure 13.65: Copy-paste and connect the FORCESPRO block.

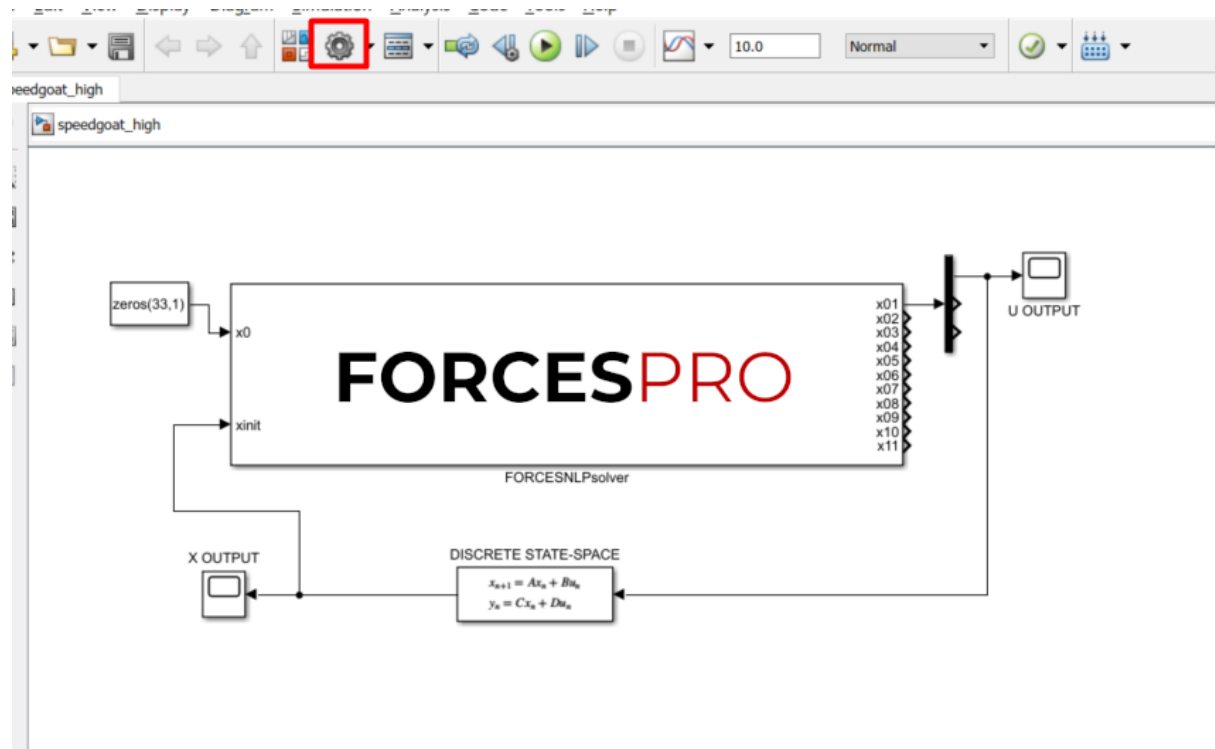


Figure 13.66: Open the Simulink model options.

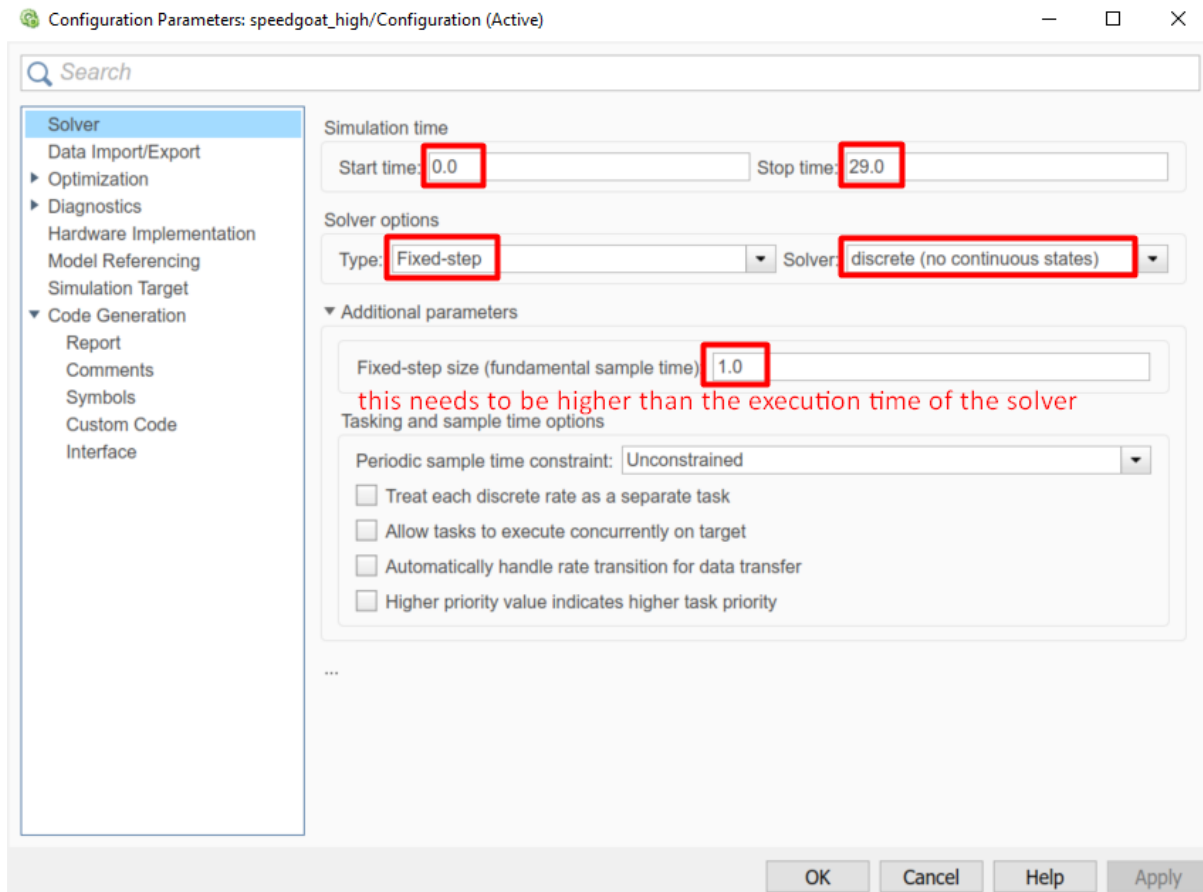


Figure 13.67: Set the Simulink solver options.

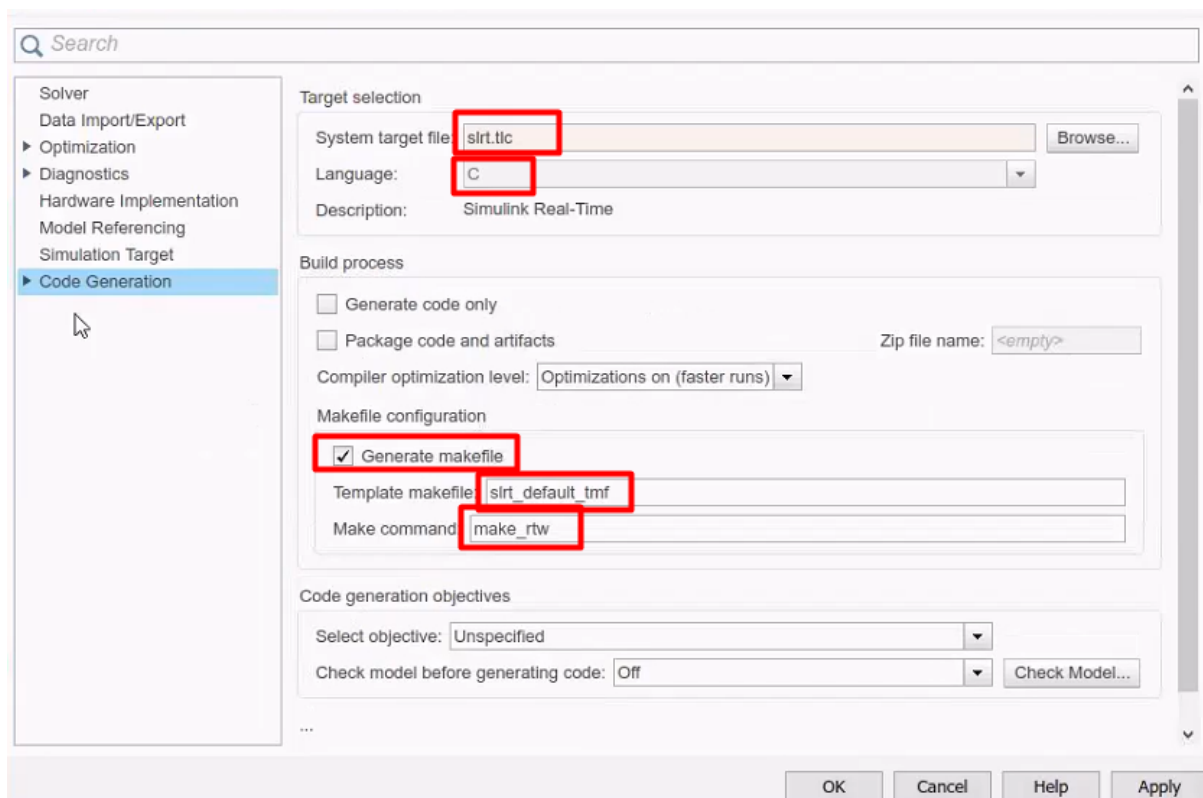


Figure 13.68: Set the Simulink code generation options.

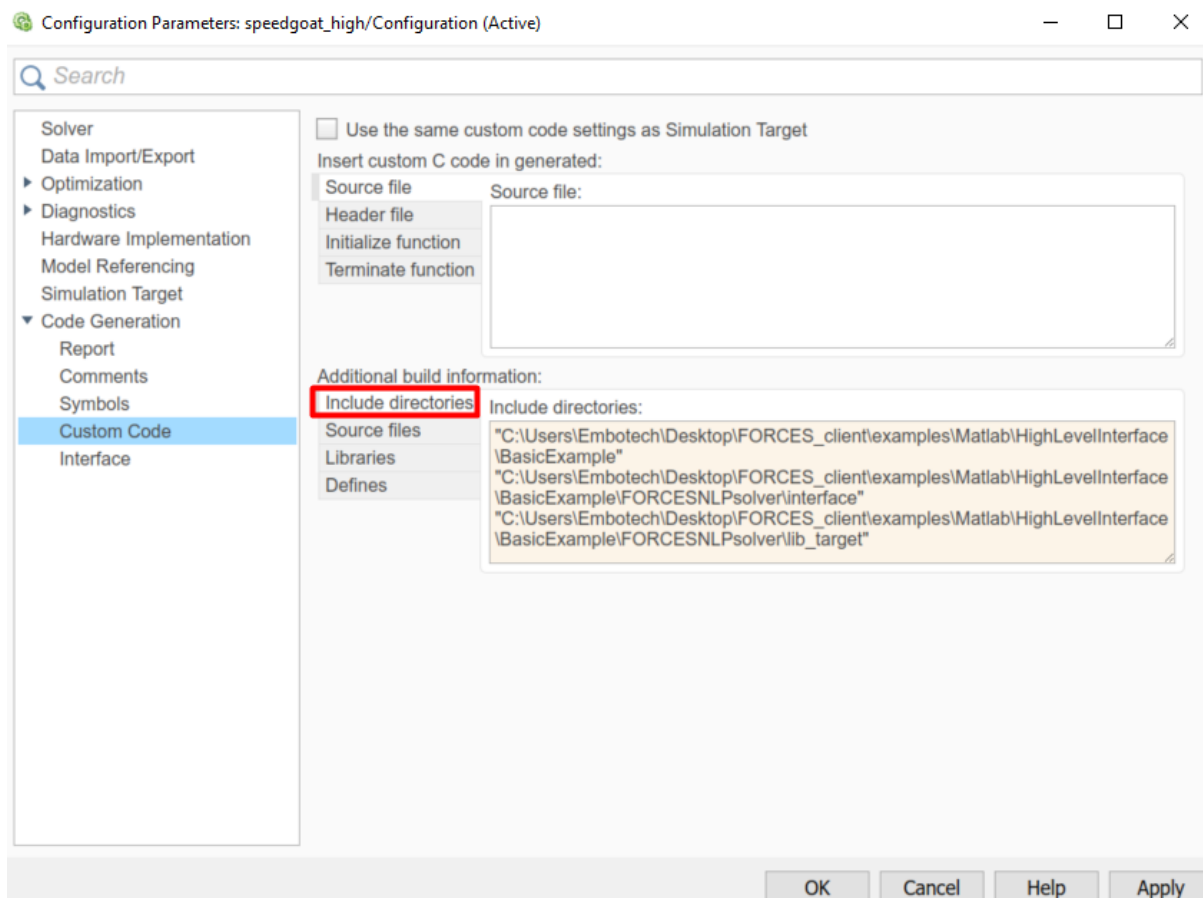


Figure 13.69: Add the directories included for the code generation.

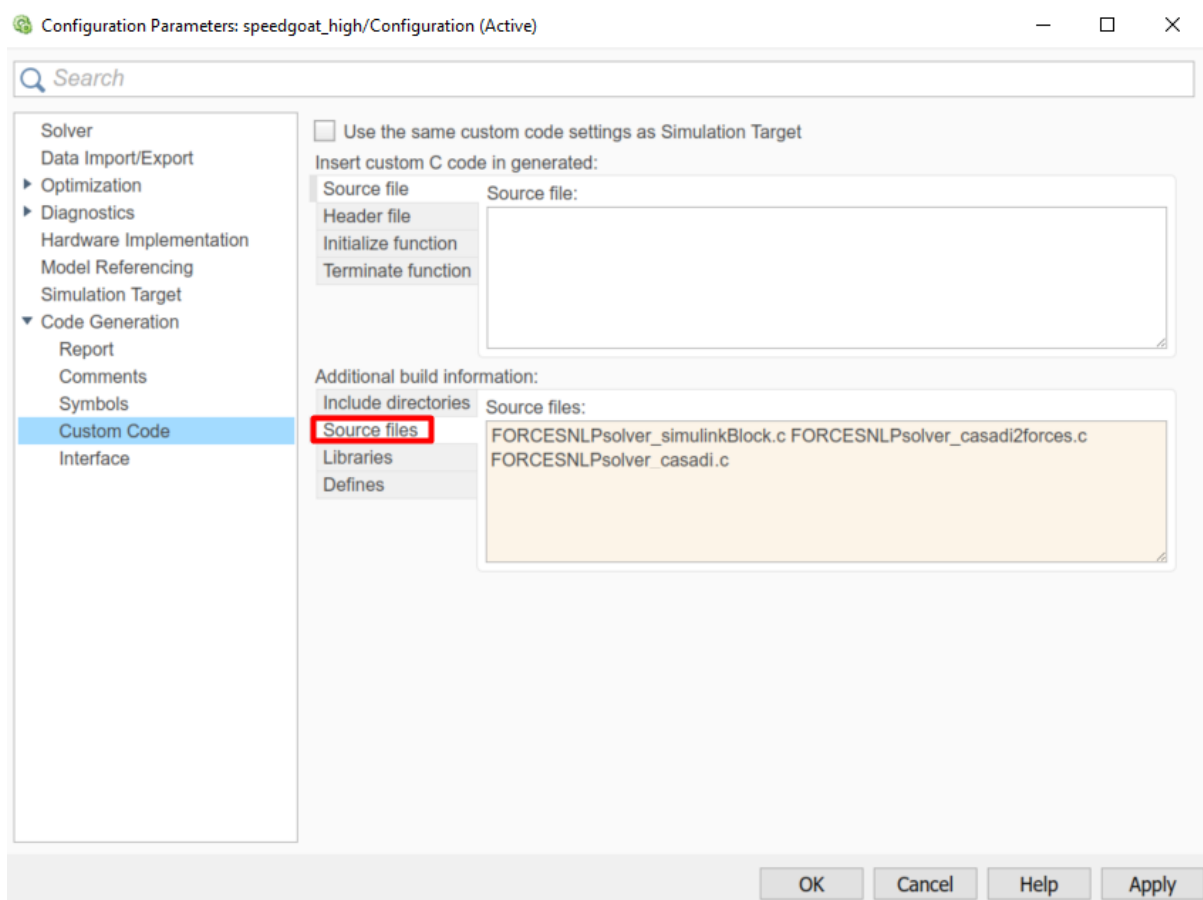


Figure 13.70: Add the source files used for the code generation.

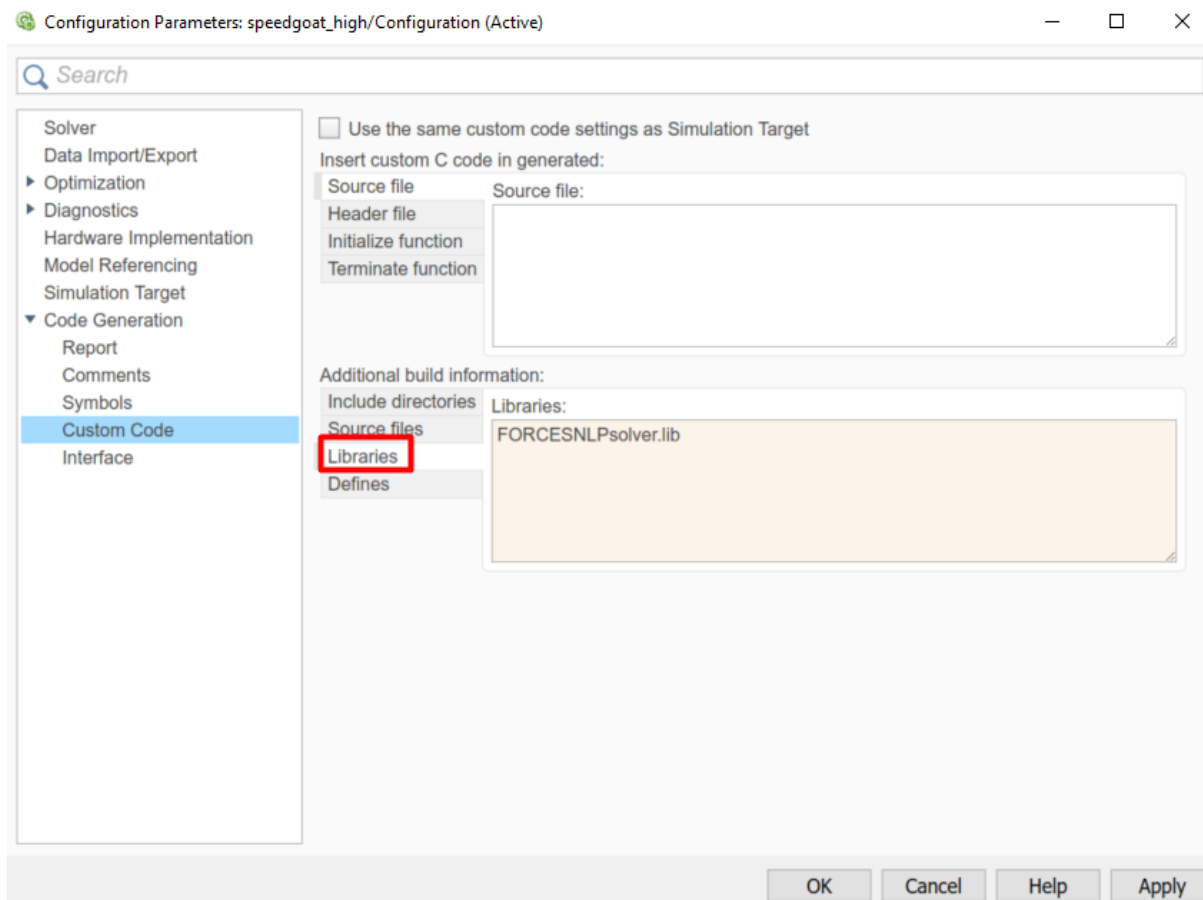


Figure 13.71: Add the libraries used for the code generation.

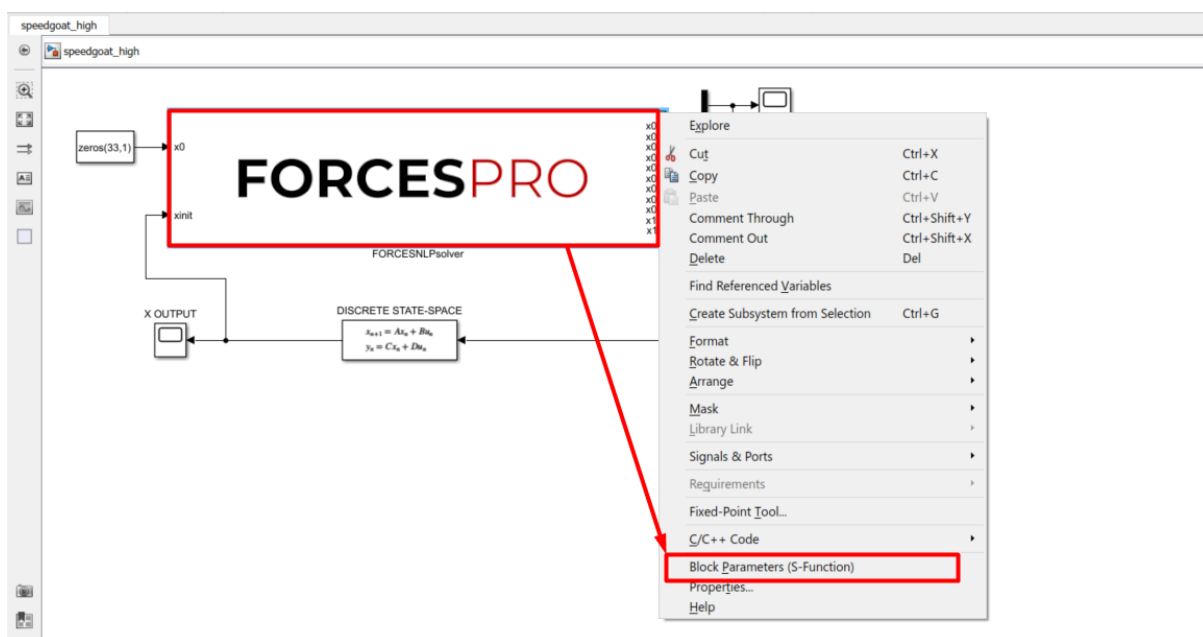


Figure 13.72: Open the FORCESPRO block's parameters.

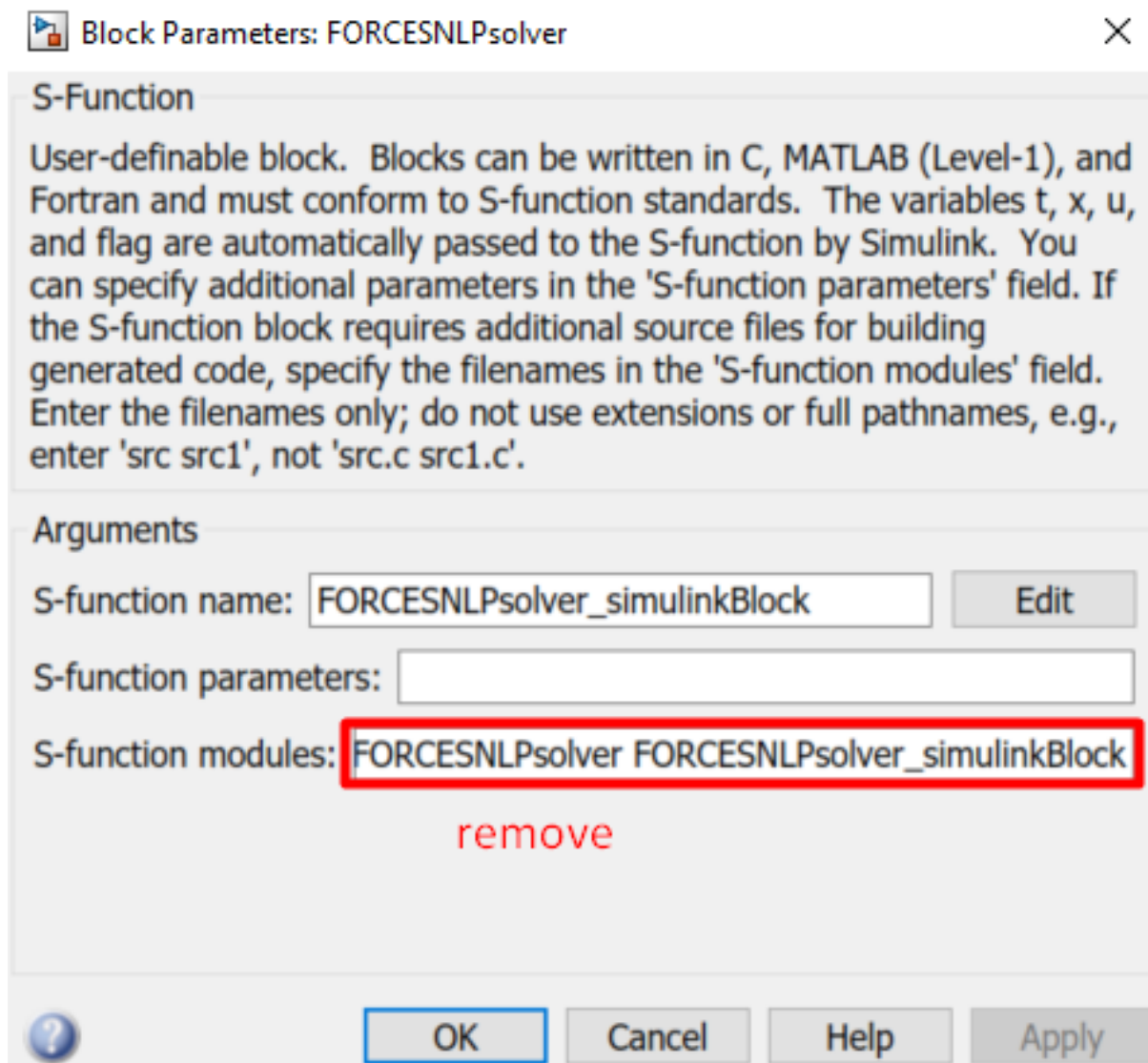


Figure 13.73: Remove the default data from the S-function module.

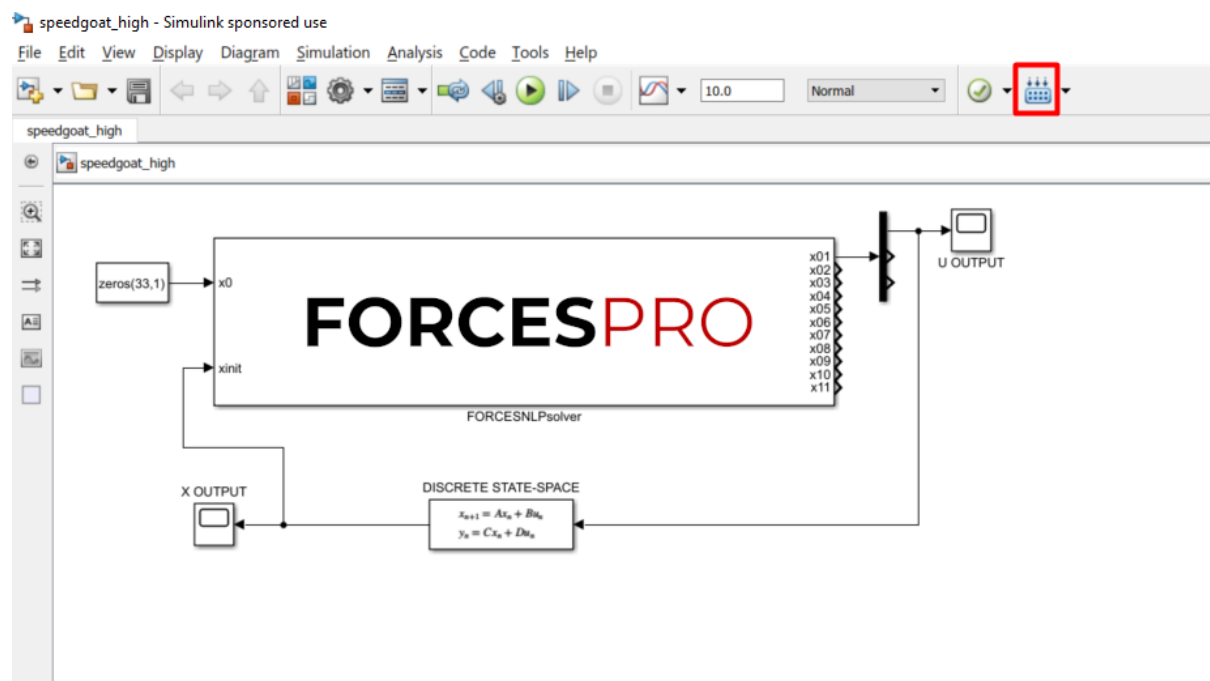


Figure 13.74: Compile the code of the Simulink model.

13.4.2 Y2F interface

Instructions

The steps to deploy and simulate a FORCESPRO controller on a Speedgoat platform are detailed below.

1. (Figure 13.75) Set the code generation options:

```
codeoptions.platform = 'Speedgoat-x86'; % to specify the platform
codeoptions.printlevel = 0; % on some platforms printing is not supported
```

and then generate the code for your solver (henceforth referred to as “simplempc_solver”, placed in the folder “Y2F”) using the Y2F interface.

2. (Figure 13.76) Create a new Simulink model using the blank model template.
3. (Figure 13.77) Populate the Simulink model with the system you want to control.
4. (Figure 13.78) Make sure the `simplempc_solver_simulinkBlock.mexw64` file (created during code generation) is on the Matlab path.
5. (Figure 13.79) Copy-paste the FORCESPRO Simulink block, contained in the created `y2f_simulink_lib.slx` Simulink model file, into your simulation model and connect its inputs and outputs appropriately.
6. (Figure 13.80) Access the Simulink model's options.
7. (Figure 13.81) In the “Solver” tab, set the options:
 - Simulation start/stop time: Depending on the simulation wanted.
 - Solver type: Discrete or fixed-step.
 - Fixed-step size: Needs to be higher than the execution time of the solver.
8. (Figure 13.82) In the “Code Generation/RTI general build options” tab, set the options:
 - System target file: `slrt.tlc`
 - Language: C
 - Generate makefile: On
 - Template makefile: `slrt_default_tmf`
 - Make command: `make_rtw`
9. (Figure 13.83) In the “Code Generation/Custom Code” tab, include the directories:
 - `Y2F\simplempc_solver\interface`
 - `Y2F\simplempc_solver\lib_target`
10. (Figure 13.84) In the “Code Generation/Custom Code” tab, add the source files:
 - `simplempc_solver_simulinkBlock.c`
 - `simplempc_solver.c`
11. (Figure 13.85) In the “Code Generation/Custom Code” tab, add the library files:
 - `internal_simplempc_solver_1.lib`
12. (Figure 13.86) Compile the code of the Simulink model. This will also automatically load the model to the connected Speedgoat platform.
13. Deployment is complete and simulations can now be run on the Speedgoat platform.

14. Run the simulation on the Speedgoat platform.

You can find the Matlab code of this simulation to try it out for yourself in the examples folder that comes with your client.

Figures

```
14
15 %% Create controller object (generates code)
16 % for a complete list of codeoptions, see
17 % https://www.embotech.com/FORCES-Pro/User-Manual/Low-level-Interface/Solver-Options
18 codeoptions = getOptions('simpleMPC_solver'); % give solver a name
19
20 codeoptions.printlevel = 0; % turn off print functions on target
21
22 codeoptions.platform = 'Speedgoat-x86'; % set platform
23
24 controller = optimizerFORCES(const, cost, codeoptions, X(:,1), U(:,1), {'xinit'}, {'\
25
26 %% Simulate
27
28
```

Figure 13.75: Set the appropriate code generation options.

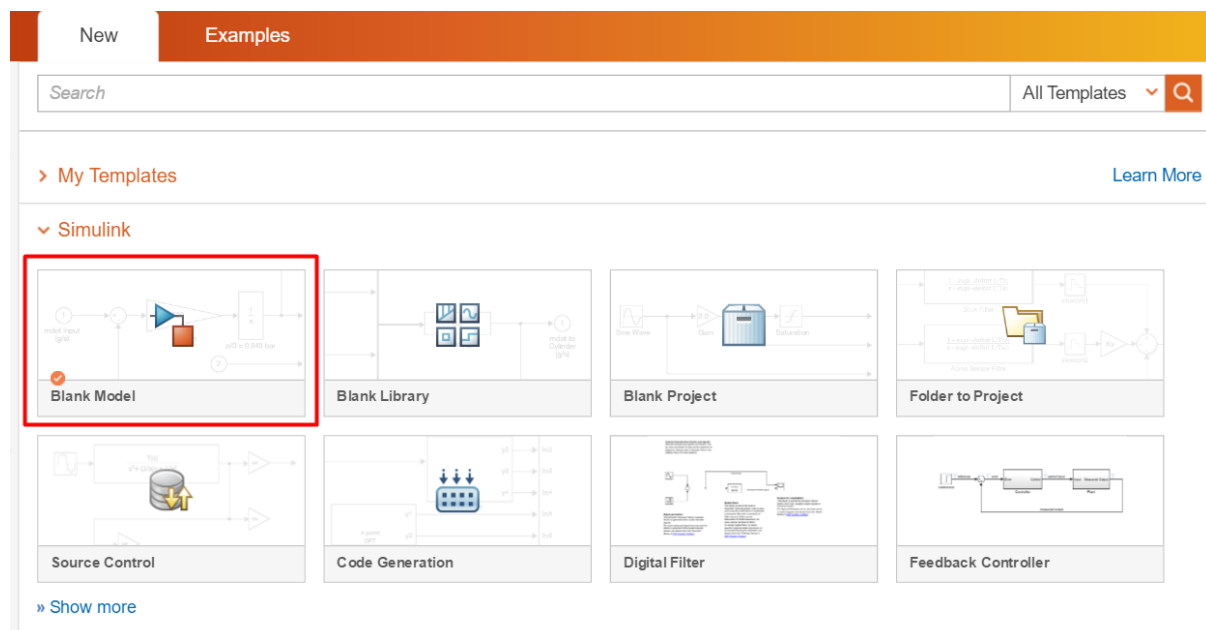


Figure 13.76: Create a Simulink model.

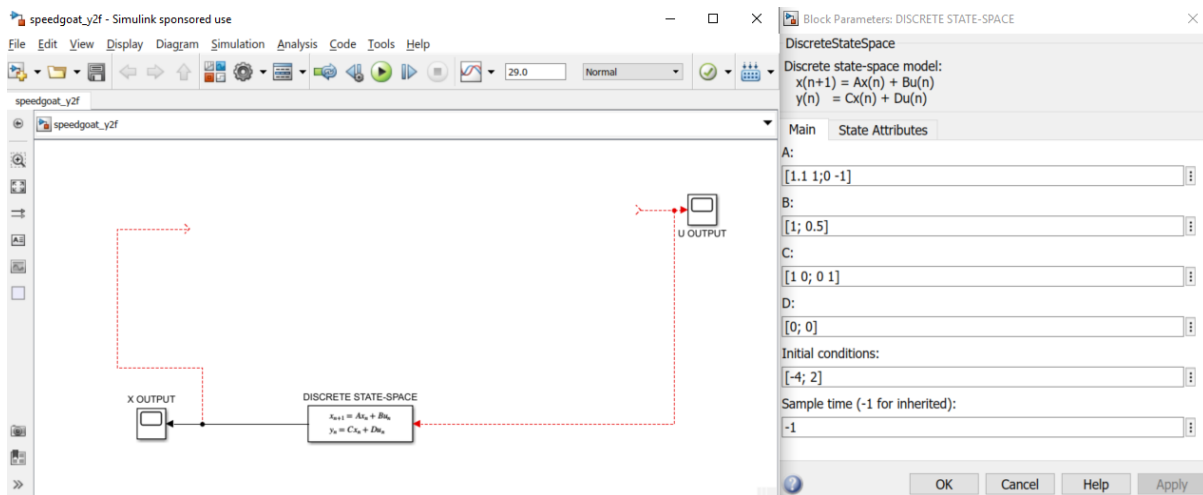


Figure 13.77: Populate the Simulink model.

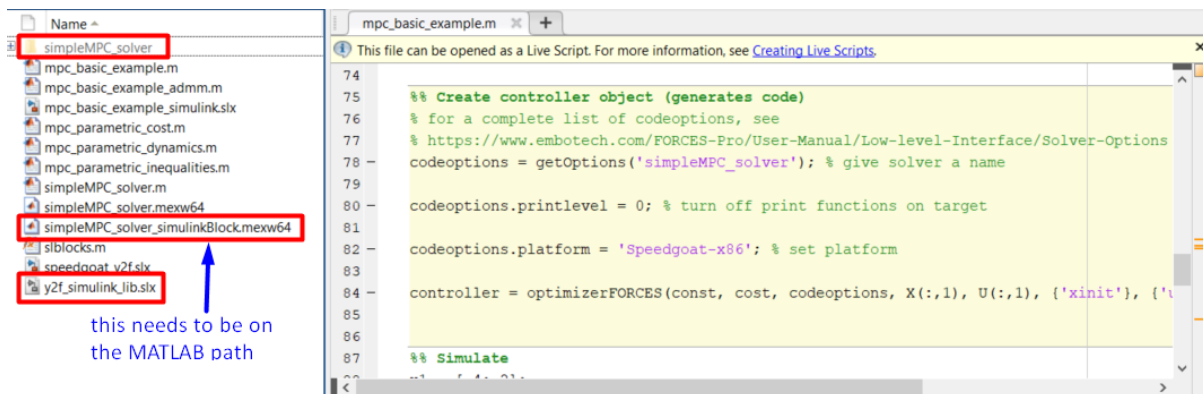


Figure 13.78: Add the folder containing the .mexw64 solver file to the Matlab path.

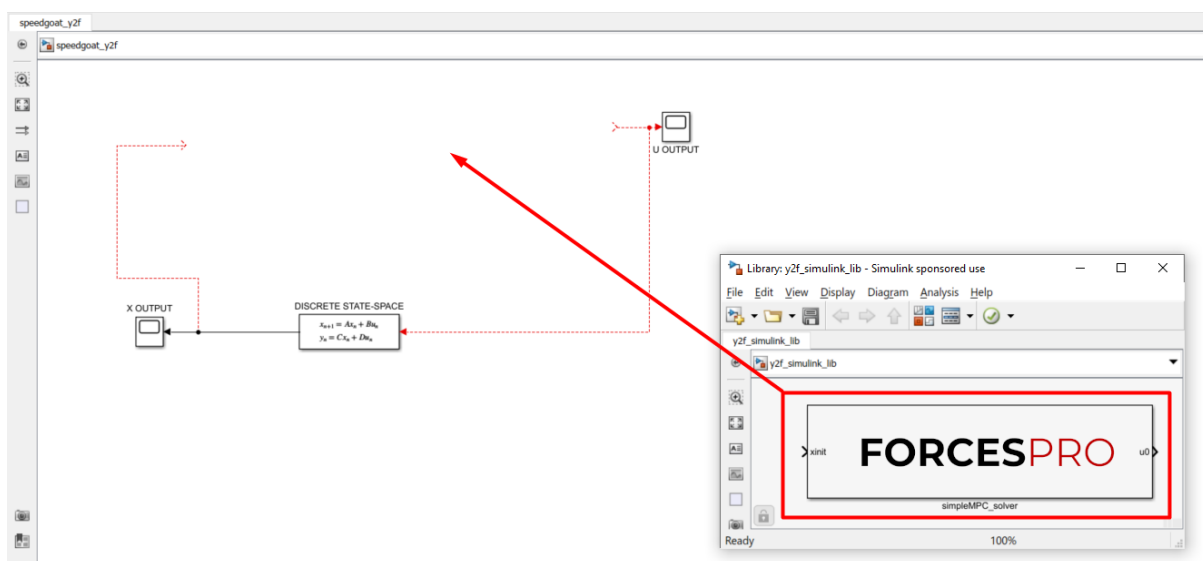


Figure 13.79: Copy-paste and connect the FORCESPRO block.

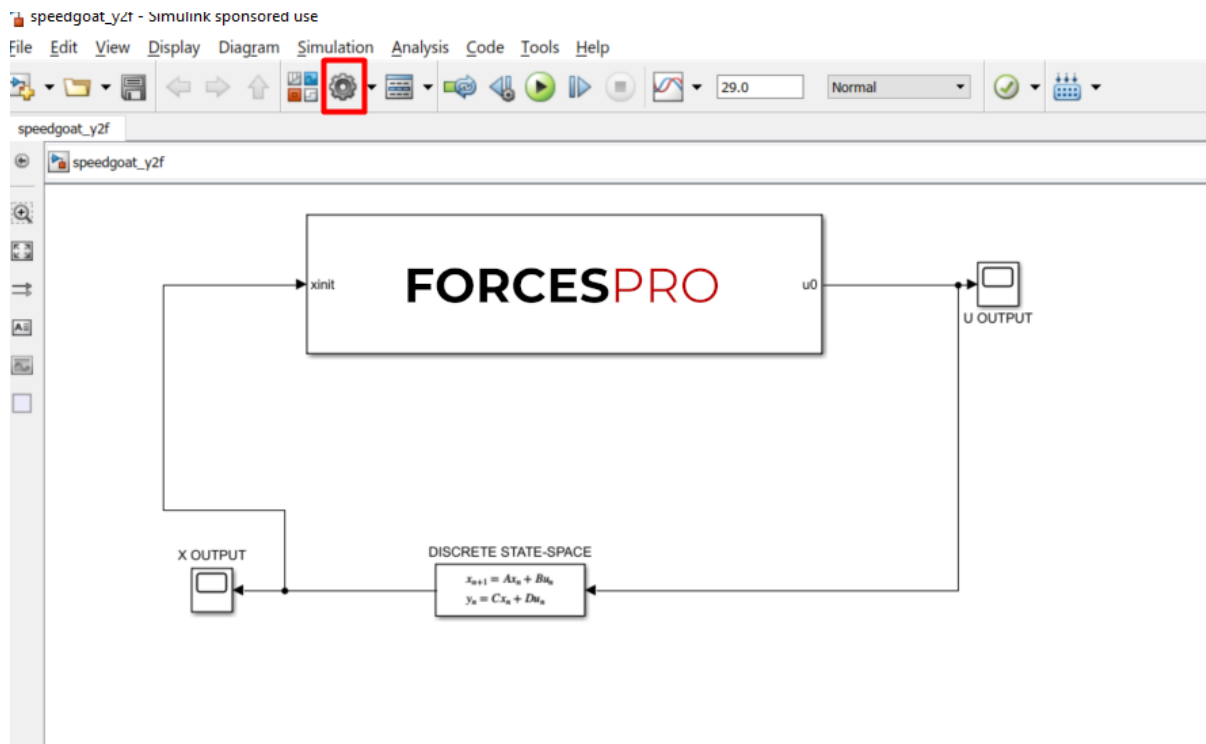


Figure 13.80: Open the Simulink model options.

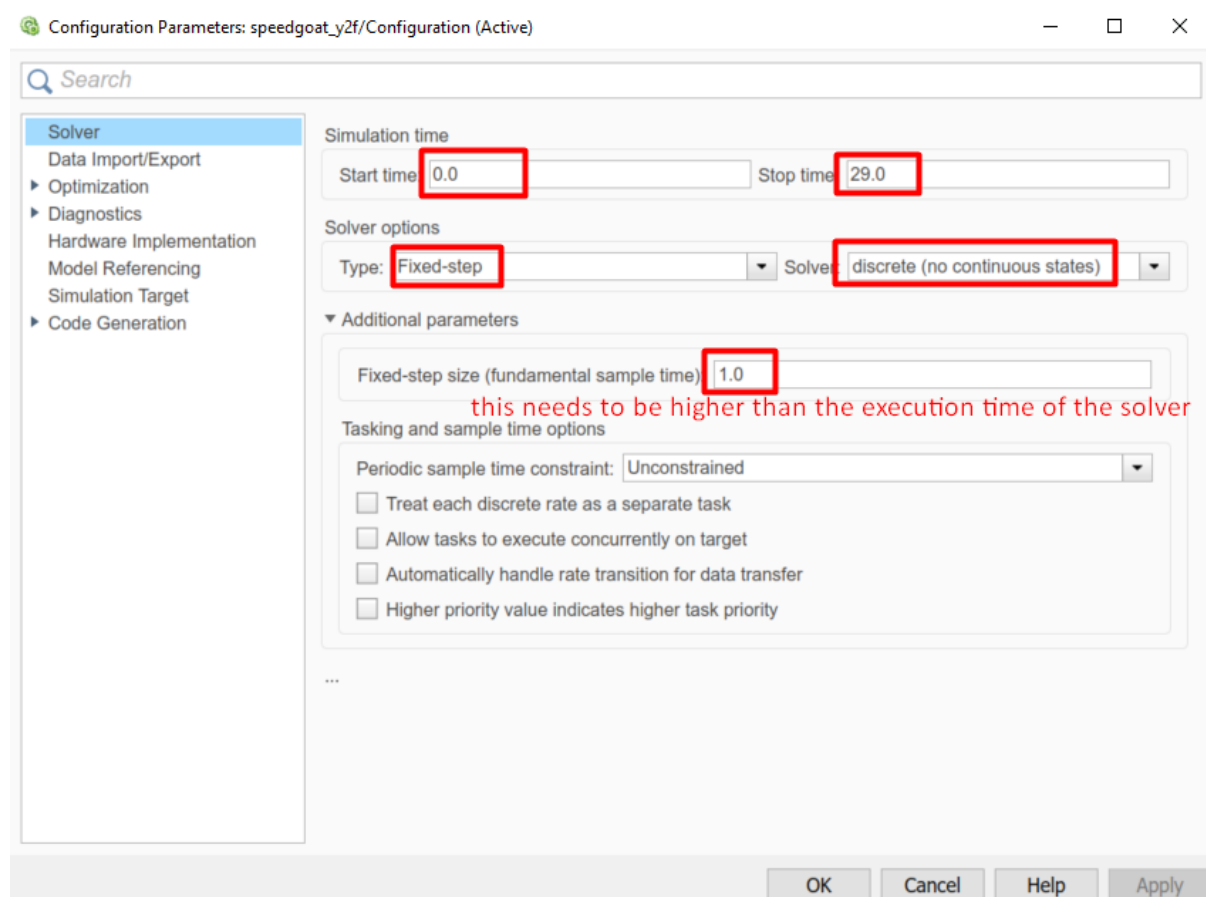


Figure 13.81: Set the Simulink solver options.

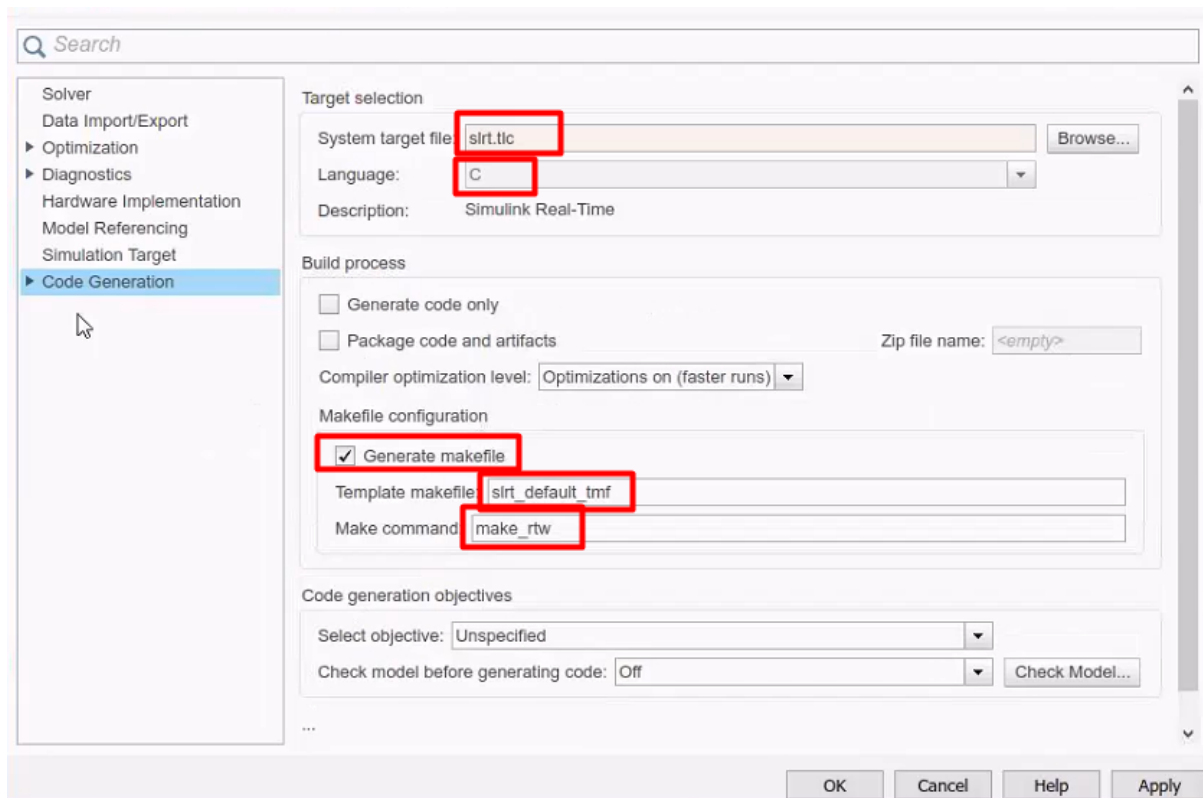


Figure 13.82: Set the Simulink code generation options.

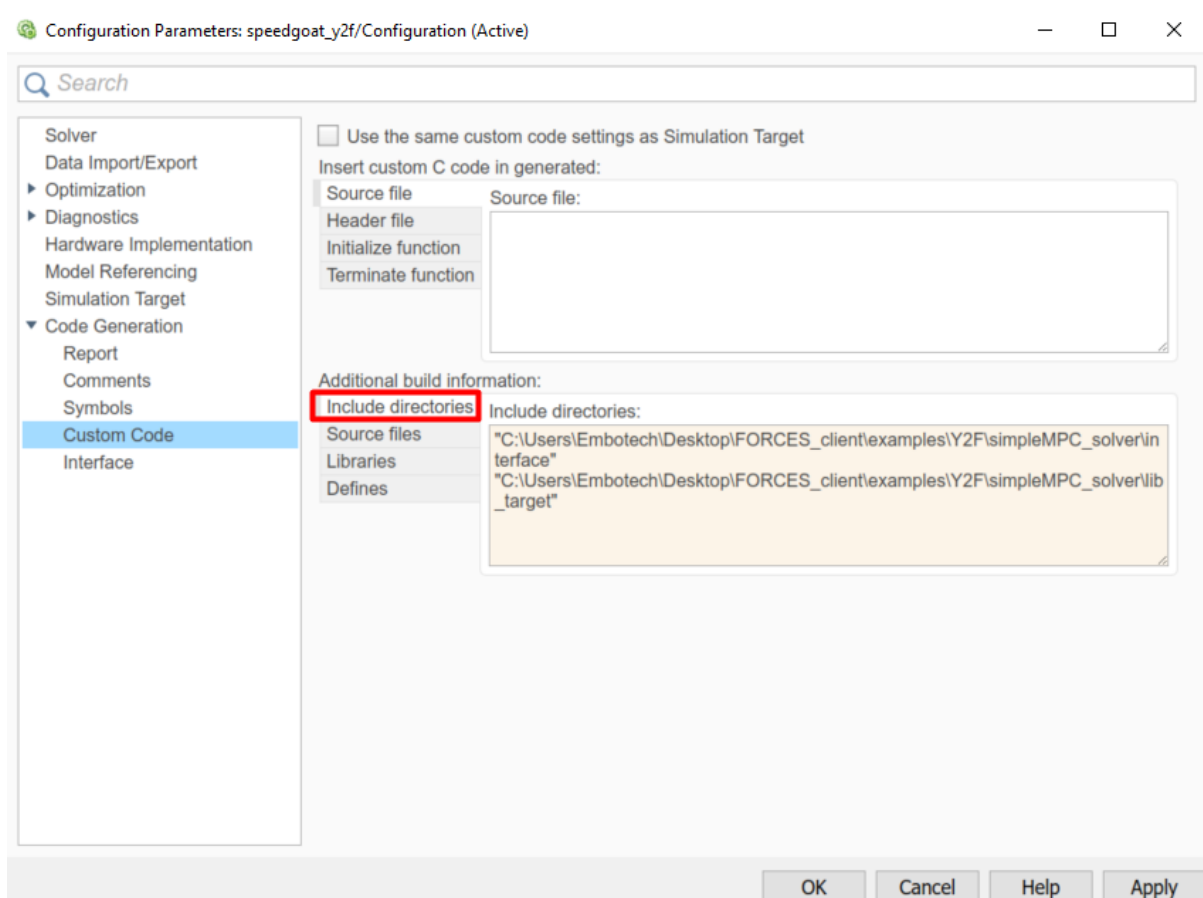


Figure 13.83: Add the directories included for the code generation.

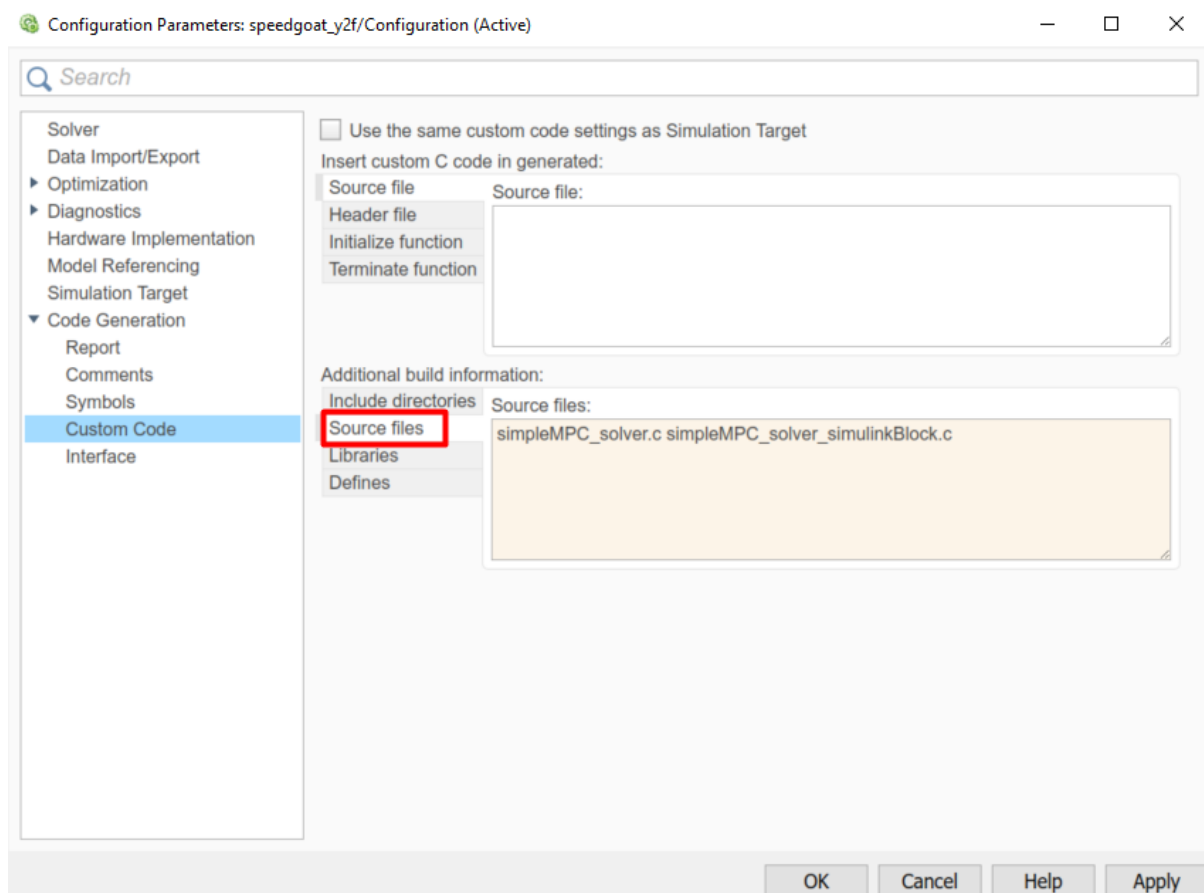


Figure 13.84: Add the source files used for the code generation.

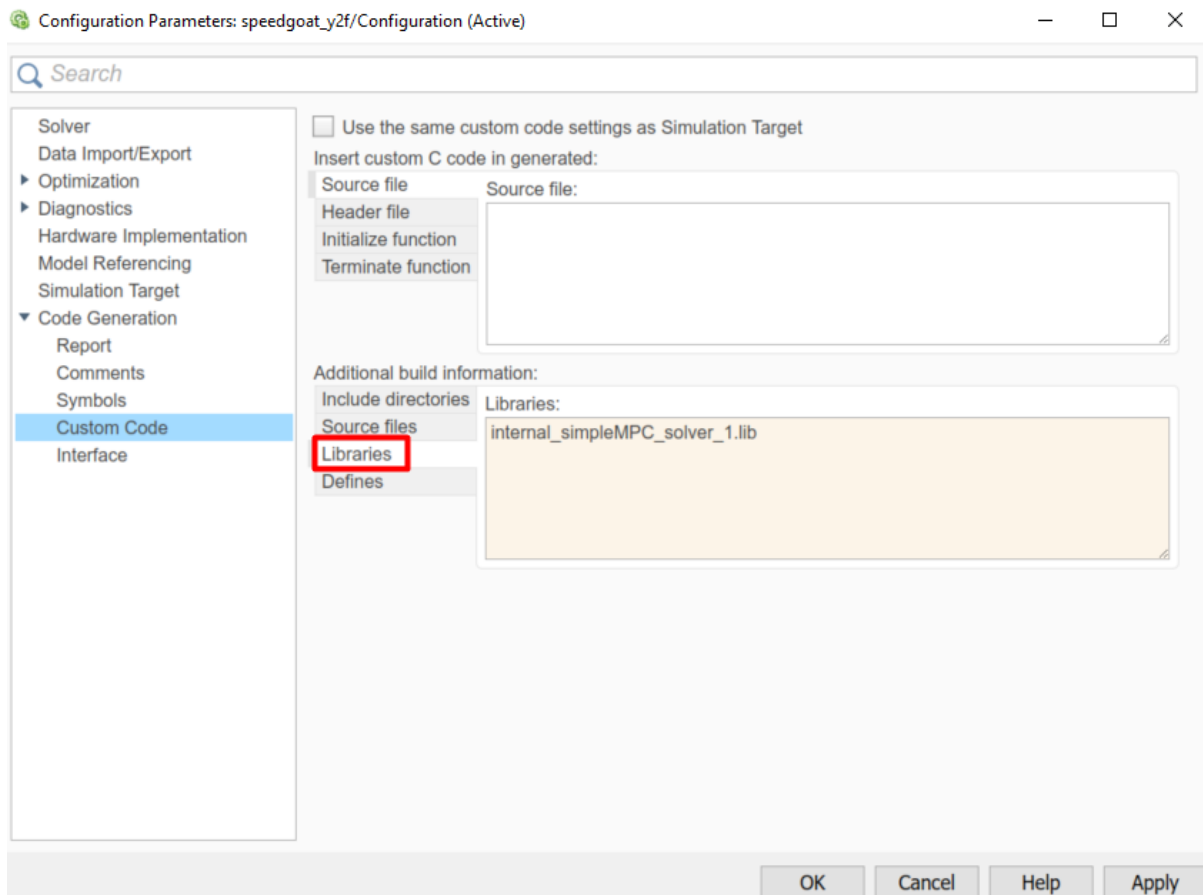


Figure 13.85: Add the libraries used for the code generation.

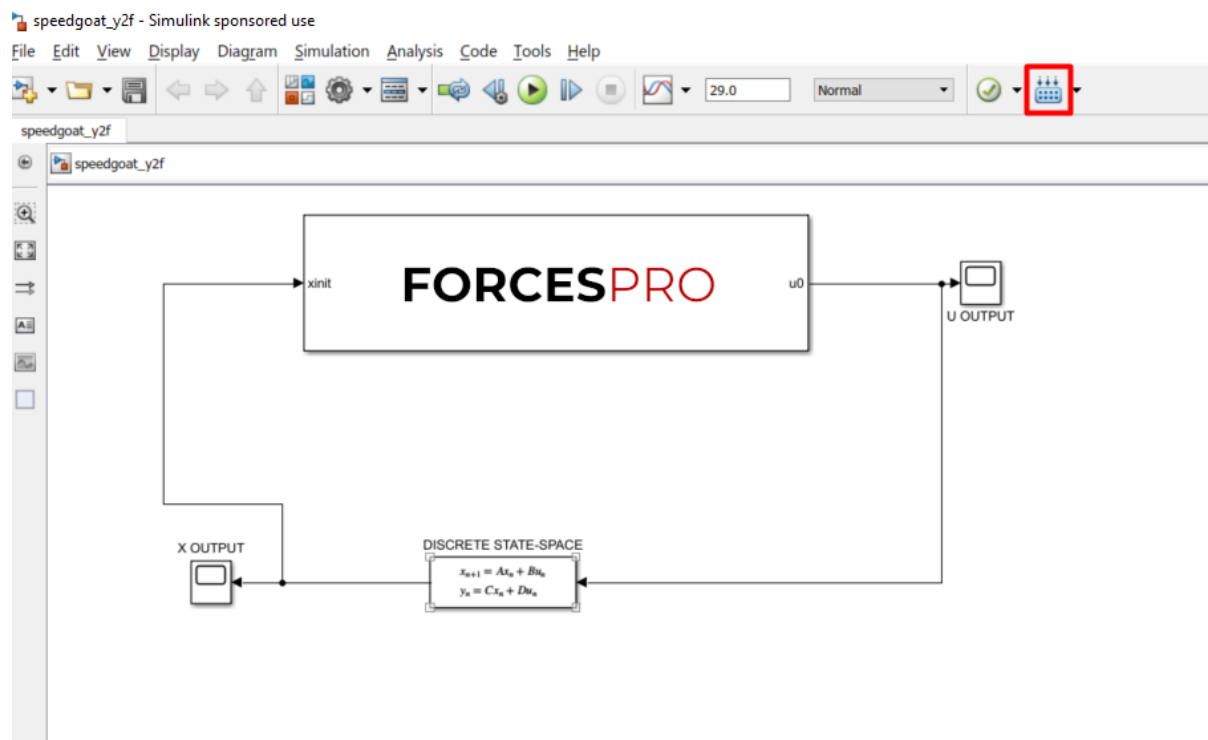


Figure 13.86: Compile the code of the Simulink model.

13.5 Speedgoat QNX

- *High-level interface*
 - *Instructions*
 - *Figures*
- *Y2F interface*
 - *Instructions*
 - *Figures*

Important: When deploying to a target hardware platform, the library included in the **lib_target** directory of the generated solver should be used instead of the library in the **lib** directory.

13.5.1 High-level interface

Instructions

The steps to deploy and simulate a FORCESPRO controller on a Speedgoat QNX platform are detailed below.

1. (Figure 13.87) Set the code generation options:

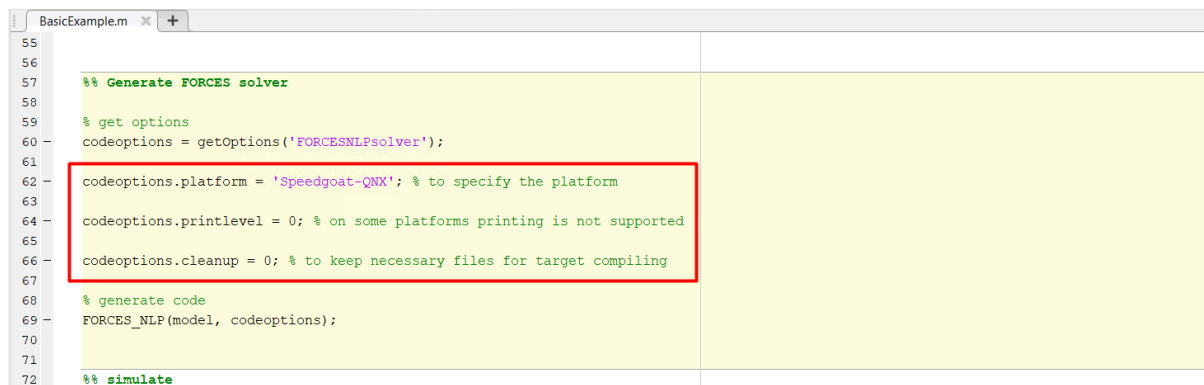
```
codeoptions.platform = 'Speedgoat-QNX'; % to specify the platform
codeoptions.printlevel = 0; % on some platforms printing is not supported
codeoptions.cleanup = 0; % to keep necessary files for target compile
```

and then generate the code for your solver (henceforth referred to as “FORCESNLPsolver”, placed in the folder “BasicExample”) using the high-level interface.

2. (Figure 13.88) Create a new Simulink model using the blank model template.
3. (Figure 13.89) Populate the Simulink model with the system you want to control.
4. (Figure 13.90) Make sure the FORCESNLPsolver_simulinkBlock.mexw64 file (created during code generation) is on the Matlab path.
5. (Figure 13.91) Open the FORCESNLPsolver_lib.mdl Simulink model file, contained in the interface folder of the FORCESNLPsolver folder created during code generation.
6. (Figure 13.92) Copy-paste the FORCESPRO Simulink block into your simulation model and connect its inputs and outputs appropriately.
7. (Figure 13.93) Access the Simulink Model’s Settings.
8. (Figure 13.94) In the “Solver” tab, set the options:
 - Simulation start/stop time: Depending on the simulation wanted.
 - Solver type: Discrete or fixed-step.
 - Fixed-step size: Needs to be higher than the execution time of the solver.
9. (Figure 13.95) In the “Code Generation” tab, set the options:
 - System target file: slrealtime.tlc
 - Generate makefile: Off

10. (Figure 13.96) In the “Code Generation/Custom Code” tab, include the directories:
 - BasicExample
 - BasicExample\FORCESNLPsolver\interface
 - BasicExample\FORCESNLPsolver\lib_target
11. (Figure 13.97) In the “Code Generation/Custom Code” tab, add the source files:
 - FORCESNLPsolver_simulinkBlock.c
 - FORCESNLPsolver_casadi2forces.c
 - FORCESNLPsolver_casadi.c
12. (Figure 13.98) In the “Code Generation/Custom Code” tab, add the library file:
 - libFORCESNLPsolver.a
13. (Figure 13.99) Access the FORCESPRO block’s parameters.
14. (Figure 13.100) Remove “FORCESNLPsolver” and “FORCESNLPsolver_simulinkBlock” from the S-function module.
15. (Figure 13.101) Compile the code of the Simulink model. This will also automatically load the model to the connected Speedgoat platform.
16. Deployment is complete and simulations can now be run on the Speedgoat platform.

Figures



The screenshot shows a MATLAB script window titled 'BasicExample.m'. The script contains the following code:

```
55
56
57 %% Generate FORCES solver
58
59 % get options
60 codeoptions = getOptions('FORCESNLPsolver');
61
62 codeoptions.platform = 'Speedgoat-QNX'; % to specify the platform
63
64 codeoptions.printlevel = 0; % on some platforms printing is not supported
65
66 codeoptions.cleanup = 0; % to keep necessary files for target compiling
67
68 % generate code
69 FORCES_NLP(model, codeoptions);
70
71
72 %% simulate
```

A red rectangular box highlights the lines 62 through 66, which define the code generation options for the Speedgoat-QNX platform.

Figure 13.87: Set the appropriate code generation options.

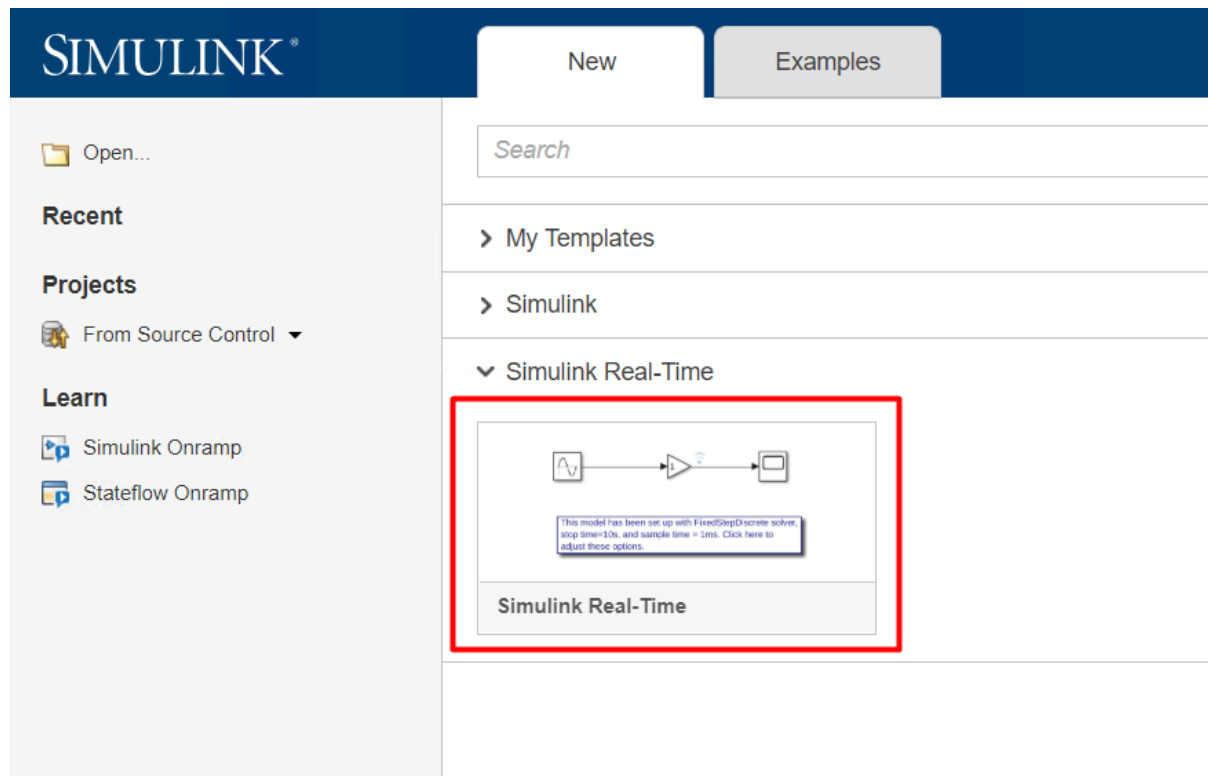


Figure 13.88: Create a Simulink model.

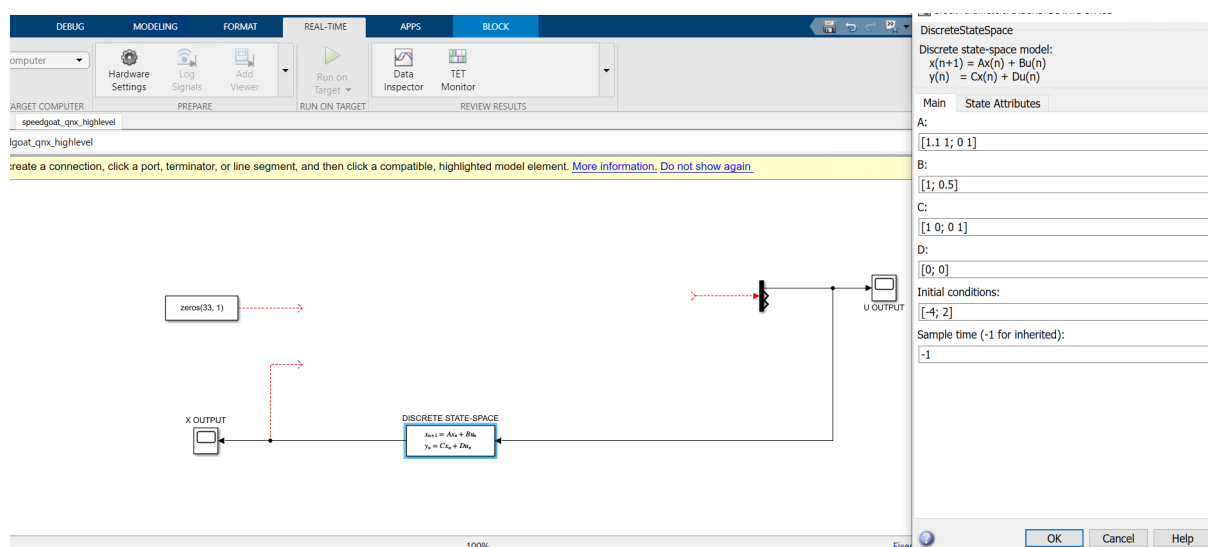


Figure 13.89: Populate the Simulink model.

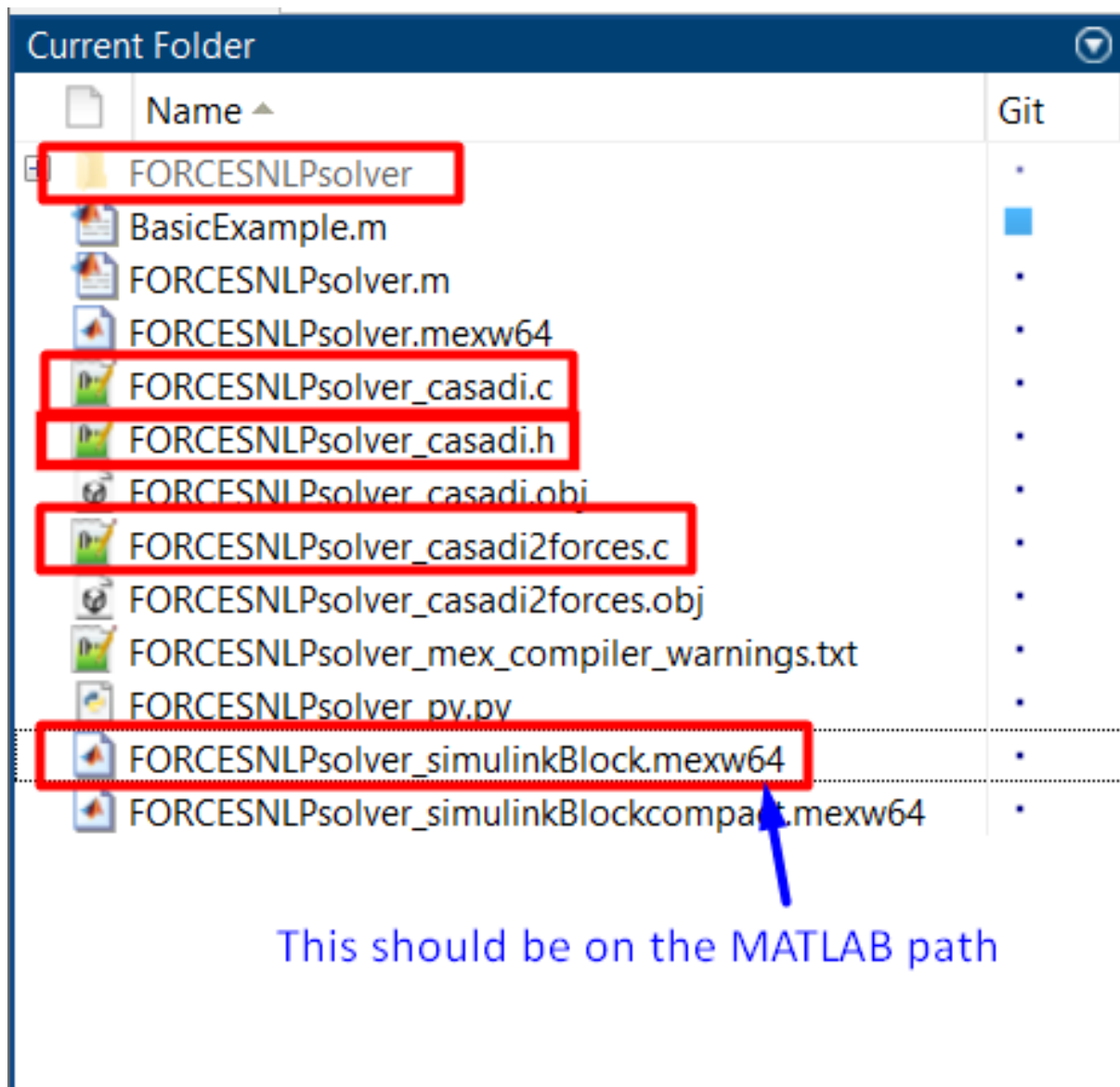


Figure 13.90: Add the folder containing the .mexw64 solver file to the Matlab path.

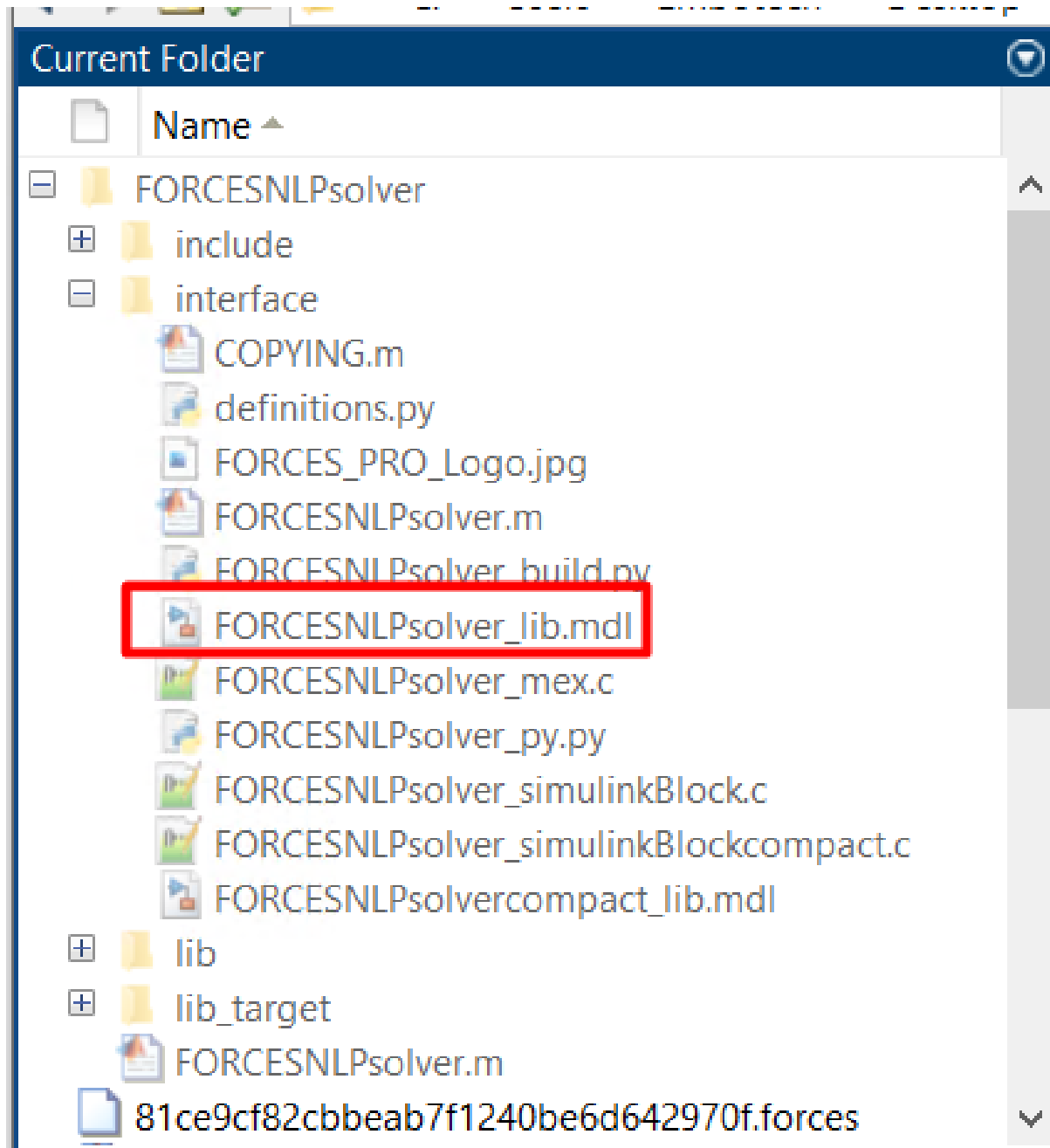


Figure 13.91: Open the generated Simulink solver model.

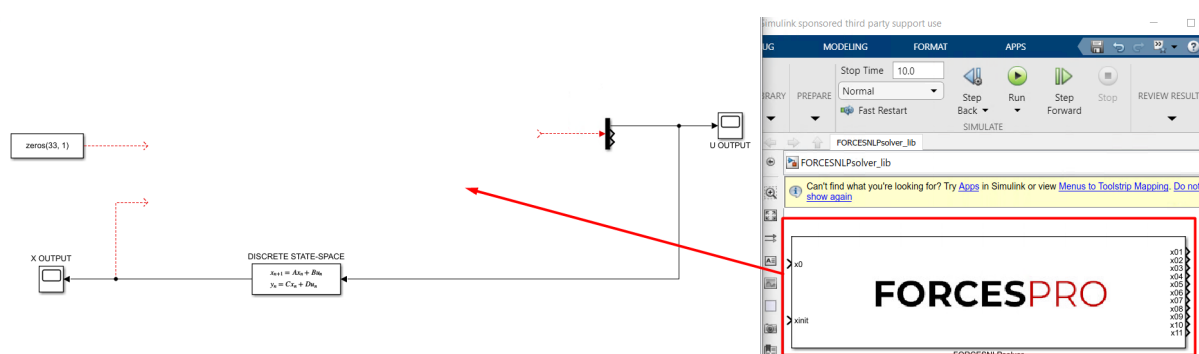


Figure 13.92: Copy-paste and connect the FORCESPRO block.

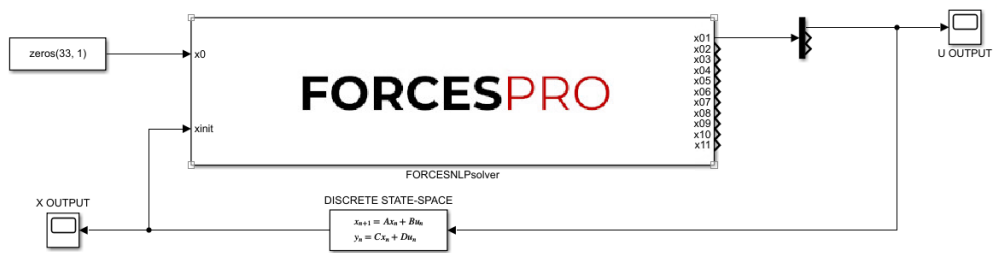
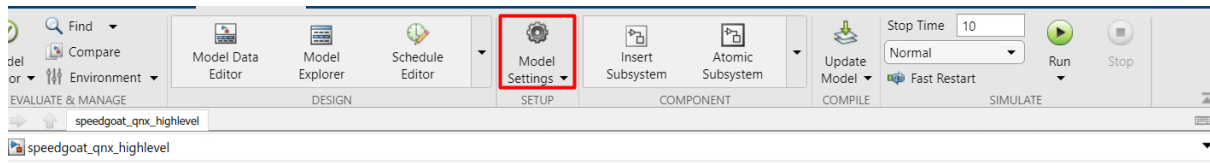


Figure 13.93: Open the Simulink Model Settings.

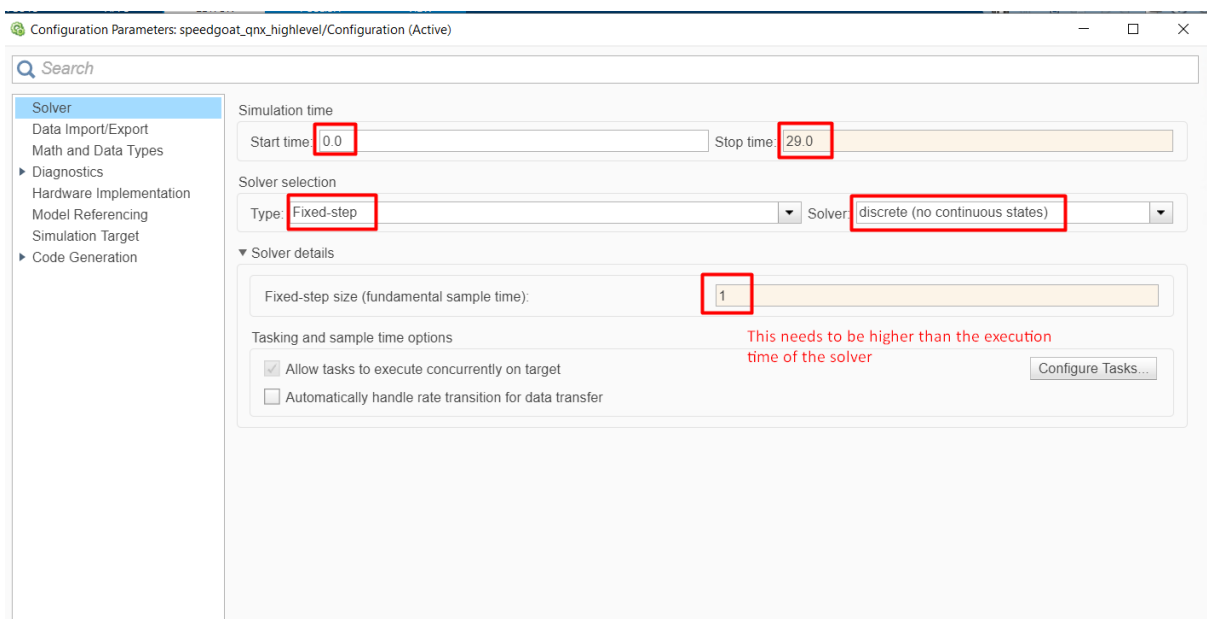


Figure 13.94: Set the Simulink solver options.

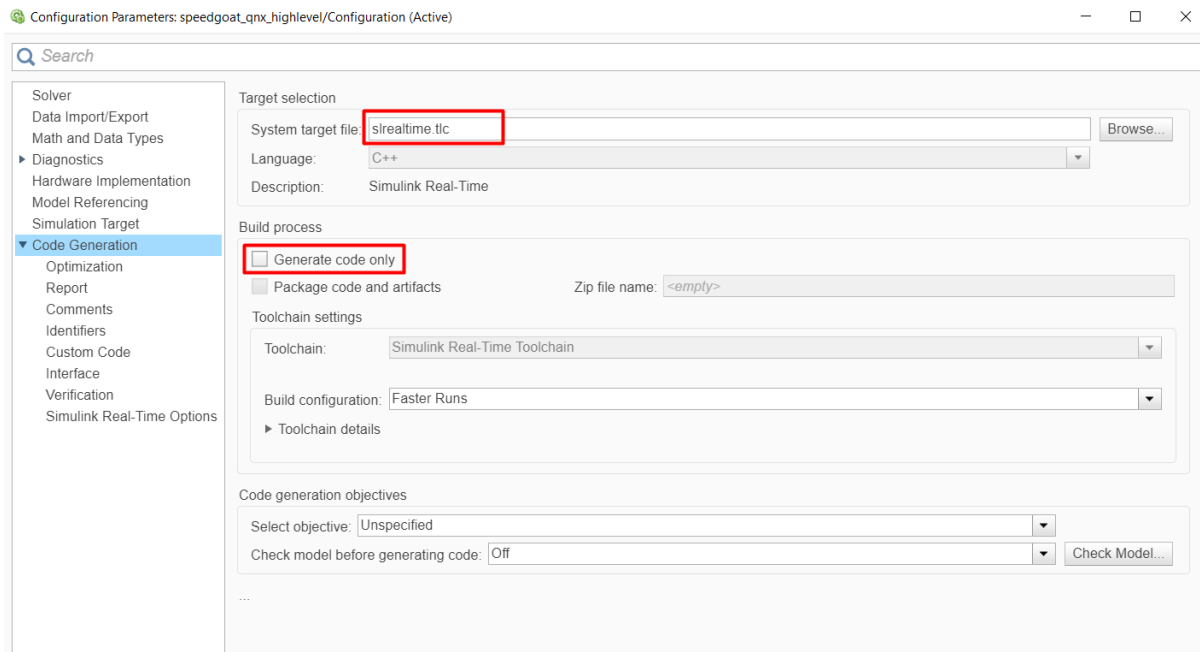


Figure 13.95: Set the Simulink code generation options.

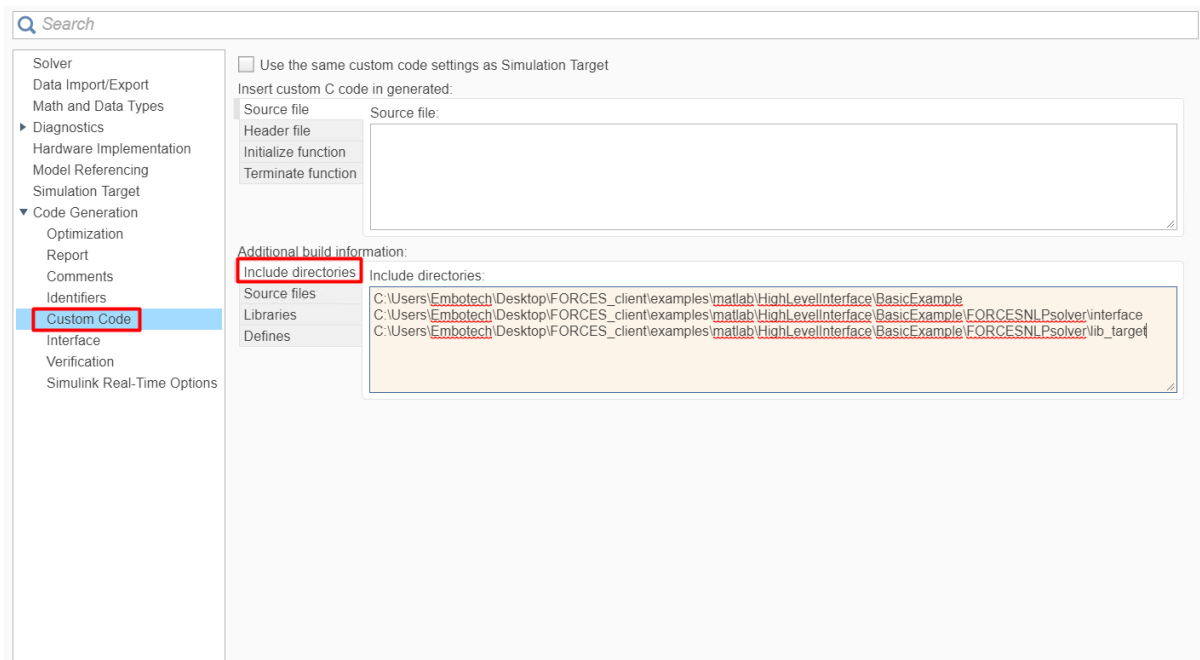


Figure 13.96: Add the directories included for the code generation.

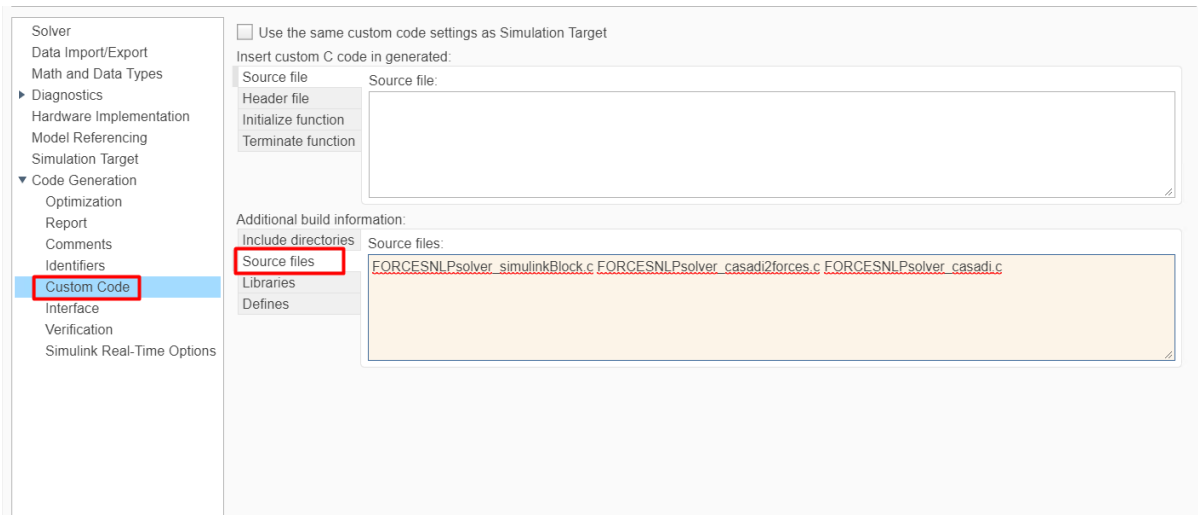


Figure 13.97: Add the source files used for the code generation.

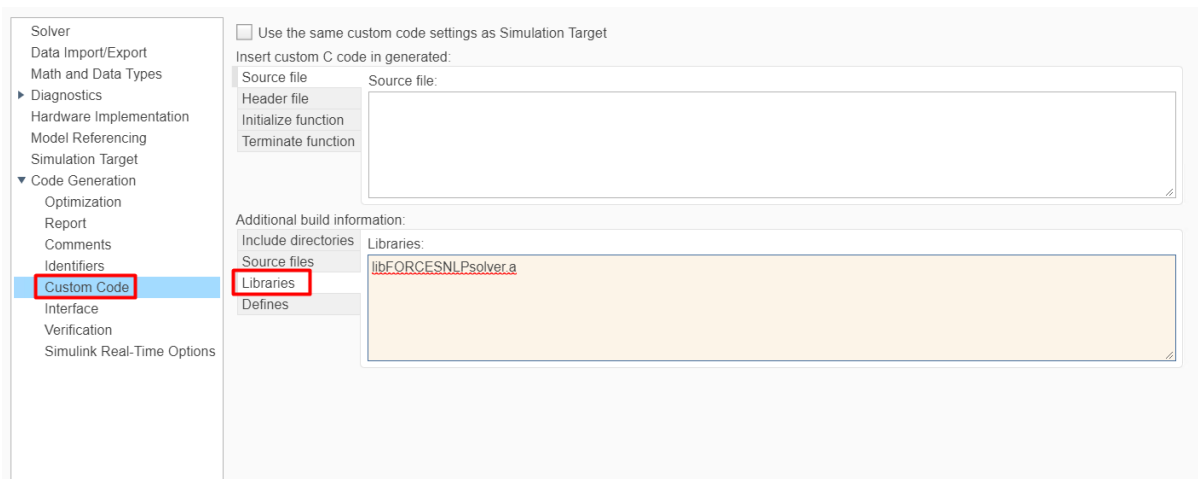


Figure 13.98: Add the libraries used for the code generation.

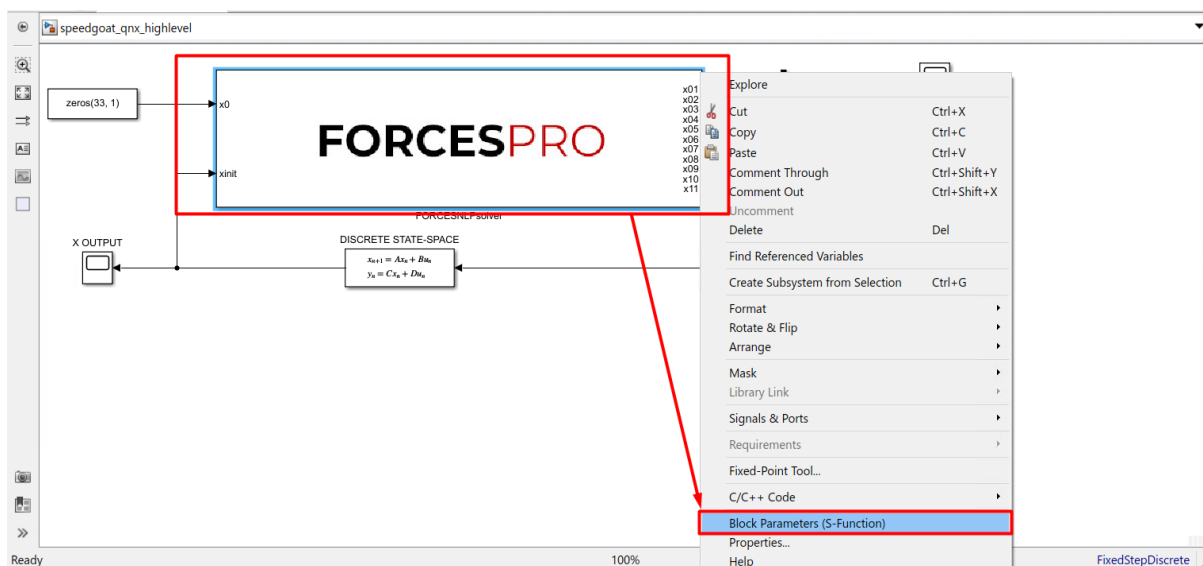


Figure 13.99: Open the FORCESPRO block's parameters.

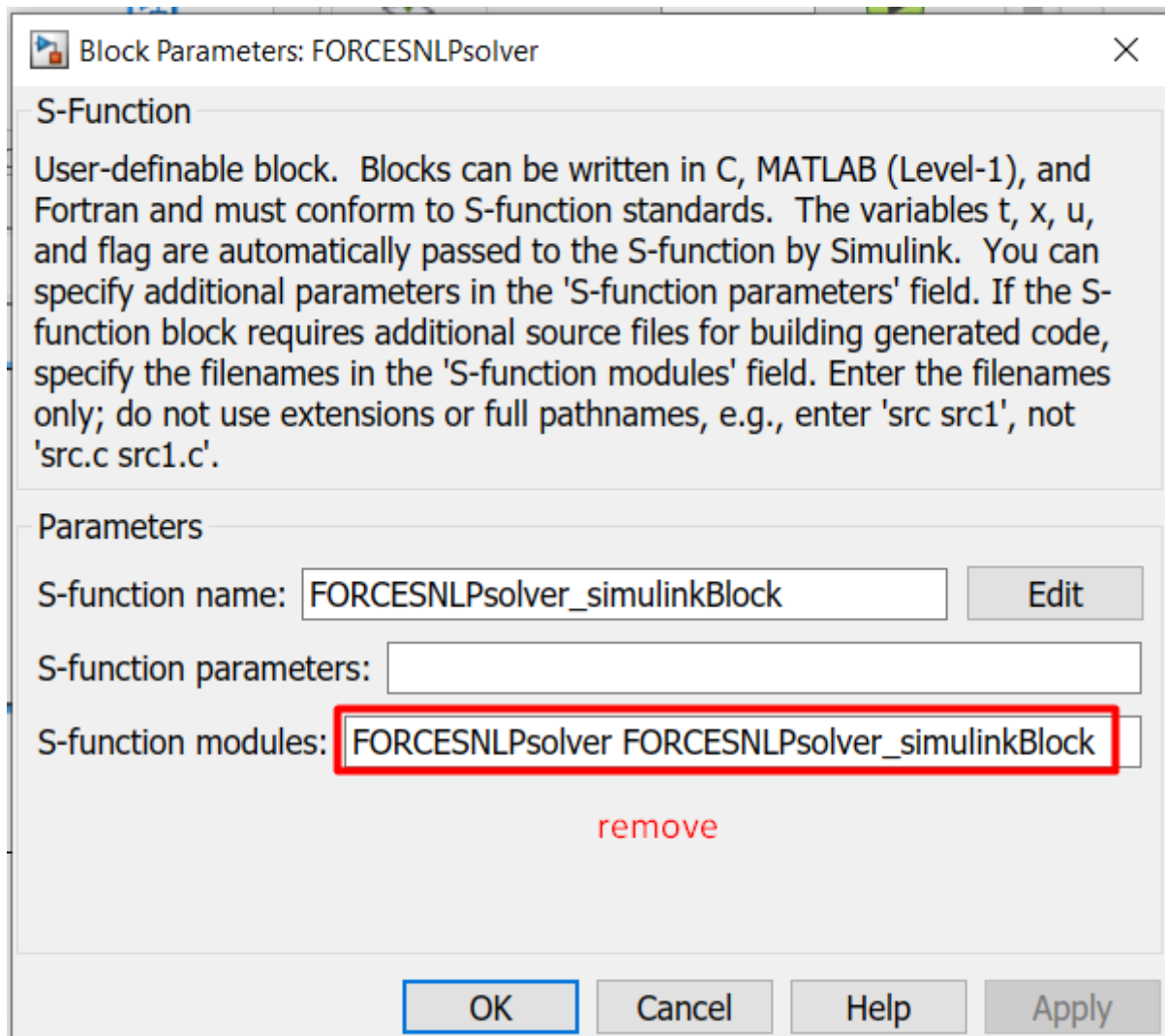


Figure 13.100: Remove the default data from the S-function module.

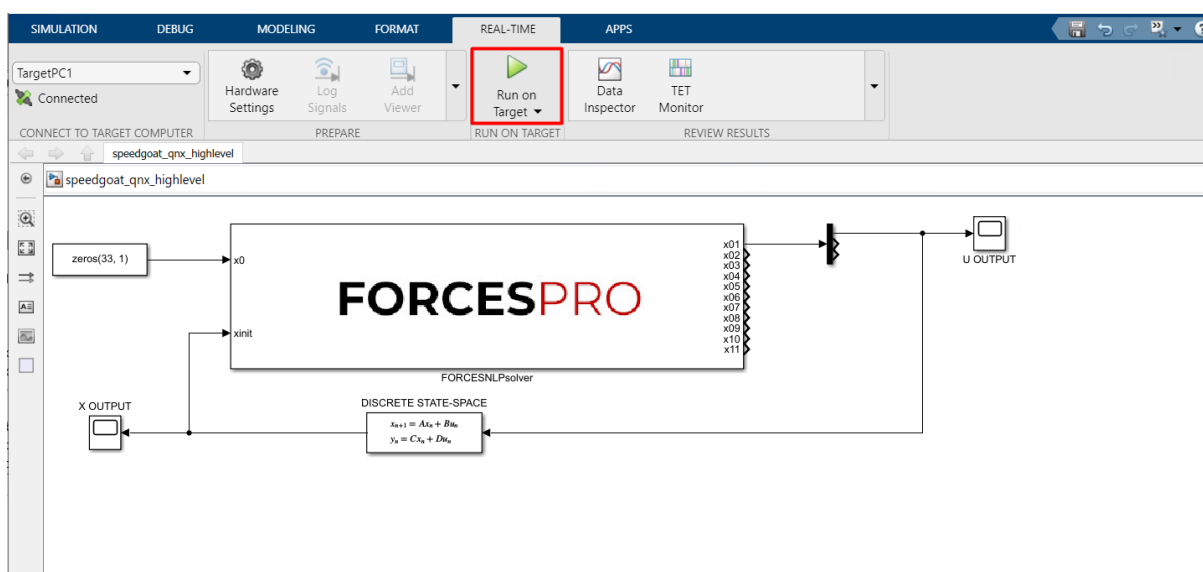


Figure 13.101: Compile the code of the Simulink model.

13.5.2 Y2F interface

Instructions

The steps to deploy and simulate a FORCESPRO controller on a Speedgoat QNX platform are detailed below.

1. (Figure 13.102) Set the code generation options:

```
codeoptions.platform = 'Speedgoat-QNX'; % to specify the platform
codeoptions.printlevel = 0; % on some platforms printing is not supported
```

and then generate the code for your solver (henceforth referred to as “simplempc_solver”, placed in the folder “Y2F”) using the Y2F interface.

2. (Figure 13.103) Create a new Simulink model using the blank model template.
3. (Figure 13.104) Populate the Simulink model with the system you want to control.
4. (Figure 13.105) Make sure the `simplempc_solver_simulinkBlock.mexw64` file (created during code generation) is on the Matlab path.
5. (Figure 13.106) Copy-paste the FORCESPRO Simulink block, contained in the created `y2f_simulink_lib.slx` Simulink model file, into your simulation model and connect its inputs and outputs appropriately.
6. (Figure 13.107) Access the Simulink Model's Settings.
7. (Figure 13.108) In the “Solver” tab, set the options:
 - Simulation start/stop time: Depending on the simulation wanted.
 - Solver type: Discrete or fixed-step.
 - Fixed-step size: Needs to be higher than the execution time of the solver.
8. (Figure 13.109) In the “Code Generation/RTI general build options” tab, set the options:
 - System target file: `slrealtime.tlc`
 - Generate makefile: Off
9. (Figure 13.110) In the “Code Generation/Custom Code” tab, include the directories:
 - Y2F
 - Y2F\simplempc_solver\interface
 - Y2F\simplempc_solver\lib_target
10. (Figure 13.111) In the “Code Generation/Custom Code” tab, add the source files:
 - `simplempc_solver_simulinkBlock.c`
 - `simplempc_solver.c`
11. (Figure 13.112) In the “Code Generation/Custom Code” tab, add the library file:
 - `libinternal_simplempc_solver_1.a`
12. (Figure 13.113) Compile the code of the Simulink model. This will also automatically load the model to the connected Speedgoat platform.
13. Deployment is complete and simulations can now be run on the Speedgoat platform.

Figures

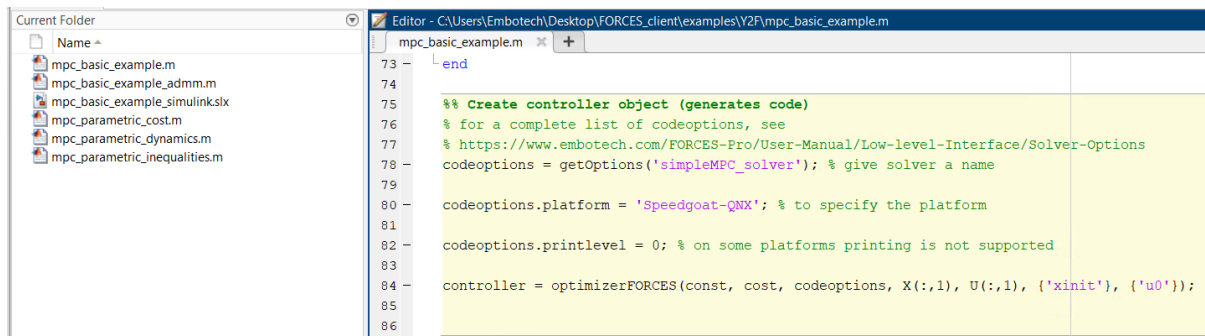


Figure 13.102: Set the appropriate code generation options.

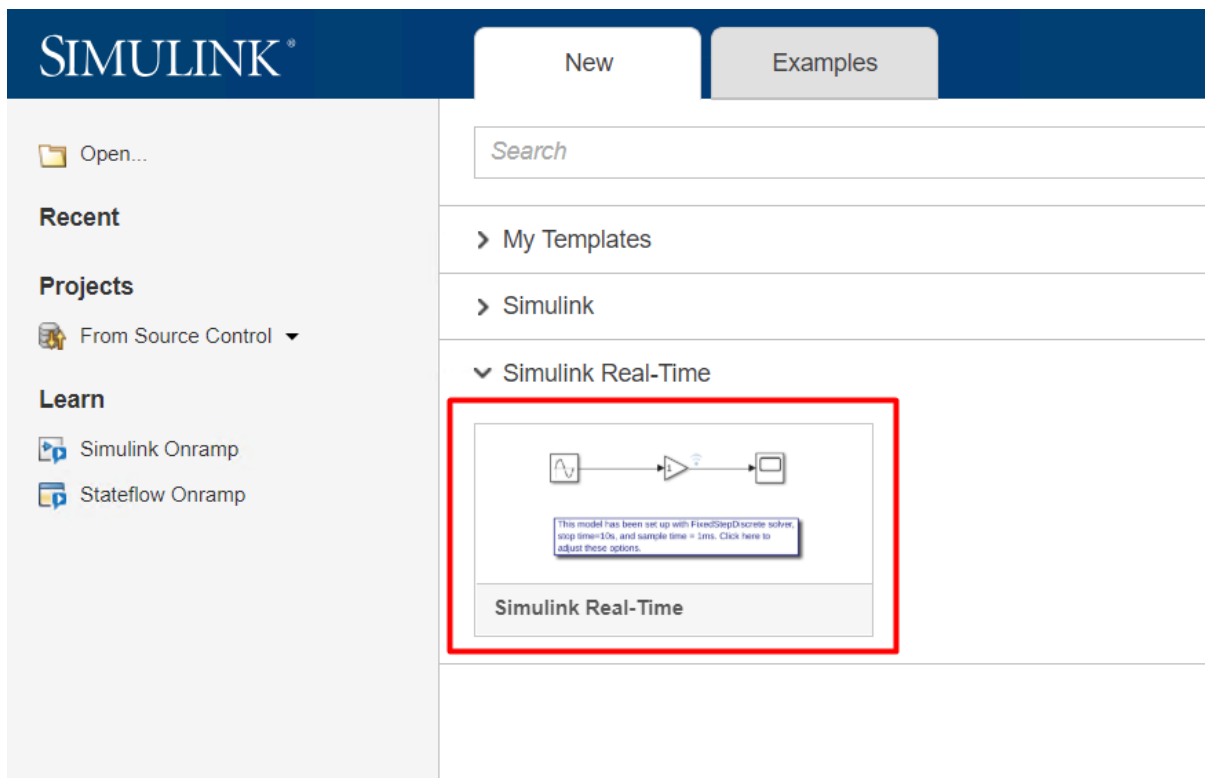


Figure 13.103: Create a Simulink model.

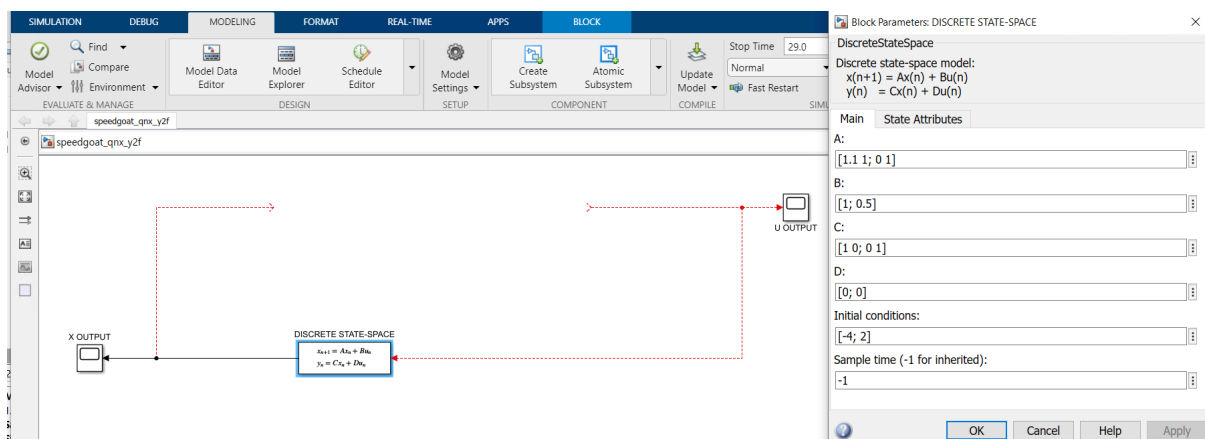


Figure 13.104: Populate the Simulink model.

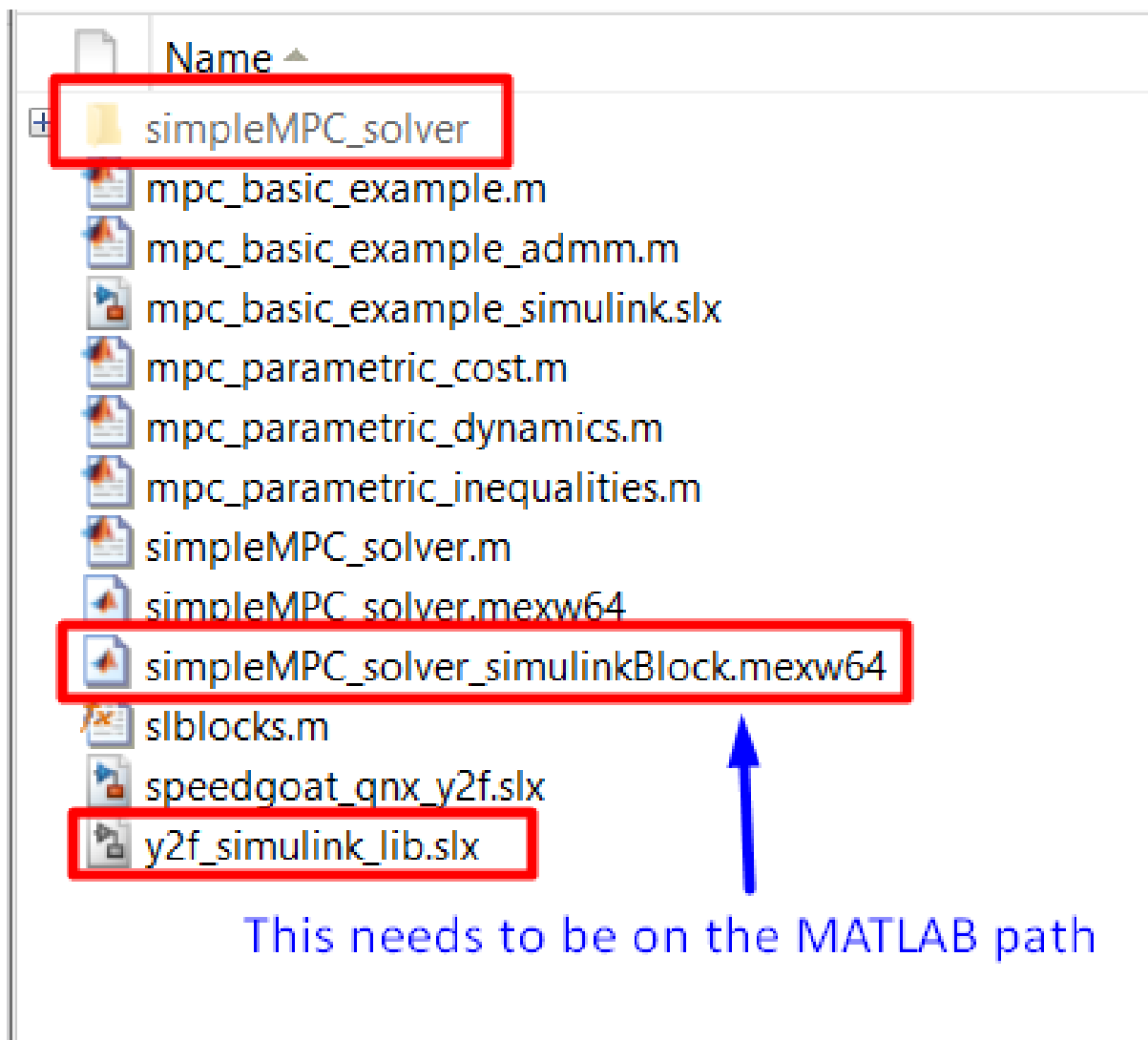


Figure 13.105: Add the folder containing the .mexw64 solver file to the Matlab path.

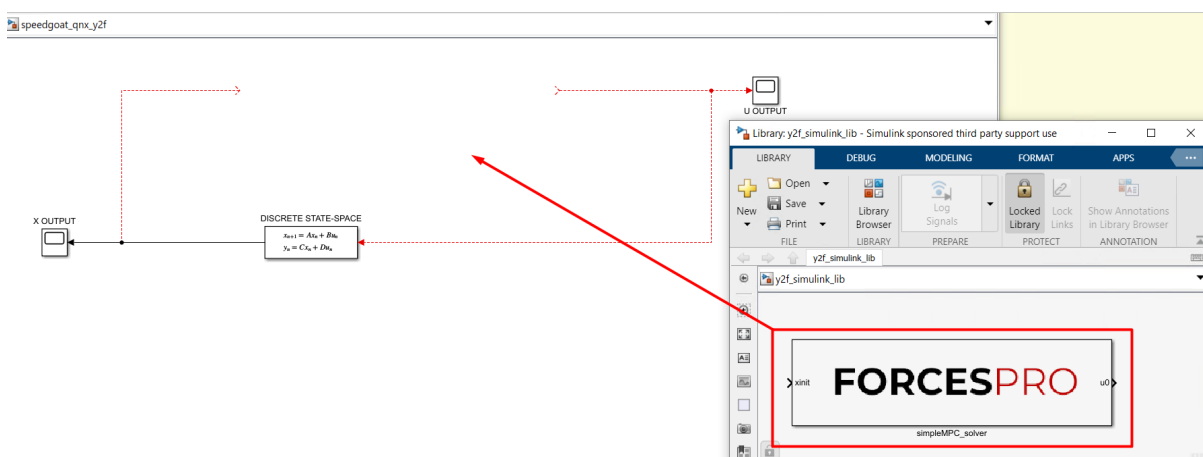


Figure 13.106: Copy-paste and connect the FORCESPRO block.

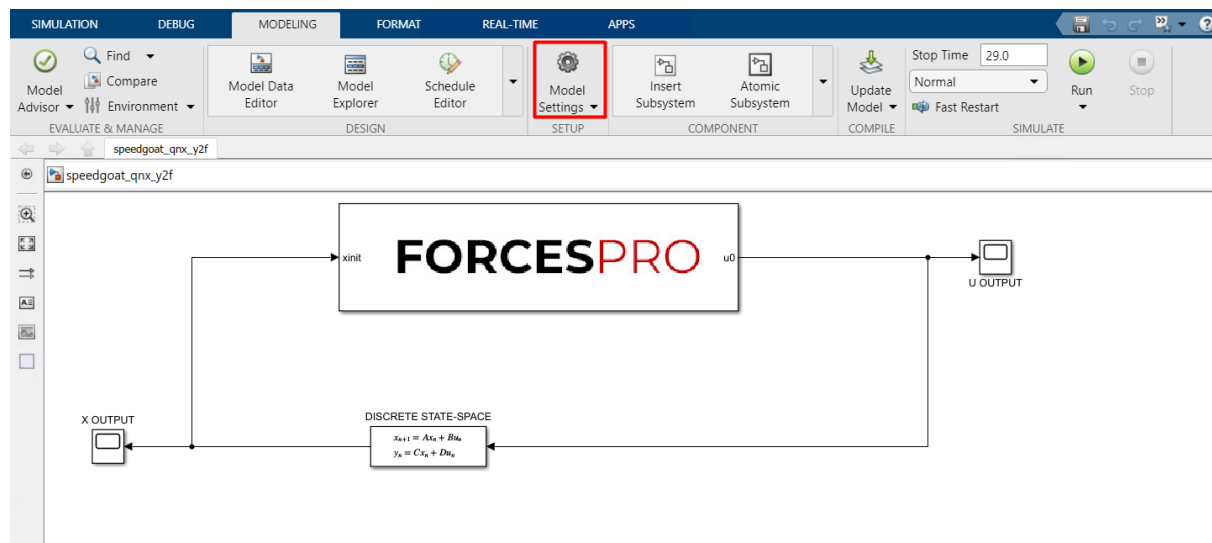


Figure 13.107: Open the Simulink Model Settings.

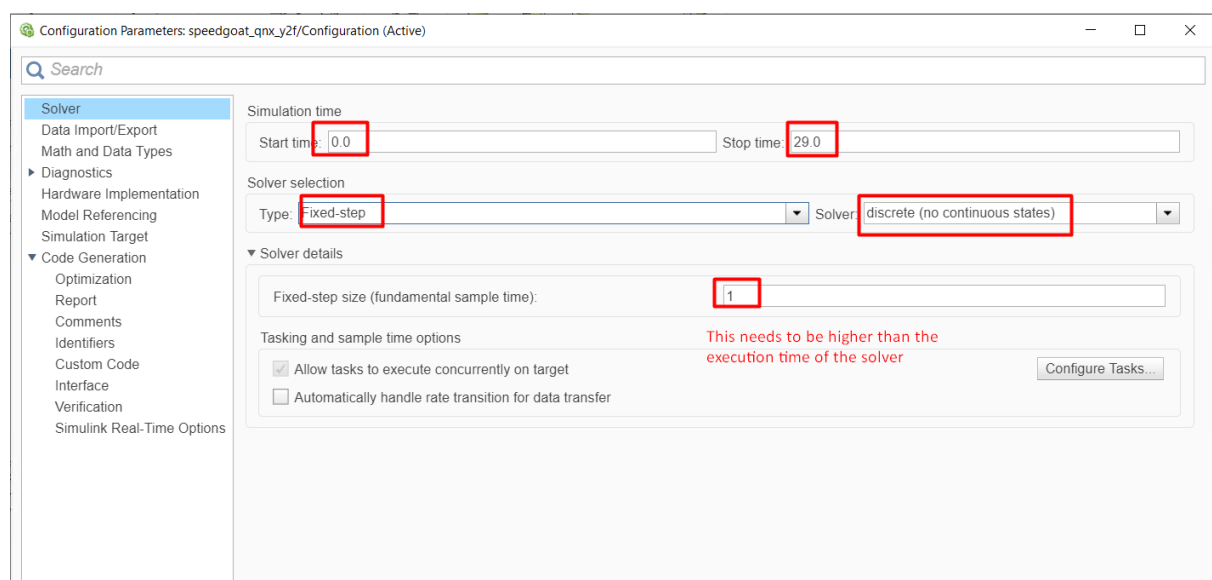


Figure 13.108: Set the Simulink solver options.

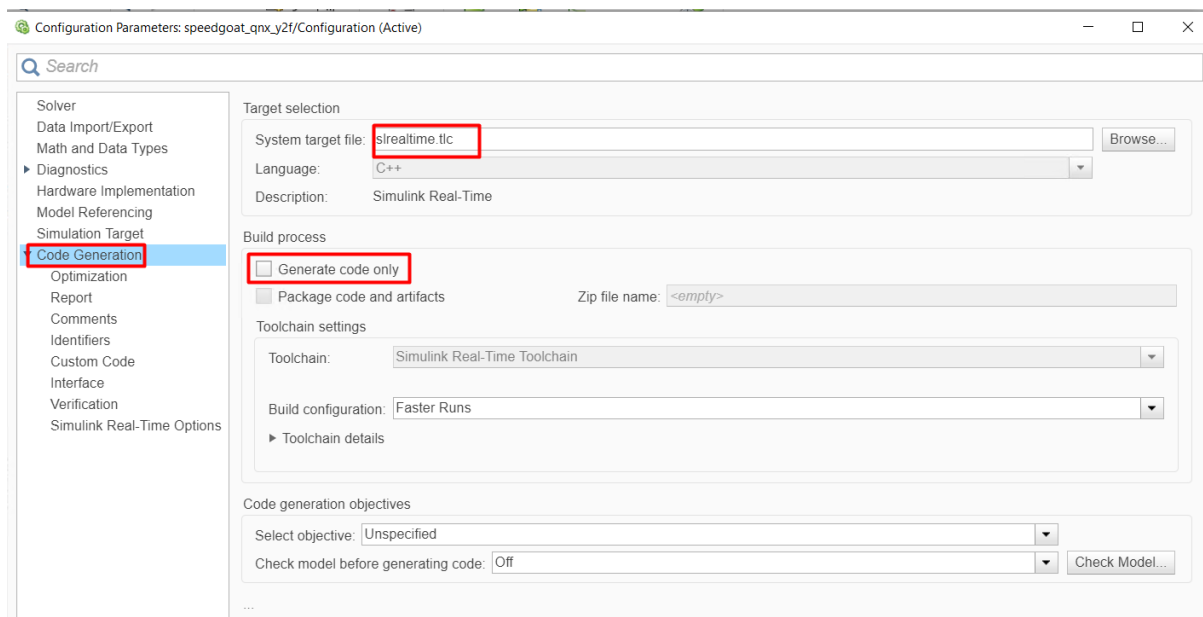


Figure 13.109: Set the Simulink code generation options.

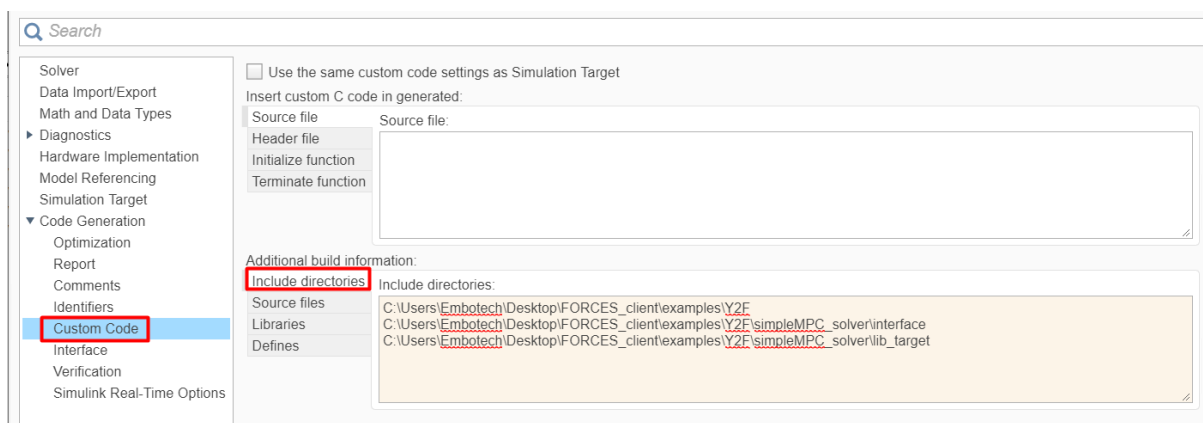


Figure 13.110: Add the directories included for the code generation.

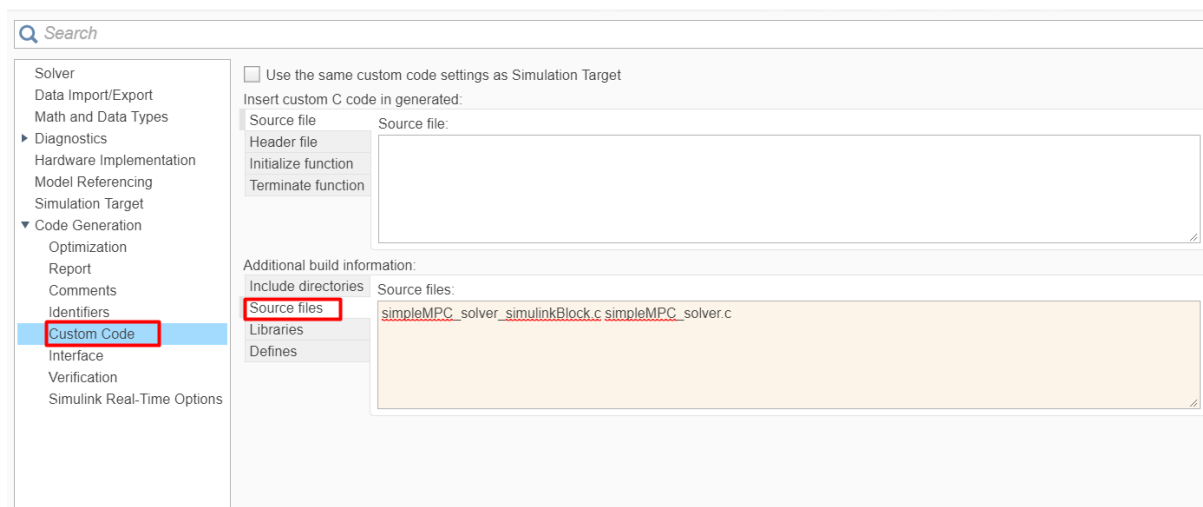


Figure 13.111: Add the source files used for the code generation.

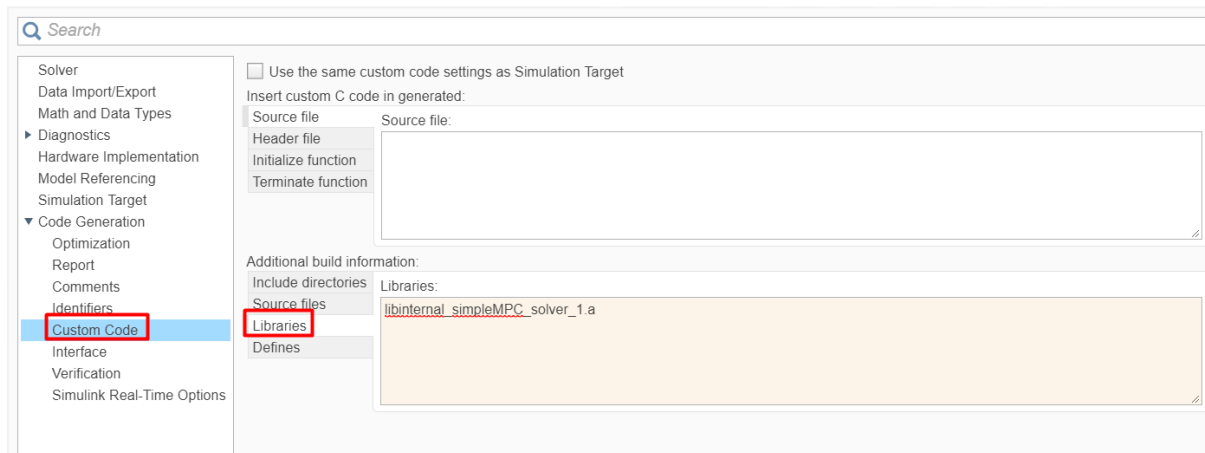


Figure 13.112: Add the libraries used for the code generation.

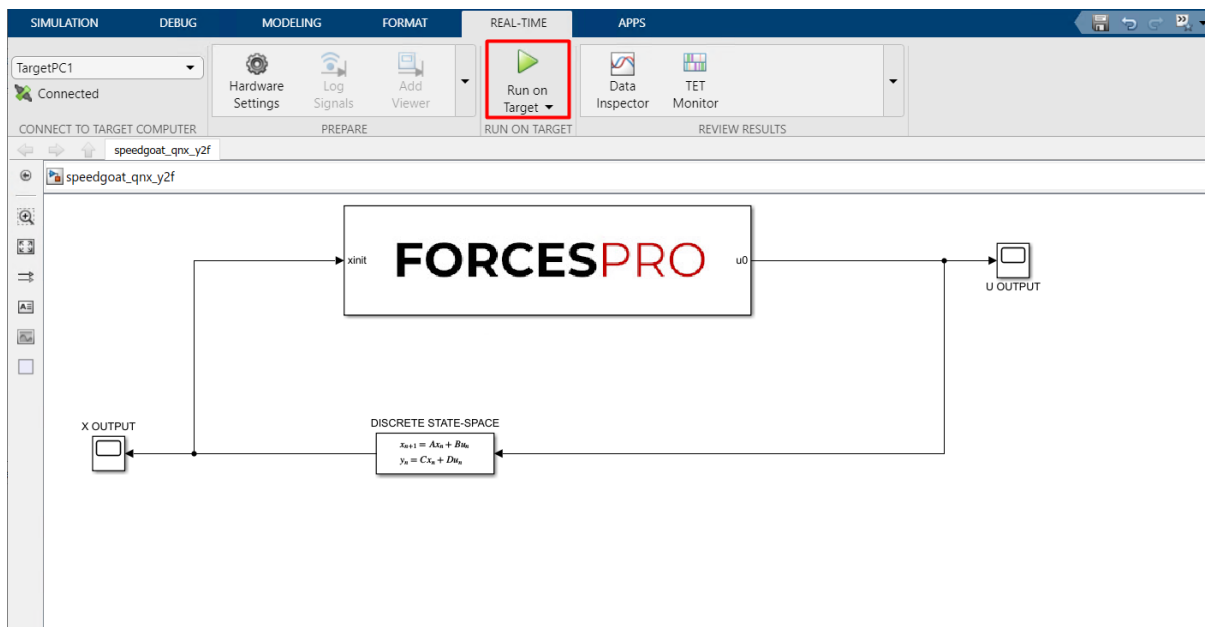


Figure 13.113: Compile the code of the Simulink model.

Chapter 14

Licensing

- *Machine Identification*
 - *Client Identification*
 - *Solver Identification*
- *Static License*
 - *System requirements for static license*
 - *Generating solvers with static license*
 - *Running solvers with static license*
- *License Files*
 - *System requirements for license files*
 - *Generating solvers with license files*
 - *Generating license files*
 - *Running solvers with license files*
- *Floating Licenses*
 - *Floating Licenses Proxy*
 - *System requirements for floating licenses*
 - *Using the Floating Licenses Proxy*
 - *Floating License Attributes*
 - *Generating solvers with floating licenses*
 - *Configure floating licenses during code generation*
 - *Running solvers with floating licenses*

14.1 Machine Identification

The FORCESPRO licensing system works by receiving unique identifiers from the machines the software runs on and enabling the machines by activating the corresponding unique identifiers. Activation of machines can be done by receiving the unique identifiers of the machines using fingerprinting executables provided in the portal and adding those unique identifiers on the portal.

For more information on machine activation see: <https://my.embotech.com/readme>

14.1.1 Client Identification

Machines running FORCESPRO clients are licensed using the machine's username and the machine's unique identifier.

14.1.2 Solver Identification

Machines running FORCESPRO solvers are licensed using the machine's unique identifier.

14.2 Static License

When generating a solver the license's state on the portal (enabled machines and expiration) is saved in the solver so that the solver can run on the enabled machines.

14.2.1 System requirements for static license

The requirement for static license checking is to have correct system clock settings (accurately showing current time, compliant to UTC time).

14.2.2 Generating solvers with static license

Static license checking is automatically enabled on a generated solver.

14.2.3 Running solvers with static license

After generating a solver, you can move it to the running platform and build it with the rest of your project.

14.3 License Files

License Files are used in order to enable solvers to run in machines that were not enabled during the time of code generation or to enable solvers to run after a license renewal (that happened after solver code generation).

14.3.1 System requirements for license files

The requirements for using license files are:

- A platform supporting I/O operations
- A platform with access to file system
- Correct system clock settings (accurately showing current time, compliant to UTC time)
- Using the MATLAB interface of FORCESPRO

14.3.2 Generating solvers with license files

License file checking is automatically enabled on a generated solver (supposing the platform supports it). The user has the option to select the name of the license file using the following codeoption:

Matlab

Python

```
% Matlab
codeoptions.license.static_license_file_name = '<filename_without_extension>'; %_
↳no paths, only filename
```

```
% Python
codeoptions.license.static_license_file_name = '<filename_without_extension>' # no_
↳paths, only filename
```

Important: The license file name must be a valid variable name

Note: Until **FORCESPRO 5.0.0**, the name of the license file could be set using the option **codeoptions.license_file_name**. This codeoption has been kept for backwards compatibility, however, setting the new option will override it.

14.3.3 Generating license files

License files can be created by using the MATLAB function `ForcesGetLicenseFile`. This function can be called with the following (optional) arguments:

- **license file name:** Name to be given to created license file (without extension). Default value: `FORCESPRO`
- **server:** `FORCESPRO` server to use to generate the license file. Default value: default server used by client

For more information on function usage run: `help ForcesGetLicenseFile` in the MATLAB Command Window.

14.3.4 Running solvers with license files

After generating a solver, you can move it to the running platform and build it with the rest of your project. After generating a license file, you can move it to your project folder.

When running a solver:

- The solver will read the license file and validate the license
- The license file needs to be in the working directory in which you execute your project (usually the directory that contains the executable)

14.4 Floating Licenses

Floating Licenses are used when the system that is enabled for running solvers needs to frequently change or is a virtualized environment (such as Docker or Virtualbox). The licensing

works by getting a temporary local lease from the floating license server in order to be able to run a solver on a machine. The connection to the floating license server is performed via a proxy server which receives the requests from the solvers, contacts the online floating license server to receive the floating license and provides it to the solver.

14.4.1 Floating Licenses Proxy

The deployment scenarios running FORCESPRO solvers do not always include the provision of an internet connection to the deployment machines. Instead, the deployment machines are managed by a centralized mechanism. The Floating Licenses Proxy allows to use this functionality for the provision of the FORCESPRO floating licenses. The Proxy can be set up either as a standalone application or as a web server in a machine which has network access with the deployment machines which will run the FORCESPRO solvers (without the need of an internet connection). This machine will listen for requests from the FORCESPRO solvers running in the deployment machines, perform the request on the online floating license server and finally return the acquired license leases to the FORCESPRO solvers. This way, the only machine requiring an internet connection will be the one running the Proxy. The solvers can be configured *during code generation* to which machine to connect to, in order to access the Floating Licenses Proxy. The packages for the Floating Licenses Proxy can be acquired in the Customer Portal in the Engineering Nodes view.

14.4.2 System requirements for floating licenses

The requirements for running the floating licenses proxy:

- A x86/x86_64 Windows or Linux platform
- An internet connection
- Correct system clock settings (accurately showing current time, compliant to UTC time)
- OS specific system or packages requirements can be found in the manual of the Floating Licenses Proxy

The requirements for enabling solvers with floating licenses are:

- A x86/x86_64 Linux platform
- A network connection of the running platform to the machine running the floating licenses proxy
- Correct system clock settings (accurately showing current time, compliant to UTC time)

14.4.3 Using the Floating Licenses Proxy

The Floating Licenses Proxy can be run as a standalone application or as a web server. Once run, no further actions are required on the Proxy's side. The FORCESPRO solvers will connect to it and receive the license leases to be validated for execution.

14.4.4 Floating License Attributes

Floating licenses are defined by the following two fields:

- **Number of Licenses:** The number of machines that can run solvers concurrently using a floating license for a FORCESPRO user.
- **Lease Time:** The time for which a local lease is valid after it has been granted. Default lease time is 10 minutes. Please contact support@embotech.com to change this.

14.4.5 Generating solvers with floating licenses

To enable floating licenses on a generated solver use the following codeoption:

Matlab

Python

```
% Matlab
codeoptions.license.use_floating_license = 1;
```

```
# Python
codeoptions.license.use_floating_license = 1
```

And select the platform to use

Matlab

Python

```
% Matlab
codeoptions.platform = 'platform_name';
```

```
# Python
codeoptions.platform = "platform_name"
```

Available platform options are:

- **Gnu-x86**
- **Gnu-x86_64**
- **Docker-Gnu-x86**
- **Docker-Gnu-x86_64**

Note: Until **FORCESPRO 5.0.0**, enabling floating licenses was done using the codeoption **codeoptions.useFloatingLicense**. This codeoption has been kept for backwards compatibility, however, setting the new option will override it.

14.4.6 Configure floating licenses during code generation

During code generation, the following codeoptions are available to configure the floating license check:

- **codeoptions.license.floating_license_server**: Selects the hostname or ip address of the machine which is running the floating license

proxy for the solver to connect to. The floating license server must be a valid uri. Default value is localhost * **codeoptions.license.floating_license_port**: Selects the port of the machine which is running the floating license proxy for the solver to connect to. The floating license server must be a valid port number. Default value is 5000 * **codeoptions.license.floating_license_file_name**: Sets the name for the local file created for the floating license.

The floating license file name must be a valid variable name. Default value is the solversname

- **codeoptions.license.floating_license_retries**: Sets the number of retries to connect to the floating license server in case a connection fails. Default value is 3

Note: If the FORCESPRO solver is run in a docker container and the Floating Licenses Proxy is run in the host of the same machine, in order for the solver to access the proxy **codeoptions.license.floating_license_server** should be set as **'host.docker.internal'**. In a Linux host, the docker container needs to be created with the following runtime option: **-add-host=host.docker.internal:host-gateway**

14.4.7 Running solvers with floating licenses

After generating a solver, you can move it to the running platform and build it with the rest of your project.

When running a solver:

- The solver will communicate with the Floating Licenses Proxy
- The Proxy will perform the request on the online floating license server
- If the number of enabled machines has not exceeded the license limits, a license lease will be returned
- If a lease had already been granted for a machine (and is still valid) the license will be extended to match the set lease time and will be returned
- The Proxy will return the accepted license lease to the FORCESPRO solver
- The solver will save the lease locally and run
- If a valid local lease already exists the solver will run without communicating with the server

When the floating license check is enabled, the run-time parameter **receive_floating_license** is available. Setting it to 1 will cause the solver to run only the license check, acquire the floating license and return. This can be used to acquire the floating license early and avoid connecting to the floating license server in subsequent executions when running the solver initialized with the problem.

Chapter 15

Solver Options

- *General options*
 - *Solver name*
 - *Print level*
 - *Maximum number of iterations*
 - *Compiler optimization level*
 - *Measure Computation time*
 - *Solver Timeout*
 - * *Introduction*
 - * *Usage*
 - * *SQP inner QP timeout*
 - * *Return Value*
 - *Running multiple instances of the same solver*
 - *Datatypes*
 - *Code generation server*
 - *Enforcing solver regeneration*
 - *Overwriting existing solvers*
 - *Skipping the Build of Simulink S-function*
 - *Solver info in Simulink block*
 - *Skipping automatic cleanup*
 - *MATLAB network communications*
 - *Python network communications*
 - *Target platform*
 - * *Cross compilation*
 - * *Mac compilation*
 - * *SIMD instructions*
 - *Tips for solving QPs in single precision*

- *MISRA 2012 compliance*
- *Optimizing code size*
- *Optimizing Linear Algebra Operations*
- *Dump problem formulation and data*
- *High-level interface options*
 - *Integrators*
 - * *Expert options for implicit integrators*
 - * *Code-generated integrators*
 - * *Linear subsystem exploitation*
 - *Accuracy requirements*
 - *Barrier strategy*
 - *Hessian approximation*
 - * *BFGS options*
 - * *Gauss-Newton options*
 - *Line search settings*
 - *Regularization*
 - * *Static regularization*
 - * *Dynamic regularization*
 - *Linear system solver*
 - * *Iterative refinement*
 - *Automatic differentiation tool*
 - *Re-use of callback code*
 - *Safety checks*
- *Convex branch-and-bound options*
- *Solve methods*
 - *Primal-Dual Interior-Point Method*
 - * *Solver Initialization*
 - * *Initial Complementary Slackness*
 - * *Accuracy Requirements*
 - * *Line Search Settings*
 - * *Regularization*
 - * *Multicore parallelization*
 - *Alternating Directions Method of Multipliers*
 - * *Accuracy requirements*
 - * *Method parameters*
 - * *Precomputations*
 - *Dual Fast Gradient Method*
 - *Primal Fast Gradient Method*

- * *Accuracy requirements*
- * *Method parameters*
- * *Warm starting*

The default solver options can be loaded when giving a name to the solver with the following command

Matlab

Python

```
codeoptions = getOptions('solvername');
```

```
stages.codeoptions = forcespro.CodeOptions('solvername') # for the low-level_
↳interface
codeoptions = forcespro.CodeOptions('solvername') # for the high-level interface
```

In the documentation below, we assume that you have created this struct and named it `codeoptions`.

Note: For the low-level interface in Python, the `codeoptions` struct has to be an element of the `stages` struct.

15.1 General options

We will first discuss how to change several options that are valid for all the FORCESPRO interfaces.

15.1.1 Solver name

The name of the solver will be used to name variables, functions, but also the MEX file and associated help file. This helps you to use multiple solvers generated by FORCESPRO within the same software project or Simulink model. To set the name of the solver use:

Matlab

Python

```
codeoptions.name = 'solvername';
```

```
codeoptions.name = 'solvername'
```

Alternatively, you can directly name the solver when generating the options struct by calling:

Matlab

Python

```
codeoptions = getOptions('solvername');
```

```
stages.codeoptions = forcespro.CodeOptions('solvername') # for the low-level_
↳interface
codeoptions = forcespro.CodeOptions('solvername') # for the high-level interface
```

15.1.2 Print level

To control the amount of information the generated solver prints to the console, set the field `printlevel` as outlined in [Table 15.1](#).

Table 15.1: Print level options

<code>printlevel</code>	Result	Dependency
0	No output will be written.	(None)
1	Summary line after each solve.	<code><stdio.h></code>
2 (default)	Summary after each iteration of solver.	<code><stdio.h></code>

Note: For `printlevel=0`, the generated solver has no dependency on any system library. Otherwise, there will be a dependency on `<stdio.h>`.

Important: `printlevel` should always be set to 0 when recording performance timings or when deploying the code on an autonomous embedded system.

15.1.3 Maximum number of iterations

To set the maximum number of iterations of the generated solver, use:

Matlab

Python

```
codeoptions.maxit = 200;
```

```
codeoptions.maxit = 200
```

The default maximum number of iterations for all solvers provided by FORCESPRO is set to 200.

15.1.4 Compiler optimization level

The compiler optimization level can be varied by changing the field `optlevel` from 0 to 3 (default):

Matlab

Python

```
codeoptions.optlevel = 0;
```

```
codeoptions.optlevel = 0
```

Important: It is recommended to set `optlevel` to 0 during prototyping to evaluate the functionality of the solver without long compilation times. Then set it back to 3 when generating code for deployment or timing measurements.

15.1.5 Measure Computation time

You can measure the time used for executing the generated code by using:

Matlab

Python

```
codeoptions.timing = 1;
```

```
codeoptions.timing = 1
```

By default the execution time is measured. The execution time can be accessed in the field `solvetime` of the information structure returned by the solver. In addition, the execution time is printed in the console if the flag `printlevel` is greater than 0.

Important: Setting timing on will introduce a dependency on libraries used for accessing the system clock. Timing should be turned off when deploying the code on an autonomous embedded system.

By default when choosing to generate solvers for target platforms, timing is disabled. You can manually enable timing on embedded platforms by using:

Matlab

Python

```
codeoptions.embedded_timing = 1;
```

```
codeoptions.embedded_timing = 1
```

15.1.6 Solver Timeout

Introduction

If you have a critical application which needs to run in a specific timeframe then it's useful to set a timeout for the solver in order to control its execution time.

The timeout works by checking the execution time of each iteration of the solver and making an estimate for next iterations as:

```
next_iteration_time = timeout_estimate_coeff * max_iteration_time
```

where:

- `max_iteration_time` is the execution time of the currently slowest iteration
- `timeout_estimate_coeff` is a coefficient used to make the estimate more conservative or forgiving. Its default value is 1.20

Usage

To enable the solver timeout you can use the following codeoption:

Matlab

Python

```
% solver_timeout can take values 0-2
codeoptions.solver_timeout = 1;
```

```
# solver_timeout can take values 0-2
codeoptions.solver_timeout = 1
```

Setting the option to 1 will enable the timeout and provide the floating point variable `solver_timeout` as a runtime parameter. Setting the option to 2 will additionally provide the floating point variable `timeout_estimate_coeff` as a runtime parameter.

Important: For MINLP solvers a timeout is automatically enabled therefore there's no need to use the above codeoptions. For more details on how to use it please check section `Mixed-integer nonlinear solver`.

Not setting the runtime parameters after enabling them with code generation will result in them taking their default values. The default values for the runtime parameters are:

- For `solver_timeout` it's -1.0 which results in timeout being disabled
- For `timeout_estimate_coeff` it's 1.20

Important: Since an estimation is required for the timeout, the solvers will always perform the first iteration (only exception are SQP methods, check the following section `SQP inner QP timeout`).

SQP inner QP timeout

With the `SQP_NLP` solve method the QP solved as part of the SQP iteration is also set to timeout based on the remaining time available to the SQP solver. The QP timeout can be useful in cases where the inner QP takes longer time to execute than expected and could otherwise cause the SQP solver to miss the timeout mark (in which case the SQP solver would time out at the start of the next iteration). If the QP times out, the SQP solver will return with the solution from the previous iteration.

If it is deemed more important to solve the whole QP and get a more updated solution rather than having a strict timeout, the inner qp timeout can be disabled with the following codeoption:

Matlab

Python

```
% this option is relevant only if codeoptions.solver_timeout is enabled
codeoptions.sqp_nlp.qp_timeout = 0;
```

```
# this option is relevant only if codeoptions.solver_timeout is enabled
codeoptions.sqp_nlp.qp_timeout = 0
```

Return Value

When solver timeout is enabled, two additional exitflags are available for the user:

Table 15.2: Timeout exitflags

Exitflag Name	Value	Description
TIMEOUT_<SOLVERNAME>	2	The solver timed out and returned the solution found up to the executed iteration
INVALID_<TIMEOUT_SOLVERNAME>	-12	The timeout provided was too small to even start a single iteration

If a normal timeout is returned, the outputs of the solver will contain the solution found up to the executed iteration. If an invalid timeout is returned, the outputs of the solver will contain the initialization of the solver (or the previous solution if it exists for SQPs).

15.1.7 Running multiple instances of the same solver

Multiple instances of the generated solver can be run in a multi-threaded environment by making use of the expert C interface. The expert interface gives the user control over the allocation of the required memory so that a different block of memory can be pre-allocated for each thread. This feature is currently implemented for the algorithms `PDIP` and `PDIP_NLP`.

The thread-safe expert interface can be requested by setting the option

Matlab

Python

```
codeoptions.threadSafeExpert = 1;
```

```
codeoptions.threadSafeExpert = 1
```

and consists of two additional C functions:

- `<solvername>_solver_mem <solvername>_mem_new()` provides a handle to the memory to be used by a solver.
- `<solvername>_solve_expert(..., <solvername>_solver_mem * mem, ...)` is the solver function (instead of `<solvername>_solve(...)`) taking the memory handle as an additional input argument.

In order to ensure thread-safety, each thread must be assigned its own memory handle.

Below an example of how to run multiple solvers in parallel using OpenMP:

```
// prepare 4 solvers
#define nSolvers = 4
FORCES_NLP_solver_mem mem[nSolvers];
FORCES_NLP_solver_params params[nSolvers];
FORCES_NLP_solver_output output[nSolvers];
FORCES_NLP_solver_info info[nSolvers];
// ... initialize params ...

// initialize memory for each thread
int nThreads = omp_get_num_threads();
int iThread;
for (iThread=0; iThread<nThreads; iThread++)
{
    mem[iThread] = FORCES_NLP_solver_mem_new();
}

// run the solvers in parallel
```

(continues on next page)

(continued from previous page)

```
int exitflag;
#pragma omp parallel for
for (iSolver=0; iSolver<nSolvers; iSolver++)
{
    int iThread = omp_get_thread_num();
    exitflag = FORCES_NLP_solver_solve_expert(&params[iSolver], &output[iSolver], &
    info[iSolver], &mem[iThread], ...);
}
```

You can find the full code of this example including instructions of how to run it in the Examples\ThreadSafe folder that comes with your client.

Alternatively (and for the algorithms not yet supported with `threadSafeExpert = 1`), use the option `threadSafeStorage = 1`. This ensures thread-safety within the default interface by relying on thread-local storage. Due to the limited amount of thread-local storage (depending on the system), using `threadSafeExpert` is recommended over using `threadSafeStorage` and `threadSafeStorage` will be deprecated in the near future.

Important: When using the code-generated integrators (see section *Code-generated integrators*) with the `threadSafeExpert` option enabled, you will have to specify via the option `nlp.max_num_threads` the maximum number of threads on which you wish to run the solver in parallel. For instance, if running the solver on a maximum of 5 threads in parallel one would set

Matlab

Python

```
codeoptions.nlp.max_num_threads = 5;
```

```
codeoptions.nlp.max_num_threads = 5
```

Important: The deployment of a Simulink model to a target platform is not supported when the `threadSafeExpert` option is enabled. To deploy a Simulink model, the `threadSafeExpert` option must be unset or disabled.

15.1.8 Datatypes

The type of variables can be changed by setting the field `floattype` as outlined in Table 15.3. This will effect all floating point variables used inside the solver and the callbacks generated by the AD tool.

Table 15.3: Data type options

floattype	Decimation	Width (bits)	Supported algorithms
'double' (default)	64 bit	Floating point	PDIP_NLP, SQP_NLP, PDIP, ADMM, DFG, FG
'float'	32 bit	Floating point	PDIP, ADMM, DFG, FG
'int'	32 bit	Fixed point	ADMM, DFG, FG
'short'	16 bit	Fixed point	ADMM, DFG, FG

Important: Unless running on a resource-constrained platform, we recommend using double precision floating point arithmetic to avoid problems in the solver. If single precision float-

ing point has to be used, reduce the required tolerances on the solver accordingly by a power of two (i.e. from 1E-6 to 1E-3).

When running the solver in double precision arithmetic, it is possible to only use single precision arithmetic for evaluating the AD tool callbacks. This can be done by setting the field `callback_floattype`; see [Table 15.4](#) and section *Single precision callbacks* for details.

Table 15.4: Callback data type options

floattype	Decimation	Width (bits)	Supported algorithms
'double' (default)	64 bit	Floating point	PDIP_NLP, SQP_NLP
'float'	32 bit	Floating point	PDIP_NLP, SQP_NLP

15.1.9 Code generation server

By default, code generation requests are routed to embotech's server. To send a code generation request to a local server, for example when FORCESPRO is used in an enterprise setting, set the following field to an appropriate value:

Matlab

Python

```
codeoptions.server = 'https://yourforcesserver.com:1234';
```

```
codeoptions.server = 'https://yourforcesserver.com:1234'
```

15.1.10 Enforcing solver regeneration

In order to avoid unnecessary calls to the code-generation server, FORCESPRO internally computes a hash of your problem formulation and codeoptions. If this hash is identical to that of an already generated solver, the existing one is reused. In situations where this is not desired, hashing can be disabled as follows:

Matlab

Python

```
codeoptions.nohash = 1;
```

```
codeoptions.nohash = 1
```

In that case, the codegen server is always contacted to re-generate a new solver.

15.1.11 Overwriting existing solvers

When a new solver is generated with the same name as an existing solver one can control the overwriting behaviour by setting the field `overwrite` as outlined in [Table 15.5](#).

Table 15.5: Overwrite existing solver options

overwrite	Result
0	Never overwrite.
1	Always overwrite.
2 (default)	Ask to overwrite.

15.1.12 Skipping the Build of Simulink S-function

By default, after code generation, the Simulink block is compiled, which may take a very long time for large problems on Windows systems. If you will not use the Simulink block, or want to build it later yourself, you can disable automatic builds by using the following option:

Matlab

Python

```
codeoptions.BuildSimulinkBlock = 0;
```

```
# does not take effect in Python
```

15.1.13 Solver info in Simulink block

FORCESPRO always generates a Simulink block encapsulating the generated solver. You can add output ports to the Simulink block to obtain the solver exit flag and other solver information (number of iterations, solve time in seconds, value of the objective function) by setting:

Matlab

Python

```
codeoptions.showinfo = 1;
```

```
codeoptions.showinfo = 1
```

By default these ports are not present in the Simulink block.

15.1.14 Skipping automatic cleanup

FORCESPRO automatically cleans up some of the files that it generates during the code generation, but which are usually not needed any more after building the MEX file. In particular, some intermediate CasADi generated files are deleted. If you would like to prevent any cleanup by FORCES, set the option:

Matlab

Python

```
codeoptions.cleanup = 0;
```

```
codeoptions.cleanup = 0
```

The default value is 1 (true).

Important: The library or object files generated by FORCESPRO contain only the solver itself. To retain the CasADi generated files for function evaluations, switch off automatic cleanup as shown above. This is needed if you want to use the solver within another software project, and need to link to it.

15.1.15 MATLAB network communications

From version 5.0.0, the MATLAB client will perform connections to a REST interface for communicating with the FORCESPRO codegen server.

To revert to an old method, either set:

```
% WSDL connection
codeoptions.server_connection = ForcesWeb.ServerConnections.WSDL;
% WSDL legacy connection
codeoptions.server_connection = ForcesWeb.ServerConnections.WSDL_legacy;
```

or change it by editing the FORCESPRO client. To do so, please edit the `+ForcesWeb/defaultServerConnection.m` function so that it returns the selected `ForcesWeb.ServerConnections` value.

Important: Setting the `codeoptions.server_connection` option will override the value in `+ForcesWeb/defaultServerConnection.m`

15.1.16 Python network communications

From version 5.0.0, the Python client will perform connections to a REST interface for communicating with the FORCESPRO codegen server.

To revert to the old method, either set:

```
# WSDL connection
codeoptions.server_connection = WSDL
```

or change it by editing the FORCESPRO client. To do so, please edit the `default_forcespro_connection.py` function so that it returns the selected `server_connections` value.

Important: Setting the `codeoptions.server_connection` option will override the value in `default_forcespro_connection.py`

From version 4.3.1, the Python client supports connections to the FORCESPRO codegen server through a proxy.

The file `forcespro_proxy.py` exists in the FORCESPRO client folder in order to set the configuration for the proxy. The format of the file is as follows:

```
# host of the proxy. Can be an IP address ("x.x.x.x") or a DNS record. Set to _
↪empty to not use a proxy
host=""
# port number of proxy to connect to. To use default set to 0
port=8888
# Protocol to connect to the proxy (http or https). To use default set to empty
protocol="http"
# Username with which to connect to the proxy. To not use a username set to empty
username="user"
# Password with which to connect to the proxy. To not use a password set to empty
password="pass"
```

Note: By default the file `forcespro_proxy.py` has an empty host entry so that no proxy is used unless set.

15.1.17 Target platform

As a default option, FORCESPRO generates code for simulation on the host platform. To obtain code for deployment on a target embedded platform, set the field `platform` to the appropriate value. The platforms currently supported by FORCESPRO are given in Table 15.6. In order to acquire licenses to use a specific `platform`, licenses can be requested on the portal by selecting the platform naming stated in the `Portal Selection`.

Table 15.6: Target platforms supported by FORCESPRO

platform	Description	Portal Selection
'Generic' (default)	For the architecture of the host platform.	'x86_64' (Engineering Node)
'x86_64'	For x86_64 based 64-bit platforms (detected OS).	'x86_64'
'x86'	For x86 based 32-bit platforms (detected OS).	'x86'
'Win-x86_64'	For Windows x86_64 based 64-bit platforms (supports Microsoft/Intel compiler).	'x86_64'
'Win-x86'	For Windows x86 based 32-bit platforms (supports Microsoft/Intel compiler).	'x86'
'Win-MinGW-x86_64'	For Windows x86_64 based 64-bit platforms (supports MinGW compiler).	'x86_64'
'Win-MinGW-x86'	For Windows x86 based 32-bit platforms (supports MinGW compiler).	'x86'
'Mac-x86_64'	For Mac x86_64 based 64-bit platforms (supports GCC/Clang compiler).	'x86_64'
'Gnu-x86_64'	For Linux x86_64 based 64-bit platforms (supports GCC compiler).	'x86_64'
'Gnu-x86'	For Linux x86 based 32-bit platforms (supports GCC compiler).	'x86'
'Docker-Gnu-x86_64'	For Linux x86_64 based 64-bit platforms on Docker (supports GCC compiler).	'Docker-Gnu-x86_64'
'Docker-Gnu-x86'	For Linux x86 based 32-bit platforms on Docker (supports GCC compiler).	'Docker-Gnu-x86'
'ARM-Generic'	For ARM Cortex 32-bit processors (Gnueabih machine type).	'ARM-Generic-Gnu'
'ARM-Generic64'	For ARM Cortex 64-bit processors (Aarch machine type).	'ARM-Generic64-Gnu'
'Integrity-ARM32'	For ARM Cortex 32-bit processors using the Integrity toolchain.	'Integrity-ARM32'
'Integrity-ARM64'	For ARM Cortex 64-bit processors using the Integrity toolchain.	'Integrity-ARM64'

Continued on next page

Table 15.6 – continued from previous page

platform	Description	Portal Selection
'ARM Cortex-M3'	For ARM Cortex M3 32-bit processors.	'ARM-Cortex-M3'
'ARM-Cortex-M4-NOFPU'	For the ARM Cortex M4 32-bit processors without a floating-point unit.	'ARM-Cortex-M4'
'ARM-Cortex-M4'	For the ARM Cortex M4 32-bit processors with a floating-point unit.	'ARM-Cortex-M4'
'ARM-Cortex-A7'	For the ARM Cortex A7 32-bit processors (Gnueabih machine type).	'ARM-Cortex-A7'
'ARM-Cortex-A8'	For the ARM Cortex A8 32-bit processors (Gnueabih machine type).	'ARM-Cortex-A8'
'ARM-Cortex-A9'	For the ARM Cortex A9 32-bit processors (Gnueabih machine type).	'ARM-Cortex-A9'
'ARM-Cortex-A15'	For the ARM Cortex A15 32-bit processors (Gnueabih machine type).	'ARM-Cortex-A15'
'ARM-Cortex-A53'	For the ARM Cortex A53 64-bit processors (Gnueabih machine type).	'ARM-Cortex-A53'
'ARM-Cortex-A72'	For the ARM Cortex A72 64-bit processors (Gnueabih machine type).	'ARM-Cortex-A72'
'TI-Cortex-A15'	For the ARM Cortex A15 32-bit processors (Gnueabih machine type).	'TI-Cortex-A15'
'NVIDIA-Cortex-A57'	For the NVIDIA Cortex A57 64-bit processors (Aarch machine type).	'NVIDIA-Cortex-A57'
'AARCH-Cortex-A57'	For the ARM Cortex A57 64-bit processors (Aarch machine type).	'AARCH-Cortex-A57'
'AARCH-Cortex-A72'	For the ARM Cortex A72 64-bit processors (Aarch machine type).	'AARCH-Cortex-A72'
'PowerPC'	For 32-bit PowerPC based platforms (supports GCC compiler).	'PowerPC-Gnu'
'PowerPC64'	For 64-bit PowerPC based platforms (supports GCC compiler).	'PowerPC64-Gnu'
'MinGW32'	For Windows x86 based 32-bit platforms (supports MinGW compiler).	'x86'
'MinGW64'	For Windows x86_64 based 64-bit platforms (supports MinGW compiler).	'x86_64'
'dSPACE-MABII'	For the dSPACE MicroAuto-Box II real-time system (supports Microtec compiler).	'dSPACE-MABII-Microtec'

Continued on next page

Table 15.6 – continued from previous page

platform	Description	Portal Selection
'dSPACE-MABIII'	For the dSPACE MicroAutoBox III real-time system (supports Gcc compiler).	'dSPACE-MABIII-Gcc'
'dSPACE-MABXII'	For the dSPACE MicroAutoBox II real-time system (supports Microtec compiler).	'dSPACE-MABII-Microtec'
'dSPACE-MABXIII'	For the dSPACE MicroAutoBox III real-time system (supports Gcc compiler).	'dSPACE-MABIII-Gcc'
'dSPACE-AutoBox'	For the dSPACE AutoBox real-time system (supports Gcc compiler).	'dSPACE-AutoBox-Gcc'
'dSPACE-MicroLabBox'	For the dSPACE MicroLabBox real-time system (supports Gcc compiler).	'dSPACE-MicroLabBox-Gcc'
'dSPACE-SCALEXIO'	For the dSPACE SCALEXIO real-time system (supports Gcc compiler).	'dSPACE-SCALEXIO-Gcc'
'Speedgoat-x86'	For Speedgoat 32-bit real-time platforms (supports Microsoft compiler and mainly MATLAB Releases 2018b up to R2020a).	'Speedgoat-x86'
'Speedgoat-x64'	For Speedgoat 64-bit real-time platforms (supports Microsoft compiler and mainly MATLAB Releases 2018b up to R2020a).	'Speedgoat-x64'
'Speedgoat-QNX'	For Speedgoat 64-bit real-time platforms (supports MATLAB Releases 2020b onwards).	'Speedgoat-QNX'
'Speedgoat-Legacy-x86'	For Speedgoat Mobile 32-bit real-time platforms (supports Microsoft compiler and Matlab Releases 2018a and earlier).	'Speedgoat-x86'
'NI-cRIO'	For National Instruments compactRIO Linux RTOS platforms (supports NILRT Gcc compiler).	'NI-cRIO'
'IAtomE680_Bachmann'	For Bachmann PLC platforms (supports VxWorks compiler).	'IAtomE680-VxWorks'

Note: If a solver for another platform is requested, FORCESPRO will still provide the simulation interfaces for the 'Generic' host platform to enable users to run simulations.

Cross compilation

To generate code for other operating systems different from the host platform, set the appropriate flag from the following list to 1:

```
codeoptions.win
codeoptions.mac
codeoptions.gnu
```

Note that this will only affect the target platform. Interfaces for the host platform will be automatically built.

Mac compilation

When compiling for mac platforms it's possible to select the compiler to be used for the web compilation. Select from the available values `gcc` (default) and `clang` with the following codeoption:

Matlab

Python

```
codeoptions.maccompiler = 'gcc'; % or 'clang'
```

```
codeoptions.maccompiler = 'gcc' # or 'clang'
```

SIMD instructions

On x86-based host platforms, one can enable the `sse` field to accelerate the execution of the solver

Matlab

Python

```
codeoptions.sse = 1;
```

```
codeoptions.sse = 1
```

On x86-based host platforms, one can also add the `avx` field to significantly accelerate the compilation and execution of the convex solver, from version 1.9.0,

Matlab

Python

```
codeoptions.avx = 1;
```

```
codeoptions.avx = 1
```

Note: Currently when options `avx` and `blkMatrices` are enabled simultaneously, `blkMatrices` is automatically disabled.

Note: When sparse parameters are present in the model, the options `avx` and `neon` are automatically set to zero.

Depending on the host platform, `avx` may be automatically enabled. If the machine on which the solver is to be run does not support AVX and the message "Illegal Instruction" is returned at run-time, one can explicitly disable `avx` by setting:

Matlab

Python

```
codeoptions.avx = -1;
```

```
codeoptions.avx = -1
```

If the host platform supports AVX, but the user prefers not to have AVX intrinsics in the generated code, one can also keep the default option value of the solver:

Matlab

Python

```
codeoptions.avx = 0;
```

```
codeoptions.avx = 0
```

On 'NVIDIA-Cortex-A57', 'AARCH-Cortex-A57' and 'AARCH-Cortex-A72' target platforms, one can also enable the field `neon` in order to accelerate the execution of the convex solver. From version 1.9.0, the typical behaviour is that the host platform gets vectorized code based on AVX intrinsics when `avx = 1`, and the target platform gets AVX vectorized code if it supports it when `avx = 1` and NEON vectorized code if it is one of the above Cortex platforms and `neon = 1`.

For single precision, the options are

Matlab

Python

```
codeoptions.floattype = 'float';  
codeoptions.neon = 1;
```

```
codeoptions.floattype = 'float'  
codeoptions.neon = 1
```

For double precision, the options are

Matlab

Python

```
codeoptions.floattype = 'double';  
codeoptions.neon = 2;
```

```
codeoptions.floattype = 'double'  
codeoptions.neon = 2
```

In case one wants to disable NEON intrinsics in the generated target code, the default value of the `neon` option is

Matlab

Python

```
codeoptions.neon = 0;
```

```
codeoptions.neon = 0
```

If NEON vectorization is being used and there is a mismatch between float precision and the value of the `neon` option, the solver is automatically generated with the following options:

Matlab

Python

```
codeoptions.floattype = 'double';
codeoptions.neon = 2;
```

```
codeoptions.floattype = 'double'
codeoptions.neon = 2
```

and a warning message is raised by the MATLAB client.

Note: From version 1.9.0, ARMv8-A NEON instructions are generated. Hence, target platforms based on ARMv7 and previous versions are currently not supported.

15.1.18 Tips for solving QPs in single precision

Solving QPs in single precision can be rather challenging, i.e. non-converging solves are likely to occur due to the lack of accuracy. In order to mitigate this undesirable behaviour, several options can be tuned to make convergence more robust. They are shown and commented in the code snippet below.

Matlab

Python

```
codeoptions.floattype = 'float';

codeoptions.regularize.epsilon = 1e-5; % Tolerance on pivot in factorization
codeoptions.regularize.delta = 5e-3;   % On-the-fly regularization coefficient in ↵
↵factorization
codeoptions.regularize.epsilon2 = 1e-5; % Tolerance on pivot in factorization
codeoptions.regularize.delta2 = 5e-3;   % On-the-fly regularization coefficient in ↵
↵factorization

codeoptions.accuracy.ineq = 1e-4;        % infinity norm of residual for ↵
↵inequalities
codeoptions.accuracy.eq = 1e-4;          % infinity norm of residual for equalities
codeoptions.accuracy.mu = 1e-6;          % absolute duality gap
codeoptions.accuracy.rdgap = 1e-4;       % relative duality gap := (pobj-dobj)/pobj

codeoptions.init = 1;
```

```
codeoptions.floattype = 'float'

codeoptions.regularize.epsilon = 1e-5 # Tolerance on pivot in factorization
codeoptions.regularize.delta = 5e-3   # On-the-fly regularization coefficient in ↵
↵factorization
codeoptions.regularize.epsilon2 = 1e-5 # Tolerance on pivot in factorization
codeoptions.regularize.delta2 = 5e-3   # On-the-fly regularization coefficient in ↵
↵factorization

codeoptions.accuracy.ineq = 1e-4        # infinity norm of residual for inequalities
codeoptions.accuracy.eq = 1e-4          # infinity norm of residual for equalities
codeoptions.accuracy.mu = 1e-6          # absolute duality gap
codeoptions.accuracy.rdgap = 1e-4       # relative duality gap := (pobj-dobj)/pobj

codeoptions.init = 1;
```

In general, the rationale behind this tuning is to make the tolerances looser and increase the regularization in the linear algebra. Note that these tips are only applicable to QP solvers. Solving NLPs in single precision is even more challenging and we currently do not offer a set of options to robustify convergence on this type of problems.

15.1.19 MISRA 2012 compliance

If your license allows it, add the following field to generate C code that is compliant with the MISRA 2012 rules:

Matlab

Python

```
codeoptions.misra2012_check = 1;
```

```
codeoptions.misra2012_check = 1
```

This option makes the generated solver code MISRA compliant. After compilation, the client also downloads a folder whose name terminates with `_misra2012_analysis`. The folder contains one summary of all MISRA violations for the solver source and header files. Note that the option only produces MISRA compliant code when used with algorithms `PDIP` and `PDIP_NLP`.

15.1.20 Optimizing code size

The size of the solver libraries generated with code option `PDIP_NLP` can be reduced by means of the option `nlp.compact_code`. By setting

Matlab

Python

```
codeoptions.nlp.compact_code = 1;
```

```
codeoptions.nlp.compact_code = 1
```

the user enables the FORCESPRO server to generate smaller code, which results in shorter compilation time and slightly better solve time in some cases. This feature is especially effective on long horizon problems.

Note: The `compact_code` option is currently only supported when using the linear systems solver `codeoptions.nlp.linear_solver = 'normal_eqs'` (which is the default choice).

The size of sparse linear algebra routines in the generated code can be reduced by changing the option `compactSparse` from 0 to 1:

Matlab

Python

```
codeoptions.compactSparse = 1;
```

```
codeoptions.compactSparse = 1
```

15.1.21 Optimizing Linear Algebra Operations

Some linear algebra routines in the generated code have available optimizations that can be enabled by changing the options `optimize_<optimization>` from 0 to 1. These optimizations change the code in order to make better use of some embedded architectures in which hardware is more limited compared to host PC architectures. Therefore, these optimizations show better results in embedded platforms such as ARM targets rather than during simulations on host PCs. The available optimizations are:

- **Cholesky Division:** This option performs the divisions included in the Cholesky factorization more efficiently to reduce its computation time.
- **Registers:** This option attempts to use the architecture's registers in order to reduce memory operations which can take significant time.
- **Use Locals:** These options (which are separated into `simple`/`heavy`/`all` in ascending complexity) make better use of data locality in order to reduce memory jumps
- **Operations Rearrange:** This option rearranges operations in order to make more efficient use of data and reduce memory jumps
- **Loop Unrolling:** This option unrolls some of the included loops in order to remove their overhead.
- **Enable Offset:** This option allows the rest of the optimizations to take place in cases where the matrix contains offsets.

Matlab

Python

```
codeoptions.optimize_choleskydivision = 1;
codeoptions.optimize_registers = 1;
codeoptions.optimize_uselocalsall = 1;
codeoptions.optimize_uselocalsheavy = 1; % overridden if uselocalsall is enabled
codeoptions.optimize_uselocalssimple = 1; % overridden if uselocalsheavy is enabled
codeoptions.optimize_operationsrearrange = 1;
codeoptions.optimize_loopunrolling = 1;
codeoptions.optimize_enableoffset = 1;
```

```
codeoptions.optimize_choleskydivision = 1
codeoptions.optimize_registers = 1
codeoptions.optimize_uselocalsall = 1
codeoptions.optimize_uselocalsheavy = 1 # overridden if uselocalsall is enabled
codeoptions.optimize_uselocalssimple = 1 # overridden if uselocalsheavy is enabled
codeoptions.optimize_operationsrearrange = 1
codeoptions.optimize_loopunrolling = 1
codeoptions.optimize_enableoffset = 1
```

15.1.22 Dump problem formulation and data

The MATLAB client of FORCESPRO provides a built-in tool to dump the problem formulation to reproduce the exact same solver for future reference. This tool is explained in detail in [Section 17](#) and can be turned on by using the setting:

```
codeoptions.dump_formulation = 1;
```

Furthermore, you can dump problem structs containing the runtime parameters from C as described in [Section 17](#). This tool is enabled for the host or/and the target platform by setting:

Matlab

Python

```
codeoptions.serializeCParamsHost = 1;
codeoptions.serializeCParamsTarget = 1;
```

```
codeoptions.serializeCParamsHost = 1
codeoptions.serializeCParamsTarget = 1
```

15.2 High-level interface options

The FORCESPRO NLP solver of the high-level interface implements a nonlinear barrier interior-point method. We will now discuss how to change several parameters in the solver.

15.2.1 Integrators

When providing the continuous dynamics the user must select a particular integrator by setting `nlp.integrator.type` as outlined in [Table 15.7](#).

Table 15.7: Integrators options

<code>nlp.integrator.type</code>	Type	Order
<code>'ForwardEuler'</code>	Explicit Euler Method	1
<code>'ERK2'</code>	Explicit Runge-Kutta	2
<code>'ERK3'</code>	Explicit Runge-Kutta	3
<code>'ERK4' (default)</code>	Explicit Runge-Kutta	4
<code>'BackwardEuler'</code>	Implicit Euler Method	1
<code>'IRK2'</code>	Implicit Runge-Kutta	2
<code>'IRK4'</code>	Implicit Runge-Kutta	4

The user must also provide the discretization interval (in seconds) and the number of intermediate shooting nodes per interval. For instance:

Matlab

Python

```
codeoptions.nlp.integrator.type = 'ERK2';
codeoptions.nlp.integrator.Ts = 0.01;
codeoptions.nlp.integrator.nodes = 10;
```

```
codeoptions.nlp.integrator.type = 'ERK2'
codeoptions.nlp.integrator.Ts = 0.01
codeoptions.nlp.integrator.nodes = 10
```

Tip: Usually an explicit integrator such as RK4 should suffice for most applications. If you have stiff systems, or suspect inaccurate integration to be the cause of convergence failure of the NLP solver, consider using implicit integrators from the table above.

Note: Note that the implicit integrators `BackwardEuler`, `IRK2` and `IRK4` currently rely on the CasADi AD tool to work.

Expert options for implicit integrators

The implicit integrators `BackwardEuler`, `IRK2` and `IRK4` do not just evaluate the differential equation, but actually solve a nonlinear equation to obtain the state trajectory. This is done by means of Newton iterations, with default values of 10 iterations for `BackwardEuler` and 5 iterations for `IRK2` and `IRK4`. These default values can be overwritten by using the following option:

Matlab

Python

```
codeoptions.nlp.integrator.newtonIter = 3;
```

```
codeoptions.nlp.integrator.newtonIter = 3
```

In order to reduce computational effort, the Jacobian of the nonlinear equation is only computed once by default. If your differential equations are highly nonlinear, it may be worth the effort to recompute it at every Newton iteration. This is achieved by means of the following option:

Matlab

Python

```
codeoptions.nlp.integrator.reuseNewtonJacobian = 0;
```

```
codeoptions.nlp.integrator.reuseNewtonJacobian = 0
```

Code-generated integrators

From FORCESPRO 4.1.0, integrators generated on the server are available when using explicit integrators `ForwardEuler`, `RK2`, `RK3` and `RK4`, and the field *continuous_dynamics* is set in the *model* structure. From FORCESPRO 4.4.0 the implicit integration scheme `IRK2` was added to the list of supported codegenerated integration schemes. These integrators result in much smaller code size than previously. They also often result in faster run times on embedded targets.

Two different methods are used to compute sensitivities associated to these integrators:

- `chainrule`, which is the default option, can also be triggered by setting

Matlab

Python

```
codeoptions.nlp.integrator.differentiation_method = 'chainrule';
```

```
codeoptions.nlp.integrator.differentiation_method = 'chainrule'
```

- `vde`, which can be triggered by settings the following option:

Matlab

Python

```
codeoptions.nlp.integrator.differentiation_method = 'vde';
```

```
codeoptions.nlp.integrator.differentiation_method = 'vde'
```

When using the `vde` option, the following options also need to be set

Matlab

Python

```
codeoptions.nlp.sensitivity.Ts = codeoptions.nlp.integrator.Ts;
codeoptions.nlp.sensitivity.nodes = codeoptions.nlp.integrator.nodes / 2;
    % When using 'ERK2' or 'ERK4' for the sensitivity computation, the number of
    ↪ nodes for the sensitivity
    % needs to be twice the number of nodes for the integrator
codeoptions.nlp.sensitivity.type = 'ERK4'; % Can also be 'ForwardEuler', 'RK2'
    ↪ depending on the application
```

```

codeoptions.nlp.sensitivity.Ts = codeoptions.nlp.integrator.Ts
codeoptions.nlp.sensitivity.nodes = codeoptions.nlp.integrator.nodes / 2
    # When using 'ERK2' or 'ERK4' for the sensitivity computation, the number of
    ↪ nodes for the sensitivity
    # needs to be twice the number of nodes for the integrator
codeoptions.nlp.sensitivity.type = 'ERK4' # Can also be 'ForwardEuler', 'RK2'
    ↪ depending on the application

```

The `vde` option is likely to change the numerical behaviour of the solver but can help for reducing the solve time in some cases, typically by having a looser integration on sensitivity.

Note: The `vde` option currently is still in an experimental state and we are working to fully robustify it. You may give it a try, but be prepared for unexpected behaviour. Also, the RK3 integration method is currently not supported with the `vde` option.

Linear subsystem exploitation

Often nonlinear optimal control problems contain linear subsystems, meaning part of the differential equation describing the dynamics of the system is linear while another part is nonlinear. By this we mean that the state x of the system can be split into two parts $x = (x_1, x_2)$ such that the differential equation $\dot{x} = c(x, u)$ (u denoting the control input) governing the dynamics of the system can be written as

$$\dot{x}_1 = A_1 x_1 + B_1 u \quad (15.1)$$

$$\dot{x}_2 = c_2(x_1, x_2, u). \quad (15.2)$$

Here A_1 and B_1 denote constant matrices and c_2 denotes a non-linear function. Since FORCESPRO 4.4.0 it is possible to exploit such subsystems for performance by performing parts of the numerical integration of the system offline. Currently this is supported only for the codegenerated ERK4 integration scheme (see *Code-generated integrators*). FORCESPRO can automatically detect a linear subsystem if it exists. One can activate the detection of linear subsystems by enabling the `codeoptions.nlp.integrator.attempt_subsystem_exploitation` option as follows:

Matlab

Python

```
codeoptions.nlp.integrator.attempt_subsystem_exploitation = 1;
```

```
codeoptions.nlp.integrator.attempt_subsystem_exploitation = 1
```

Optionally, in combination with setting this option, one can also specify the state indices of the linear subsystem manually. These indices are specified as a numpy array of integers in Python and a vector of indices in Matlab via the field `model.linIdx`. For example, in a case when $x \in \mathbb{R}^2$, $u \in \mathbb{R}$ and the right-hand-side c of the ODE describing the dynamics of the system is given by

$$c(x, u) = \begin{pmatrix} x_2 \\ x_1 \\ \cos(x_1) + \sin(x_2) + x_3 + u \end{pmatrix},$$

one would have to specify

Matlab

Python

```
model.linInIdx = [1, 2];
```

```
model.linInIdx = np.array([0, 1], dtype=np.int)
```

Note the 1-based indexing in Matlab and the 0-based indexing in Python. For further details on how to exploit linear subsystems using FORCESPRO, see *Controlling a crane using a FORCESPRO NLP solver*.

Note: For large systems (more than about 16 states) there might be a considerable overhead in determining the indices of the linear subsystem automatically. In case you encounter such an overhead, you can avoid it by manually specifying `model.linInIdx` as shown above.

15.2.2 Accuracy requirements

One can modify the termination criteria by altering the KKT tolerance with respect to stationarity, equality constraints, inequality constraints and complementarity conditions, respectively, using the following fields:

Matlab

Python

```
% default tolerances
codeoptions.nlp.TolStat = 1e-5; % inf norm tol. on stationarity
codeoptions.nlp.TolEq = 1e-6; % tol. on equality constraints
codeoptions.nlp.TolIneq = 1e-6; % tol. on inequality constraints
codeoptions.nlp.TolComp = 1e-6; % tol. on complementarity
```

```
# default tolerances
codeoptions.nlp.TolStat = 1e-5 # inf norm tol. on stationarity
codeoptions.nlp.TolEq = 1e-6 # tol. on equality constraints
codeoptions.nlp.TolIneq = 1e-6 # tol. on inequality constraints
codeoptions.nlp.TolComp = 1e-6 # tol. on complementarity
```

All tolerances are computed using the infinity norm $\|\cdot\|_\infty$.

15.2.3 Barrier strategy

The strategy for updating the barrier parameter is set using the field:

Matlab

Python

```
codeoptions.nlp.BarrStrat = 'loqo';
```

```
codeoptions.nlp.BarrStrat = 'loqo'
```

It can be set to 'loqo' (default) or to 'monotone'. The default settings often leads to faster convergence, while 'monotone' may help convergence for difficult problems.

15.2.4 Hessian approximation

The way the Hessian of the Lagrangian function is computed can be set using the field:

Matlab

Python

```
codeoptions.nlp.hessian_approximation = 'bfgs';
```

```
codeoptions.nlp.hessian_approximation = 'bfgs'
```

FORCESPRO currently supports BFGS updates ('bfgs') (default) and Gauss-Newton approximation ('gauss-newton'). Exact Hessians will be supported in a future version. Read the subsequent sections for the corresponding Hessian approximation method of your choice.

BFGS options

When the Hessian is approximated using BFGS updates, the initialization of the estimates can play a critical role in the convergence of the method. The default value is the identity matrix, but the user can modify it using e.g.:

Matlab

Python

```
codeoptions.nlp.bfgs_init = diag([0.1, 10, 4]);
```

```
codeoptions.nlp.bfgs_init = np.diag(np.array([0.1, 10, 4]))
```

Note that BFGS updates are carried out individually per stage in the FORCESPRO NLP solver, so the size of this matrix is the size of the stage variable. Also note that this matrix must be positive definite. When the cost function is positive definite, it often helps to initialize BFGS with the Hessian of the cost function.

This matrix is also used to restart the BFGS estimates whenever the BFGS updates are skipped several times in a row. The maximum number of updates skipped before the approximation is re-initialized is set using:

Matlab

Python

```
codeoptions.nlp.max_update_skip = 2;
```

```
codeoptions.nlp.max_update_skip = 2
```

The default value for `max_update_skip` is 2.

In order to set the BFGS initialization through the `bfgs_init` codeoption one must first come up with a guess for a good BFGS initialization. One way to do so is to first run the solver without any user-defined BFGS initialization (i.e. not setting `codeoptions.nlp.bfgs_init`) and using the BFGS matrix reached upon convergence as an initialization. One can export the BFGS matrix by setting

Matlab

Python

```
% diagonal of BFGS
codeoptions.exportBFGS = 1;
% lower triangular of BFGS
codeoptions.exportBFGS = 2;
```

```
# diagonal of BFGS
codeoptions.exportBFGS = 1
# lower triangular of BFGS
codeoptions.exportBFGS = 2
```

Istead of specifying the BFGS initialization at codegen one can also specify it at run-time. In order to do this one should set

Matlab

Python

```
codeoptions.nlp.parametricBFGSinit = 1;
```

```
codeoptions.nlp.parametricBFGSinit = 1
```

before generating the FORCESPRO solver. Having done this, the generated solver will expect an input `problem.BFGSinitLower<stage number>` for every stage. This is a vector which specifies the BFGS hessian initialization in LOWER TRIANGULAR ROW MAJOR format. Thus, in order to specify e.g. the matrix

$$\begin{pmatrix} a_1 & 0 & 0 \\ 0 & a_2 & 0 \\ 0 & 0 & a_3 \end{pmatrix}$$

for constants $a_1, a_2, a_3 > 0$ as the BFGS inialization at stage 6 out of 50 stages in total, one would specify

Matlab

Python

```
problem.BFGSinitLower06 = [a_1, 0, a_2, 0, 0, a_3];
```

```
problem["BFGSinitLower06"] = np.array([a_1, 0, a_2, 0, 0, a_3])
```

Gauss-Newton options

For problems that have a least squares objective, i.e. the cost function can be expressed by a vector-valued function $r_k : \mathbb{R}^n \rightarrow \mathbb{R}^m$ which implicitly defines the objective function as:

$$f_k(z_k, p_k) = \frac{1}{2} \|r_k(z_k, p_k)\|_2^2,$$

the Gauss-Newton approximation of the Hessian is given by:

$$\nabla_{xx}^2 L_k \approx \nabla r_k(z_k, p_k) \nabla r_k(z_k, p_k)^\top$$

and can lead to faster convergence and a more reliable method. When this option is selected, the functions r_k have to be provided by the user in the field `LSobjective`. For example if $r(z) = \sqrt{100}z_1^2 + \sqrt{6}z_2^2$, i.e. $f(z) = 50z_1^2 + 3z_2^2$, then the following code defines the least-squares objective (note that r is a vector-valued function):

Matlab

Python

```
model.objective = @(z) 0.1* z(1)^2 + 0.01*z(2)^2;
model.LSobjective = @(z) [sqrt(0.2)*z(1); sqrt(0.02)*z(2)];
```

```
# not yet implemented
```

Important: The field `LSobjective` will have precedence over `objective`, which need not be defined in this case.

When providing your own function evaluations in C, you must populate the Hessian argument with a positive definite Hessian.

15.2.5 Line search settings

The line search first computes the maximum step that can be taken while maintaining the iterates inside the feasible region (with respect to the inequality constraints). The maximum distance is then scaled back using the following setting:

Matlab

Python

```
% default fraction-to-boundary scaling
codeoptions.nlp.ftbr_scaling = 0.9900;
```

```
# default fraction-to-boundary scaling
codeoptions.nlp.ftbr_scaling = 0.9900;
```

15.2.6 Regularization

To avoid ill-conditioned saddle point systems, FORCESPRO employs two different types of regularization, static and dynamic regularization.

Static regularization

Static regularization of the augmented Hessian by $\delta_w I$, and of the multipliers corresponding to the equality constraints by $-\delta_c I$ helps avoid problems with rank deficiency. The constants δ_w and δ_c vary at each iteration according to the following heuristic rule:

$$\begin{aligned}\delta_w &= \eta_w \min(\mu, \|c(x)\|)^{\beta_w} \cdot (i+1)^{-\gamma_w} + \delta_{w,\min} \\ \delta_c &= \eta_c \min(\mu, \|c(x)\|)^{\beta_c} \cdot (i+1)^{-\gamma_c} + \delta_{c,\min}\end{aligned}$$

where μ is the barrier parameter and i is the number of iterations.

This rule has been chosen to accommodate two goals: First, make the regularization dependent on the progress of the algorithm - the closer we are to the optimum, the smaller the regularization should be in order not to affect the search directions generated close to the solution, promoting superlinear convergence properties. Second, the amount of regularization employed should decrease with the number of iterations to a certain minimum level, at a certain sublinear rate, in order to prevent stalling due to too large regularization. FORCESPRO NLP does not employ an inertia-correcting linear system solver, and so relies heavily on the parameters of this regularization to be chosen carefully.

You can change these parameters by using the following settings:

Matlab

Python

```
% default static regularization parameters
codeoptions.nlp.reg_eta_dw = 1e-4;
codeoptions.nlp.reg_beta_dw = 0.8;
codeoptions.nlp.reg_min_dw = 1e-9;
codeoptions.nlp.reg_gamma_dw = 1.0/3.0;

codeoptions.nlp.reg_eta_dc = 1e-4;
codeoptions.nlp.reg_beta_dc = 0.8;
codeoptions.nlp.reg_min_dc = 1e-9;
codeoptions.nlp.reg_gamma_dc = 1.0/3.0;
```



```
# default static regularization parameters
codeoptions.nlp.reg_eta_dw = 1e-4
codeoptions.nlp.reg_beta_dw = 0.8
codeoptions.nlp.reg_min_dw = 1e-9
codeoptions.nlp.reg_gamma_dw = 1.0/3.0

codeoptions.nlp.reg_eta_dc = 1e-4
codeoptions.nlp.reg_beta_dc = 0.8
codeoptions.nlp.reg_min_dc = 1e-9
codeoptions.nlp.reg_gamma_dc = 1.0/3.0
```

Note that by choosing $\delta_w = 0$ and $\delta_c = 0$, you can turn off the progress and iteration dependent regularization, and rely on a completely static regularization by $\delta_{w,\min}$ and $\delta_{c,\min}$, respectively.

Dynamic regularization

Dynamic regularization regularizes the matrix on-the-fly to avoid instabilities due to numerical errors. During the factorization of the saddle point matrix, whenever it encounters a pivot smaller than ϵ , it is replaced by δ . There are two parameter pairs: (ϵ, δ) affects the augmented Hessian and (ϵ_2, δ_2) affects the search direction computation. You can set these parameters by:

Matlab

Python

```
% default dynamic regularization parameters
codeoptions.regularize.epsilon = 1e-12; % (for Hessian approx.)
codeoptions.regularize.delta = 4e-6; % (for Hessian approx.)
codeoptions.regularize.epsilon2 = 1e-14; % (for Normal eqs.)
codeoptions.regularize.delta2 = 1e-14; % (for Normal eqs.)
```

```
# default dynamic regularization parameters
codeoptions.regularize.epsilon = 1e-12 # (for Hessian approx.)
codeoptions.regularize.delta = 4e-6 # (for Hessian approx.)
codeoptions.regularize.epsilon2 = 1e-14 # (for Normal eqs.)
codeoptions.regularize.delta2 = 1e-14 # (for Normal eqs.)
```

15.2.7 Linear system solver

The interior-point method solves a linear system to find a search direction at every iteration. FORCESPRO NLP offers the following four linear solvers:

- 'normal_eqs' (default): Solving the KKT system in normal equations form.
- 'symm_indefinite': improved variant of 'symm_indefinite_legacy' introduced in FORCESPRO version 5.0.0; roughly as efficient as normal_eqs but more robust.
- 'symm_indefinite_fast': Solving the KKT system in augmented / symmetric indefinite form, using regularization and positive definite Cholesky factorizations only. This is often the fastest solver but may be less numerical stable than symm_indefinite.
- 'symm_indefinite_legacy': Solving the KKT system in augmented / symmetric indefinite form; may be removed in a future release

The linear system solver can be selected by setting the following field:

Matlab

Python

```
codeoptions.nlp.linear_solver = 'symm_indefinite';
```

```
codeoptions.nlp.linear_solver = 'symm_indefinite'
```

It is recommended to try different linear solvers as the robustness and speed of the solvers are problem-dependent. The overall most robust method is `symm_indefinite`, which is also very efficient. For certain problems `normal_eqs` and `'symm_indefinite_fast'` may be slightly faster than `symm_indefinite` but possibly also slightly less numerically stable.

Note: Independent of the linear system solver choice, the generated code is always library-free and statically allocated, i.e. it can be embedded anywhere.

Note: From FORCESPRO version 5.0.0 onwards, the option `symm_indefinite` refers to an improved version; use `symm_indefinite_legacy` to restore the previous default.

The `'normal_eqs'` solver is the standard FORCESPRO linear system solver based on a full reduction of the KKT system (the so-called normal equations form). It works well for standard problems, especially convex problems or nonlinear problems where the BFGS or Gauss-Newton approximations of the Hessian are numerically sufficiently well conditioned.

The `'symm_indefinite'` solver is numerically more robust than `'normal_eqs'` and `symm_indefinite_fast` and typically similarly efficient. It is an improved variant of the `'symm_indefinite_legacy'`. Furthermore, it implements iterative refinement which further improves numerical stability (see [Iterative refinement](#)).

The `'symm_indefinite_fast'` solver is typically the fastest solver. Currently only used for receding-horizon/MPC-like problems where dimensions of all stages are equal (except for the first and last stage, those are handled separately).

The `'symm_indefinite_legacy'` solver is the most robust one, but currently replaced by an at least equally robust improved variant.

Iterative refinement

The linear solver `'symm_indefinite'` supports iterative refinement to further improve numerical stability. Iterative refinement is recommended for problems that don't converge due to numerical issues but can be safely disabled (default) for most problems. In order to enable iterative refinement, set `codeoptions.nlp.refinement_steps` to the desired number of steps > 0 . Two types of iterative refinement are implemented which can be selected by setting `codeoptions.nlp.refinement_type` as outlined in [Table 15.8](#).

Table 15.8: Options for setting iterative refinement type

<code>nlp.refinement_type</code>	Description
0	Includes additional modification (default)
1	Strictly based on the original linear system

15.2.8 Automatic differentiation tool

If external functions and derivatives are not provided directly as C code by the user, FORCESPRO makes use of an automatic differentiation (AD) tool to generate efficient C code for all the functions (and their derivatives) inside the problem formulation. Currently, two different AD tools (or four different AD tool versions) are supported that can be chosen by means of the setting `nlp.ad_tool` as summarized in [Table 15.9](#).

Table 15.9: Automatic differentiation tool options

nlp.ad_tool	Tool	URL
'casadi'	CasADi (as in path or v3.5.5)	CasADi
'casadi-2.4.2'	CasADi v2.4.2	CasADi
'casadi-3.5.1'	CasADi v3.5.1	CasADi
'casadi-3.5.5'	CasADi v3.5.5	CasADi
'symbolic-math-tbx'	MathWorks Symbolic Math Toolbox	MathWorks

Note that MathWorks Symbolic Math Toolbox requires an additional license, which is why the default option is set to

Matlab

Python

```
codeoptions.nlp.ad_tool = 'casadi';
```

```
codeoptions.nlp.ad_tool = 'casadi'
```

Also note that the use of implicit integrators `BackwardEuler`, `IRK2` and `IRK4` (see [Section 15.2.1](#)) currently still rely on using the CasADi AD tool.

15.2.9 Re-use of callback code

When defining your NLP problem formulation using an AD tool, you may specify objective functions, dynamic equations and constraints separately on each stage. In order to reduce the size of the generated callback code, FORCESPRO will perform a check whether all these callbacks are identical on any two or more stages and if so, only generates the callback code for those stages once. However, checking for exact identity can be tricky and may sometimes lead to false results. By default, FORCESPRO performs a less strict check for identity resulting in less duplicated callback code. If you observe that two stages are wrongly identified as identical, you can enable a more strict check by using the following codeoption:

Matlab

Python

```
codeoptions.nlp.strictCheckDistinctStages = 1;
```

```
# not yet supported
```

Note that using this option may be overly conservative and lead to duplicated callback code for different stages that are actually identical.

15.2.10 Safety checks

By default, the output of the function evaluations is checked for the presence of NaNs or INFs in order to diagnose potential initialization problems. In order to speed up the solver one can remove these checks by setting:

Matlab

Python

```
codeoptions.nlp.checkFunctions = 0;
```

```
codeoptions.nlp.checkFunctions = 0
```

15.3 Convex branch-and-bound options

The settings of the FORCESPRO mixed-integer branch-and-bound convex solver are accessed through the `codeoptions.mip` struct. It is worthwhile to explore different values for the settings in [Table 15.10](#), as they might have a severe impact on the performance of the branch-and-bound procedure.

Note: All the options described below are currently not available with the FORCESPRO non-linear solver. For mixed-integer nonlinear programs and the available options, please have a look at paragraph [Mixed-integer nonlinear solver](#).

Table 15.10: Branch-and-bound options

Setting	Values	Default
<code>mip.timeout</code>	Any value ≥ 0	31536000 (1 year)
<code>mip.mipgap</code>	Any value ≥ 0	0
<code>mip.branchon</code>	'mostAmbiguous', 'leastAmbiguous'	'mostAmbiguous'
<code>mip.stageinorder</code>	0 (OFF), 1 (ON)	1 (ON)
<code>mip.explore</code>	'bestFirst', 'depthFirst'	'bestFirst'
<code>mip.inttol</code>	Any value > 0	1E-5
<code>mip.queueSize</code>	Any integer value ≥ 0	1000

A description of each setting is given below:

- `mip.timeout`: Timeout in seconds, after which the search is stopped and the best solution found so far is returned.
- `mip.mipgap`: Relative sub-optimality after which the search shall be terminated. For example, a value of 0.01 will search for a feasible solution that is at most 1%-suboptimal. Set to zero if the optimal solution is required.
- `mip.branchon`: Determines which variable to branch on after having solved the relaxed problem. Options are 'mostAmbiguous' (i.e. the variable closest to 0.5) or 'leastAmbiguous' (i.e. the variable closest to 0 or 1).
- `mip.stageinorder`: Stage-in-order heuristic: For the branching, determines whether to fix variables in order of the stage number, i.e. first all variables of stage i will be fixed before fixing any of the variables of stage $i + 1$. This is often helpful in multistage problems, where a timeout is expected to occur, and where it is important to fix the early stages first (for example MPC problems). Options are 0 for OFF and 1 for ON.
- `mip.explore`: Determines the exploration strategy when selecting pending nodes. Options are 'bestFirst', which chooses the node with the lowest lower bound from all pending nodes, or 'depthFirst', which prioritizes nodes with the most number of fixed binaries first to quickly reach a node.
- `mip.inttol`: Integer tolerance for identifying binary solutions of relaxed problems. A solution of a relaxed problem with variable values that are below `inttol` away from binary will be declared to be binary.
- `mip.queueSize`: Maximum number of pending nodes that the branch and bound solver can store. If that number is exceeded during the search, the solver quits with an `exitflag` value of -2 and returns the best solution found so far.

15.4 Solve methods

As a default optimization method the primal-dual interior-point method is used. Several other methods are available. To change the solve method set the `solvemethod` field as outlined in [Table 15.11](#).

Table 15.11: Solve methods

solvemethod	Method	Description
'PDIP_NLP'	Nonlinear Primal-Dual Interior-Point method	The Nonlinear Primal-Dual Interior-Point method is the most stable and robust method for most nonlinear problems.
'SQP_NLP'	Sequential Quadratic Programming method	The Sequential Quadratic Programming method may be more efficient on mildly nonlinear problems.
'PDIP'	Primal-Dual Interior-Point method	The Primal-Dual Interior-Point method is the most stable and robust method for most convex problems.
'ADMM'	Alternating Direction Methods of Multipliers	For some problems, ADMM may be faster. The method variant and several algorithm parameters can be tuned in order to improve performance.
'DFG'	Dual Fast Gradient method	For some problems with simple constraints, our implementation of the dual fast gradient method can be the fastest option. No parameters need to be tuned in this method.
'FG'	Fast Gradient method	For problems with no equality constraints (only one stage) and simple constraints, the primal fast gradient method can give medium accuracy solutions extremely quickly. The method has several tuning parameters that can significantly affect the performance.

15.4.1 Primal-Dual Interior-Point Method

The Primal-Dual Interior-Point method is the default optimization method for either nonlinear/nonconvex or convex problems. It is a stable and robust method for most of the problems.

Solver Initialization

The performance of the solver can be influenced by the way the variables are initialized. The default method (cold start) should work in most cases extremely reliably, so there should be no need in general to try other methods, unless you are experiencing problems with the default initialization scheme. To change the method of initialization in FORCESPRO set the field `init` to one of the values in [Table 15.12](#).

Table 15.12: PDIP solver initialization

init	Method	Initialization method
0 (default)	Cold start	Set all primal variables to 0, and all dual variables to the square root of the initial complementarity gap μ_0 : $z_i = 0, s_i = \sqrt{\mu_0}, \lambda_i = \sqrt{\mu_0}$. The default value is $\mu_0 = 10^6$.
1	Centered start	Set all primal variables to zero, the slacks to the RHS of the corresponding inequality, and the Lagrange multipliers associated with the inequalities such that the pairwise product between slacks and multipliers is equal to the parameter μ_0 : $z_i = 0, s_i = b_{\text{ineq}}$ and $s_i \lambda_i = \mu_0$.
2	Primal warm start	Set all primal variables as provided by the user. Calculate the residuals and set the slacks to the residuals if they are sufficiently positive (larger than 10^{-4}), or to one otherwise. Compute the associated Lagrange multipliers such that $s_i \lambda_i = \mu_0$.

Initial Complementary Slackness

The default value for μ_0 is 10^6 . To use a different value, use:

Matlab

Python

```
codeoptions.mu0 = 10;
```

```
codeoptions.mu0 = 10;
```

Accuracy Requirements

The accuracy for which FORCESPRO returns the OPTIMAL flag can be set as follows:

Matlab

Python

```
codeoptions.accuracy.ineq = 1e-6; % infinity norm of residual for inequalities
codeoptions.accuracy.eq = 1e-6; % infinity norm of residual for equalities
codeoptions.accuracy.mu = 1e-6; % absolute duality gap
codeoptions.accuracy.rdgap = 1e-4; % relative duality gap := (pobj-dobj)/pobj
```

```

codeoptions.accuracy.ineq = 1e-6 # infinity norm of residual for inequalities
codeoptions.accuracy.eq = 1e-6   # infinity norm of residual for equalities
codeoptions.accuracy.mu = 1e-6   # absolute duality gap
codeoptions.accuracy.rdgap = 1e-4 # relative duality gap := (pobj-dobj)/pobj

```

Line Search Settings

If FORCESPRO experiences convergence difficulties, you can try selecting different line search parameters. The first two parameters of `codeoptions.linesearch`, `factor_aff` and `factor_cc` are the backtracking factors for the line search (if the current step length is infeasible, then it is reduced by multiplication with these factors) for the affine and combined search direction, respectively.

Matlab

Python

```

codeoptions.linesearch.factor_aff = 0.9;
codeoptions.linesearch.factor_cc = 0.95;

```

```

codeoptions.linesearch.factor_aff = 0.9
codeoptions.linesearch.factor_cc = 0.95

```

The remaining two parameters of the field `linesearch` determine the minimum (`minstep`) and maximum step size (`maxstep`). Choosing `minstep` too high will cause the generated solver to quit with an exitcode saying that the line search has failed, i.e. no progress could be made along the computed search direction. Choosing `maxstep` too close to 1 is likely to cause numerical issues, but choosing it too conservatively (too low) is likely to increase the number of iterations needed to solve a problem.

Matlab

Python

```

codeoptions.linesearch.minstep = 1e-8;
codeoptions.linesearch.maxstep = 0.995;

```

```

codeoptions.linesearch.minstep = 1e-8
codeoptions.linesearch.maxstep = 0.995

```

Regularization

During factorization of supposedly positive definite matrices, FORCESPRO applies a regularization to the i -th pivot element if it is smaller than ϵ . In this case, it is set to δ , which is the lower bound on the pivot element that FORCESPRO allows to occur.

Matlab

Python

```

codeoptions.regularize.epsilon = 1e-13; % if pivot element < epsilon ...
codeoptions.regularize.delta = 1e-8;    % then set it to delta

```

```

codeoptions.regularize.epsilon = 1e-13 # if pivot element < epsilon ...
codeoptions.regularize.delta = 1e-8    # then set it to delta

```

Multicore parallelization

FORCESPRO supports the computation on multiple cores, which is particularly useful for large problems and long horizons (the workload is split along the horizon to multiple cores). This is implemented by the use of OpenMP and can be switched on by using

Matlab

Python

```
codeoptions.parallel = 1;
```

```
codeoptions.parallel = 1
```

By default multicore computation is switched off.

When the parallel option is enabled with 1 (`codeoptions.parallel = 1`), the maximum number of threads to be used is set as the maximum number of threads available to OpenMP (`max_number_of_threads`). Additionally, a runtime parameter `num_of_threads` is created to control the number of threads in runtime. The allowed range of values for the runtime parameter is `[1, max_number_of_threads]`. Leaving the parameter unset or setting a value outside the allowed range will lead in execution with the maximum number of threads (`max_number_of_threads`).

The maximum number of threads can also be set manually during code generation by setting:

Matlab

Python

```
% <max_number_of_threads> larger than 1
codeoptions.parallel = <max_number_of_threads>;
```

```
# <max_number_of_threads> larger than 1
codeoptions.parallel = <max_number_of_threads>
```

15.4.2 Alternating Directions Method of Multipliers

FORCESPRO implements several optimization methods based on the ADMM framework. Different variants can handle different types of constraints and FORCESPRO will automatically choose an ADMM variant that can handle the constraints in a given problem. To manually choose a specific method in FORCESPRO, use the `ADMMvariant` field of `codeoptions`:

Matlab

Python

```
codeoptions.ADMMvariant = 1; % can be 1 or 2
```

```
codeoptions.ADMMvariant = 1 # can be 1 or 2
```

where variant 1 is as follows:

$$\begin{aligned} & \text{minimize} && \frac{1}{2}y^\top Hy + f^\top y \\ & \text{subject to} && Dy = c \\ & && \underline{z} \leq z \leq \bar{z} \\ & && y = z \end{aligned}$$

and variant 2 is as follows:

$$\begin{aligned} & \text{minimize} && \frac{1}{2} y^\top H y + f^\top y \\ & \text{subject to} && D y = c \\ & && A y = z \\ & && z \leq b \end{aligned}$$

Accuracy requirements

The accuracy for which FORCESPRO returns the OPTIMAL flag can be set as follows:

Matlab

Python

```
codeoptions.accuracy.consensus = 1e-3; % infinity norm of the consensus equality
codeoptions.accuracy.dres = 1e-3; % infinity norm of the dual residual
```

```
codeoptions.accuracy.consensus = 1e-3 # infinity norm of the consensus equality
codeoptions.accuracy.dres = 1e-3 # infinity norm of the dual residual
```

Note that, in contrast to primal-dual interior-point methods, the required number of ADMM iterations varies very significantly depending on the requested accuracy. ADMM typically requires few iterations to compute medium accuracy solutions, but many more iterations to achieve the same accuracy as interior-point methods. For feedback applications, medium accuracy solutions are typically sufficient. Also note that the ADMM accuracy requirements have to be changed depending on the problem scaling.

Method parameters

ADMM uses a regularization parameter ρ , which also acts as the step size in the gradient step. The convergence speed of ADMM is highly variable in the parameter ρ . Its value should satisfy $\rho > 0$. This parameter can be tuned using the following command:

Matlab

Python

```
codeoptions.ADMMrho = 1;
```

```
codeoptions.ADMMrho = 1
```

In some cases it may be possible to let FORCESPRO choose the value ρ automatically. To enable this feature set:

Matlab

Python

```
codeoptions.ADMMautorho = 1;
```

```
codeoptions.ADMMautorho = 1
```

Please note that this does not guarantee that the choice of ρ will be optimal.

ADMM can also include an 'over-relaxation' step that can improve the convergence speed. This step is typically useful for problems where ADMM exhibits very slow convergence and can be tuned using the parameter α . Its value should satisfy $1 \leq \alpha \leq 2$. This step using the following command:

Matlab

Python

```
codeoptions.ADMMalpha = 1;
```

```
codeoptions.ADMMalpha = 1
```

Precomputations

For problems with time-invariant data, FORCESPRO can compute full matrix inverses at code generation time and then implement matrix solves online by dense matrix-vector multiplication. In some cases, especially when the prediction horizon is long, it may be better to factorize the matrix and implement matrix solves using forward and backward solves with the pre-computed factors. To manually switch on this option, use the `ADMMfactorize` field of `codeoptions`.

When the data is time-varying, or when the prediction horizon is larger than 15 steps, FORCESPRO automatically switches to a factorization-based method.

Matlab

Python

```
codeoptions.ADMMfactorize = 0;
```

```
codeoptions.ADMMfactorize = 0
```

15.4.3 Dual Fast Gradient Method

For some problems with simple constraints, our implementation of the dual fast gradient method can be the fastest option. No parameters need to be tuned in this method.

15.4.4 Primal Fast Gradient Method

For problems with no equality constraints (only one stage) and simple constraints, the primal fast gradient method can give medium accuracy solutions extremely quickly. The method has several tuning parameters that can significantly affect the performance.

Accuracy requirements

The accuracy for which FORCESPRO returns the OPTIMAL flag can be set as follows:

Matlab

Python

```
codeoptions.accuracy.gmap = 1e-5; % infinity norm of the gradient map
```

```
codeoptions.accuracy.gmap = 1e-5 # infinity norm of the gradient map
```

The gradient map is related to the difference with respect to the optimal objective value. Just like with other first-order methods, the required number of FG iterations varies very significantly depending on the requested accuracy. Medium accuracy solutions can typically be computed very quickly, but many iterations are needed to achieve the same accuracy as with interior-point methods.

Method parameters

The user has to determine the step size in the fast gradient method. The convergence speed of FG is highly variable in this parameter, which should typically be set to be one over the maximum eigenvalue of the quadratic cost function. This parameter can be tuned using the following command:

Matlab

Python

```
codeoptions.FGstep = 1/1000;
```

```
codeoptions.FGstep = 1/1000
```

In some cases it may be possible to let FORCESPRO choose the step size automatically. To enable this feature set:

Matlab

Python

```
codeoptions.FGautostep = 1;
```

```
codeoptions.FGautostep = 1
```

Warm starting

The performance of the fast gradient method can be greatly influenced by the way the variables are initialized. Unlike with interior-point methods, fast gradient methods can be very efficiently warm started with a good guess for the optimal solution. To enable this feature set:

Matlab

Python

```
codeoptions.warmstart = 1;
```

```
codeoptions.warmstart = 1
```

When the user turns warm start on, a new parameter `z_init_0` is automatically added. The user should set it to be a good guess for the solution, which is typically available when solving a sequence of problems.

Chapter 16

Modelling Utilities

- *Interpolations (e.g. splines)*
 - *Polynomial Parameterization*
 - *Automatic Fit from Data*
 - *Application Example*
- *Smooth Approximations*
 - *Smooth Minimum*
 - *Smooth Maximum*

Like any derivative-based optimization solver, FORCESPRO works best if all functions defining the optimization problem are sufficiently smooth (i.e. at least continuously differentiable once). Both the Matlab and the Python client of FORCESPRO come along with a couple of utility functions to assist the user with setting up such smooth problem formulations. This chapter provides details on those utility functions for modelling.

16.1 Interpolations (e.g. splines)

If a given function is based on measurement data (or any other set of discrete data points), one can interpolate between those data points to yield a continuous function. FORCESPRO can either create such a function directly from the data points or allows you to provide a polynomial parameterization that can be used inside your symbolic problem formulation.

16.1.1 Polynomial Parameterization

A polynomial parameterization can be obtained by providing a vector containing $M+1$ break points (defining M interpolation intervals or pieces) as well as an array defining M sets of $N+1$ polynomial coefficients, each set defining a local polynomial of order N for each of those pieces.

Calling the line

Matlab

Python

```
f = ForcesInterpolation(breaks, coefs);
```

```
f = forcespro.modelling.Interpolation(breaks, coefs)
```

will yield a symbolic representation of a polynomial in standard form

$$f(x) = \sum_{j=0}^N c_{ij} x^j \quad \forall b_{i-1} \leq x \leq b_i \quad \forall i \in \{1, \dots, M\},$$

where b denotes the break points `breaks` and c denotes the coefficients `coefs`. $f(x)$ can be a scalar or a κ -dimensional function, i.e. `coefs` may be given for a multi-valued interpolation. For more details on how to pass those input parameters, we refer to the respective help function as the format differs slightly between the Matlab and the Python client to follow domain-specific conventions.

In case your coefficients are defined relative to beginning of each piece, you can call

Matlab

Python

```
f = ForcesInterpolation(breaks, coefs, 'pp');
```

```
f = forcespro.modelling.Interpolation(breaks, coefs, 'pp')
```

to yield a symbolic representation of a polynomial in “piecewise polynomial” form

$$f(x) = \sum_{j=0}^N c_{ij} (x - b_i)^j \quad \forall b_{i-1} \leq x \leq b_i \quad \forall i \in \{1, \dots, M\}.$$

Note: In addition to providing fixed numerical values for break points and coefficients, you may also pass symbolic quantities for some or all of those! This will allow you to change the parameterization of your interpolation on the fly, e.g. by means of real-time parameters that are passed to the FORCESPRO solver.

The symbolic interpolation f can now be used inside your problem formulation by evaluating it, either at a fixed value or at any symbolic quantity, e.g.

Matlab

Python

```
% assuming a state vector x and a control input u
y = f(x(1)) + u(1);
```

```
% assuming a state vector x and a control input u
y = f(x[0]) + u[0]
```

Important: Symbolic interpolations are currently only supported when using CasADi as AD tool.

16.1.2 Automatic Fit from Data

In case you do not want to specify break points and coefficients yourself, you can fit data points directly by calling:

Matlab

Python

```
f = ForcesInterpolationFit(X, Y, method);
```

```
f = forcespro.modelling.InterpolationFit(X, Y, kind)
```

Here, x and y are vectors (say, of dimension L) of data points to yield an interpolation that satisfies

$$f(X_i) = Y_i \quad \forall i \in \{1, \dots, L\}.$$

The third argument `method/kind` specifies the method to be used to obtain that fit using built-in functionality of either Matlab (see Table [Table 16.1](#)) or Python (see Table [Table 16.2](#)).

The symbolic interpolation f can be used the same way as described in section [Section 16.1.1](#).

Table 16.1: Interpolation Method for Matlab (see Matlab's `interp1` for more details)

method	Description
'linear'	Piecewise linear
'nearest'	Piecewise constant, value from nearest data point
'next'	Piecewise constant, value from next data point
'previous'	Piecewise constant, value from previous data point
'spline' (default)	Piecewise cubic spline
'pchip'	Shape-preserving piecewise cubic spline

Table 16.2: Interpolation Method for Python (see SciPy's `interpolation` class for more details)

kind	Description
'cubic' (default)	Piecewise cubic spline
'pchip'	Shape-preserving piecewise cubic spline

16.1.3 Application Example

A full example on how to use interpolations inside your problem formulation can be found in the `examples` folder that comes with your client. See the files `ObstacleAvoidance/ObstacleAvoidance_splines.m` (MATLAB) and `ObstacleAvoidance/obstacle_avoidance_splines.py` (Python), respectively. Therein, both road limits are defined as splines and are enforced as inequality constraints.

16.2 Smooth Approximations

There are a number of useful basic functions that are not differentiable everywhere. For some of them FORCESPRO provides a built-in smooth approximation and we plan to add more in an upcoming release.

16.2.1 Smooth Minimum

The minimum value of two scalars is not differentiable at the points where both values are identical. You can use the following smooth approximation instead:

Matlab

Python

```
c = ForcesMin(a, b);
```

```
c = forcespro.modelling.smooth_min(a, b)
```

This function accepts an optional third argument to trade-off smoothness and approximation quality. The default value is set to $1e-8$; higher values make the function smoother but less accurate.

16.2.2 Smooth Maximum

The maximum value of two scalars is not differentiable at the points where both values are identical. You can use the following smooth approximation instead:

Matlab

Python

```
c = ForcesMax(a, b);
```

```
c = forcespro.modelling.smooth_max(a, b)
```

This function accepts an optional third argument to trade-off smoothness and approximation quality. The default value is set to $1e-8$; higher values make the function smoother but less accurate.

Chapter 17

Dumping Problem Formulation and Data

- *Why to use the dump tool?*
- *How to use the dump tool?*
 - *Legacy dumps*
 - * *Dumping the problem formulation*
 - * *Dumping problem data*
 - * *Running a dumped problem*
 - * *Limitations of legacy dumps*
 - *Symbolic dumps*
 - * *Dumping the problem formulation*
 - * *Dumping problem data*
 - * *Dumping the problem formulation and data at once*
 - * *Running a dumped problem*
 - * *Limitations of symbolic dumps*
 - *Problem dumps from C*
 - * *Download and install msgpack for C*
 - * *Enable the Generation of the Dump Functions*
 - * *Dumping Problem Data*
 - * *Loading Problem Data*

17.1 Why to use the dump tool?

Along with its clients, FORCESPRO provides a tool that allows the user to dump the formulation and actual data of an optimization problem. This information allows to exactly reproduce the same solver for a given formulation and to feed it with exactly the same data to yield exactly the same results (provided it is run on the very same target hardware). The problem formulation and data is stored in “stand-alone” `mat` or `json` files, and the problem data can

also be saved in binary format. This means there is no need to keep copies of other files that may be used to specify the formulation (such as the dynamic equations), except for formulations relying on external callbacks provided as C code (see [External function evaluations in C](#)).

The dump tool may be helpful for a couple of use cases such as:

- *Debugging*: a dumped problem allows you to re-run single solver calls without the need to have your full simulation environment up and running.
- *External support*: you may send a dumped problem to whomever is in charge of providing support and it will enable that person to exactly reproduce your issue.
- *Testing*: keeping dumps of problems that performed as expected can be used to run regression tests to ensure they work as expected after future changes.

Note that, depending on the dump type you choose (see [How to use the dump tool?](#)), the dump tool either stores your problem formulation on a symbolic level or keeps a copy of the C code generated by the automatic differentiation tool. Thus, keep the following in mind:

Important: A dumped problem will contain complete information about the solver that you have setup. In particular, it may be used to reverse-engineer your problem formulation (including dynamic model, objective function, constraints etc.). Thus, only share a dumped problem with persons that have a right to obtain this information.

17.2 How to use the dump tool?

The dump tool currently provides three different dump types. Section [Legacy dumps](#) describes the so-called *legacy dump* that is available in the MATLAB client only and does not store the full symbolic formulation. Section [Symbolic dumps](#) describes the more recent *symbolic dump* that is also available in the Python client, stores the full symbolic formulation, but requires CasADi v3.5.x to work. In section [Problem dumps from C](#), you learn how to dump a problem struct (containing the runtime parameters) from C. This is useful when you work on the embedded system and you don't want to use the MATLAB and Python interface for dumping.

17.2.1 Legacy dumps

Legacy dumps are available for the MATLAB client only and store a pre-processed problem formulation including C code generated by the automatic differentiation tool. This variant is somewhat less explicit and is supposed to work with all supported AD tools, and is therefore still the default dump type if not specified otherwise by the user.

Creating a legacy dump of a problem consists of two steps:

1. *Dumping the problem formulation*: once a new solver has been generated, a `formulation` struct, the `codeoptions` struct and optionally the `outputs` struct need to be stored.
2. *Dumping problem data*: for each problem instance, the `problem_params` struct needs to be stored. It is possible to store data of multiple problem instances for the same problem formulation.

Dumping the problem formulation

For dumping the problem formulation, the following three steps need to be taken:

1. *Enabling creation of a formulation dump:* This is done by using the option

```
codeoptions.dump_formulation = 1;
```

2. *Obtaining the dumped formulation:* Calling `FORCES_NLP` with the before-mentioned code option enabled will make it return a `formulation` struct as *third* output argument

```
[stages, codeoptions, formulation] = FORCES_NLP( model, codeoptions, outputs );
```

3. *Storing the necessary structs into a file:* After calling `FORCES_NLP`, you should use the following function to store both the `formulation` and `codeoptions` struct

```
[tag, fullFilename] = ForcesDumpFormulation( formulation, codeoptions, outputs,  
→ label, dumpDirectory );
```

All but the first two arguments are optional. Pass `outputs` if your problem formulation contains outputs. Moreover, you may pass an additional `label` used inside the filenames (or pass an empty string) and `dumpDirectory` for storing the dumped formulation (the default is the current working directory). The function `ForcesDumpFormulation` will create a `mat` file in the specified directory containing the passed information. The filename is automatically chosen and will contain the name of your solver, your label, a unique tag, a timestamp as well as the suffix `_F`, e.g. `myFORCESSolver_ABC3DEFGHIJ_20200101120000000_F.mat`. The returned `fullFilename` is a string consisting of the directory and the filename of the dump.

Note that this function returns a `tag` that is unique for a given formulation and code options. It is strongly recommended to use it when dumping corresponding problem data.

Dumping problem data

Assuming your generated FORCESPRO solver is called `myFORCESSolver` and you are calling it with the following command

```
[output, exitflag, info] = myFORCESSolver( problem );
```

then dumping the problem data of any problem instance is as simple as calling

```
fullFilename = ForcesDumpProblem( problem, tag, dumpDirectory );
```

Here, you need to provide both the problem parameter struct as well as the unique `tag` that has been generated when dumping the problem formulation. The third argument `dumpDirectory` for storing the dumped problem data is optional (with the default being the current working directory). The function `ForcesDumpProblem` will create a `mat` file in the specified directory containing the passed information. The filename is automatically chosen and will contain the name of your solver, the unique tag (including any label passed when dumping the formulation), a timestamp as well as the suffix `_P`, e.g. `myFORCESSolver_ABC3DEFGHIJ_20200101120001000_P.mat`. The returned `fullFilename` is a string consisting of the directory and the filename of the dump.

There is no limit on the number of problem instances that you may dump that way.

Running a dumped problem

After you have dumped a problem formulation and at least one set of problem data, you can use those `mat` files to exactly reproduce your solver and problem instances. To do so, you need to perform the following two steps (where we assume you have stored the two files `myFORCESSolver_ABC3DEFGHIJ_20200101120000000_F.mat` and `myFORCESSolver_ABC3DEFGHIJ_20200101120001000_P.mat` at a location in your MATLAB path):

1. *Re-generate the FORCESPRO solver* by loading the formulation mat file and using its content to call the code generation:

```
F = load('myFORCESSolver_ABC3DEFGHIJ_20200101120000000_F.mat');
FORCES_NLP( F.formulation,F.codeoptions,F.outputs );
```

This will re-create the solver MEX function `myFORCESSolver`. Note that the third input struct containing the `outputs` is only available if you included it into your dump.

2. *Running the solver with dumped problem data* by loading the data mat file and using its content to call the generated solver:

```
P = load('myFORCESSolver_ABC3DEFGHIJ_20200101120001000_P.mat');
myFORCESSolver( P.problem );
```

You may repeat this step for as many problem instances as you have dumped.

Tip: To get the filenames of dumped problems and formulations in a directory, simply use the function:

```
[formulationFilename, problemFilename] = ForcesFindDumpedProblems( tag,
↳dumpDirectory );
```

Both arguments are optional. If `tag` is not given, the function returns any dumped filenames regardless of their tag. The default `dumpDirectory` is the current working directory. `problemFilenames` is a cell array of problem filenames.

Limitations of legacy dumps

Legacy dumps have the following limitations:

- They are only available via the MATLAB client of FORCESPRO.
- They cannot be used if you pass external functions in form of C code.

These limitations can be overcome by using a symbolic dump.

17.2.2 Symbolic dumps

Symbolic dumps directly store symbolic expressions of your problem formulation and codeoptions after converting both into the text-based JSON format. This variant thus reveals your complete problem formulation to anybody with whom you share those JSON files! While you should thus handle those symbolic dumps with care, they offer more flexibility than the legacy dumps and are also available via the Python client of FORCESPRO.

Creating a symbolic dump of a problem consists of two steps:

1. *Dumping the problem formulation:* you need to store your `model` struct, the `codeoptions` struct and optionally the `outputs` struct, which can be done even before generating the actual solver code.
2. *Dumping problem data:* for each problem instance, the `problem params` struct needs to be stored. It is possible to store data of multiple problem instances for the same problem formulation (in either a single file or multiple files).

Both steps may also be performed at once.

Dumping the problem formulation

For dumping the problem formulation in a symbolic way, just call the following function:

Matlab

Python

```
[tag, fullFilename] = ForcesDumpFormulation( model, codeoptions, outputs, ...  
                                             label, dumpDirectory, ForcesDumpType.DumpSymbolics );
```

```
tag, full_filename = forcespro.dump.save_formulation(model, codeoptions,   
↳ outputs=None,  
                                                    label=None, path=None)
```

In MATLAB, the last argument enables the use of a symbolic dump. This parameter is not required in Python since there is only the symbolic way to dump problems so far. Pass `outputs` if your problem formulation contains outputs. Moreover, you may pass an additional `label` used inside the filenames (or pass an empty string) and `dumpDirectory` (keyword `path` in Python) for storing the dumped file (the default is the current working directory). When calling this way, the function `ForcesDumpFormulation` will create a `json` file in the specified directory containing the passed information. The filename is automatically chosen and will contain the name of your solver, your label, a unique tag, a timestamp as well as the suffix `_F`, e.g. `myFORCESsolver_ABC3DEFGHIJ_20200101120000000_F.json`. The returned string `fullFilename` consists of the dump directory and the filename of the dump.

Note that this function returns a `tag` that is unique for a given formulation and code options. It is strongly recommended to use it when dumping corresponding problem data. However, the MATLAB and the Python client generate different tags for the same mathematical formulation.

Dumping problem data

Assuming your generated FORCESPRO solver is called `myFORCESsolver` and you are calling it with the following command

Matlab

Python

```
[output, exitflag, info] = myFORCESsolver( problem );
```

```
output, exitflag, info = my_forces_solver.solve(problem);
```

then dumping the problem data of any problem instance is as simple as calling

Matlab

Python

```
fullFilename = ForcesDumpProblem( problems, tag, dumpDirectory, ForcesDumpType.  
↳ DumpSymbolics );
```

```
full_filename = forcespro.dump.save_problem(problems, tag, dump_directory)
```

In MATLAB, the last argument enables the use of a symbolic dump. This parameter is not required in Python since there is only the symbolic way to dump problems so far. You need to provide either a single problem parameter struct (dictionary in Python) or an array (list in Python) of problem parameter structs using `problems`. Besides, the unique tag that

has been generated when dumping the problem formulation is required. The third argument `dumpDirectory` for storing the dumped problem data is optional (with the default being the current working directory). The functions `ForcesDumpProblem` or `forcespro.dump.save_formulation` will create a `json` file in the specified directory containing the passed information. The filename is automatically chosen and will contain the name of your solver, the unique tag (including any label passed when dumping the formulation), a timestamp as well as the suffix `_P`, e.g. `myFORCESsolver_ABC3DEFGHIJ_20200101120001000_P.json`. The returned string `fullFilename` consists of the dump directory and the filename of the dump.

There is no limit on the number of problem instances that you may dump that way.

Dumping the problem formulation and data at once

For dumping both the problem formulation and all problem data at once in a symbolic way, just call the following function:

Matlab

Python

```
[tag, fullFilename] = ForcesDumpAll( model, codeoptions, outputs, ...
                                   label, dumpDirectory, problems, ForcesDumpType.DumpSymbolics );
```

```
tag, full_filename = forcespro.dump.save_all(model, codeoptions, outputs, \
                                             label, dump_directory, problems)
```

In MATLAB, the last argument enables the use of a symbolic dump. This parameter is not required in Python since there is only the symbolic way to dump problems so far. You need to provide the `model` and the `codeoptions` containing your formulation. Pass `outputs` if your problem formulation contains outputs. Moreover, you may pass an additional `label` used inside the filenames (or pass an empty string) and `dumpDirectory` for storing the dumped file (the default is the current working directory). Furthermore, `problems` may be either a single set of problem data or a cell array (list in Python) of many problem data sets that you want to dump along with the problem formulation.

When calling this way, the function `ForcesDumpAll` will create a `json` file in the specified directory containing the passed information. The filename is automatically chosen and will contain the name of your solver, your label, a unique tag, a timestamp as well as the suffix `_A`, e.g. `myFORCESsolver_ABC3DEFGHIJ_20200101120000000_A.json`. The returned string `fullFilename` consists of the dump directory and the filename of the dump.

Note that this function returns a `tag` that is unique for a given formulation and `codeoptions` and that you may want to record. However, the MATLAB and the Python client generate different tags for the same mathematical formulation.

Running a dumped problem

After you have dumped a problem formulation and at least one set of problem data, you can use either a matching pair of `_F/_P` files or any single `_A` file in JSON format to exactly reproduce your solver and problem instances. To do so, you need to perform the following two steps:

1. Load problem formulation and data from JSON file or files calling:

Matlab

Python

```
[model, codeoptions, outputs, additionalData, problems] = ...
    ForcesLoadSymbolicDump( formulationFilename,
    problemFilenames );
```

(continues on next page)

(continued from previous page)

```
model, options, outputs, additional, problems = \
    forcespro.dump.load(formulation_filename, problem_filename)
```

`problemFileNames` may either be a single file name or a cell array (list in Python) containing all the problem data set that you want to load. In case you have dumped both formulation and problem data set(s) at once within a single file, just pass that one as `formulationFilename` and do not specify `problemFileNames`. The returned `problems` variable is an array (list in Python) containing all problem sets found in the dumps.

2. *Re-generating and running the solver with dumped information* by simply calling:

Matlab

Python

```
FORCES_NLP( model,codeoptions,outputs );
myFORCESsolver( problems(1) );
% and more problem instances if present
```

```
solver = model.generate_solver(codeoptions, outputs)
result, exitflag, info = my_forces_solver.solve(problems[1])
# and more problem instances if present
```

Tip: To get the filenames of dumped problems and formulations in a directory, simply use the function:

Matlab

Python

```
[formulationFilename, problemFilename] = ForcesFindDumpedProblems( tag,
    ↪dumpDirectory );
```

```
formulation_filename, problem_filenames = forcespro.dump.find_problems(tag, dump_
    ↪directory)
```

Both arguments are optional. If `tag` is not given, the function returns any dumped filenames regardless of their tag. The default `dumpDirectory` is the current working directory. `problemFileNames` is a cell array (list in Python) of problem filenames.

Limitations of symbolic dumps

Symbolic dumps only work with CasADi v3.5.x for reasons beyond our control, which is why we currently do not plan to extend support to CasADi v2.4.2 or MathWorks' Symbolic Math Toolbox.

17.2.3 Problem dumps from C

Problem dumps from C consider only the `params` struct containing the runtime parameters that are passed to the solver in each solver call. In order to save or load `params` structs, you can call the dump tool from any C script. This offers the opportunity to work directly on the embedded system. The data is stored in binary format. The problem dumps from C use the `msgpack-c` library.

Important: The problem dumps from C require dynamic memory allocation. This is because of the dependency on the *msgpack-c* library. Please check if your embedded platform supports dynamic memory allocation.

Before dumping problems from C for the first time, you need to install msgpack as described in [Download and install msgpack for C](#). Then, the dumping procedure consists of the following three steps:

1. *Enabling the generation of the dump functions:* When generating your solver, you need to set a codeoption in order to enable the generation of the dump functions.
2. *Dumping problem data:* Call the generated *serialize* function in order to dump a *params* struct. Exactly one *params* struct can be stored at a time.
3. *Loading problem data:* Call the generated *deserialize* function in order to load a *params* struct. Exactly one *params* struct can be stored at a time.

Download and install msgpack for C

Since the dump tool for problems from C requires msgpack, make sure you installed the library. You can either clone the [github repository](#) or you can simply download msgpack as a [zip file](#). For the installation of the library, you need `gcc >= 4.1.0` and `cmake >= 2.8.1`.

How to install:

- **Windows:**

1. Run `cmake .` in your terminal from the *msgpack-c-c_master* folder.
2. Open the generated *msgpack.sln* file (located in the same folder) in Visual Studio and click *Build*. The generated library is located in *msgpack-c-c_master/Debug*.

- **Other platforms:**

1. Run `cmake .` in your terminal from the *msgpack-c-c_master* folder.
2. Run `make`. The generated library is located in *msgpack-c-c_master*.

For more information about the installation of msgpack, see the *README.md* on [github](#).

Enable the Generation of the Dump Functions

Before generating your solver you need to enable the generation of the dump functions. You can specify whether you want to dump from your host platform or/and from your target platform. For dumping from the host platform set:

Matlab

Python

```
codeoptions.serializeCParamsHost = 1;
```

```
codeoptions.serializeCParamsHost = 1
```

and for dumping from your specified target platform set:

Matlab

Python

```
codeoptions.serializeCParamsTarget = 1;
```



```
codeoptions.serializeCParamsTarget = 1
```

Dumping Problem Data

This section explains how to write and run a C script that dumps your problem data based on the high-level basic example (see *High-level interface: Basic example*). We assume your C script is in the same folder as your generated solver.

You can find the code of this example script to try it out for yourself in the `examples` folder that comes with your client.

1. Include your solver header called `<solvername>.h`. In the solver header, the `<solvername>_params` struct and the dumping routines `<solvername>_serialize` and `<solvername>_deserialize` are defined. Note that the params struct for binary problems is called `<solvername>_binaryparams` and for mixed integer problems it is `<solvername>_integerparams`.

```
#include "FORCESNLPsolver/include/FORCESNLPsolver.h"
```

2. Create a params struct and fill it with your data:

```
/* create params struct */
FORCESNLPsolver_params params;

/* fill params struct with data */
params.xinit[0] = -4.;
params.xinit[1] = 2.;
for (int i = 0; i < 33; i++)
{
    params.x0[i] = 0.0;
}
```

3. Choose a filename for the dump and call the serialization routine:

```
const char filename[] = "dump.msgpack";
int successSerialize = FORCESNLPsolver_serialize(&params, filename);
```

4. Compile your script:

```
$ <Compiler_exec> my_C_dump_script.c <compiled_solver> -L<msgpack_lib_
→path> -l<msgpack_lib> <additional_libs>
```

Where:

- `<Compiler_exec>` is your compiler (for example `gcc`)
- `my_C_dump_script.c` is your script that calls the `serialize` function (for example `serializationCParams_HighLevel_BasicExample.c`)
- `<compiled_solver>` is your compiled solver library (static or shared):
 - For Linux/MacOS/MinGW it is `libFORCESNLPsolver.a` or `libFORCESNLPsolver.so` in the `lib` or `lib_target` directory
 - For Windows it is `FORCESNLPsolver_static.lib` or `FORCESNLPsolver.lib` in the `lib` or `lib_target` directory
- `<msgpack_lib_path>` specifies your path to the compiled msgpack library
 - For Linux/MacOS/MinGW it is the path to your `msgpack-c-c_master` folder
 - For Windows it is the path to your `msgpack-c-c_master/Debug` folder
- `<msgpack_lib>` specifies the name of the compiled msgpack library

- For the static library on Windows set it to msgpackc_import
- Otherwise, it is msgpackc
- <additional_libs> are possible libraries that need to be linked to resolve existing dependencies.
 - For Linux/MacOS it's usually necessary to link the math library (-lm)
 - For Windows you usually need to link the iphlpapi.lib library (it's distributed with the Intel Compiler, MinGW as well as Matlab) and sometimes some additional intel libraries (those are included in the FORCESPRO client under the folder libs_Intel – if missing they are downloaded after code generation)

The following shows how to compile the dump example script on Linux:

```
$ gcc serializationCParams_HighLevel_BasicExample.c FORCESNLPsolver/lib/
↳ libFORCESNLPsolver.so -L/path/to/msgpack-c -lmsgpackc -lm
```

Loading Problem Data

This section explains how to write and run a C script that loads a dumped C params struct based on the high-level basic example (see *High-level interface: Basic example*). We assume your C script is in the same folder as your generated solver.

You can find the code of this example script to try it out for yourself in the examples folder that comes with your client.

1. Include your solver header called <solvername>.h.

```
#include "FORCESNLPsolver/include/FORCESNLPsolver.h"
```

2. Create an empty params struct:

```
FORCESNLPsolver_params dumped_params;
```

3. Call the deserialization routine and pass the filename you chose when dumping the problem data:

```
int successDeserialize = FORCESNLPsolver_deserialize(&dumped_params,
↳ filename);
```

4. Compile your script:

```
$ <Compiler_exec> my_C_dump_script.c <compiled_solver> -L<msgpack_lib_
↳ path> -l<msgpack_lib> <additional_libs>
```

Where:

- <Compiler_exec> is your compiler (for example gcc)
- my_C_dump_script.c is your script that calls the deserialize function (for example serializationCParams_HighLevel_BasicExample.c)
- <compiled_solver> is your compiled solver library (static or shared):
 - For Linux/MacOS/MinGW it is libFORCESNLPsolver.a or libFORCESNLPsolver.so in the lib or lib_target directory
 - For Windows it is FORCESNLPsolver_static.lib or FORCESNLPsolver.lib in the lib or lib_target directory
- <msgpack_lib_path> specifies your path to the compiled msgpack library

- For Linux/MacOS/MinGW it is the path to your `msgpack-c-c_master` folder
- For Windows it is the path to your `msgpack-c-c_master/Debug` folder
- `<msgpack_lib>` specifies the name of the compiled msgpack library
 - For the static library on Windows set it to `msgpackc_import`
 - Otherwise, it is `msgpackc`
- `<additional_libs>` are possible libraries that need to be linked to resolve existing dependencies.
 - For Linux/MacOS it's usually necessary to link the math library (`-lm`)
 - For Windows you usually need to link the `iphlpapi.lib` library (it's distributed with the Intel Compiler, MinGW as well as Matlab) and sometimes some additional intel libraries (those are included in the FORCESPRO client under the folder `libs_Intel` – if missing they are downloaded after code generation)

The following shows how to compile the dump example script on Linux:

```
$ gcc serializationCParams_HighLevel_BasicExample.c FORCESNLPsolver/lib/  
→libFORCESNLPsolver.so -L/path/to/msgpack-c -lmsgpackc -lm
```


Chapter 18

Frequently asked questions

- *Features of FORCESPRO*
- *Issues during code generation*
- *Issues when running the solver*
- *Simulink interface*
- *Code deployment*
- *Other topics*

18.1 Features of FORCESPRO

- **I have been using FORCES in the past. Why should I use FORCESPRO?**

The development of the free version of FORCES by ETH (forces.ethz.ch) has been discontinued, and the code generation service is no longer available.

The professional version of FORCESPRO comes with professional support, additional interfaces, and a large performance increase.

- **Can FORCESPRO target dSpace hardware?**

Yes, FORCESPRO can be seamlessly integrated in the dSpace design flow with the new Simulink interface. For more details see *dSPACE deployment through Simulink Coder* and *dSPACE deployment through ConfigurationDesk*.

- **Can I use FORCESPRO for non-multistage programs?**

Yes, FORCESPRO supports the case $N = 1$, i.e. a general QCQP of the form

$$\begin{aligned}
 &\text{minimize} && \frac{1}{2}z^T H z + f^T z \\
 &\text{subject to} && D z = c \\
 &&& \underline{z} \leq z \leq \bar{z} \\
 &&& A z \leq b \\
 &&& z^T Q z + q^T z \leq r
 \end{aligned}$$

In order to use this feature, simply call `stages=MultistageProblem(1)` and fill in the matrices as described in *Low-level interface*.

- **I need to re-linearize the model of my plant each sampling time. Does FORCESPRO support this?**

When re-linearizing non-linear dynamics, you obtain in each sampling time a different matrix A , B and also a new affine part g :

$$x_{k+1} = Ax_k + Bu_k + g$$

FORCESPRO supports changing these variables at run-time by defining them as parameters.

- **I don't have a state-space model of my system. Can I still use FORCESPRO to design an optimal controller?**

Yes, the graphical interface allows one to design optimal controllers for models described by a Simulink diagram - there is no need for equations. If you have a model in another form, please send us a feature request and we will try to support your model type as soon as possible.

18.2 Issues during code generation

- **I get the following error message when generating code: 'Error downloading URL. Your network connection may be down or your proxy settings improperly configured.'**

Your current MATLAB configuration is not accepting our website's SSL certificate. Please follow [this link](#) to add our certificate to Matlab's list of certificates manually. You can download the embotech certificate using your browser.

- **I get the following error message when generating code: 'Invalid MEX-file. The specified module could not be found.'**

Please install the Visual Studio redistributable libraries from [here](#).

- **I get the following error when generating code: 'java.io.IOException: Server is not responding, it might not support the current protocol. Missing ServerHello.'**

Some MATLAB versions and some Java installations give problems when communicating using HTTPS from MATLAB. Please edit the file callSoapService.m. Search for the line

```
url = URL(endpoint);
```

and replace it with

```
url = URL([], endpoint, sun.net.www.protocol.https.Handler)
```

- **I get the following error when generating code: 'java.io.IOException: The issuer can not be found in the trusted CA list.'**

Some MATLAB versions and some Java installations give problems when communicating using HTTPS from MATLAB. Please edit the file callSoapService.m. Search for the line

```
url = URL(endpoint);
```

and replace it with

```
url = URL([], endpoint, sun.net.www.protocol.https.Handler)
```

- **I get the following error when generating code: 'javax.net.ssl.SSLException: Unrecognized SSL message, plaintext connection?'**

If you are using the enterprise version of FORCESPRO (separate server in your company network), had previously altered the file callSoapService.m to accept secure HTTP connections and the enterprise server is listening on an HTTP port, you receive this error. To fix: Please edit the file callSoapService.m. Search for the line

```
url = URL([], endpoint, sun.net.www.protocol.https.Handler)
```

and replace it by the default

```
url = URL(endpoint);
```

• **I get the following error when generating code:**

```
Server was unable to process request. ---> There is no parameter that maps to c of ↳  
↳stage 1
```

However, according to the multistage formulation, my D_1 is empty in my problem, so c_1 should also be empty.**

We recommend to reformulate the optimization variables for each stage so that D_1 is not empty for performance reasons.

If this is not possible and D_1 must remain empty, then the inter-stage equality constraint equations become

$$C_{i-1}z_{i-1} + D_i z_i = c_{i-1}$$

instead of

$$C_{i-1}z_{i-1} + D_i z_i = c_i$$

• **I get the following error message when using the MATLAB interface: "Unable to cast object of type 'csmatio.types.MLDouble' to type 'csmatio.types.MLStructure'."**

Please check that you have your MEX compiler correctly set up. If the problem persists please send your MATLAB and platform settings to support@embotech.com.

• **I get the following error message when using the Python interface: 'csma-tio.io.MatlabIOException: Incorrect Matlab array class: int32'**

Make sure that the parametric data is passed to the solver as numpy arrays of floating point numbers, i.e. instead of

```
problem['Q'] = np.array([1 1])
```

use

```
problem['Q'] = np.array([1.0 1.0])
```

• **The code generation process gets stuck displaying 'Generating and compiling code...' and sometimes it returns an error after 10 minutes.**

By default, the code is compiled with all optimizations turned on (-O3). When the size of your code is large, typically when you have a long prediction horizon, it can take a very long time to compile the code with all optimizations turned on. If this process takes too long the server times out and returns a compilation error. You can reduce the compilation time by changing the compiler optimization flags to -O0, -O1, or -O2. You can change this setting using the following flag set to the appropriate value.

```
codeoptions.optlevel = 2;
```

18.3 Issues when running the solver

• **When I run the solver in MATLAB I get the following error: '??? Error using ==> TestSolver freopen of stdout did not work.'**

This is a printing error that occurs in some old versions of MATLAB because stdout is not defined inside MEX files. Supported versions of MATLAB should not produce this error. You can avoid this error by setting

```
codeoptions.printlevel = 0;
```

- **My solver is producing a segmentation fault.**

When the solver has a large amount of parameters or the problem is relatively large, compiling with `codeoptions.optlevel = 0;` can produce a segmentation fault. Please try to increase the value of `codeoptions.optlevel` or submit a bug report to support@embotech.com.

- **ADMM does not converge for my problem.**

Unlike interior-point methods, the convergence of ADMM depends on the problem scaling. If the matrices for the problem data have very high condition numbers and norms, ADMM can converge extremely slowly regardless of the algorithm parameters. In some cases, ADMM might not converge at all due to severe accumulation of numerical errors.

However, often the problem is choosing the right ADMM parameters ρ and α to obtain fast convergence of the algorithm.

- **The solver outputs exitcode -7.**

Exitcode -7 means that the solver could not proceed. A common cause is the problem being infeasible. FORCESPRO does not have infeasibility detection to speed up the solution time. However, one can use the function `stages2qcqp` to convert the FORCESPRO problem into a standard (QC)QP that can be given to standard QP solvers like quadprog, MOSEK or CPLEX to check for infeasibility.

- **I am generating code from 32-bit MATLAB. When I run the code it produces a seg-fault. What is the problem?**

By default, the code is compiled with all optimizations turned on (-O3). We have observed that sometimes there are problems when linking on 32-bit versions of MATLAB. This problem does not occur when the compiler optimization flags are set to -O0, -O1, or -O2. You can change this setting using the following flag set to the appropriate value.

```
codeoptions.optlevel = 2;
```

- **I am getting exitflag -6, -8 or -10 when I run my solver**

In this case it is a good idea to check that the nonlinear functions provided to the solver are well-defined and that they don't produce "NaN"s or "Inf"s. See section *Calling the nonlinear functions from Matlab or Python* for how to call the nonlinear functions along with their derivatives directly in MATLAB or Python. If the solver returns exitflag -6, -8 or -10 in the first iteration one needs to check that

Matlab

Python

```
problem.x0
```

```
problem['x0']
```

does not yield NaN or Inf when the nonlinear functions are evaluated on it. E.g. if one has generated a solver named `FORCESsolver` which does not use any real-time parameters, one needs to check that the following code does not produce an error

Matlab

Python


```

jj = 1;
for ss = 1:model.N
    z = problem.x0[jj:(jj+model.nvar)];
    c, jacc = FORCESsolver_dynamics(z, [], ss);
    ineq, jacineq = FORCESsolver_inequalities(z, [], ss);
    obj, gradobj = FORCESsolver_objective(z, [], ss);
    assert( any(isnan(c) | isinf(c), 'all'), ['Encountered NaNs or Infs in c at_
↪stage ', num2str(ss) ]);
    assert( any(isnan(jacc) | isinf(jacc), 'all'), ['Encountered NaNs or Infs in_
↪jacc at stage ', num2str(ss) ]);
    assert( any(isnan(ineq) | isinf(ineq), 'all'), ['Encountered NaNs or Infs in_
↪ineq at stage ', num2str(ss) ]);
    assert( any(isnan(jacineq) | isinf(jacineq), 'all'), ['Encountered NaNs or Infs_
↪in jacineq at stage ', num2str(ss) ]);
    assert( any(isnan(obj) | isinf(obj), 'all'), ['Encountered NaNs or Infs in obj_
↪at stage ', num2str(ss) ]);
    assert( any(isnan(gradobj) | isinf(gradobj), 'all'), ['Encountered NaNs or Infs_
↪in gradobj at stage ', num2str(ss) ]);
    jj = jj + model.nvar;
end
disp('Did not encounter any NaNs or Infs');

```

```

import numpy as np

jj = 0
x0 = problem['x0']
for ss in range(model.N):
    z = x0[jj:model.nvar]
    c, jacc = solver.dynamics(z, stage=ss)
    ineq, jacineq = solver.ineq(z, stage=ss)
    obj, gradobj = solver.objective(z, stage=ss)
    assert any(np.isnan(c) or np.isinf(c)), 'Encountered NaN in c at stage ' +_
↪str(ss)
    assert any(np.isnan(jacc) or np.isinf(jacc)), 'Encountered NaN in jacc at_
↪stage ' + str(ss)
    assert any(np.isnan(ineq) or np.isinf(ineq)), 'Encountered NaN in ineq at_
↪stage ' + str(ss)
    assert any(np.isnan(jacineq) or np.isinf(jacineq)), 'Encountered NaN in_
↪jacineq at stage ' + str(ss)
    assert any(np.isnan(obj) or np.isinf(obj)), 'Encountered NaN in obj at_
↪stage ' + str(ss)
    assert any(np.isnan(gradobj) or np.isinf(gradobj)), 'Encountered NaN in_
↪gradobj at stage ' + str(ss)
    jj = jj + model.nvar
print('Did not encounter NaNs')

```

Note: See also *Real-time SQP Solver: Robotic Arm Manipulator (MATLAB & Python)* for an example of how to simulate the dynamics of the system directly in MATLAB and Python.

18.4 Simulink interface

- **When I have a long prediction horizon I have too many input and output ports that I need to wire up in my Simulink interface. When I change my prediction horizon I need to re-wire them all again and this is a pain.**

The new version of FORCESPRO provides a ‘compact’ version of all Simulink interfaces that can be called with stacked parameters and has a small and constant number of input ports

independent of the prediction horizon.

To check the dimensions of the new stacked parameters click on the 'Help' button in the dialogue of the 'compact' Simulink block.

18.5 Code deployment

- **I get the following error message when deploying a solver on dSpace hardware: 'OPUS MAKE: Don't know how to make ...'**

This is well-known deployment issue with compiled files. During building for target the compiler is looking for the source code of the solver. The resulting object file is added in the folder `<solvername>_<target_ext>` which is automatically generated by the compiler. Therefore, to use the object file you need to move it to that folder in order for the compiler to detect it and skip compilation. A possible workaround is to use the static library of the solver as specified in *dSPACE deployment through Simulink Coder*.

18.6 Other topics

- **How can I obtain information about the KKT conditions at the solution?**

The *printlevel* solver option allows the user to control how much information is printed by the solver. See here for more information on how to define solver options.

When *printlevel* is set to 2 the solver outputs information related to the KKT conditions at every iteration. In particular:

- *res_eq* is the maximum $\|C_{i-1}z_{i-1} + D_i z_i - c_i\|_\infty$ for all i ,
- If we rewrite all inequality constraints as $Gz \leq g$ and s are slack variables for the same constraints, *res_ineq* is equal to $\|Gz - g + s\|_\infty$,
- If λ are the Lagrange multipliers for the inequality constraints, μ is equal to $\lambda^\top s$ divided by the number of constraints, i.e. the average complementary slackness.

- **What system information am I sharing by using FORCESPRO?**

When contacting the solver generation server, the FORCESPRO client sends the following system information:

- Machine username
- MAC address
- Fingerprints

The fingerprint is platform dependent. We create two fingerprints using different system information to create hashes and validate with either of them in order to have a more stable validation:

- For Windows, each fingerprint uses a subset of the below information:
 - * Mac addresses
 - * CPU ID (register with machine support)
 - * Volume Serial Number
 - * Volume GUID
- For MacOS, each fingerprint uses a subset of the below information:
 - * Cputype and Cpusubtype
 - * Network node hostname

- * Mac addresses
- For Linux, each fingerprint uses a subset of the below information:
 - * Network node hostname
 - * /etc/machine-id
 - * Mac addresses
 - * Linux user uid

The above information is hashed to create the fingerprint which means that it cannot be recovered by using the fingerprint.

· **Why am I being asked to update the FORCESPRO client software every now and then?**

We have a development policy of continuous deployment, which unfortunately means that we have to ask users to update their clients every time there is a substantial change in the code. To make this process easier and faster, FORCESPRO comes with a functionality that allows users to update their clients by simply typing the following in the MATLAB command prompt:

```
>> updateClient
```


Bibliography

- [GörSch] Göhrle, C.; Schindler, A.; Wagner, A.; Sawodny, O.: Design and Vehicle Implementation of Preview Active Suspension Controllers. IEEE Transactions on Control Systems Technology, pp.1135–1142, vol. 22, no. 3, May 2014
- [HarMac14] Hartley, E. N.; Maciejowski, J. M.: Field programmable gate array based predictive control system for spacecraft rendezvous in elliptical orbits. In Optimal Control Applications and Methods, Mar 2014
- [VukLoock] Vukov, Milan & Van Loock, Wannes & Houska, Boris & Ferreau, Joachim & Swevers, Jan & Diehl, Moritz. (2012). Experimental validation of nonlinear MPC on an overhead crane using automatic code generation. Proceedings of the American Control Conference. 6264-6269. 10.1109/ACC.2012.6315390.
- [QuirDiehl] Quirynen, Rien & Gros, Sebastien & Diehl, Moritz. (2013). Efficient NMPC for nonlinear models with linear subsystems. Proceedings of the IEEE Conference on Decision and Control. 5101-5106. 10.1109/CDC.2013.6760690.
- [SicSci09] Siciliano, B.; Sciavicco, L.; Villani, L.; Oriolo, G.. Robotics: Modelling, planning and control. Berlin: Springer, 2009.
- [BerUnb] S. Daniel-Berhe; H. Unbehauen: Experimental physical parameter estimation of a thyristor driven DC-motor using the HMF-method. Control Engineering Practice, 6:615–626, 1998
- [GarJor77] Garrard, W.L.; Jordan, J.M.: Design of Nonlinear Automatic Control Systems. In: Automatica 1977, vol. 13, 497-505.