CHALLENGES IN HEAT NETWORK TOPOLOGY OPTIMIZATION

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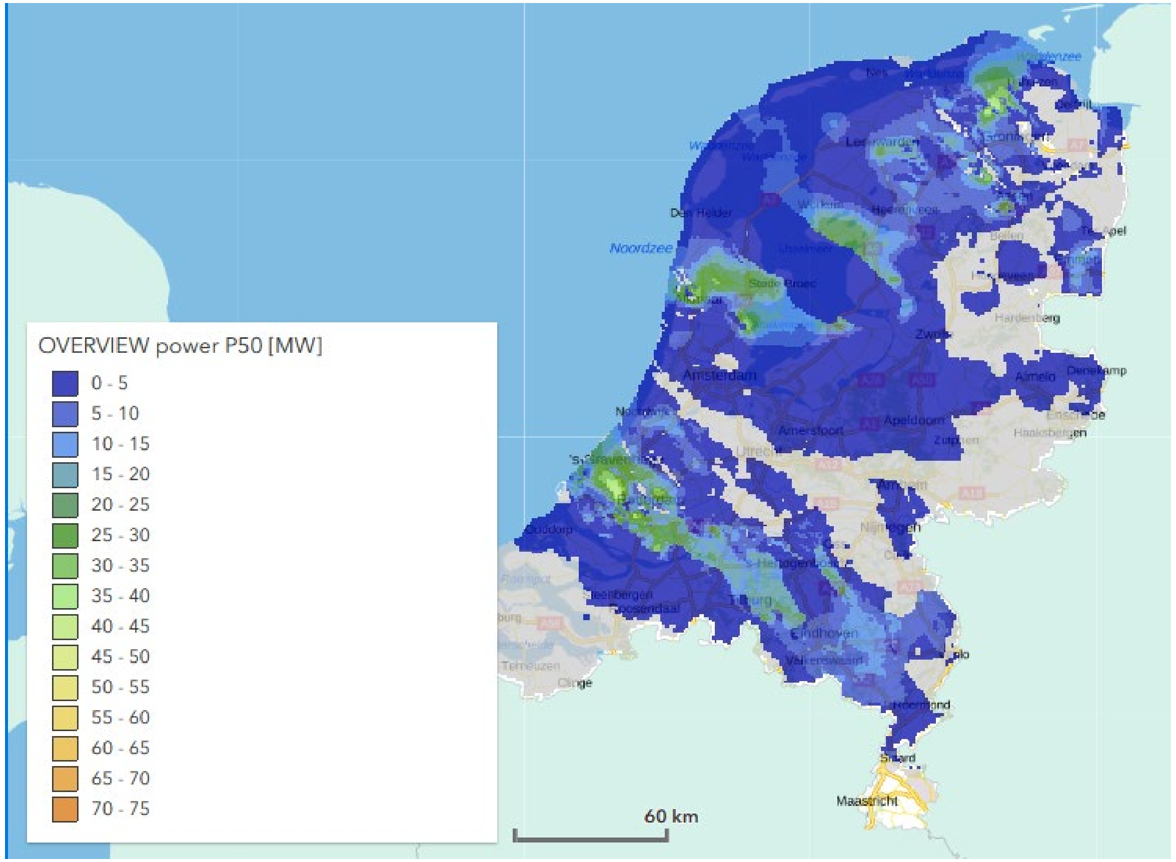
PROBLEM DEFINITION

- Among other solutions (hydrogen admixing to the gas grid, decentralized heat pumps etc.), transition towards a sustainable heat supply requires **many** new heat networks in NL.

- Currently, heat grids are designed through evaluation of manually drafted topologies.

- During design, there can be many design goals and large uncertainties in many design aspects.
  - Infeasible to evaluate all possibilities.
  - This leads to suboptimal grid designs!

Geothermal Power Estimates in The Netherlands

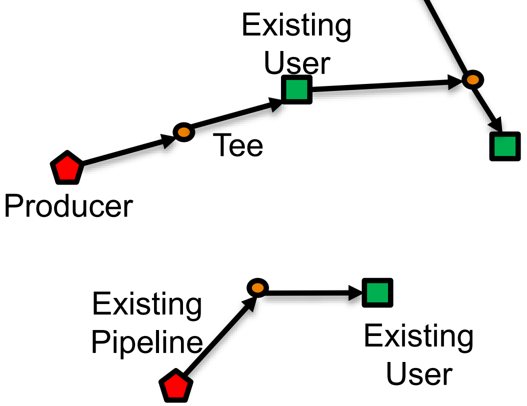


https://www.thermogis.nl

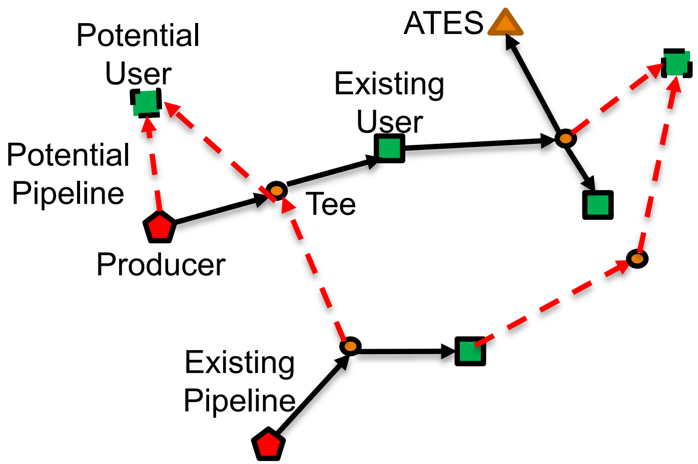
GOAL

- **(Final) Goal** : **Methodology for assisted grid design optimization**
- For a given set of actors (e.g. producers, consumers etc.), the method should;
  - generate topologies, optimized on relevant KPIs (e.g. CAPEX/OPEX, Revenues, Network fairness, etc.),
  - handle design parameters stochastically (e.g. expansion of the grid/future actors, uncertainty on prices/demand/supply) and optimize the grid concept under uncertainty (*robust optimization).*

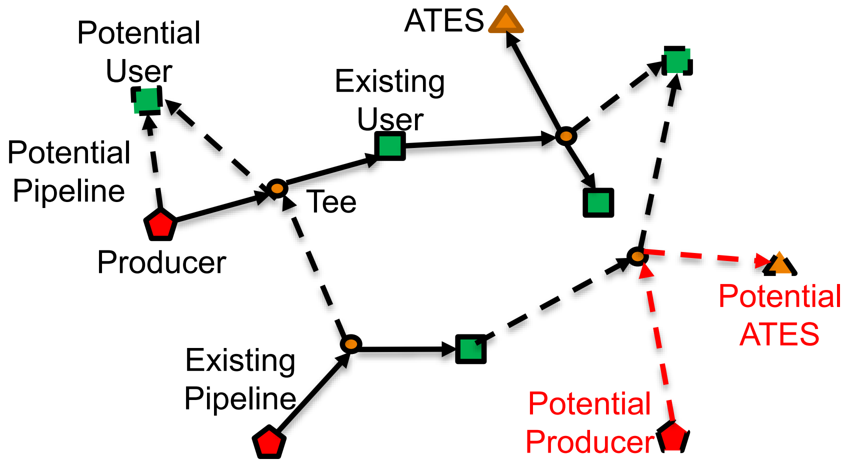
Original



Where (How) to expand?

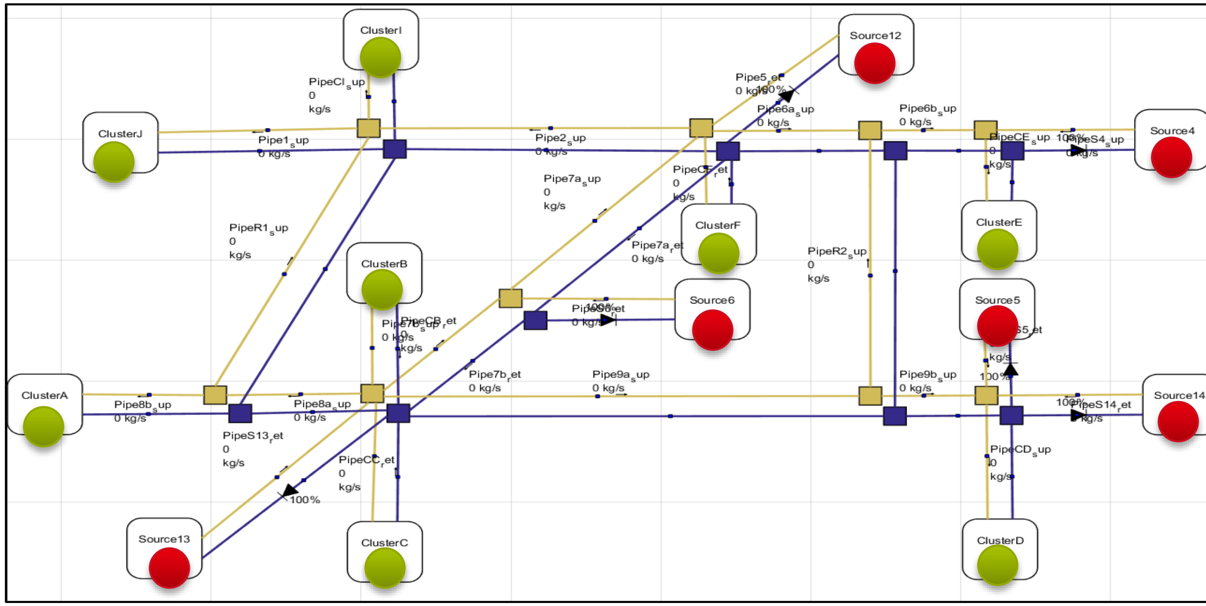


Is the grid design "fair" for all actors?



INHOUSE HEAT NETWORK SIMULATOR

- Solver for momentum and energy equations.
- System controller to drive the system (pumps/valves).
- Solver and pre/post-processing in MATLAB.
- Easy prototyping of new concepts (system controllers, optimizers etc).
- Model Creation: ESDL Web Editor (GIS based).
- Many component models (Geo. Well, ATES, Heat Pump, PV Panels etc.) with different levels of detail from respective TNO departments.
- Currently being tested by engineering companies.



Sources and Demand

https://smartenergysystems.eu/wp-content/uploads/2019/04/Track12_Booij.pdf
More on ESDL in session 30.

EXAMPLE CASE 1

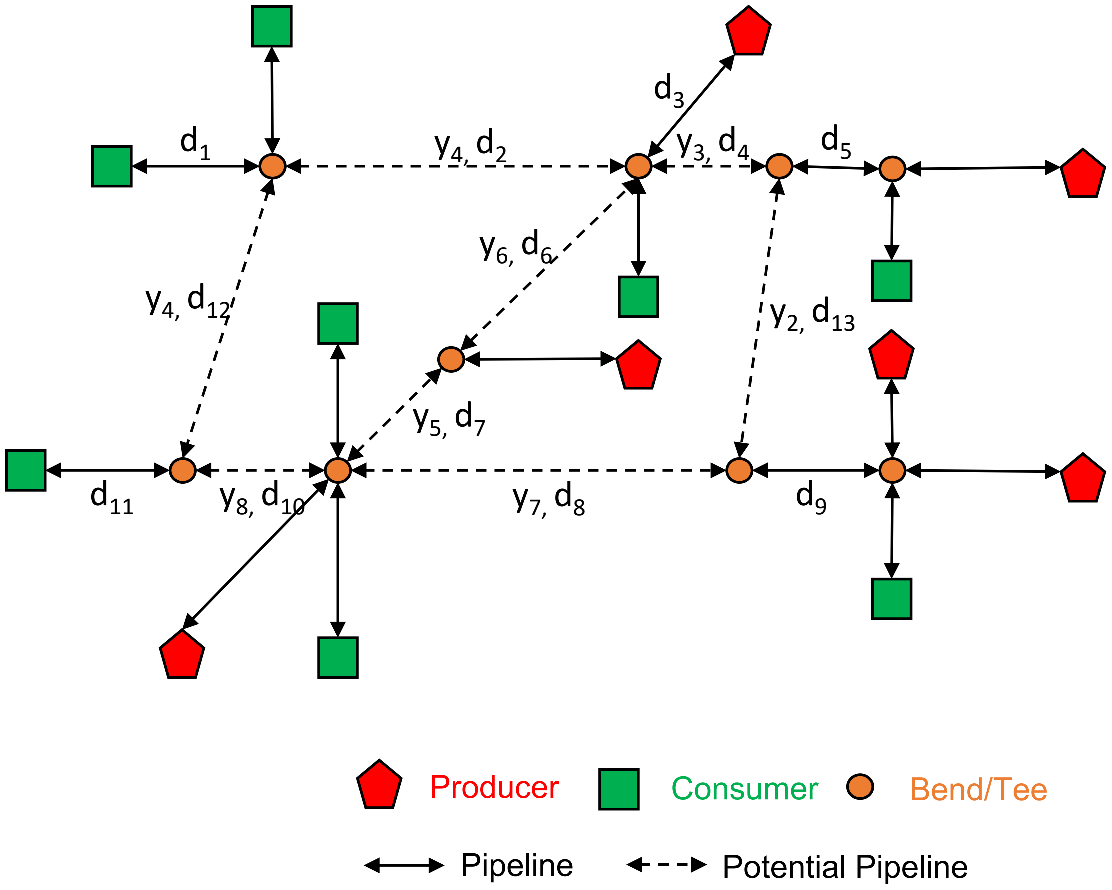
- Objective function J: *Total Cost of Ownership (TCO)*

$$J(u) = TCO(u) = \sum_{E=\begin{Bmatrix} sources \\ pipes \\ pumps \end{Bmatrix}} \left(E^{Capex} + E^{Opex}\right)$$

- Variables $u = (y, d)$:
  - 8 binaries for pipelines $y = (y_1, y_2, \ldots, y_8)$
  - 13 diameters $d = (d_1, d_2, \ldots, d_{13})$
- Constraints (not allowing disconnected networks)
  - $y_2 + y_3 \geq 1$; $y_2 + y_5 + y_8 \geq 1$; etc…
- Optimization problem:

$$\min_{\substack{u=(y,d) \\ y_i \in \{0,1\} \\ d_i \in [0,1]}} J(u)$$

Based on real case; 6 producers, 8 demand clusters

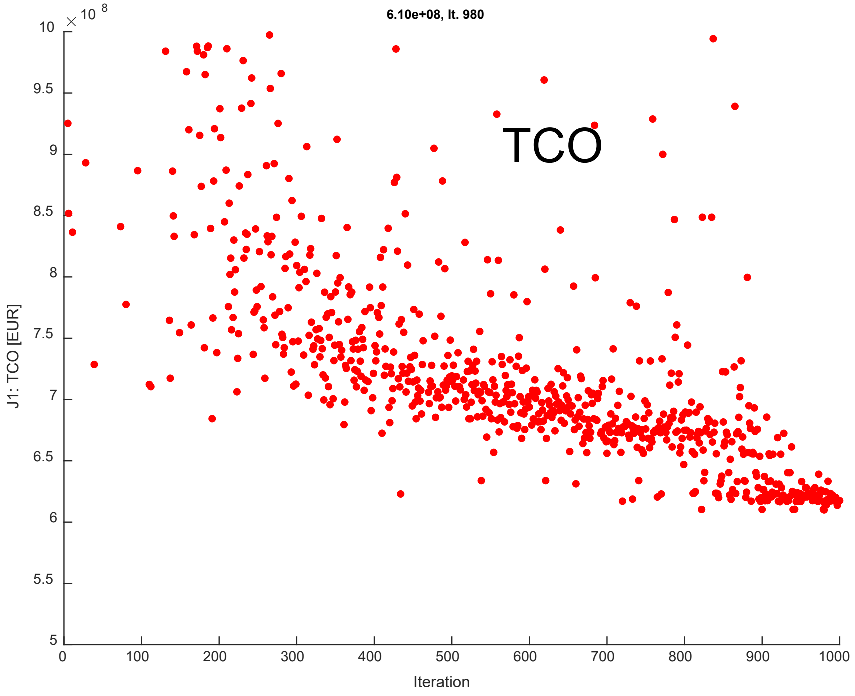


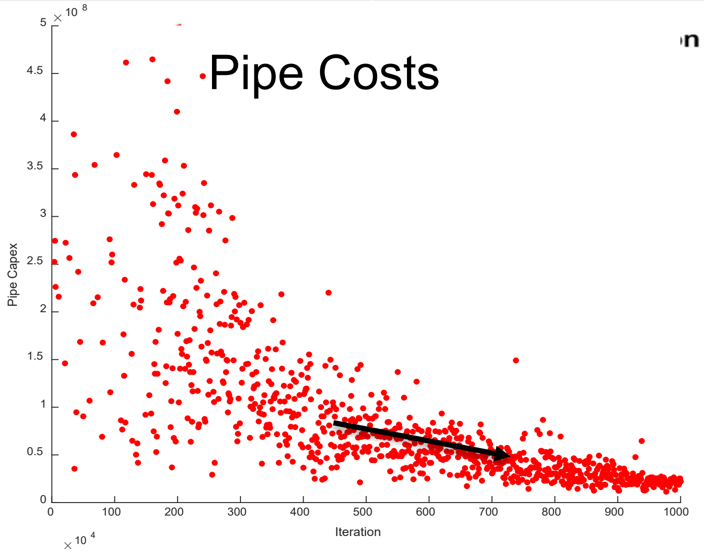
SOLUTION APPROACH

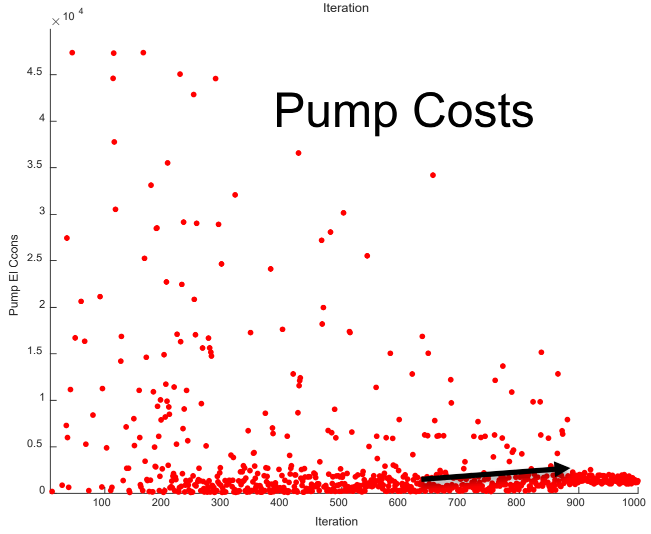
- DAKOTA used as framework
  - From Sandia National Laboratories (http://dakota.sandia.gov)
  - Open source
  - Ships several optimizers
  - Parallelization features
  - Allows set up of iterative workflows such as Nested loops, Hybrid optimization,…
- Optimization running on HPC
- Optimizers that can handle both integer and continuous variables
  - Pattern search methods
  - Branch and bound method
  - Genetic algorithms (used in this presentation)

RESULTS CASE 1

- Using a genetic algorithm (SOGA)





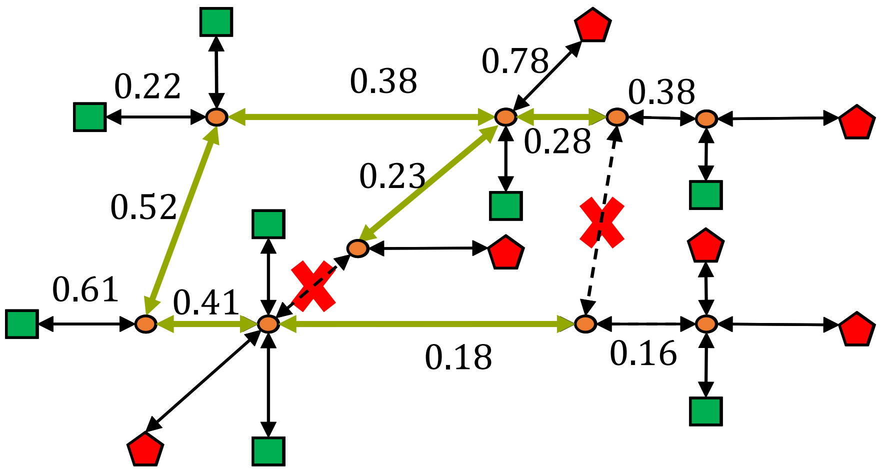


- Convergence can be improved using hybrid optimization
  - Use GA to globally explore the variable space followed by a local (gradient based) optimizer

RESULTS CASE 1

- Minimum TCO found after 980 iterations

Optimized design

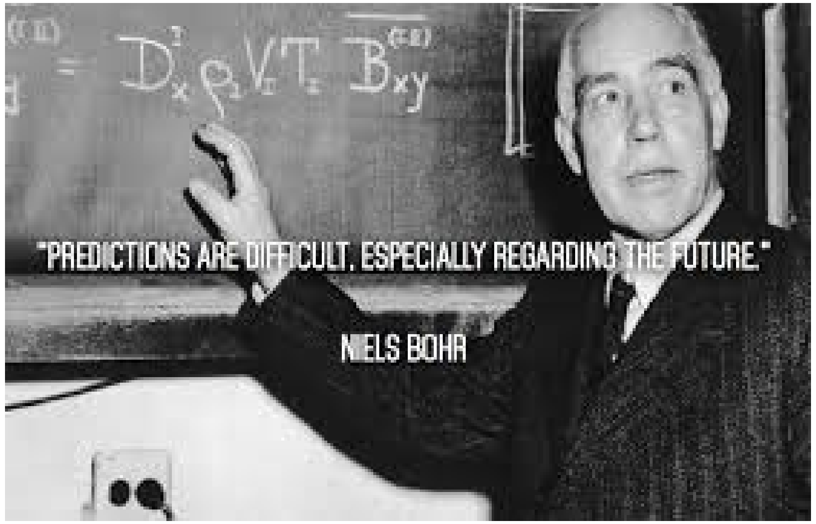


No Pipe line

Pipe line

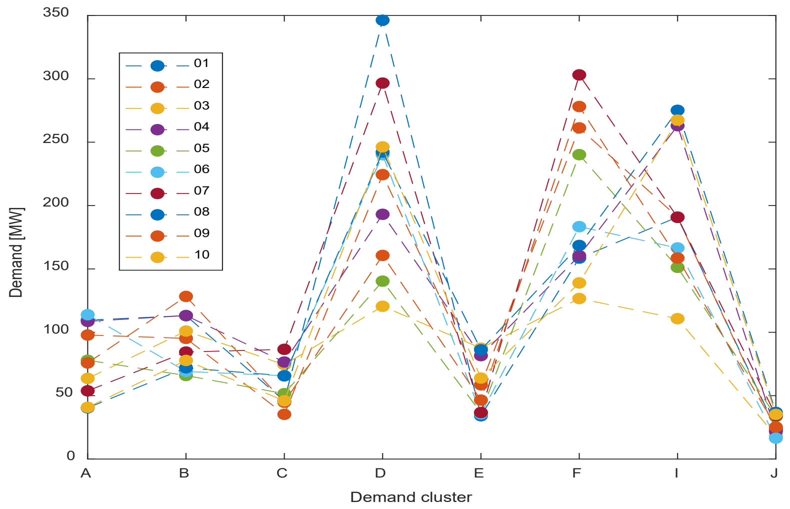
Planned Pipe line
(not part of optimization)

UNCERTAINTY



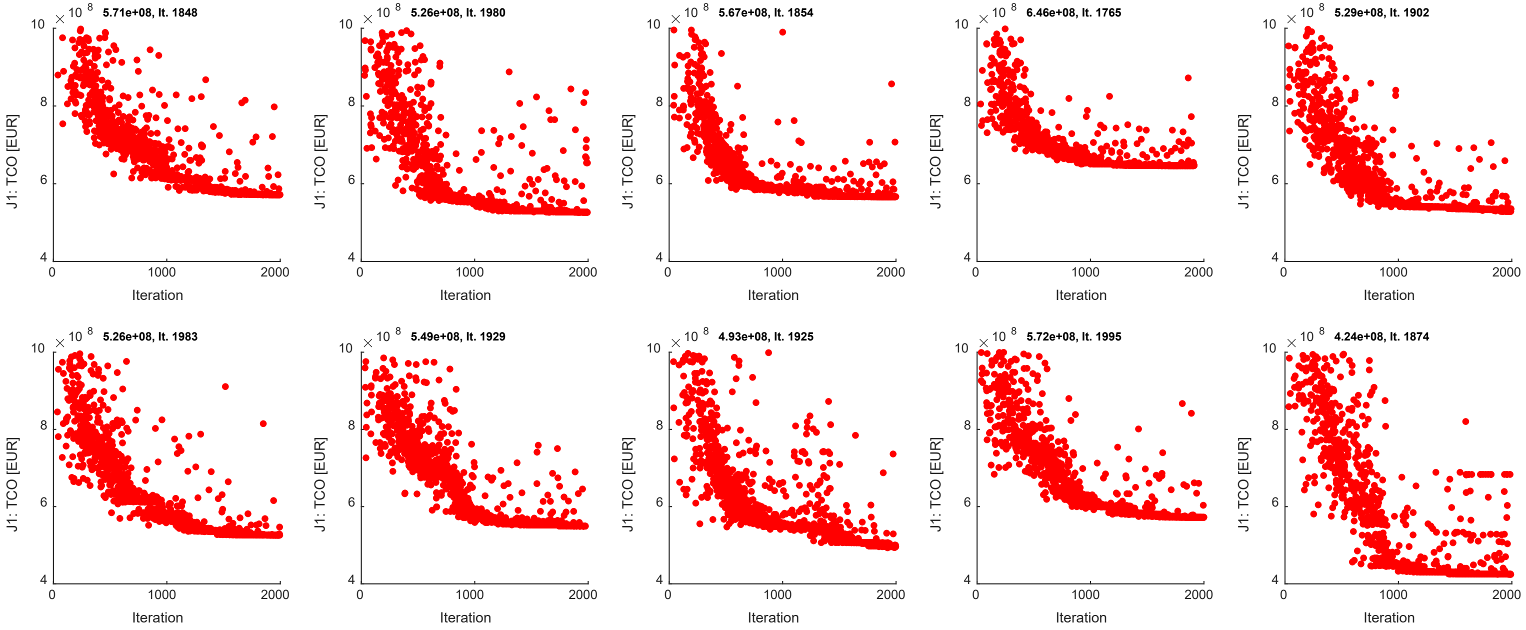
- In previous example no uncertainty assumed (deterministic optimization)
- In practise large uncertainties may be presents concerning future
  - Demands
  - Energy prices
  - Heat sources availabilities
  - Urban and industrial developments
- Future proof topology design needs to account for increasing uncertainty over time
- Example case 2
  - Same base case as before but with uncertainty in demand
  - Assume that uncertainty is captured in 10 equiprobable realizations

Sequence of connected point is a single realization



DETERMINISTIC OPTIMIZATION PER REALIZATION

- Objective function J (e.g. TCO) depends also on realization so $J = J(u, r)$ with $u = (y, d)$ topology design and $r \in \{r_1, \ldots, r_{10}\}$ a realization
- 10 Deterministic Optimization problems: minimize the objective functions $J(u, r_1), \ldots, J(u, r_{10})$



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OPTIMAL DESIGNS PER REALIZATION

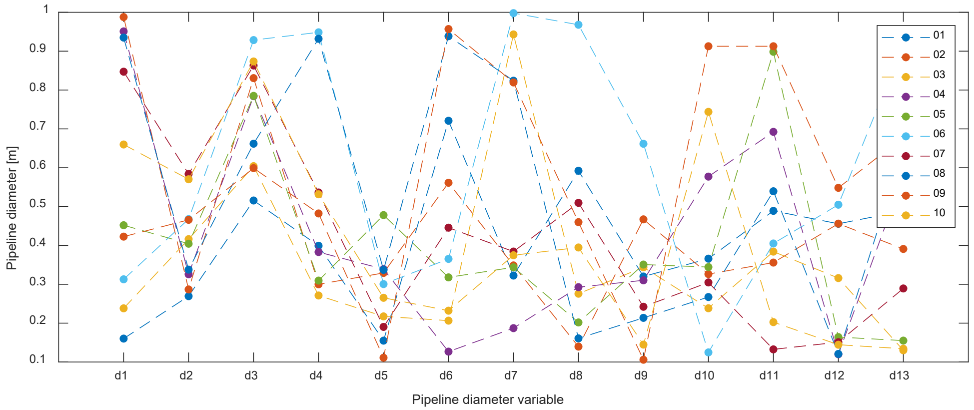
Pipelines

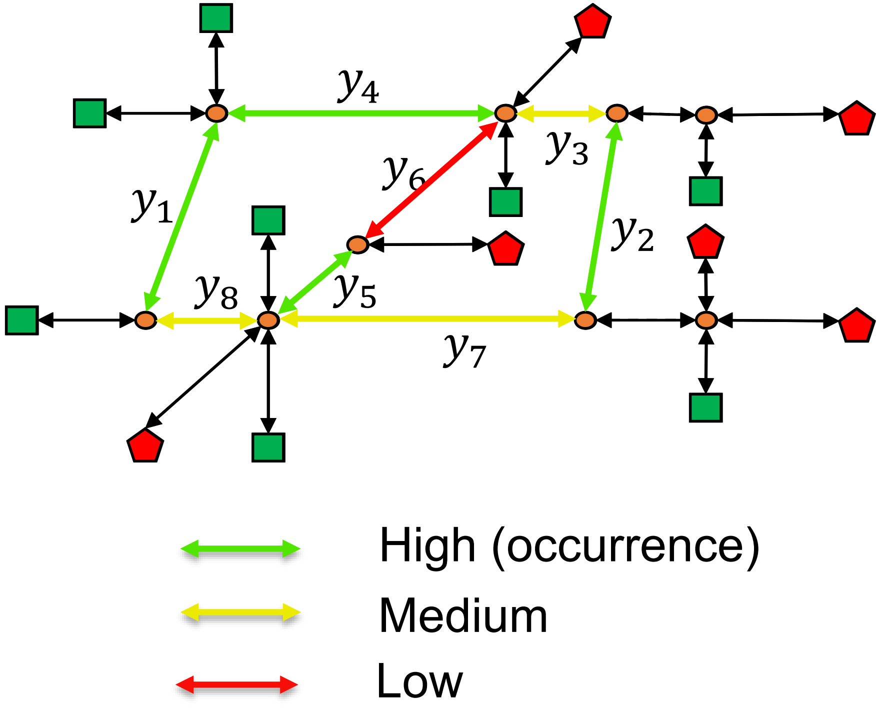
Realizations

	y1	y2	y3	y4	y5	y6	y7	y8	TCO ($x10^8$)
1	1	1	1	1	1	0	0	1	5.7
2	1	1	1	1	1	0	0	1	5.3
3	0	1	1	1	0	1	1	0	5.7
4	1	0	1	1	1	0	1	1	6.5
5	1	1	0	1	1	0	1	1	5.3
6	1	1	1	1	1	0	1	0	4.8
7	1	1	1	1	1	0	1	0	5.5
8	1	1	0	1	1	0	0	0	4.9
9	1	1	0	1	0	1	1	1	5.7
10	1	1	1	1	1	0	1	0	4.2

8 different topologies

Diameters

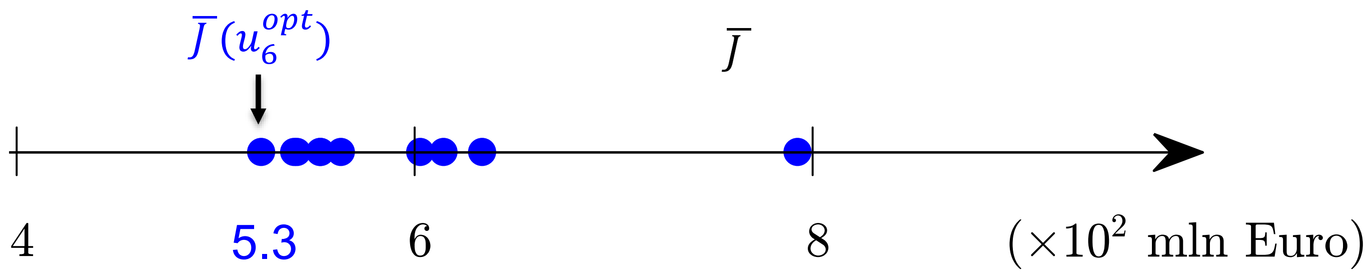




OVERALL PERFORMANCE OF THE FOUND SOLUTIONS

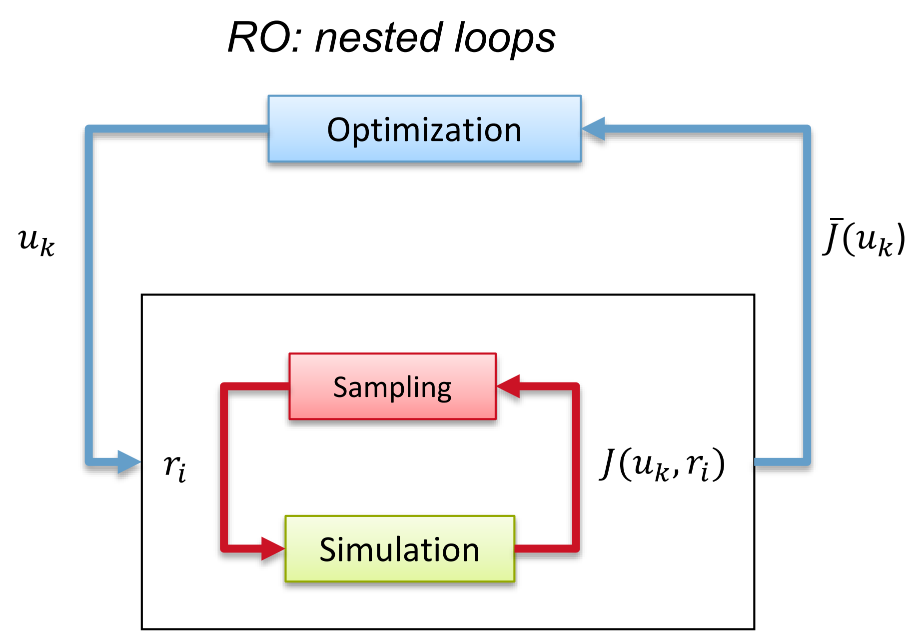
How good do the solutions perform for all realizations?

- For each realization r_i , $i = 1, \dots, 10,$ an optimal design u_i^{opt} is calculated
- Performance measure is the expected objective function value $\bar{J}(u) = \frac{1}{10}\sum_{i=1}^{10} J(u, r_i)$ for design u
- Performance of the 10 optimal designs:



- Optimized design u_6^{opt} for realization 6 performs best among the 10 designs
- This is still a suboptimal solution => rigorous approach is Robust Optimization

ROBUST OPTIMIZATION (RO)



- Let uncertainty (demands, prices,…) be captured by realizations $r_1, r_2, \dots, r_M$
- Robust optimization:

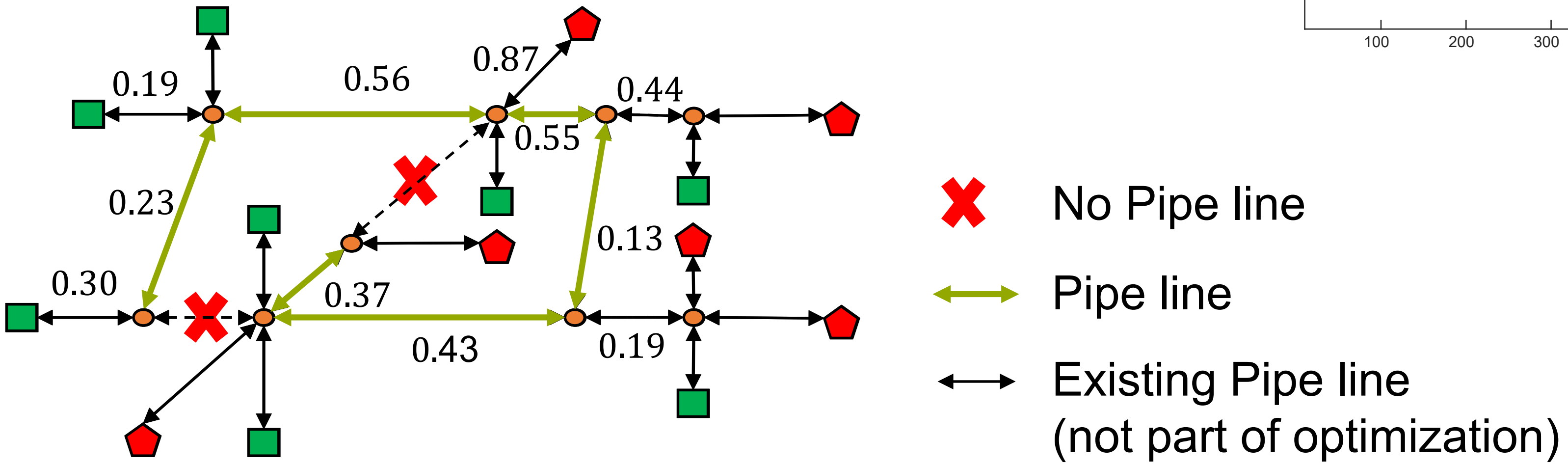
> Given realizations $r_1, r_2, \dots, r_M$, find topology design u that minimizes the expected value $\bar{J}(u) = \frac{1}{M}\sum_{i=1}^{M} J(u, r_i)$

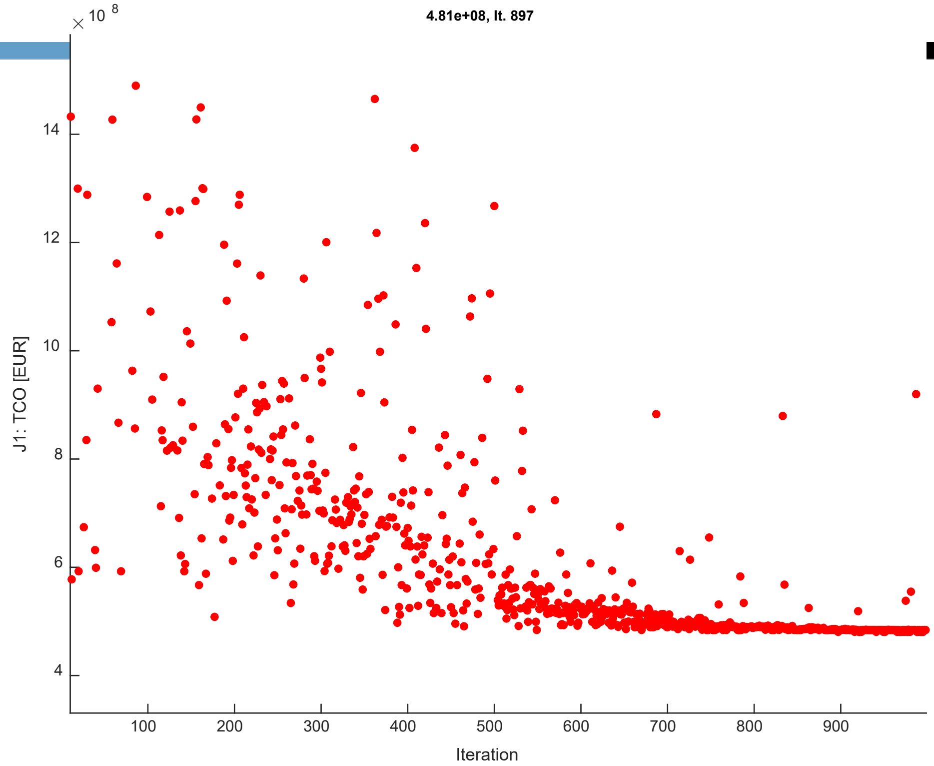
- Robust optimization aims at finding a topology design that is “good” for all realizations
- RO is CPU expensive: M simulations to calculate $\bar{J}(u)$
  - Parallelization is essential

ROBUST OPTIMIZATION

- Minimum TCO found after 897 iterations
- Solution:

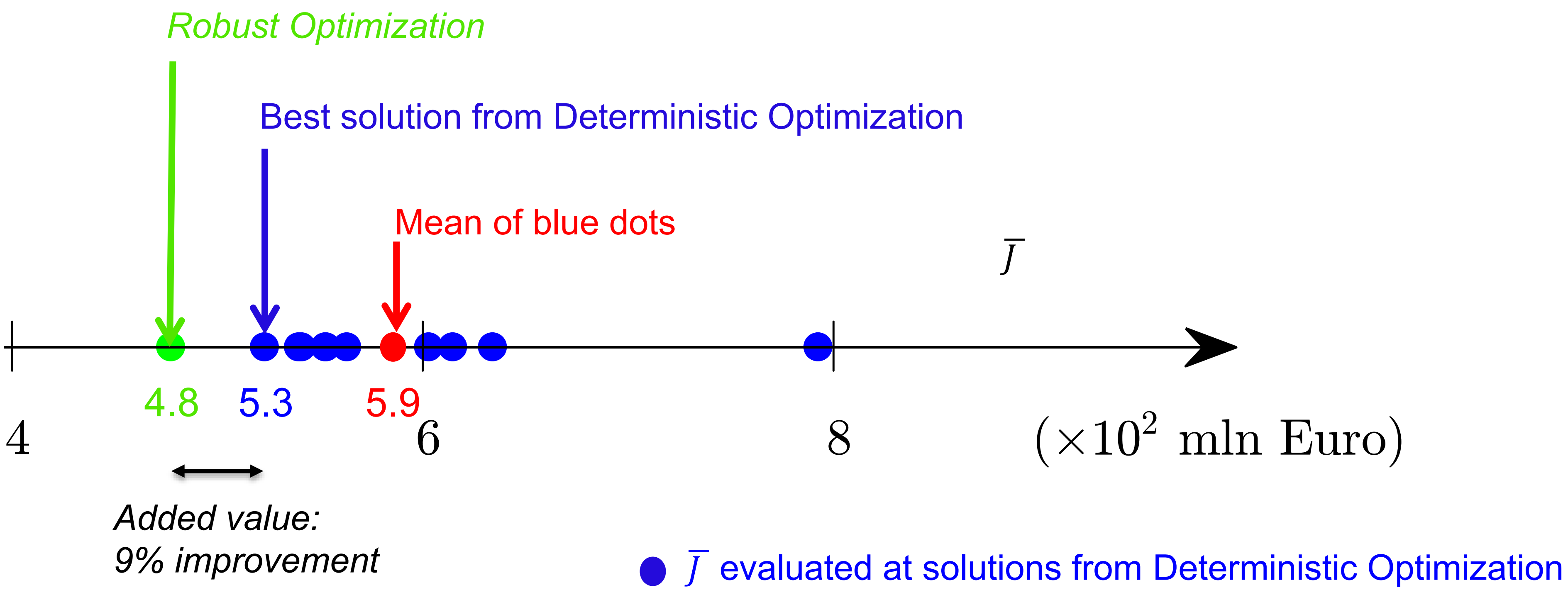
Optimized design





ADDED VALUE ROBUST OPTIMIZATION

- Added value of RO through comparison with solutions from deterministic optimization



WRAP UP/CONCLUSIONS

First steps presented towards a framework/methodology for assisting heat network designing

- Heat network design => optimization problem with continuous and binary variables
- An optimization framework was setup to solve the mixed integer optimization problem allowing
  - use of several optimizer, hybrid optimization, multi-objective optimization, constraints
- Optimization under uncertainty (Robust Optimization) was setup
  - Added value demonstrated

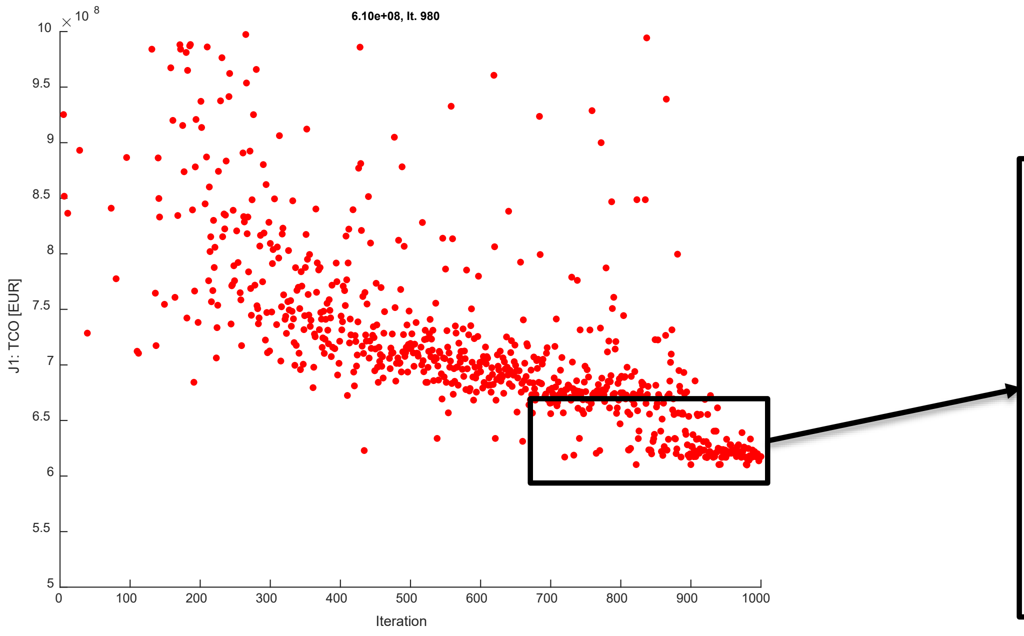
Next steps

- Network fairness/ load balancing
  - Investigating solution approach using Quantum Algorithms (Dwave's 2000Q system)
- Incremental network design
- CPU Efficiency

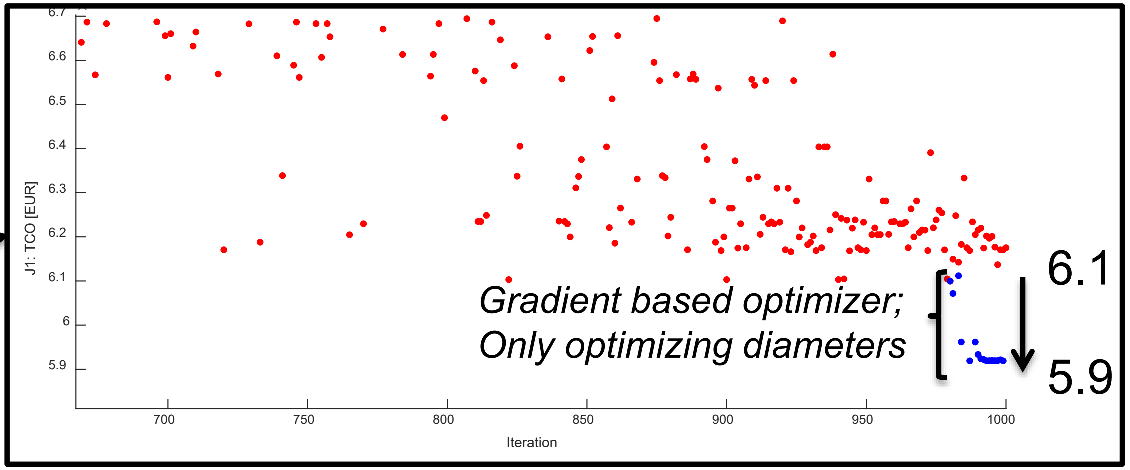
BACKUP SLIDES

HYBRID OPTIMIZATION

- Hybrid:
  - Use GA as global optimizer to explore the variable space
  - Use gradient based optimizer as local optimizer



Further reduction of objective



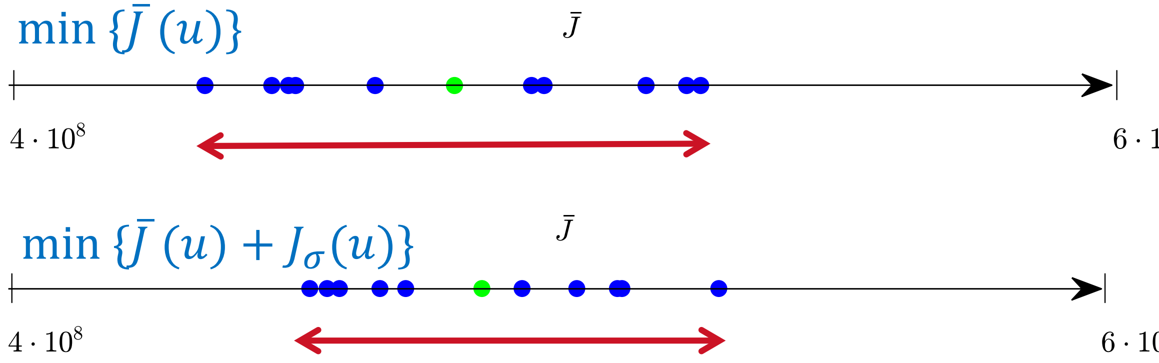
ROBUST OPTIMIZATION

- Robust Optimization (RO): Deals with uncertainty in a rigorous way and aims at finding a design that is good for all realizations.

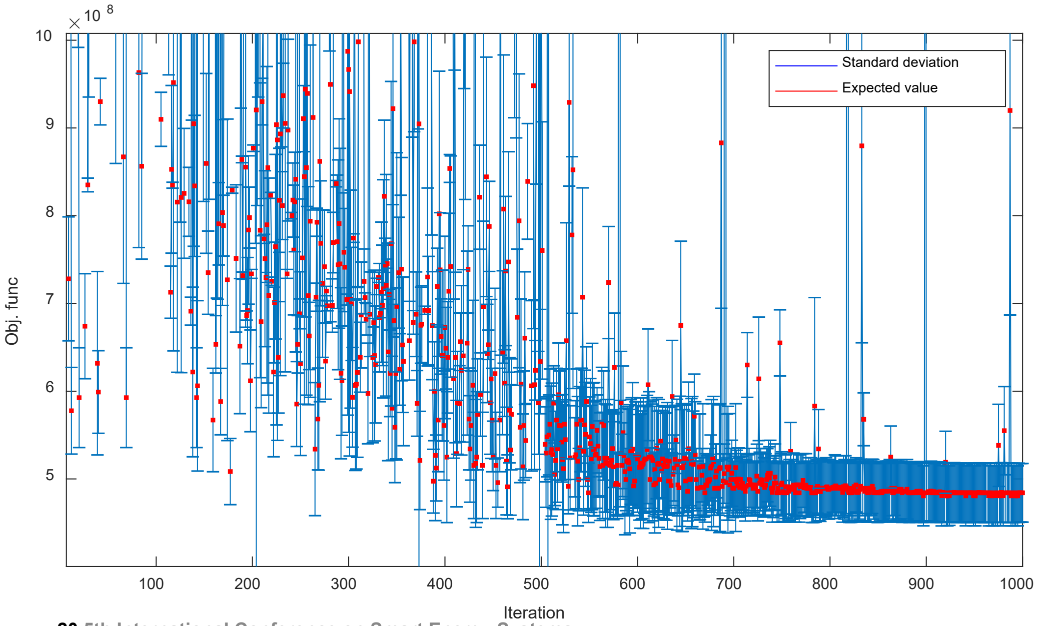
- Framing the problem
  - Design vector: u (consisting of binaries y and diameters d)
  - Parameter vector: r (the demands of users)
  - Objective function: $J = J(u, r)$ (cost function e.g. TCO)
  - Input-output system: $u, r \longrightarrow$ Heat Network S Simulator $\longrightarrow J(u, r)$

REDUCING RISK

- Besides minimizing expectation $\bar{J}$ one may desire to reduce risk
- Measures of risk:
  - Standard deviation J_σ
  - Spread at downside only: Semi- standard deviation



Reduced spread at the cost of Expectation value



Spread as measure for risk