GridPenguin: A District Heating Network Simulator

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Presented by: **Jichen Wu**

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Introduction

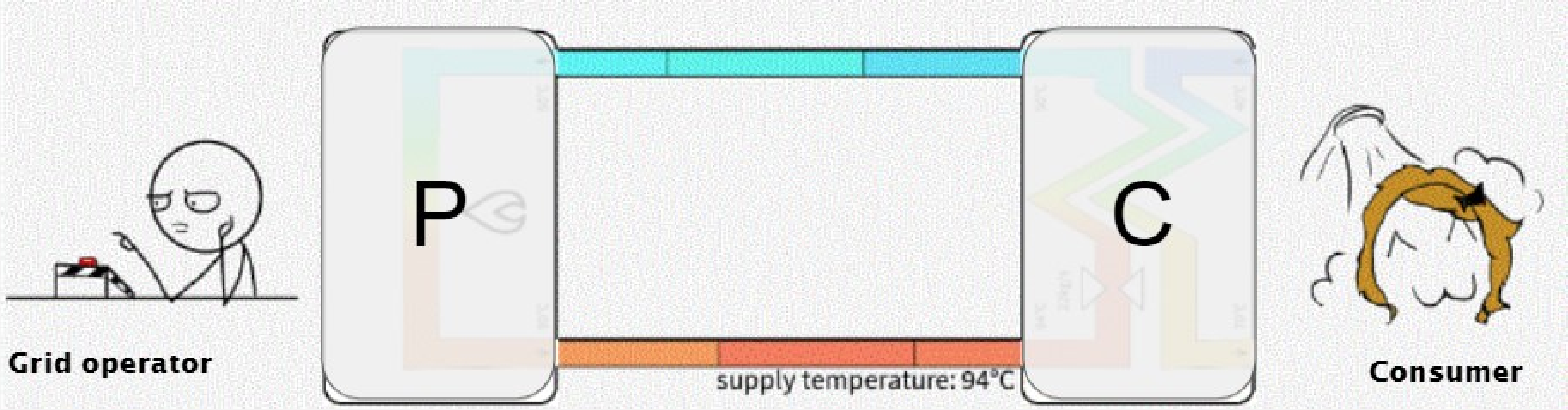


Diagram of district heating

Introduction

Literature of DHS optimization

ELSEVIER

Volume 1

Research | Open Access | Published: 24 September 2021

Optimization of district heating production with thermal storage using mixed-integer nonlinear programming with a new initialization approach

A MINLP optimization of the configuration and

the design of a distric

Building and Environment

1-159

Optimal Control of District Heating Systems using Dynamic Simulation and Mixed Integer Linear Programming

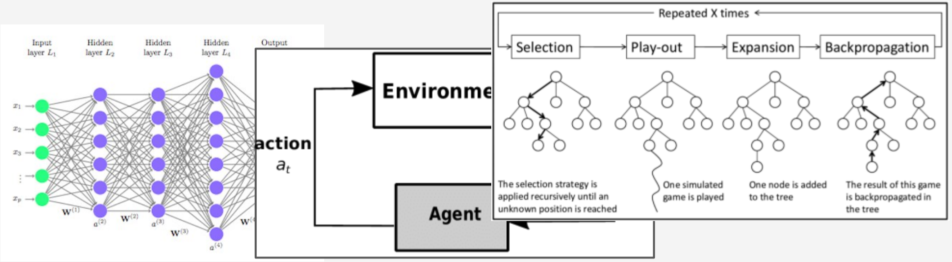
Building and Environment

Linear programming optimization of heat distribution in a district-heating system by valve adjustments and substation retrofit

Introduction

Why machine learning methods are interesting

No guarantee for optimal/ good solution in time



Deep learning

Reinforcement learning

Monte Carlo tree search

Difficult to implement ML In DHS optimizing

Introduction

Why is our work important

Problem 1:
Which algorithm (and model) works best under which circumstances?

=> benchmark to compare different algorithms

Problem 2:
What is the potential of data-driven machine learning methods?

Introduction

Why is our work important

Problem 1:
benchmark to compare different algorithms

Problem 2:
Data-driven machine learning is rarely used

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Volume 117, Part 2, 15 December 2016, Pages 450-464

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Linear programming optimization of heat
distribution in a district-heating system by valve
adjustments and subs

Optimal Control of District Heating Systems using Dynamic Simulation and Mixed Integer Linear Programming

↓

GridPenguin

↓

Solution quality rank:	Speed rank:	Stability rank:
1: …	1: …	1: …
2: …	2: …	2: …
3: …	3: …	3: …

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GridPenguin ← Your grid

Algorithms rank:
1: …
2: …
3: …

Introduction

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Problem 1:
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Grid structure

↓

GridPenguin

↓

Data Data Data Data Data

↓

Deep learning Reinforcement learning

Monte Carlo Tree Search ....

Model Implementation

How we built GridPenguin

Model Implementation

Design choices

The simulation of heat and temperature:

$$\nabla Q = h \cdot A \cdot (T_t - T_{env})$$

$$T_{end} = (T_{start} - T_{env}) \cdot e^{-(\nabla t \cdot R_\lambda)/(A \cdot \rho \cdot c)} + T_{env}$$

$$\nabla Q = (T_{in} - T_{out}) \cdot \dot{m} \cdot c$$

$$u = \frac{k}{\dot{m}^{-q} + \dot{m}'^{-q}}$$

$$\dot{m}' = \nabla Q/((T'_{out} - T'_{in}) \cdot c)$$

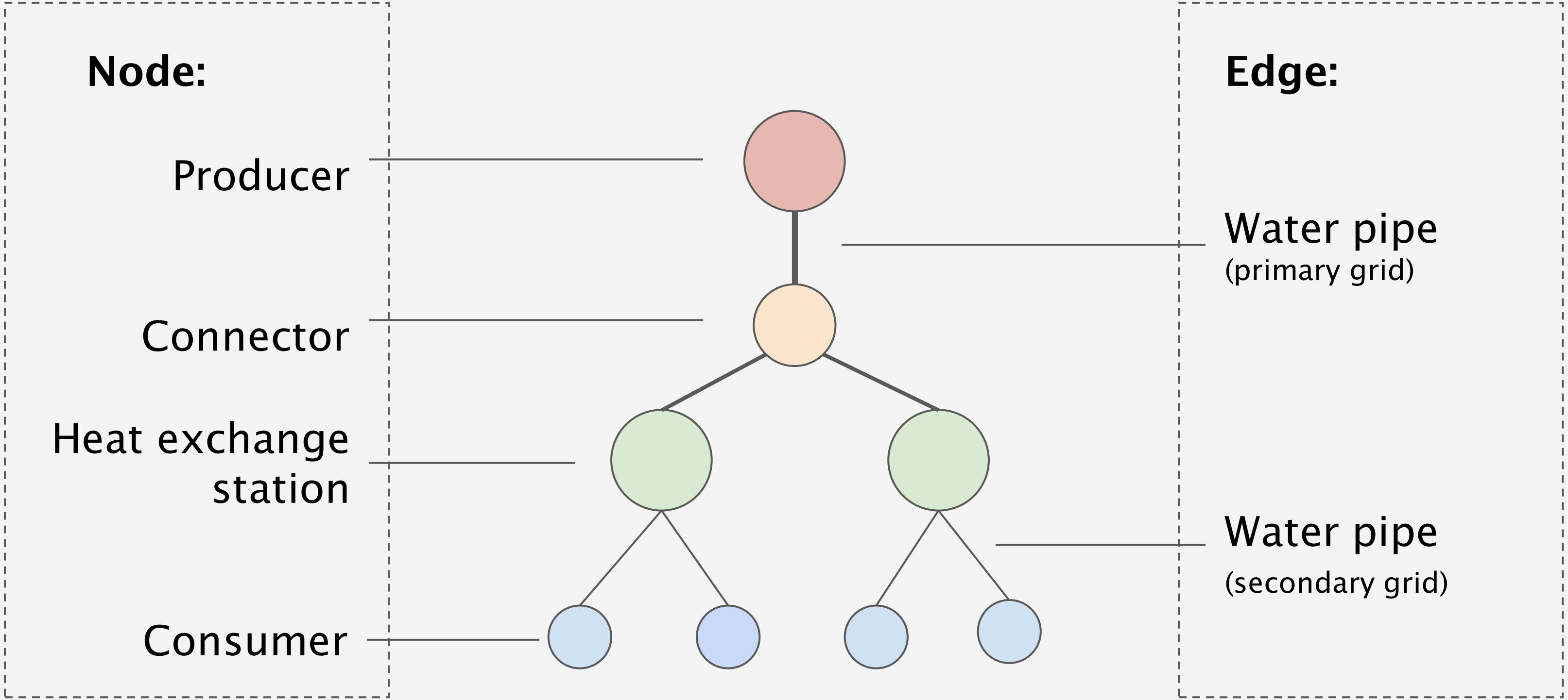
$$\phi = \begin{cases} ntu/(1+ntu) & \text{if } C_r = 1 \\ 1 - e^{-ntu} & \text{if } C_r = 0 \\ \frac{1-e^{-ntu\cdot(1-C_r)}}{1-C_r\cdot e^{-ntu\cdot(1-C_r)}} & \text{otherwise} \end{cases}$$

The simulation of pressure:

$$\nabla p = f \cdot \dot{m}^2$$

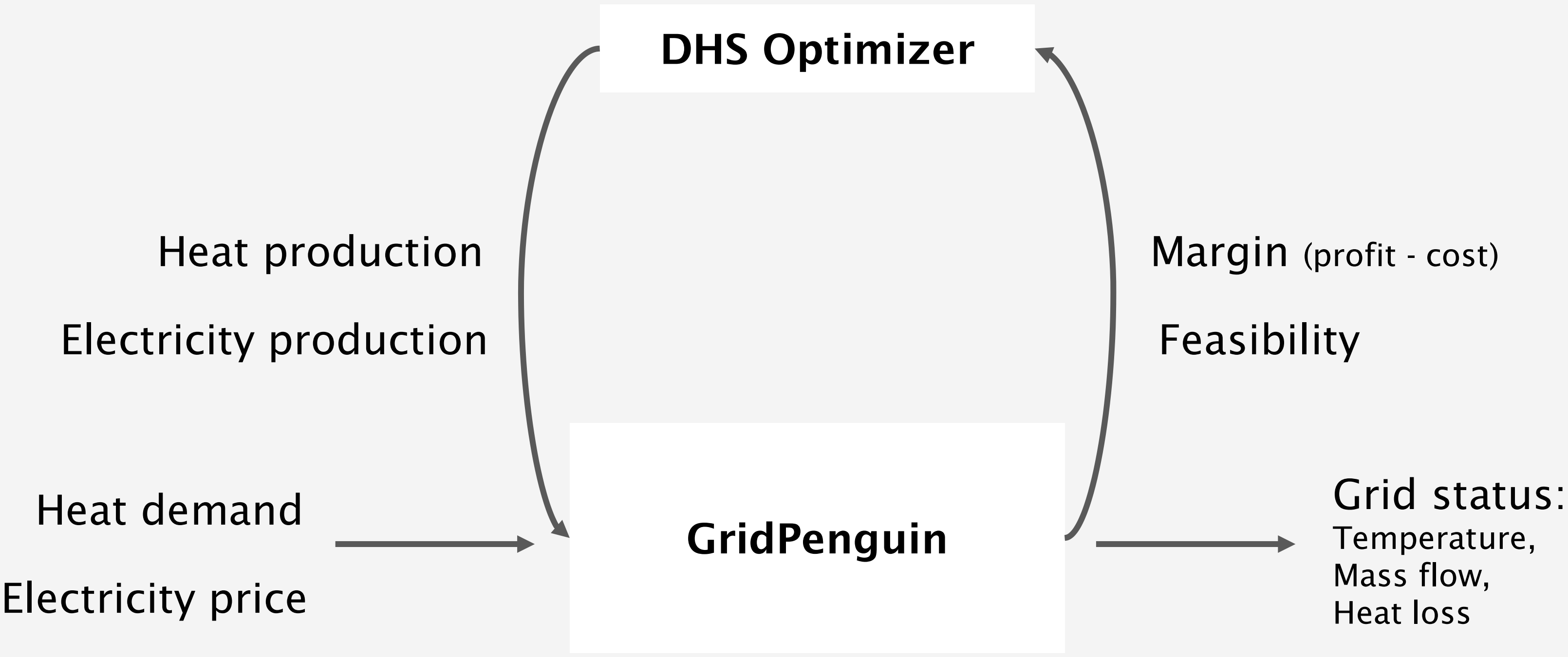
Model Implementation

Design choices



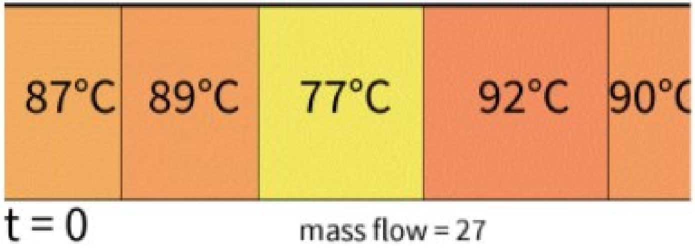
Model Implementation

Interface



Model Implementation

The Edge



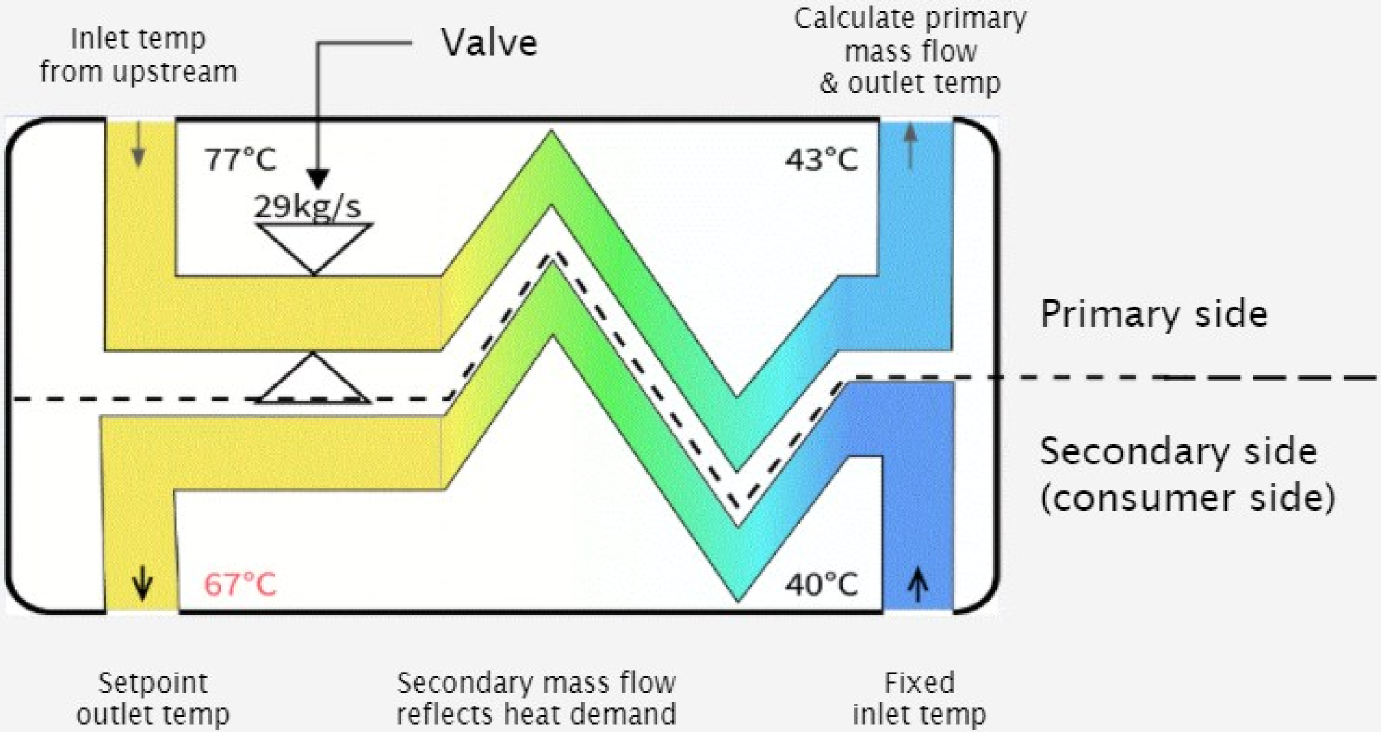
Example (called from downstream):

1. get mass flow from downstream
2. push block(s) out
3. calculate outlet temperature
4. get inlet temperature from upstream
5. add new block
6. calculate heat loss and pressure loss

How water is propagated:
The node method

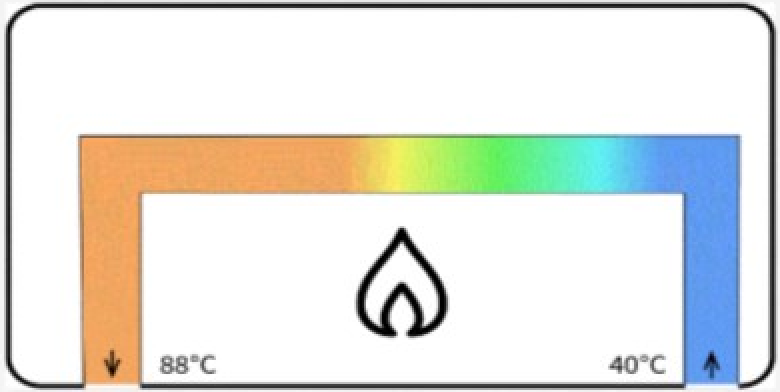
Model Implementation

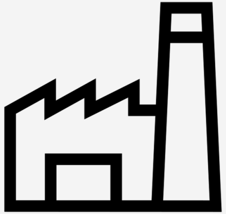
The Consumer/ Heat Exchanger



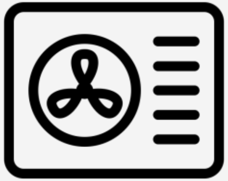
Model Implementation

The Producer





CHP



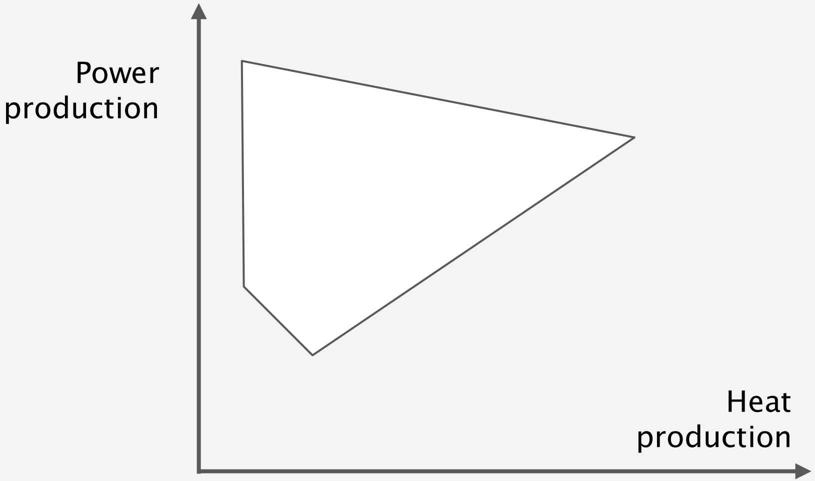
Heat pump

Geothermal

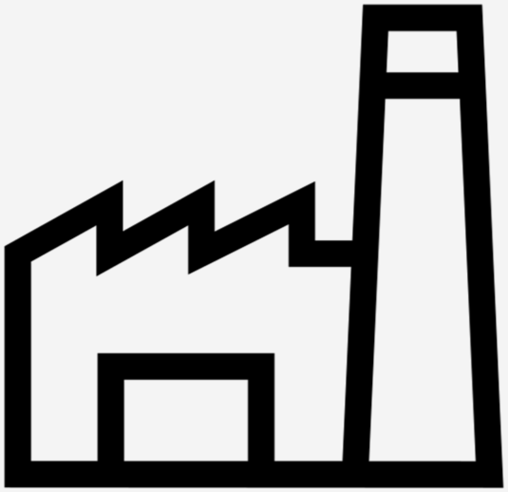
Boiler

Model Implementation

The Producer



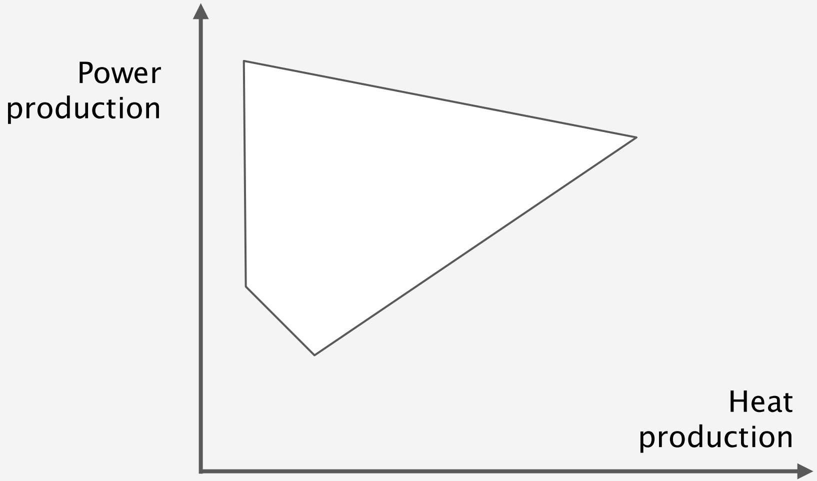
The operation region



CHP

Model Implementation

The Producer



The operation region

Cost-related variables:

Operation cost

Start up cost

Maintenance cost

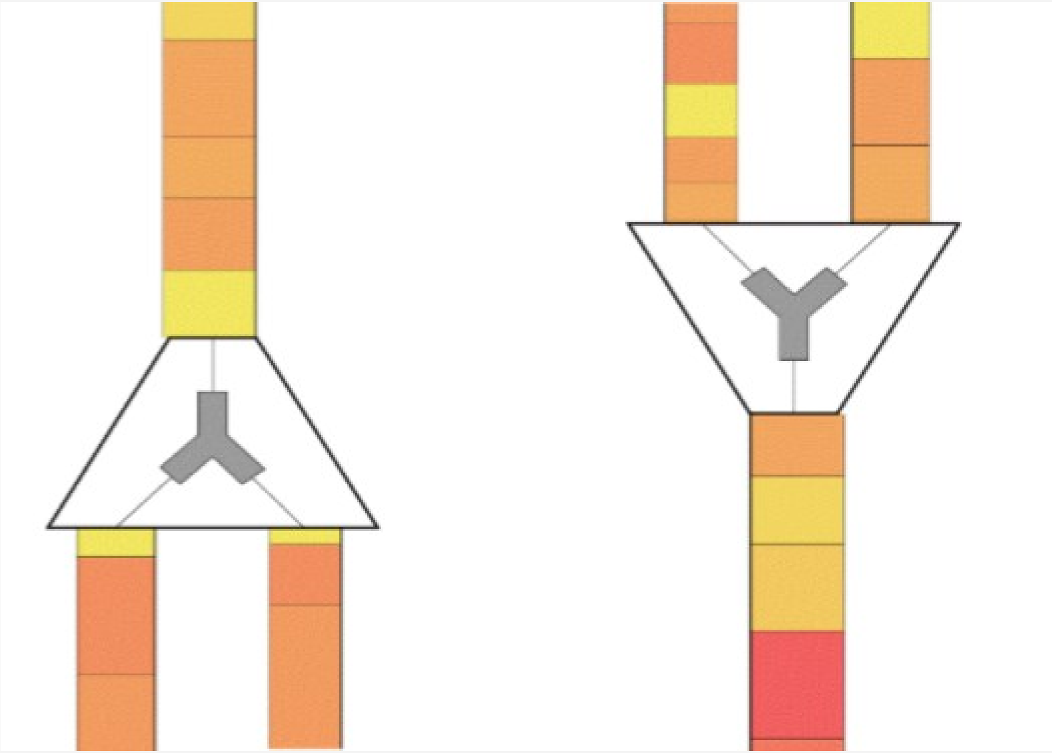
Constraints:

Ramp of heat/electricity

Max temperature

Model Implementation

The Connector



Split water

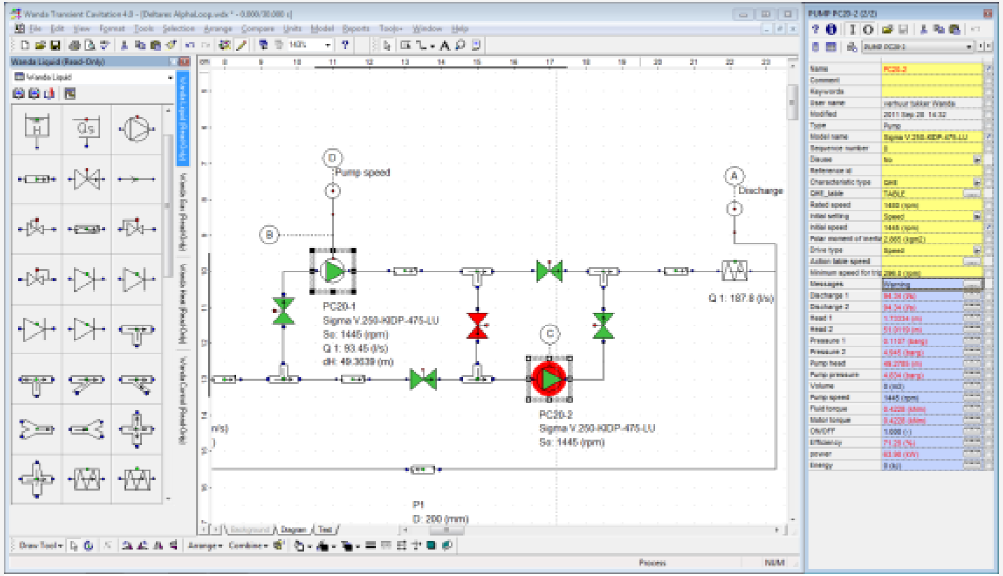
Join water

Model Validation

How GridPenguin compares to other software and a real grid

Model Validation: Wanda

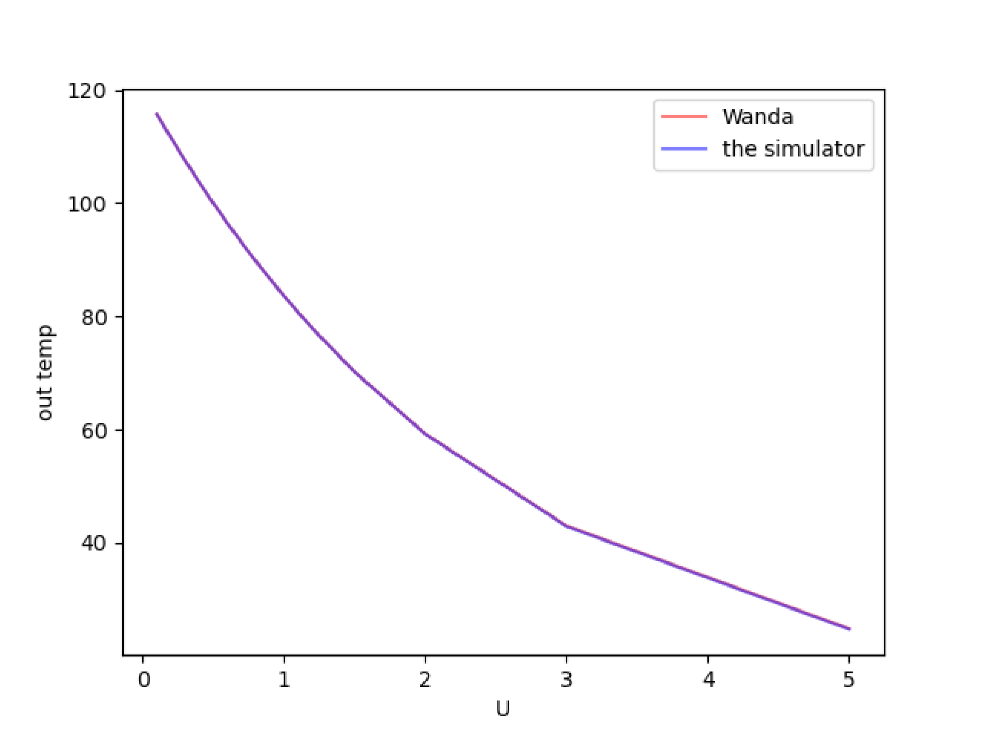
Why we chose Wanda



Images from https://www.deltares.nl/

Model Validation: Wanda

Heat loss comparison



Constant mass flow
Heat loss (out temp)
- U (heat transfer rate)

Model Validation: Wanda

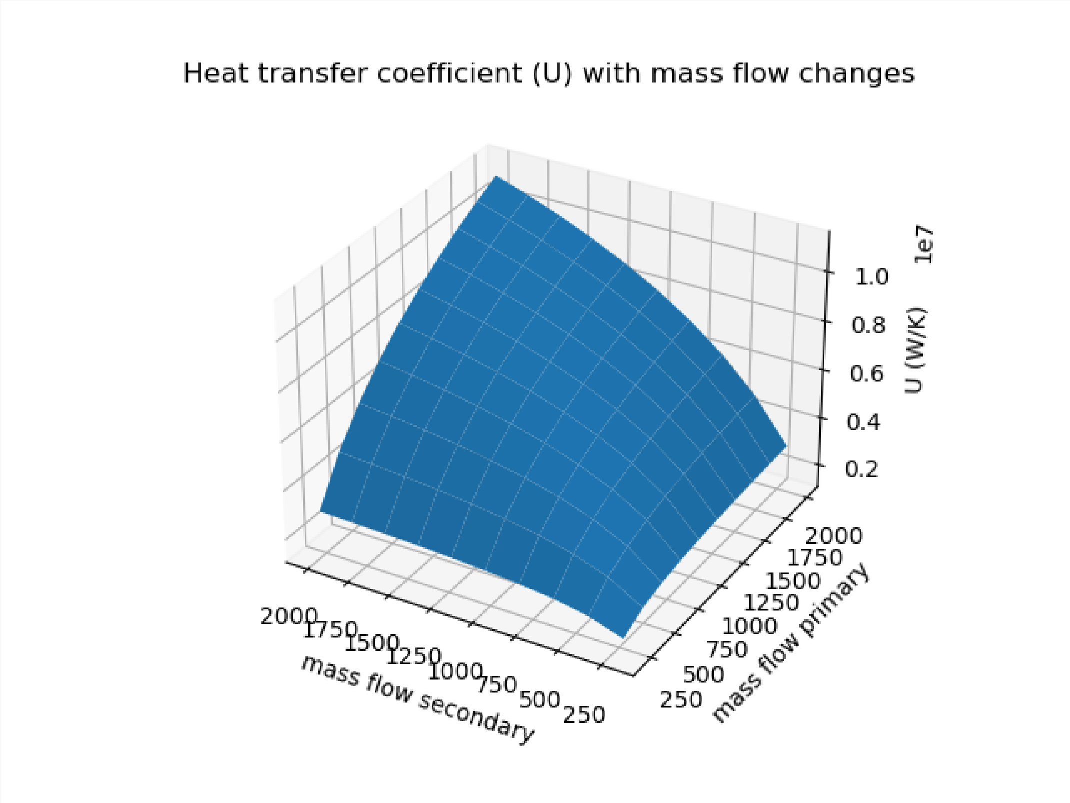
Heat loss comparison

Flow speed change rate ($*10^{-6} m/s^2$)	difference
4.95	-0.000123
1.21	-0.000693
0.46	-0.00340

Table 5: Heat loss difference at different mass flow changing rate

Model Validation: Wanda

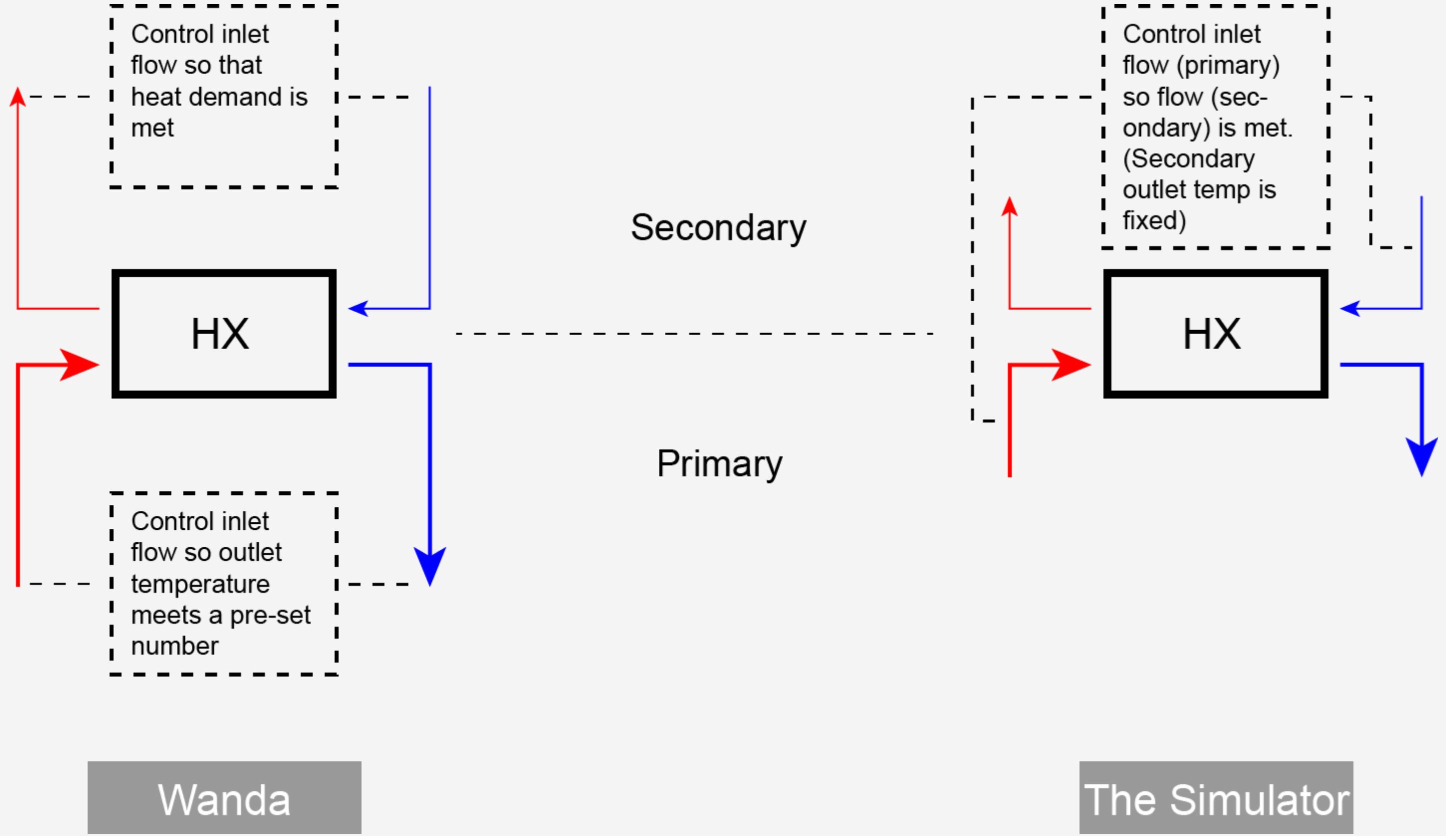
Heat exchanger



The nonlinear relation between
heat transfer coefficient
and mass flow

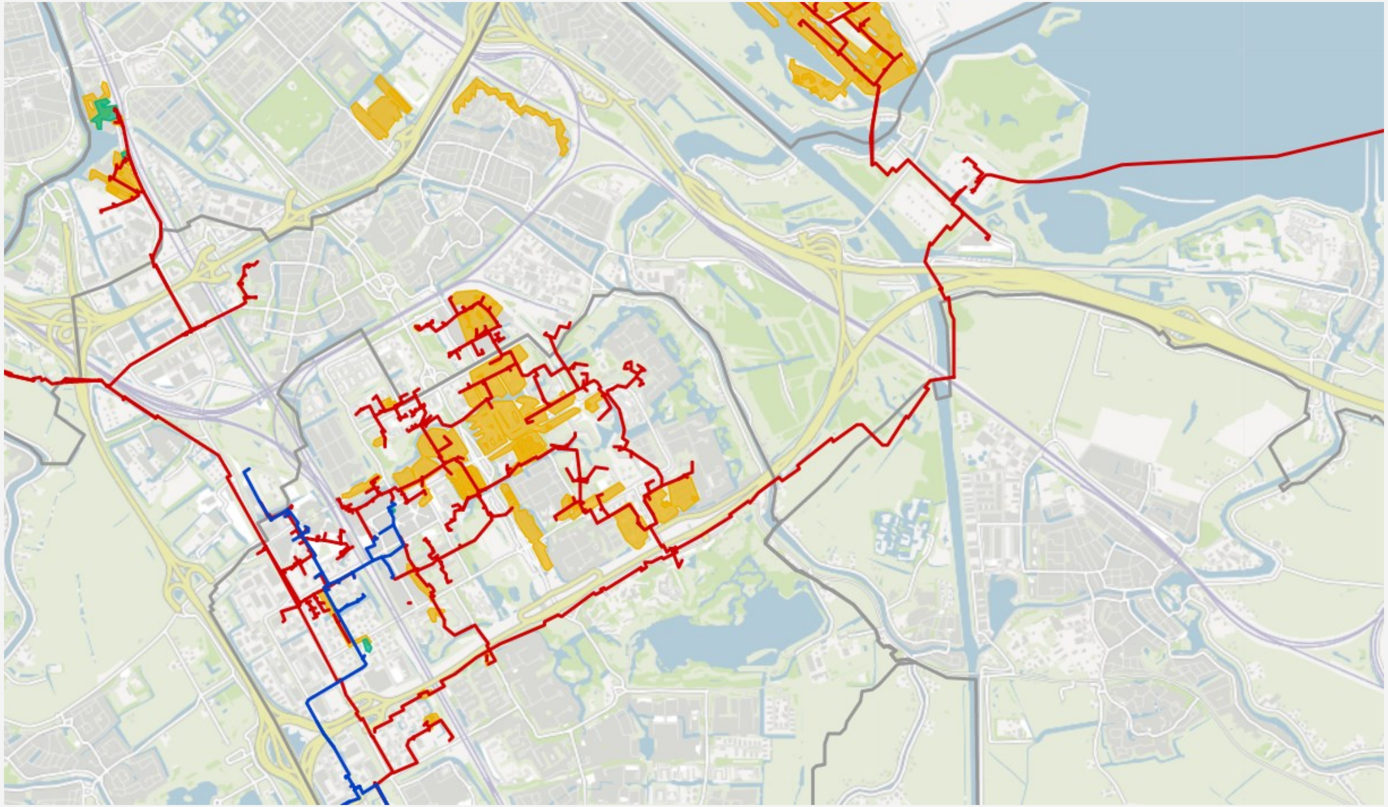
Model Validation: Wanda

Heat exchanger



Model Validation: Real Grid

Amsterdam south grid



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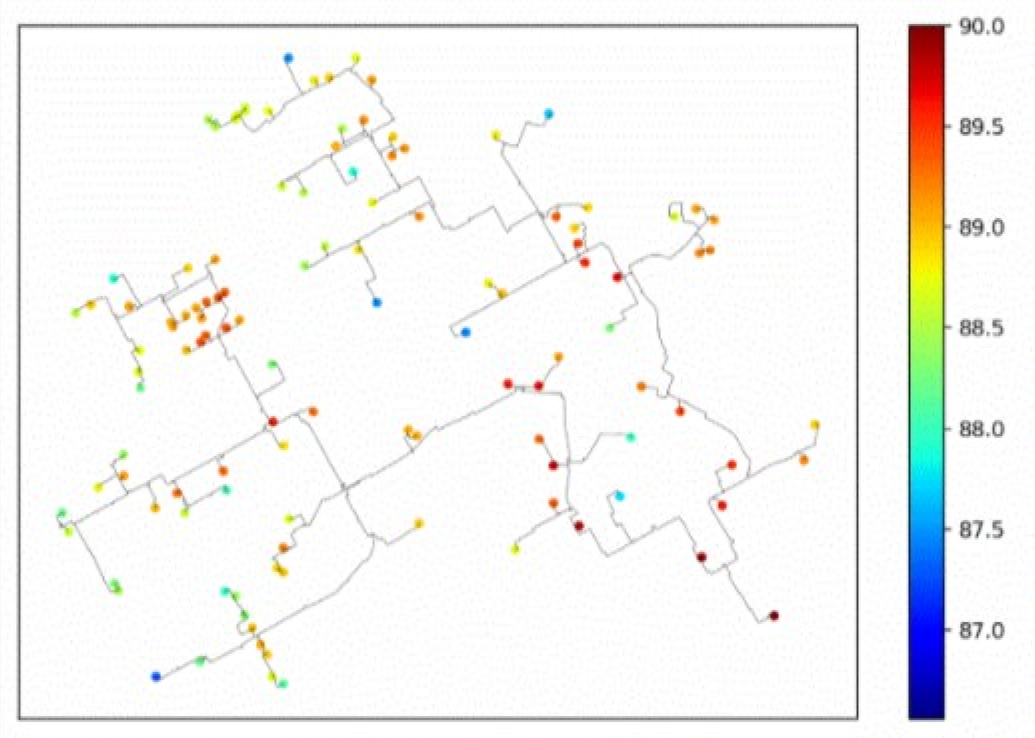

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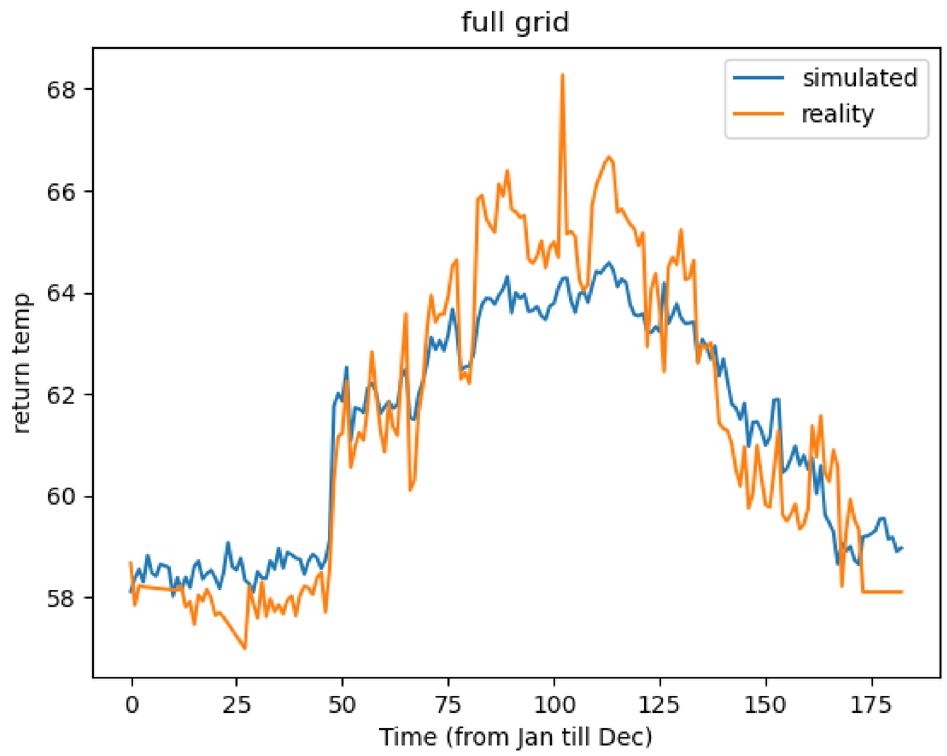

Compare simulated data
to real data

Future Works

Within GridPenguin

1. Implementation of storage and more producer types
2. Study of influence of simplified pressure
3. More complex grid topology

Around GridPenguin
(algorithms for optimization)

4. Reinforcement learning
5. Constraint optimization
6. Monte Carlo tree search
7. Mathematical optimization

Conclusion

1. The literature lacks a way to accurately and fast simulate DHS.

2. We propose GridPenguin as a solution. We aim to use it as a benchmark tool as well as to facilitate usage of machine learning.

3. With an earlier software as well as a real grid we show the accuracy of GridPenguin.