A framework for simulation and model predictive control of hybrid district heating systems

Authors: Gerald Schweiger [a], Per-Ola Larsson [b], Stéphane Velut [b], Patrick Lauenburg [c]

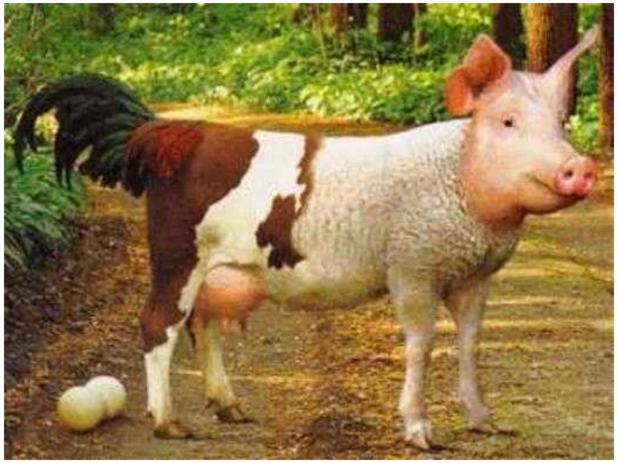
(a) AEE – Institut für Nachhaltige Technologien (AEE INTEC)
A-8200 Gleisdorf, Feldgasse 19
AUSTRIA

(b) Modelon AB
223 70 Lund, Ideon Science ParkBeta 6 buildingScheelevägen 17
SWEDEN

(c)Lund University Division of Efficient Energy
3223 63 Lund, Kårhuset, John Ericssons väg
SWEDEN

Motivation

"Another new framework for simulation and MPC of hybrid Energy system"



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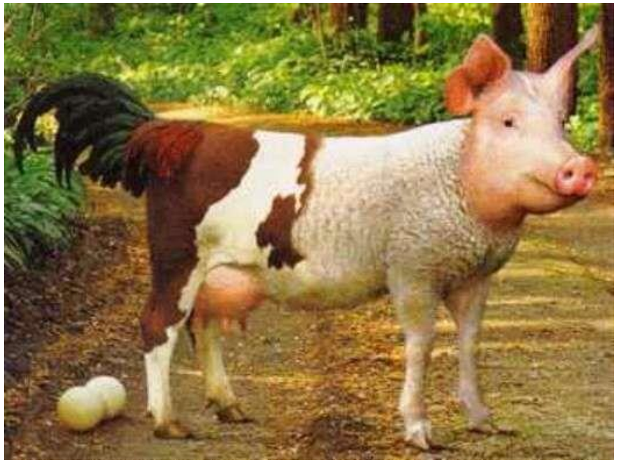
Motivation

"Another new framework for simulation and MPC of hybrid Energy system"

We can't do everything; not everything is new …but…



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[…] joint effort of industry, applied research and university to further develop tools and methods for **detailed** simulation and optimization of (future) city (district) energy systems.

Motivation

Simulation, Optimal control, MPC (**M**odel **P**redictive **C**ontrol)

Typical use-cases

- To investigate design of new city districts
- To find optimal control strategies for different system settings

Requirements for the simulation/optimal control method given by the real world

- **Dynamics**: The simulation and optimal control must capture all important dynamics
- **Multi-domain**: The framework must be designed to analyze multi-domain problems

Requirements

➔ given by mathematics and physics

- Nonlinear models
- Stiff systems
- Hybrid systems: event handling & variable time steps

➔ given by simulation/optimization method

- Simulation: "acceptable" ratio of eigenvalues
- Optimal control: reduce complexity of models or network topology
- Optimal control : C^2 (Twice continuous differentiability)
- Optimal control: Handle MINLP [**M**ixed **I**nteger **N**onlinear **P**rograms]

➔ given by the "user"

- Robust, flexible, adoptable, extensible
- "Master-algorithm"

Main contributions

First integrated framework for simulation and model predictive control of hybrid district heating system

- Uses a non-causal, equation based modelling language (Modelica) and a high-level, large-scale dynamic optimization method
- Possibility to impose constraints on physically relevant variables
- Multiphysics, multi domain
- Suitable for stiff systems
- Flexibility, modular expandability, reusability of models
- co-simulation possible

The framework

Unified Network Representation

Optimal Control / MPC library

MILP library

Detailed simulation library

The framework

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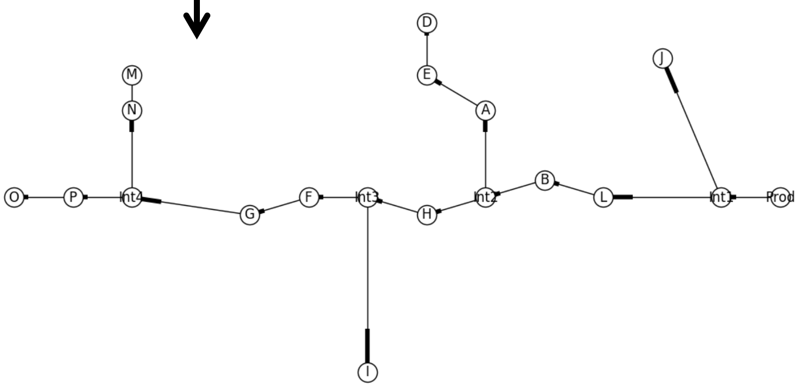
MILP library

Detailed simulation library

Python library



The framework

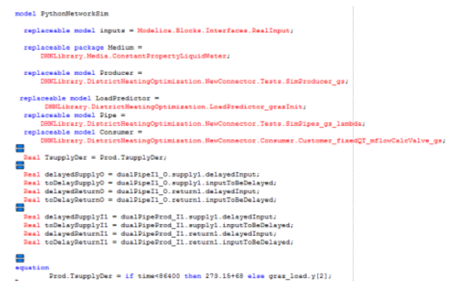
Unified Network Representation

Optimal Control / MPC library

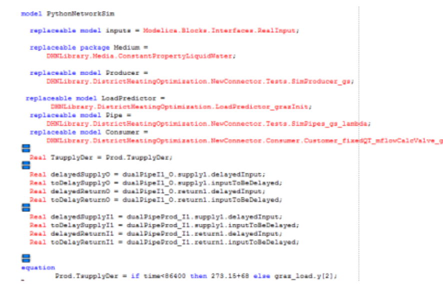
MILP library

Detailed simulation library

Python / NetworkX

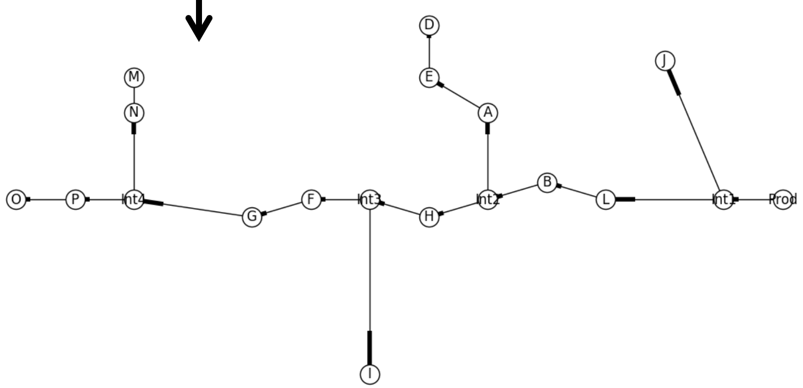


Library X



Library Y

a



The framework

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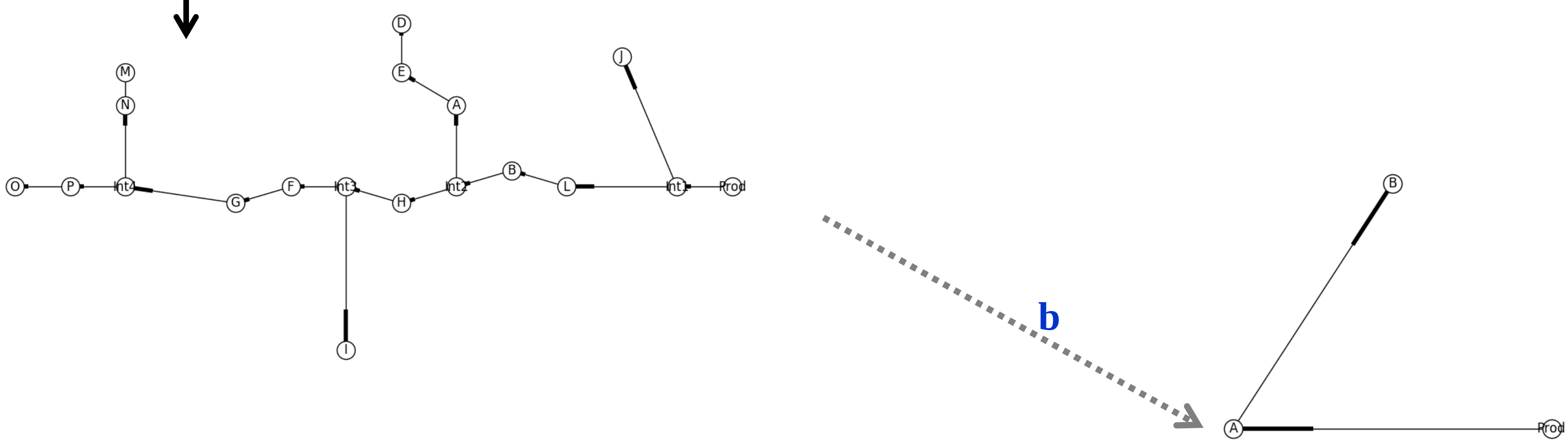
MILP library

Detailed simulation library

Python / NetworkX



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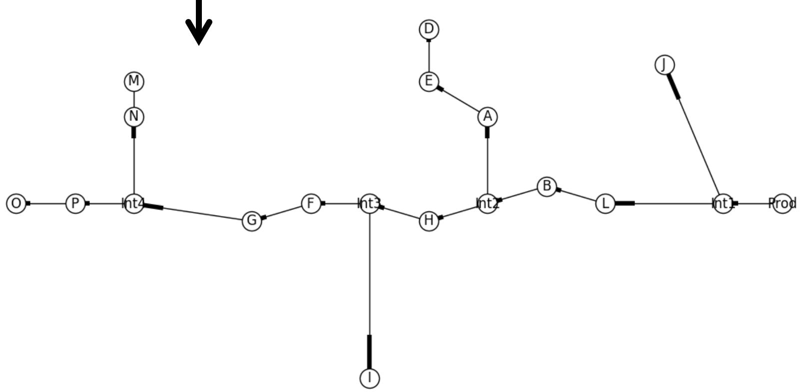
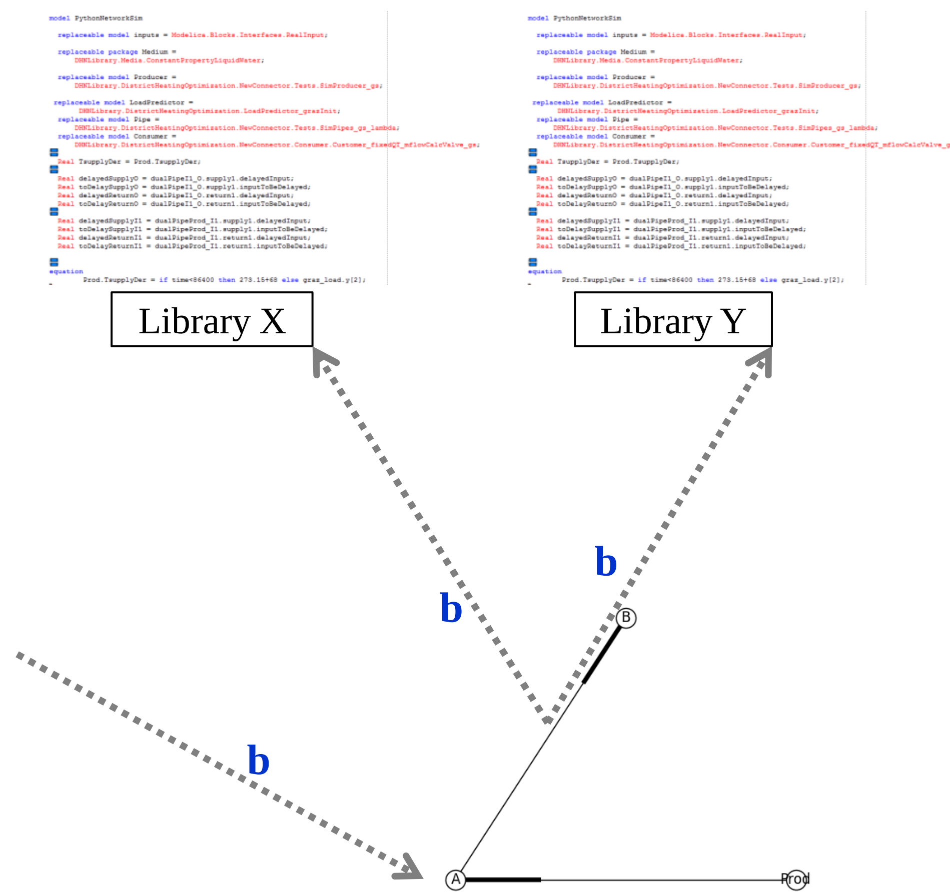
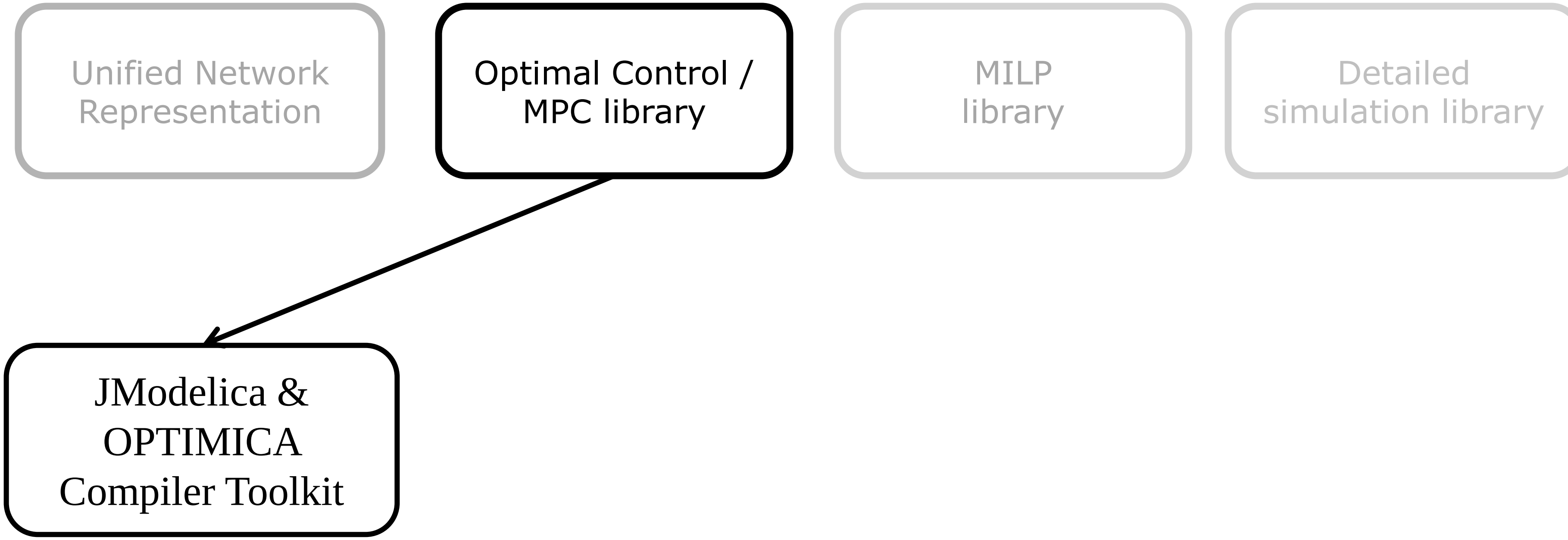




The framework



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JModelica & OPTIMICA Compiler Toolkit

$$\underset{u(t)}{\text{minimize}} \quad \phi\left(t_f, x\left(t_f\right)\right) + \int_{t_0}^{t_f} L(t, x(t), u(t))\,dt$$

$$s.t.\ F\left(t, \dot{x}(t), x(t), u(t)\right) = 0$$

$$x(0) = x_0$$

Path constraints: $g_i(x(t), u(t) \leq 0$

Point constraints: $g_e(x(t), u(t) = 0$

Collocation method

Convert infinite to a finite dimensional optimization problem

Solve NLP

[Nonliner programm]

The framework

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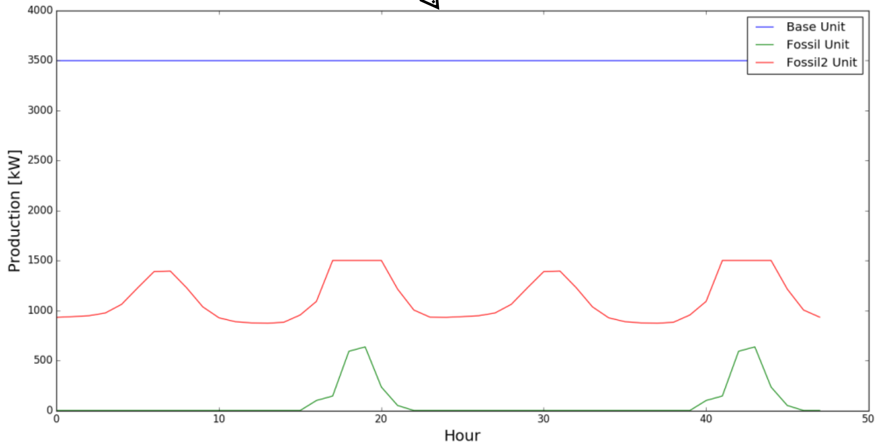
MILP library

Detailed simulation library

Solve MILP



The framework

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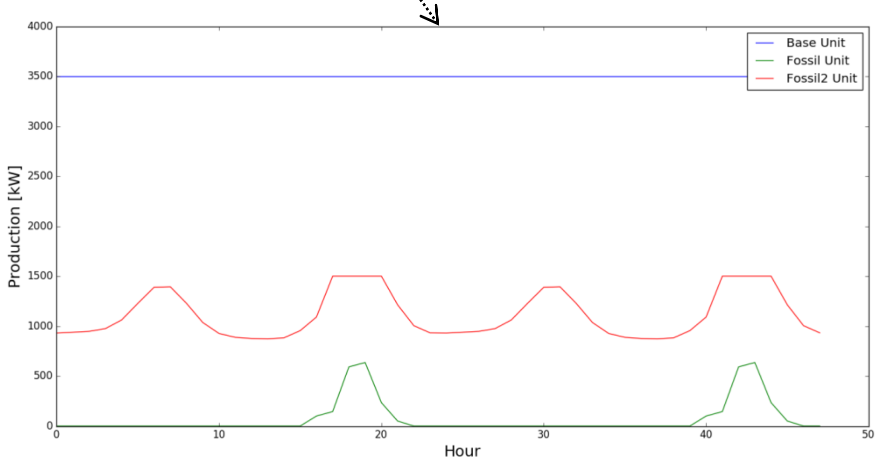
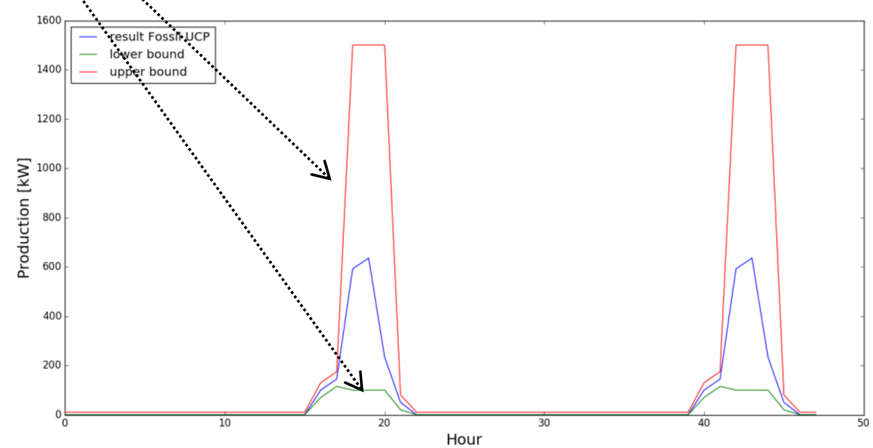
Detailed simulation library

Solve MILP → Calculate upper /lower constraints → Translate into optimal control/MPC constraints





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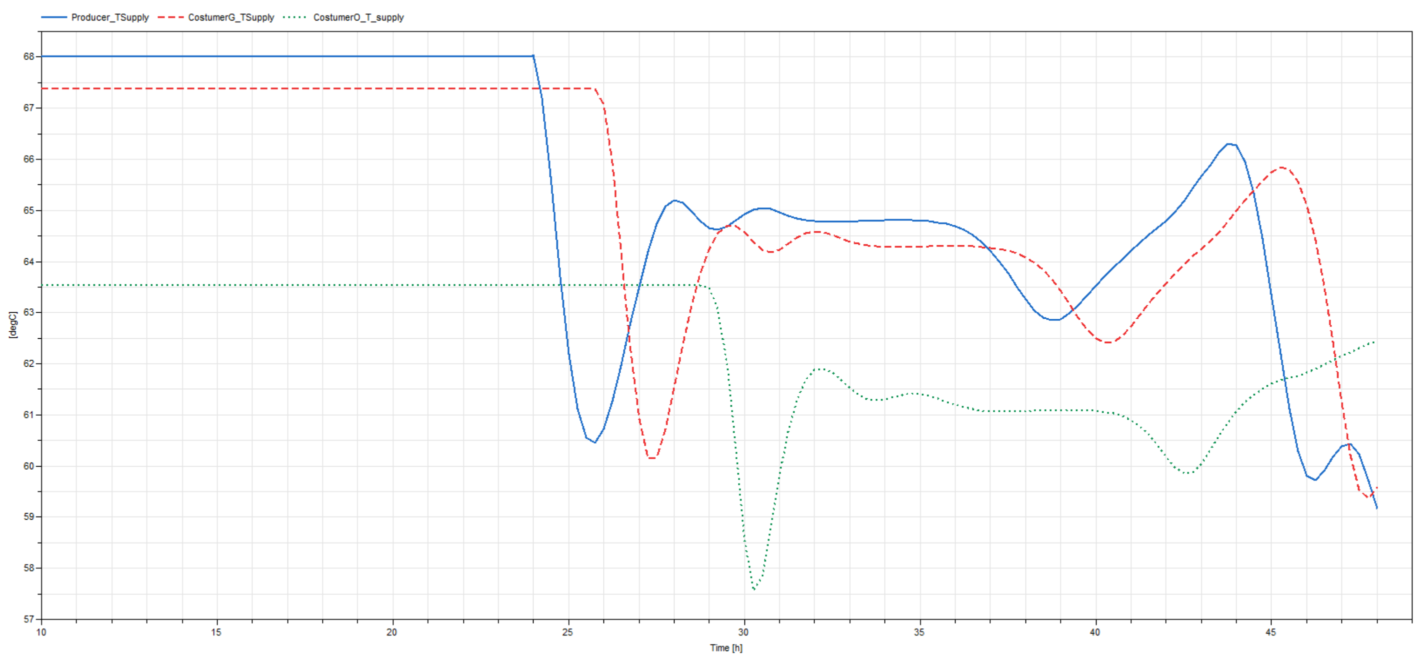
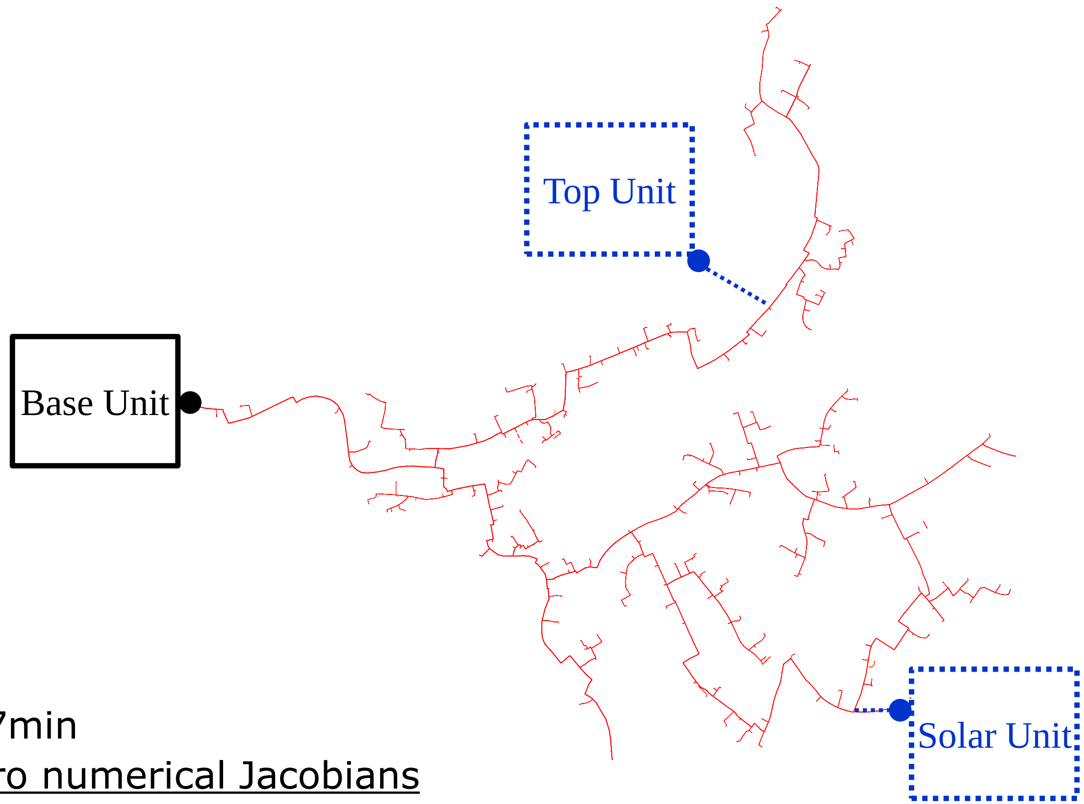
Development Highlight

- Precise, numerically robust district heating pipe model (plug-flow approach based on Modelica spatialDistribution operator)



Use case „ScaleTest“



System details

- Consumer: 103
- Total length: 14.000m
- Loop

Model details

- Components: ~ 2.800
- Variables: ~ 50.000
- Equations: ~22.000

Case „base“

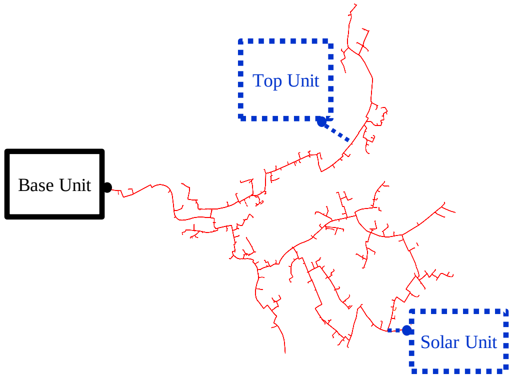
- One „Base Unit“ 4MW
- Computation time 1day → 7min
- Zero nonlinear systems, zero numerical Jacobians

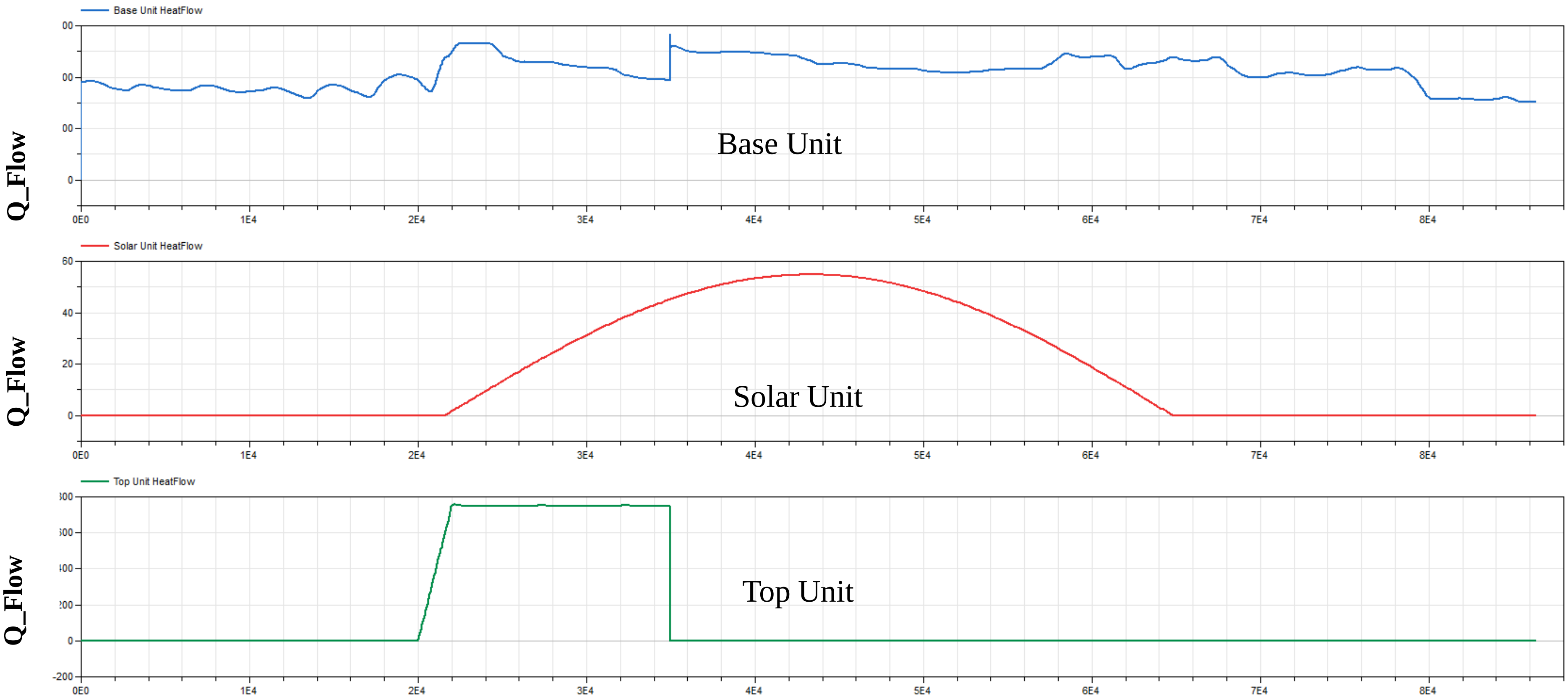
Case „modified“

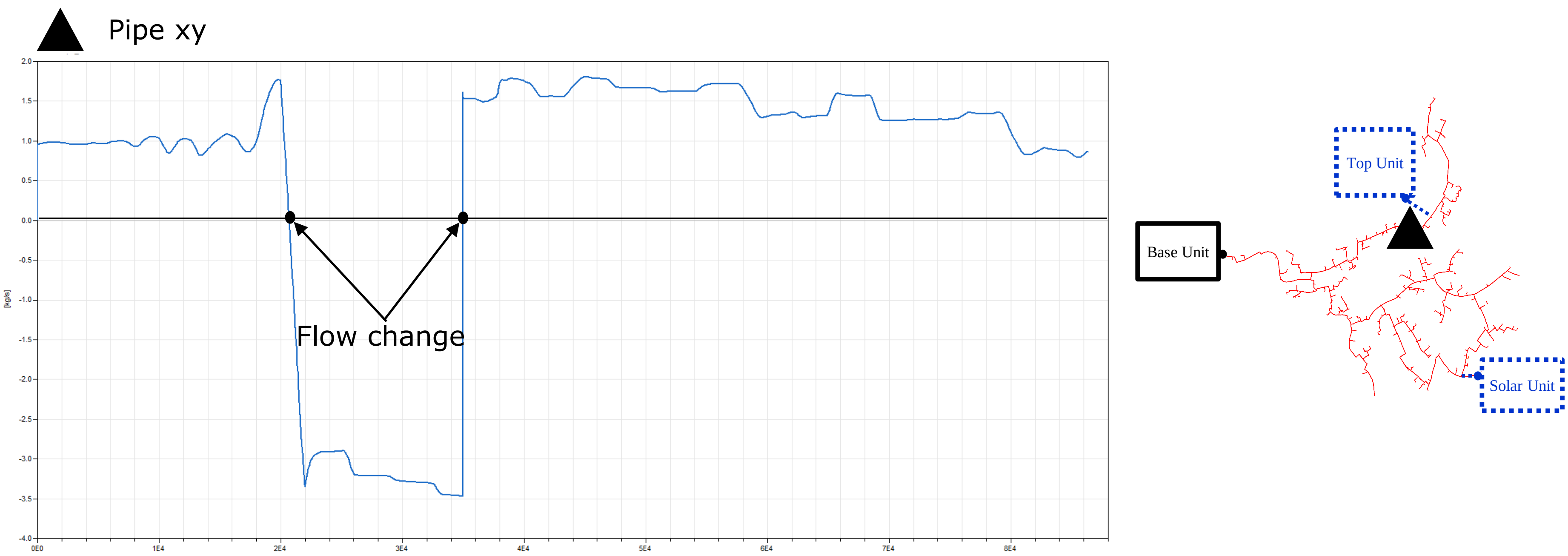
- „Base Unit“ 4MW, „Top Unit“ 750kW, „Solar Unit“ 55kWp
- Computation time 1day → 8min
- Zero nonlinear systems, zero numerical Jacobians

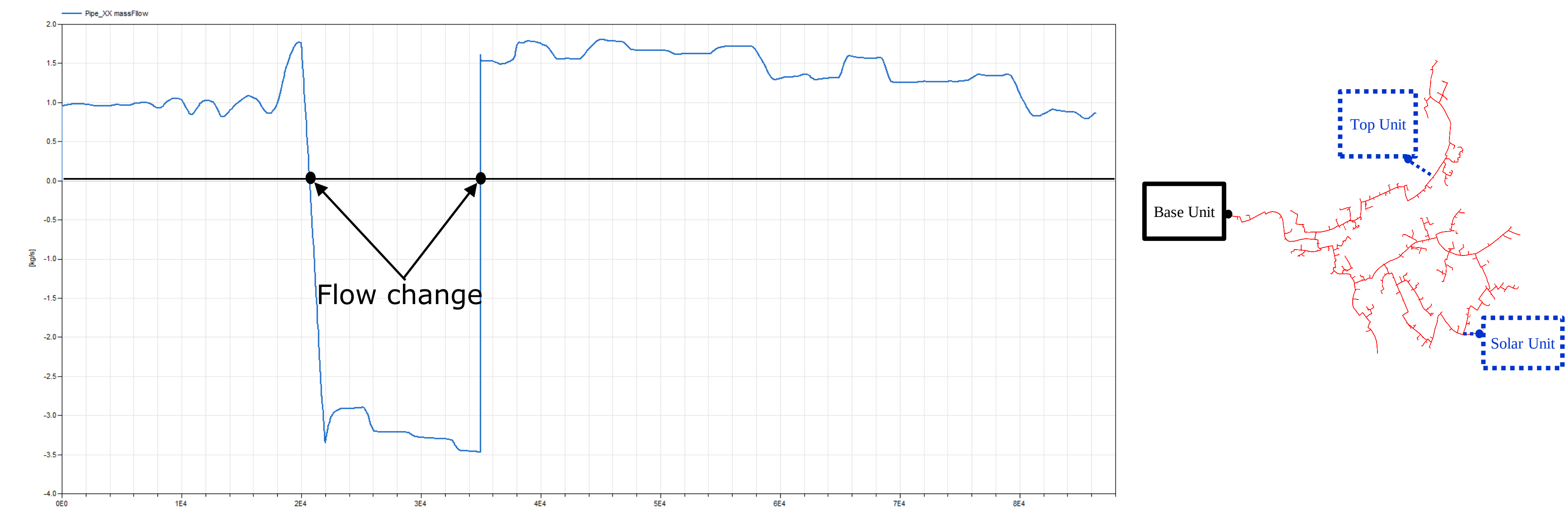
Numerical challengens

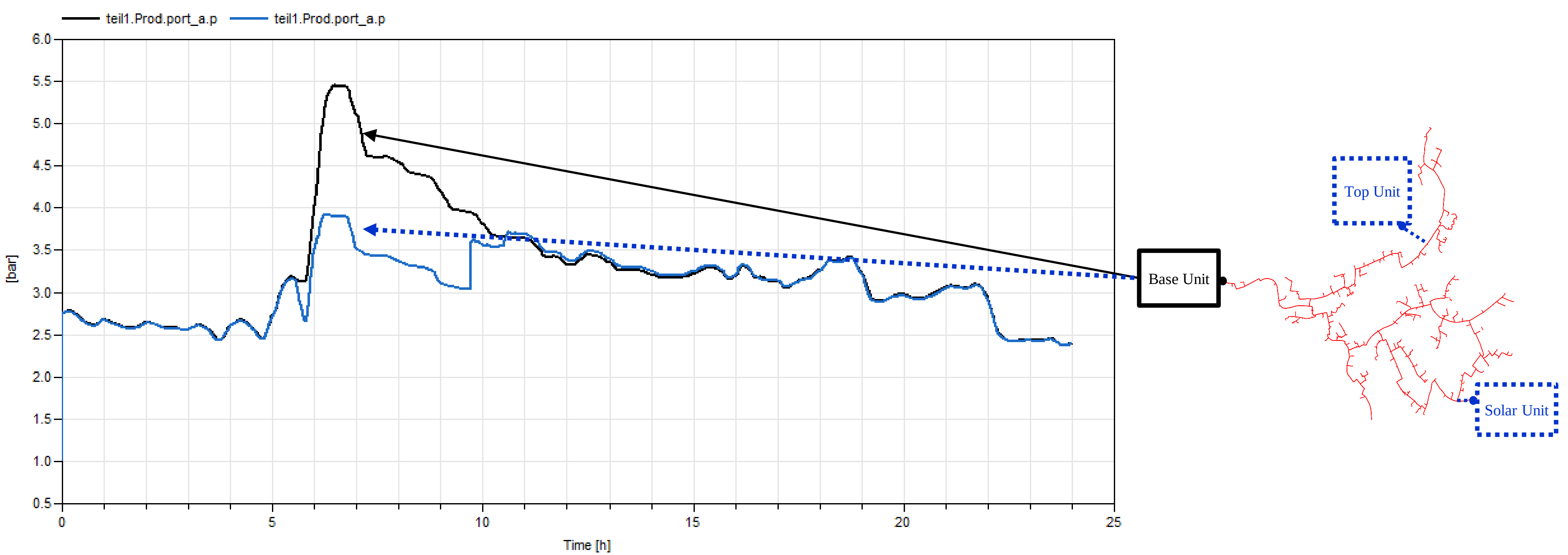
- Fast transients
- Reverse flow & zero flow states
- Temperature-wave propagation

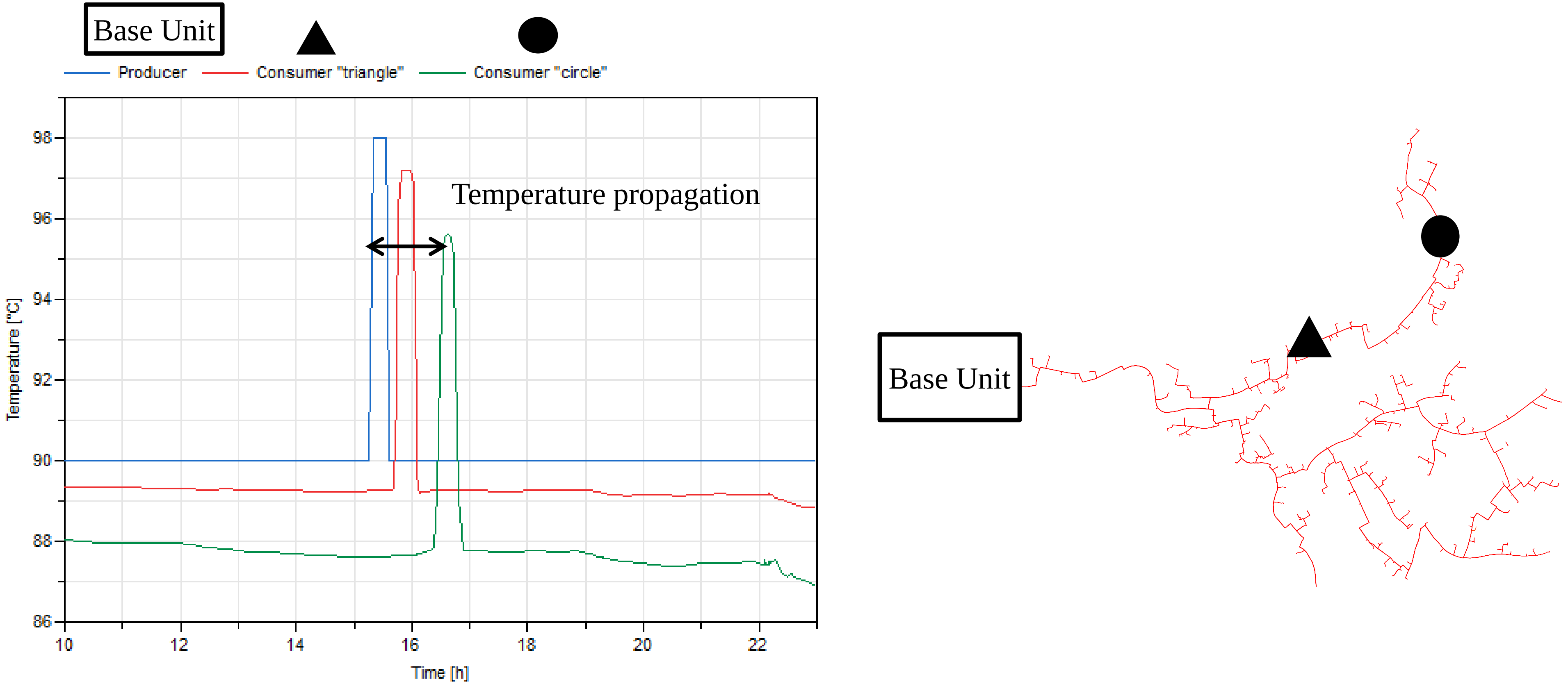


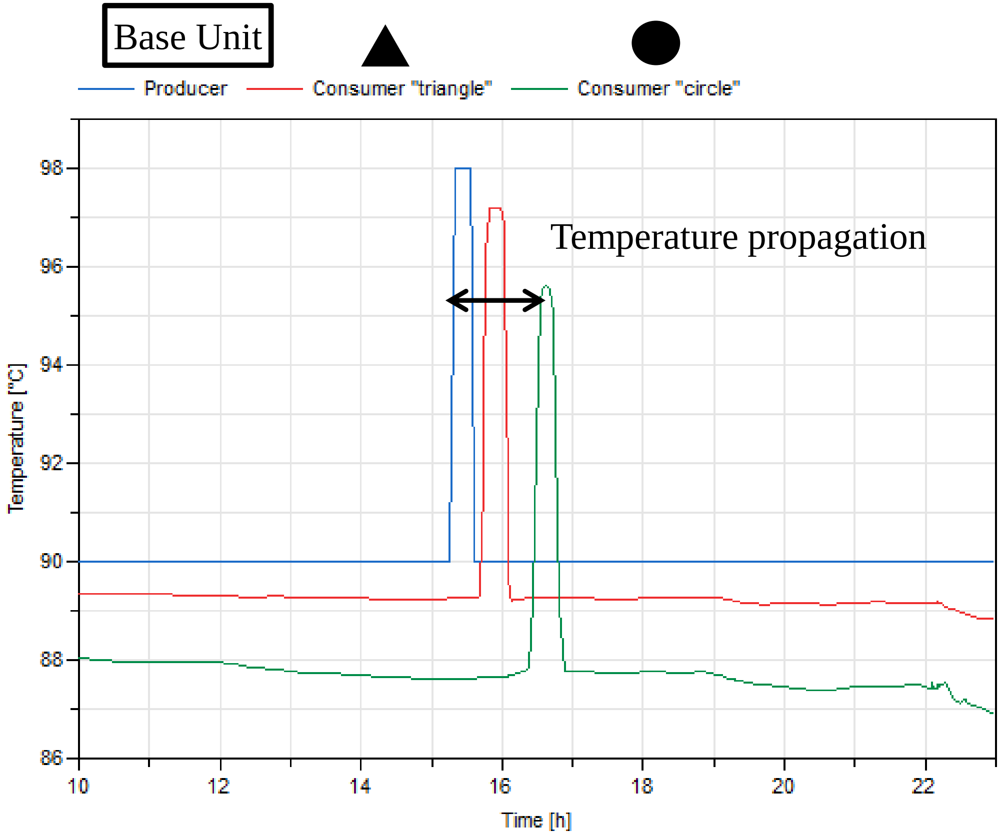


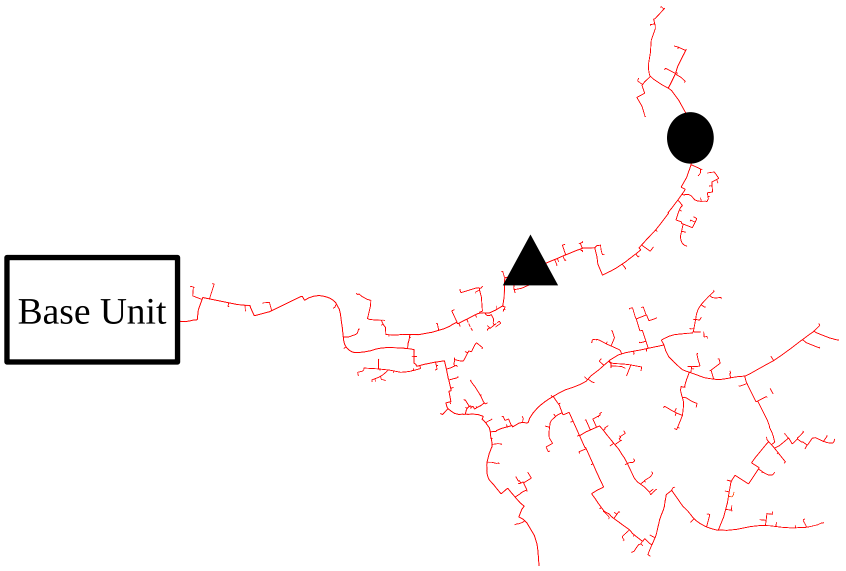

Pipe xy
Flow change
[kg/s]
2.0
1.5
1.0
0.5
0.0
-0.5
-1.0
-1.5
-2.0
-2.5
-3.0
-3.5
-4.0
0E0
1E4
2E4
3E4
4E4
5E4
6E4
7E4
8E4
Base Unit
Top Unit
Solar Unit


Pipe_XX massFlow
[kg/s]
Flow change
Base Unit
Top Unit
Solar Unit


teil1.Prod.port_a.p
teil1.Prod.port_a.p
[bar]
Time [h]
Base Unit
Top Unit
Solar Unit


Base Unit
Producer
Consumer "triangle"
Consumer "circle"
Temperature propagation
Temperature [°C]
98
96
94
92
90
88
86
10
12
14
16
18
20
22
Time [h]
Base Unit





Insights

- Robust library
- Focus on numerical improvements!!! → Address large scale problems
- Accurate delay propagation
- Accurate heat-loss model
- Flexible hydraulic models

Use case „Optimal-control / MPC“

System details

- Consumer: 16
- Total length: 4194m

Model details

- Variables: ~10.100
- Equations: ~4.500
- Computation time (**Sim**) 1day → 26sec

Goal:

- Challenge robustness
- Aggregation: 16 → 2 consumer
- Validate temperature propagation
  - mass flow dependent

Assumptions & constraints

- max(Prod_mflow) = 50 kg/s
- Objective: min T_supply

Numerical challenges

- Mass flow dependent transport delay for optimization
- Twice continuously differentiable approximations of several functions

Validation

- Result optimal control vs. apply optimal trajectories on complex models & network topology
- Validate mass flow dependent delay
- Validate heat-loss models

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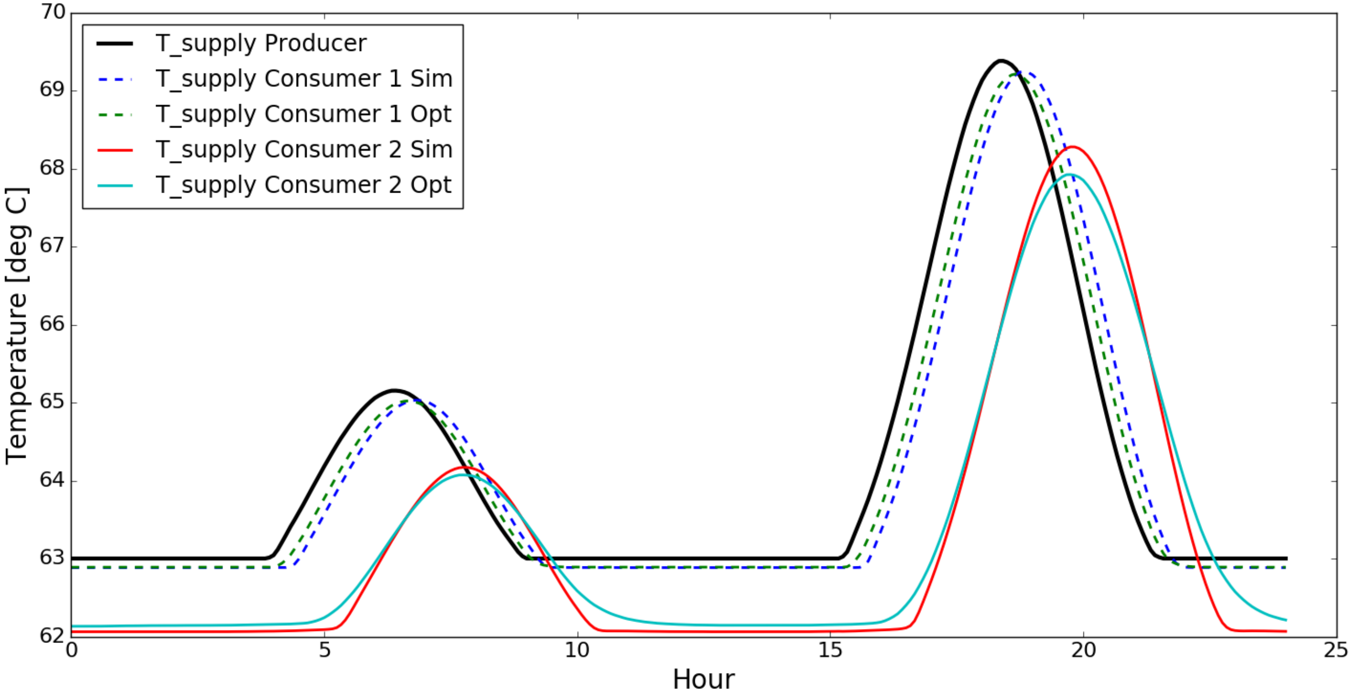

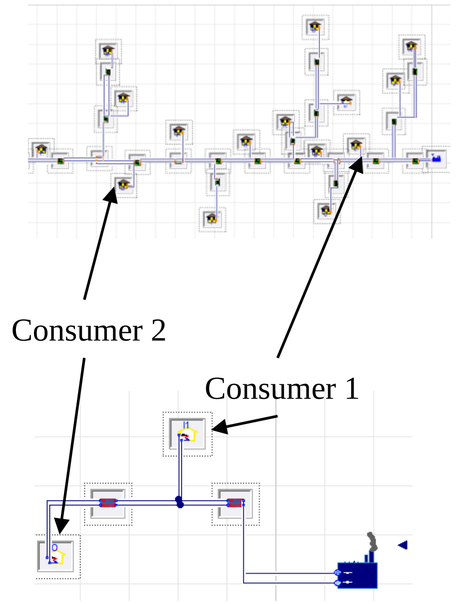

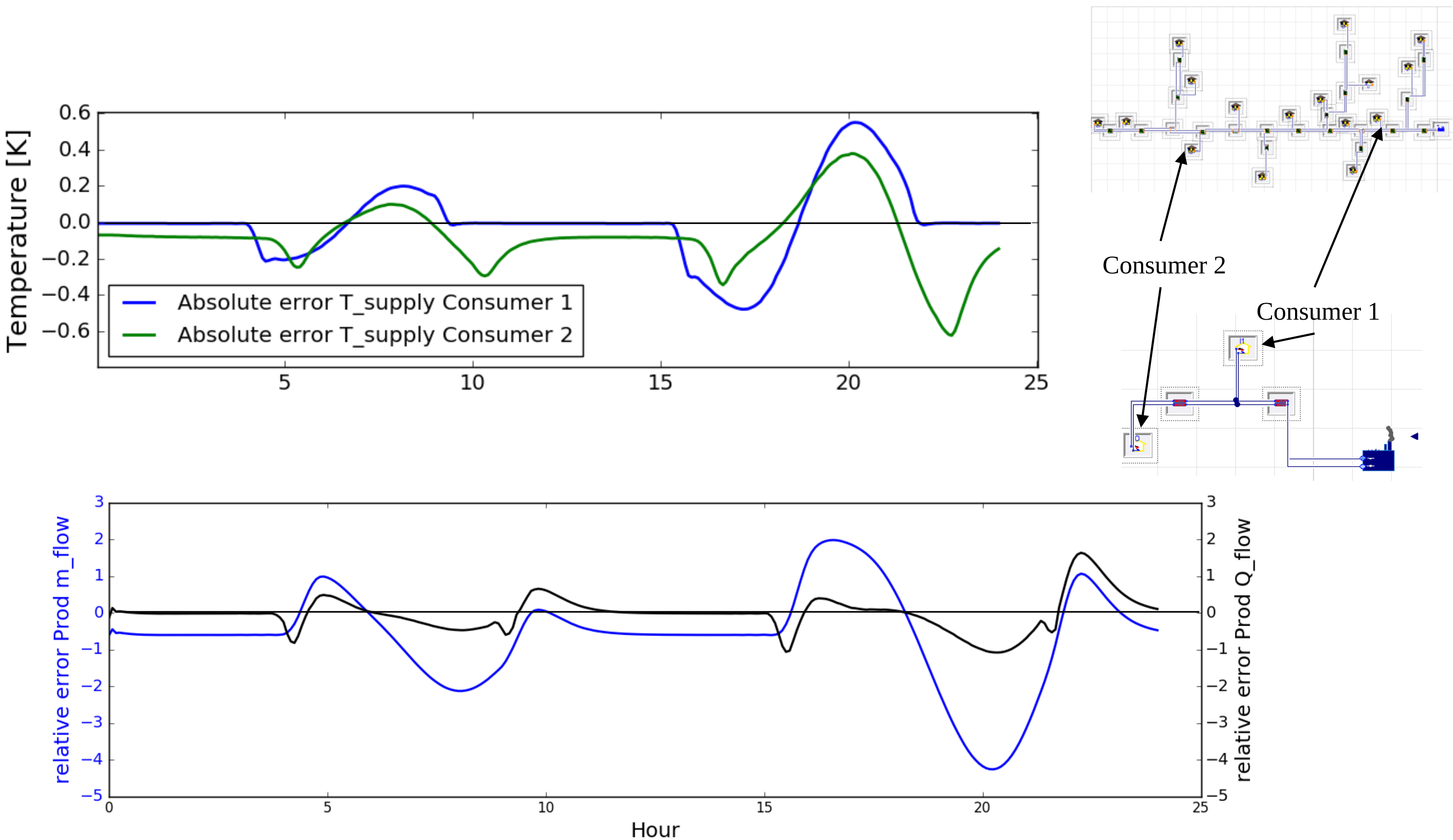

Temperature [K]
Absolute error T_supply Consumer 1
Absolute error T_supply Consumer 2
Consumer 2
Consumer 1
relative error Prod m_flow
relative error Prod Q_flow
Hour

Insights

Scale of optimal control / MPC problem

- 41.000-90.000 variables [2 vs. 5 consumer left]
- 40.000 -89.000 constraints [2 vs. 5 consumer left]
- Medium sized problem for NLP Solver
- Computation time for the whole chain 1day: 4-8min

Validation

- Low max/min errors → precise mass flow dependent delay within optimal control/MPC
- Mean errors over a optimization horizont→ „ neglectable“
- Accurate aggregation method

Outlook

- MILP → units at different geographical positions
- Optimal control→ handle reverse flow
- Integrate detailed models of power system into the optimal control library
- MPC Big-Scale-Validation based on measured data