Multi-Objective Design and Operation Optimization for District Heating Networks

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(Zuse Institute Berlin | MODAL EnergyLab)

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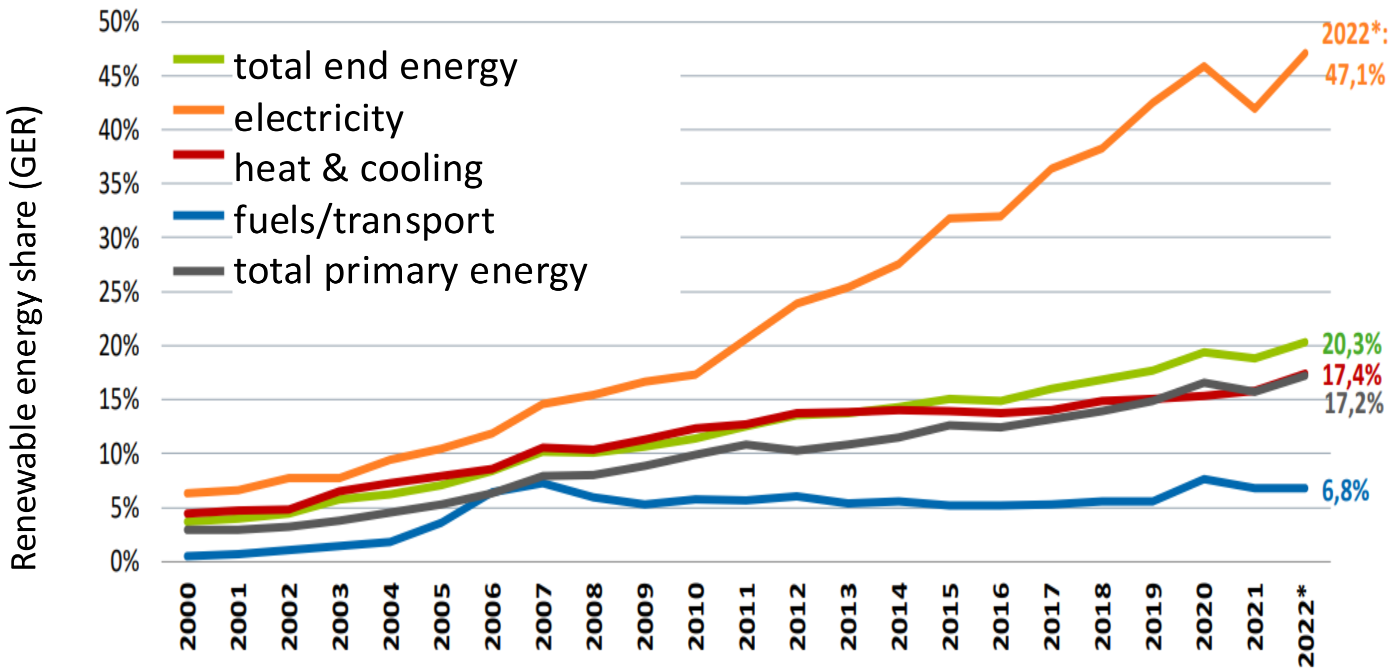
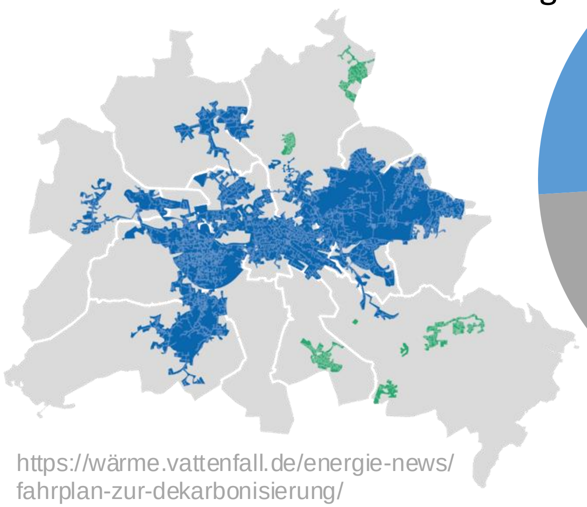
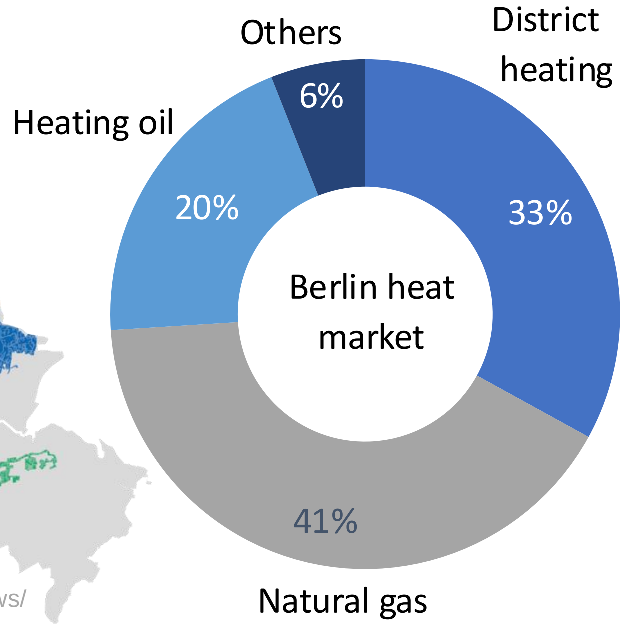
The energy transition needs both heat and power transformation



- District heating networks can play a significant role in the decarbonization
- 6 million German households (= 14%) are connected to DHNs

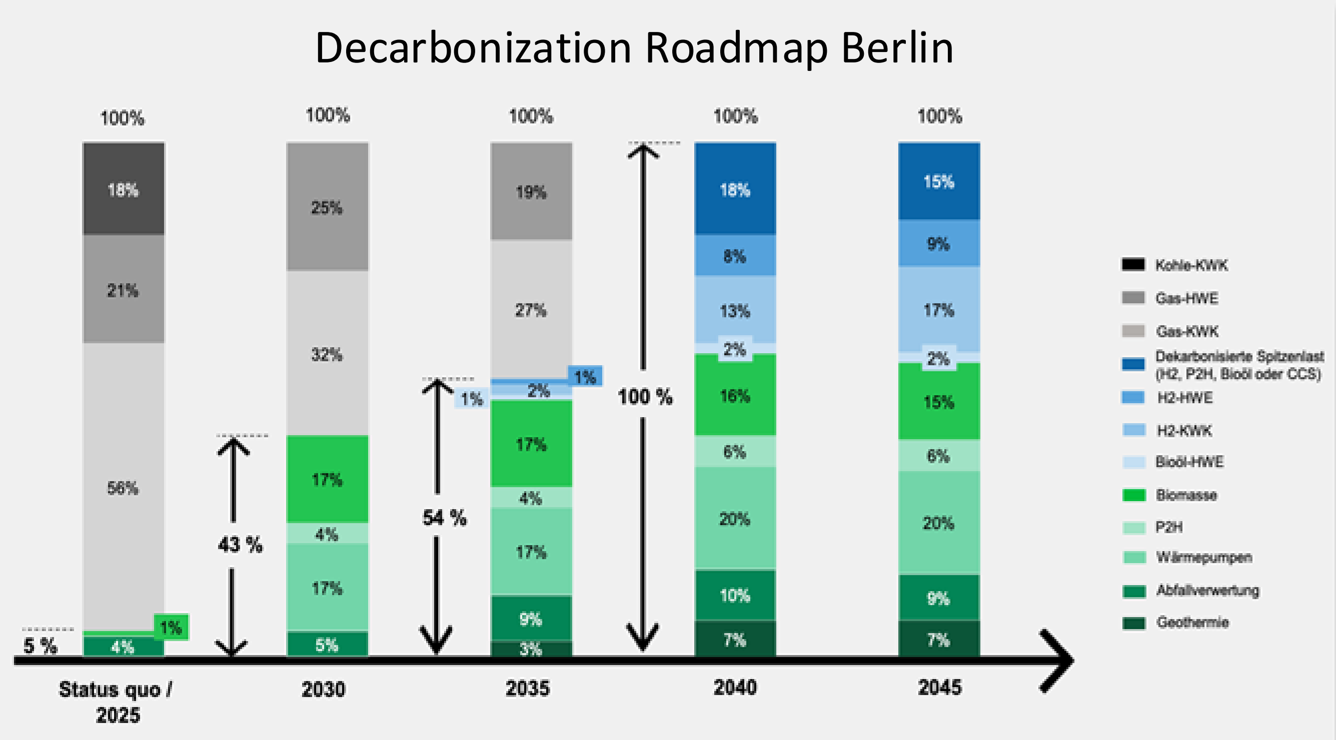


https://wärme.vattenfall.de/energie-news/fahrplan-zur-dekarbonisierung/



- Heat sector including space heat, process heat & cooling adds up to 59% of the German end energy
- Share of EE in power sector already > 45% while heat sector remains below 20%

Exploring transformation pathways on an urban scale



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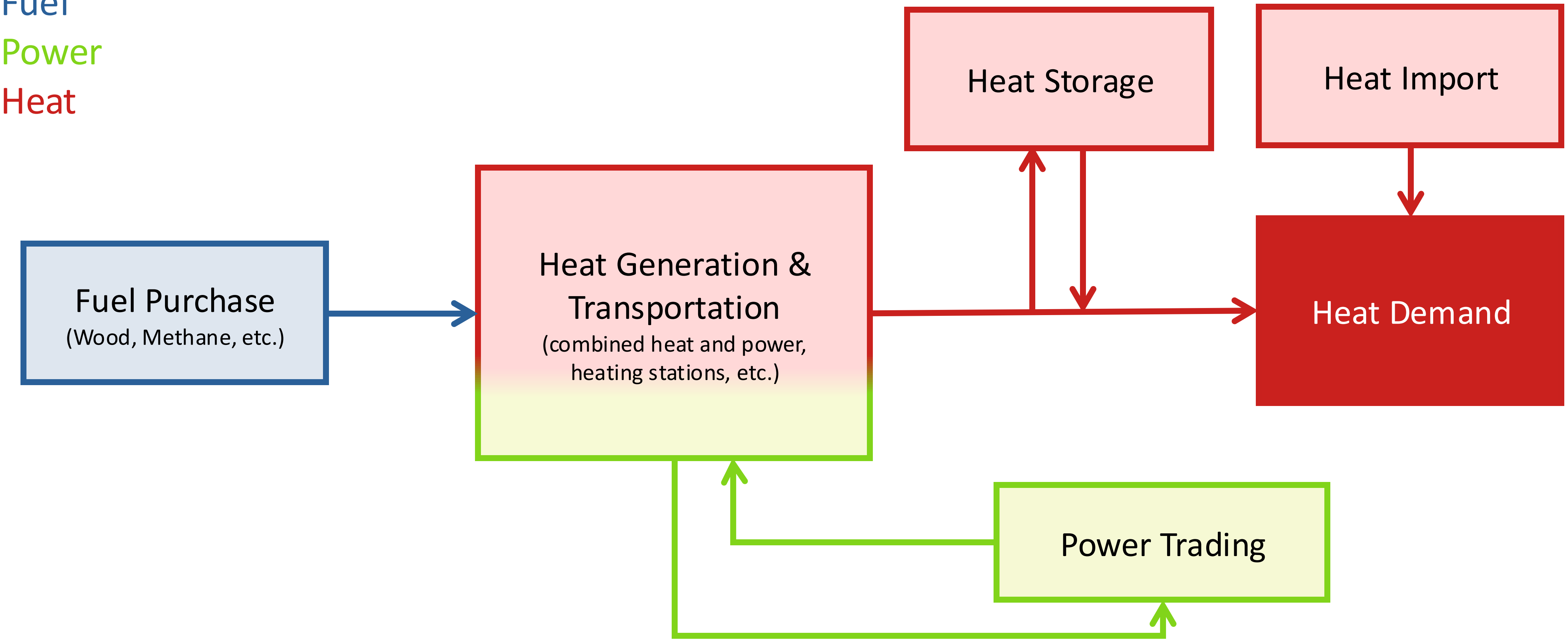
Goals:

- Exploring transformation pathways with reasonable trade-offs between economic and environmental targets
- Long-term investment planning of an energy provider on an urban scale

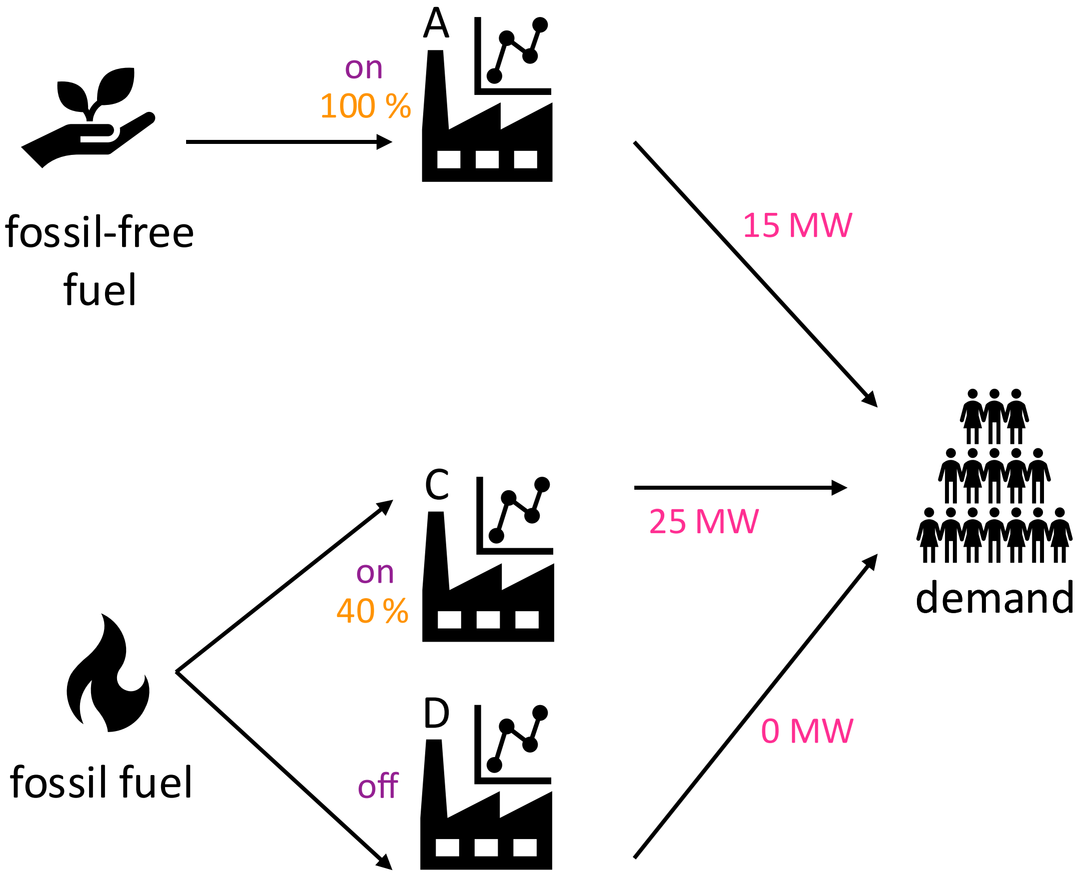
District heating network model

Fuel
Power
Heat



<u>Input</u>: demand/price forecast time series

Operation optimization



The **operation optimization** is modeled as a **unit commitment problem**:

- **commitment decisions**: whether a unit is producing/storing energy at a time,
- **production decisions**: how much energy a unit is producing/storing at a time,
- **network flow decisions**: how much energy is flowing on each edge of the grid

MIP: operation optimization

<u>Main Variables</u>:

$z_{i,t} \in \{0,1\}$	**operation of unit i at time t**
$x^r_{t,i^{in}}, x^r_{t,i^{out}} \in \mathbb{R}_{\geq 0}$	**incoming/outgoing flow of resource r at unit i at time t**
$s_{i,t} \in \{0,1\}$	activation of a unit i at time t
$h^r_{t,k} \in \mathbb{R}_{\geq 0}$	level of resource r in storage k at time t
$p^r_t \in \mathbb{R}_{\geq 0}$	purchased amount of resource r at time t
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R	set of resources
I	set of generating units
K	set of storage units
T	set of time steps
D^r	demand of resource r
a, c	storage and capacity parameters

<u>Objectives:</u>

$$\min \sum_{t \in T} costs^{op}(z_t, s_t, h_t, p_t, e_t, x_t)$$

MIP: operation optimization

Constraints

$$\sum_{i\in I} x^r_{t,i^{out}} + \sum_{k\in K} x^r_{t,k^{out}} + p^r_t = D^r + \sum_{i\in I} x^r_{t,i^{in}} + \sum_{k\in K} x^r_{t,k^{in}} + e^r_t \qquad \forall r \in R \qquad \text{resource balancing}$$

$$x^{r_2}_{t,i^{out}} = \varphi^{r_1,r_2}_{i,t}\left(x^{r_1}_{t,i^{in}}\right) \qquad \forall i \in \mathrm{I}, \mathrm{t} \in T, r_1, r_2 \in R \qquad \text{resource conversion}$$

$$s_{i,t} \leq z_{i,t}, \quad s_{i,t} \leq 1 - z_{i,t}, \quad s_{i,t} \geq z_{i,t} - z_{i,t-1} \qquad \forall i \in I, t \in T \qquad \text{activation}$$

$$\sum_{\tau\in T^{up}_{i,t}} \left(s_{i,t} - z_{i,t}\right) \leq 0, \quad \sum_{\tau\in T^{down}_{i,t}} \left(s_{i,t} + z_{i,t} - 1\right) \leq 0 \qquad \forall i \in I, t \in T \qquad \text{minimum up and down times}$$

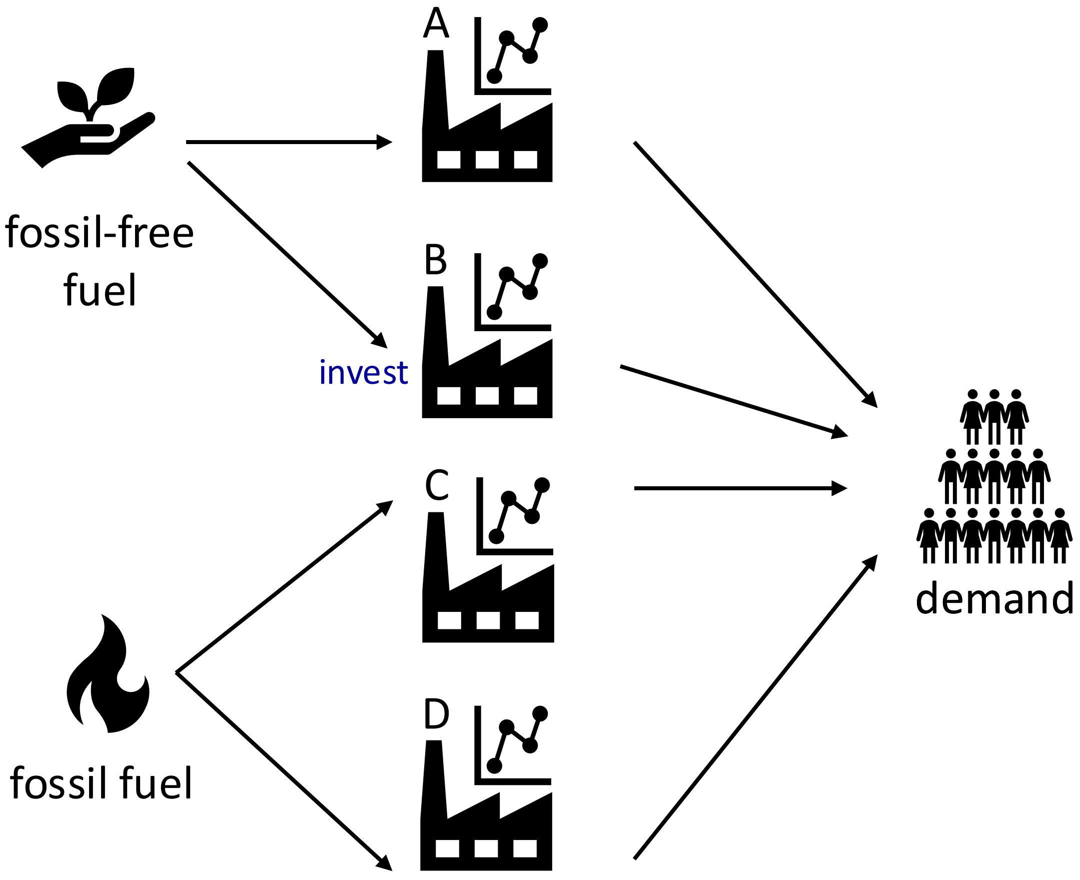
$$x^r_{t+1,i^{out}} - x^r_{t,i^{out}} \leq a^{up}_i, \quad x^r_{t,i^{out}} - x^r_{t+1,i^{out}} \leq a^{down}_i \qquad i \in \mathrm{I}, \mathrm{t} \in T, r \in R \qquad \text{ramping}$$

$$h^r_{t+1,k} = a^{loss}_{t,k} h^r_{t,k} + a^{load}_{t,k} x^r_{t,k^{in}} - a^{unload}_{t,k} x^r_{t,k^{out}} \qquad \mathrm{k} \in K, \mathrm{t} \in T, r \in R \qquad \text{storage management}$$

$$h, x, p, e \leq c_{max}, \quad h, x, p, e \geq c_{min} \qquad \text{capacities}$$

z = operation,	x = flow,	s = activation,
h = storage level,	p = resource import,	e = resource export

Design optimization



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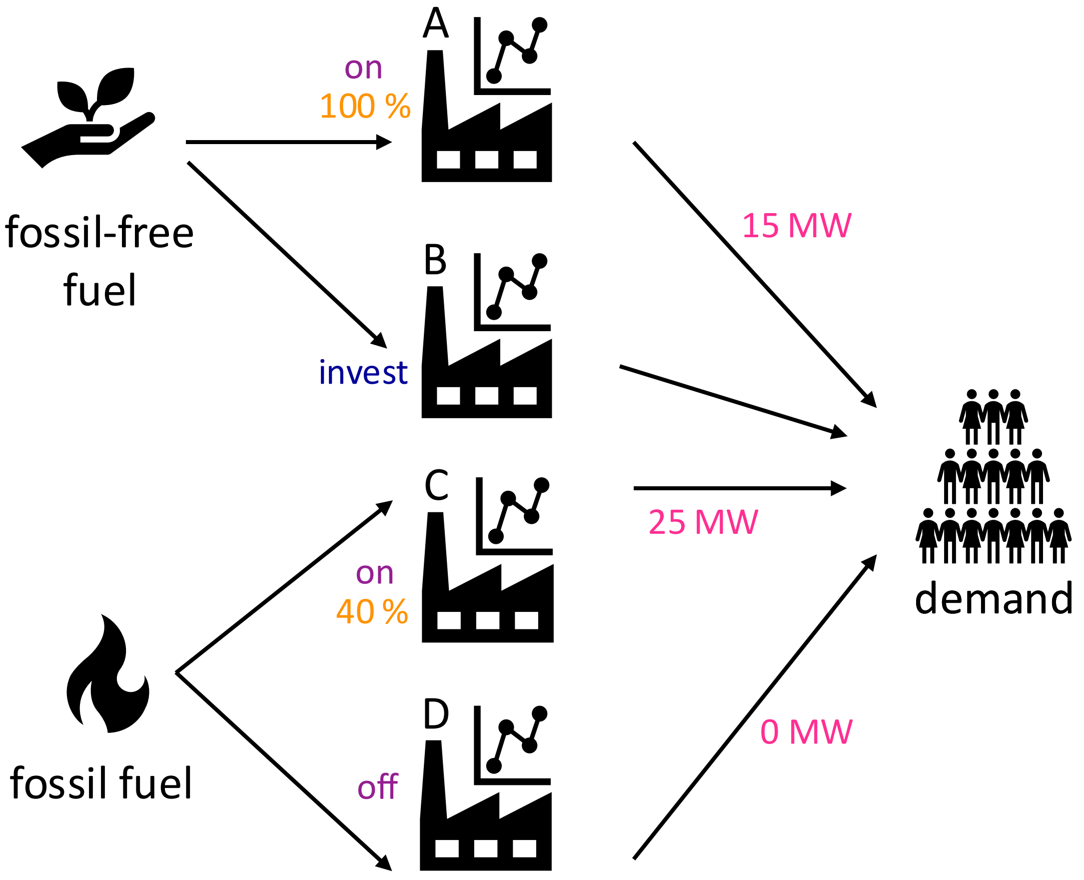
+

Design optimization or investment planning comprises:

- **design/investment decisions**: whether an investment is selected.

Design and operation optimization



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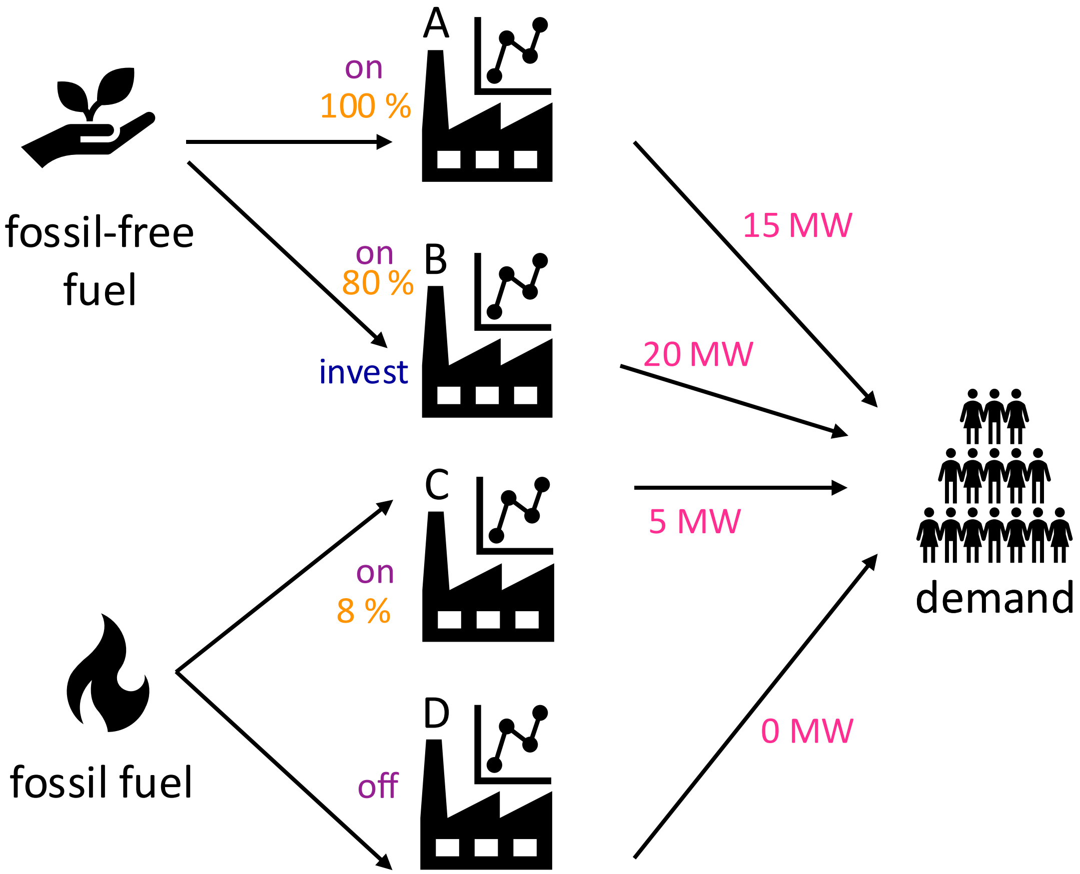

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BEW Berliner Energie und Wärme

MIP: design and operation optimization

ZIB ZUSE INSTITUTE BERLIN MODAL FORSCHUNGSCAMPUS

Main Variables:

$z_{i,t} \in \{0,1\}$	operation of unit i at time t
$x^r_{t,i^{in}}, x^r_{t,i^{out}} \in \mathbb{R}_{\geq 0}$	incoming/outgoing flow of resource r at unit i at time t
$\hat{\mathbf{z}}_i \in \{0,1\}$	**investment decision for unit i**
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$$\min \sum_{t \in T} costs^{op}(z_t, s_t, h_t, p_t, e_t, x_t) + costs^{inv}(\hat{\mathbf{z}})$$

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$\sum_{i\in I} x^r_{t,i^{out}} + \sum_{k\in K} x^r_{t,k^{out}} + p^r_t = D^r + \sum_{i\in I} x^r_{t,i^{in}} + \sum_{k\in K} x^r_{t,k^{in}} + e^r_t$	$\forall r \in R$	resource balancing
$\boldsymbol{z_{i,t} \leq \hat{z}_i}$	$\boldsymbol{\forall i \in I, t \in T}$	**investment decision**
$x^{r_2}_{t,i^{out}} = \varphi^{r_1,r_2}_{i,t}\left(x^{r_1}_{t,i^{in}}\right)$	$\forall i \in \mathrm{I}, \mathrm{t} \in T, r_1, r_2 \in R$	resource conversion
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$x^r_{t+1,i^{out}} - x^r_{t,i^{out}} \leq a^{up}_i, \quad x^r_{t,i^{out}} - x^r_{t+1,i^{out}} \leq a^{down}_i$	$i \in \mathrm{I}, \mathrm{t} \in T, r \in R$	ramping
$h^r_{t+1,k} = a^{loss}_{t,k} h^r_{t,k} + a^{load}_{t,k} x^r_{t,k^{in}} - a^{unload}_{t,k} x^r_{t,k^{out}}$	$\mathrm{k} \in K, \mathrm{t} \in T, r \in R$	storage management
$h, x, p, e \leq c_{max}, \quad h, x, p, e \geq c_{min}$		capacities

z = operation, **$\hat{z}$ = investment decision**, x = flow, s = activation,
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Objectives:

$$\min \sum_{t \in T} costs^{op}(z_t, s_t, h_t, p_t, e_t, x_t) + costs^{inv}(\hat{\mathbf{z}})$$

MIP: multi-objective design and operation optimization

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Objectives:

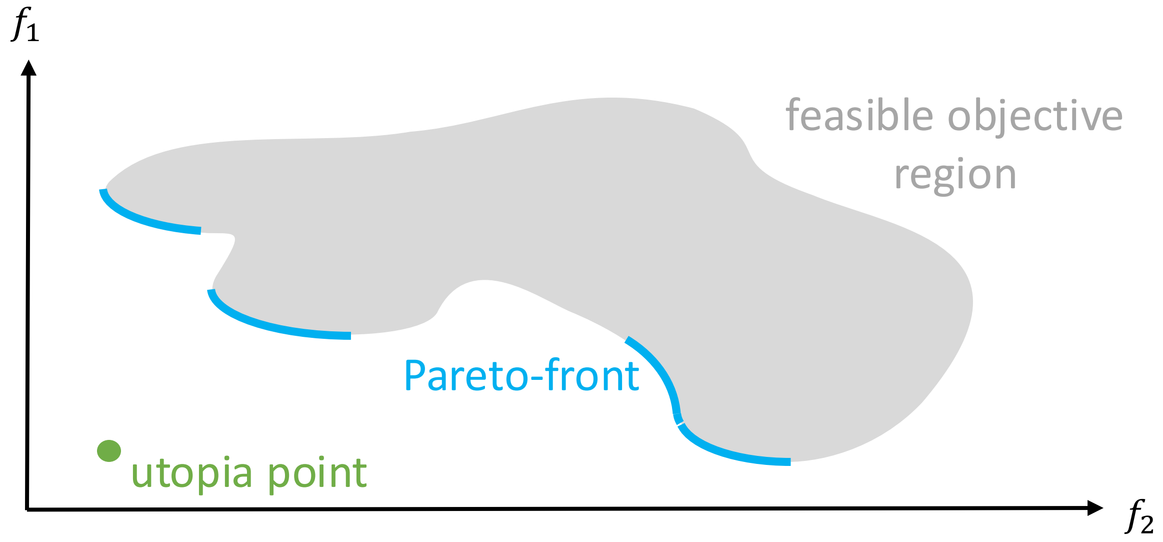
$$\min\left(\underbrace{f_1^{inv}(\hat{z}) + \sum_{t\in T} f_1^{op}(z_t, s_t, h_t, p_t, e_t, x_t)}_{\text{costs}}, \quad \underbrace{\sum_{t\in T} f_2(p_t, x_t)}_{\text{emissions}}, \quad \underbrace{\sum_{t\in T} f_3(x_t)}_{\text{CHP heat}} \right)$$

(CHP = combined heat and power plants)

Multi-objective optimization (MOO)

Let $f_i\colon X \to \mathbb{R}$, $i \in \{1, \dots, k\}$ be k objective functions of a minimization problem. Given two feasible solutions $x_1, x_2 \in X$, x_1 **dominates** x_2 if

$$\forall i \in \{1, \dots, k\}\colon f_i(x_1) \le f_i(x_2) \text{ and } \exists i \in \{1, \dots, k\}\colon f_i(x_1) < f_i(x_2).$$



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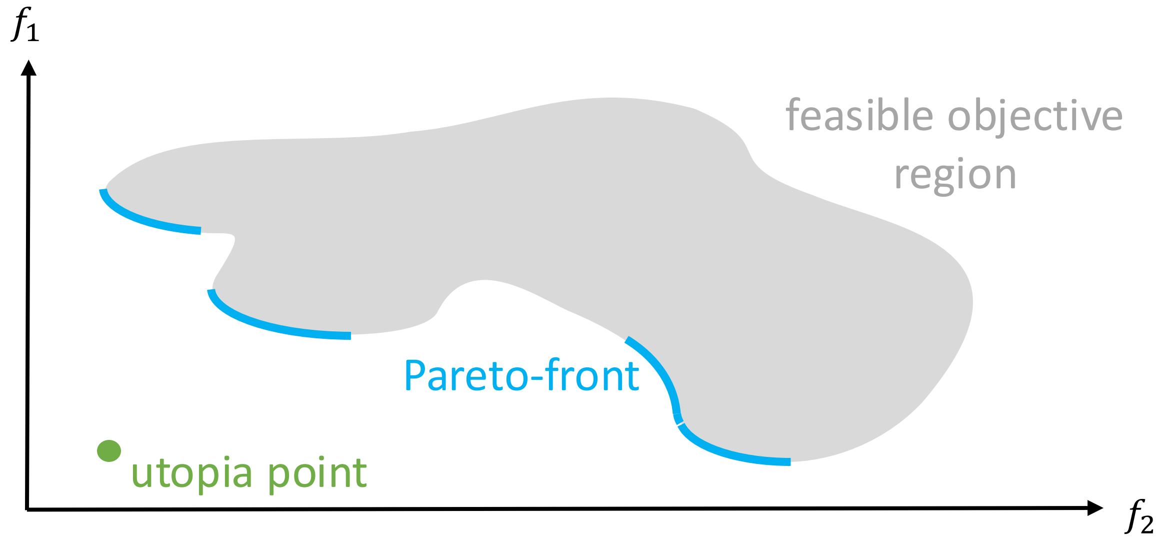

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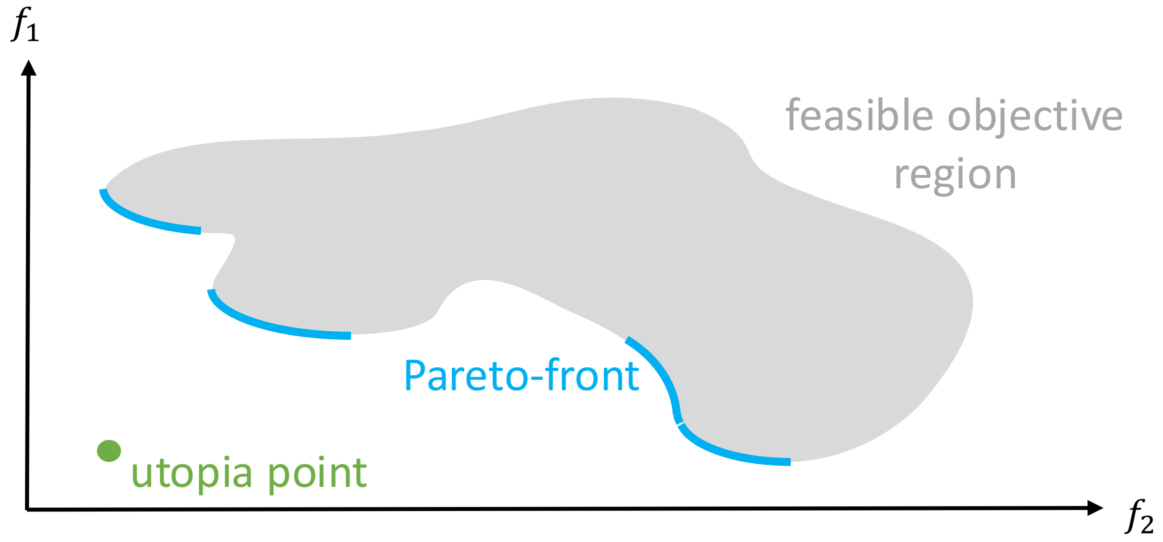
The set of Pareto-optimal solutions is called **Pareto-front**.



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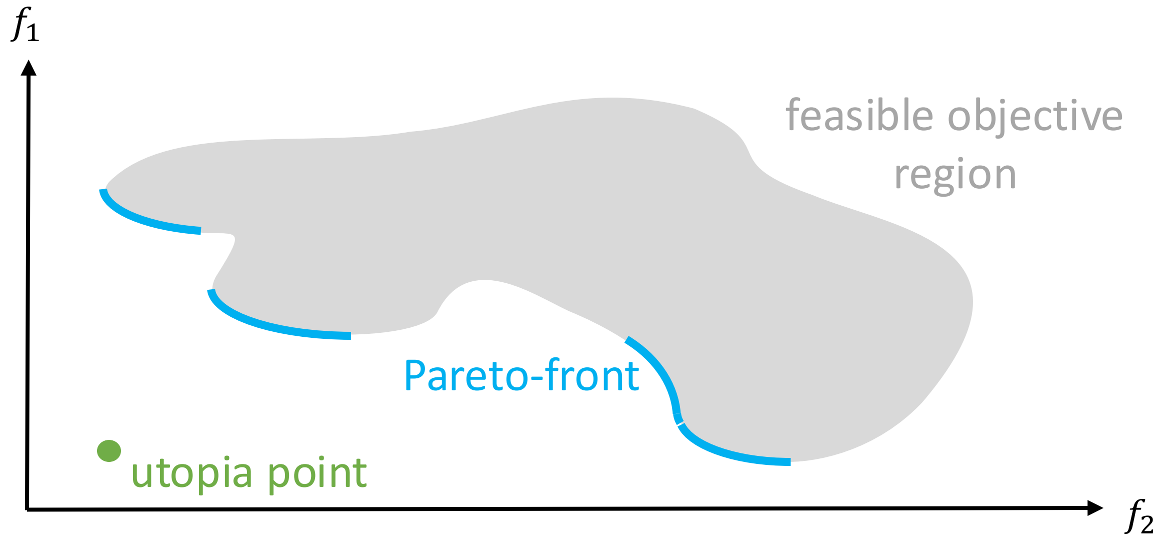

→ Compute a relevant subset of the Pareto-front.
→ Transform a multi-objective problem into a single-objective problem by combining the objectives *somehow*.

Classical MOO approaches

Weighted sum

$$\min_x \; f_1(x), f_2(x), f_3(x) \quad \text{s.t.} \quad x \in X$$

+

$$(w_1, w_2, w_3) \in [0,1]^3 \qquad \sum_i w_i = 1$$

$$\min_x \; w_1 f_1(x) + w_2 f_2(x) + w_3 f_3(x) \quad s.t. \quad x \in X$$

Classical MOO approaches

Weighted sum

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→

$$\min_x \; w_1 f_1(x) + w_2 f_2(x) + w_3 f_3(x) \quad s.t. \quad x \in X$$

Epsilon constraint

$$\min_x \; f_1(x), f_2(x), f_3(x) \quad \text{s.t.} \quad x \in X$$

+

$$(\varepsilon_2, \varepsilon_3) \in \mathbb{R}^2$$

→

$$\begin{aligned} \min_x \; & f_1(x) \\ s.t. \; & x \in X \\ & f_2(x) \le \varepsilon_2 \\ & f_3(x) \le \varepsilon_3 \end{aligned}$$

Classical MOO approaches

Weighted sum

$$\min_x \; f_1(x), f_2(x), f_3(x) \quad \text{s.t.} \quad x \in X$$

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$$(w_1, w_2, w_3) \in [0,1]^3, \quad \sum_i w_i = 1$$

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$$\min_x \; w_1 f_1(x) + w_2 f_2(x) + w_3 f_3(x) \quad s.t. \quad x \in X$$

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→

$$\begin{aligned} \min_x \;& f_1(x) \\ s.t. \;& x \in X \\ & f_2(x) \leq \varepsilon_2 \\ & f_3(x) \leq \varepsilon_3 \end{aligned}$$

Lexicographic optimization

$$\min_x \; f_1(x), f_2(x), f_3(x) \quad \text{s.t.} \quad x \in X$$

→

$$f_1^{opt} = \min_x \; f_1(x) \quad s.t. \quad x \in X$$

$$\begin{aligned} f_2^{opt} = \min_x \;& f_2(x) \\ s.t. \;& x \in X \\ & f_1(x) \leq f_1^{opt} \end{aligned}$$

$$\begin{aligned} f_3^{opt} = \min_x \;& f_3(x) \\ s.t. \;& x \in X \\ & f_1(x) \leq f_1^{opt} \\ & f_2(x) \leq f_2^{opt} \end{aligned}$$

Classical MOO approaches

	weighted sum	epsilon constraint	lexicographic
number of generated solutions	number of weight vector samples	number of epsilon vector samples	1
number of unique, non-dominated solutions	major reduction by filtering for non-dominated solutions		1
placement of solutions	only on convex hull of Pareto-front	on convex and non-convex parts of Pareto-front	
number of optimization calls	number of weight samples	number of epsilon samples	number of objectives

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	often used in practice	*often best solution quality, but computational effort*	*used when one solution is enough*

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Design and operation optimization for 2 objectives

Lexicographic optimization

$$\min_x \quad f_1(x), f_2(x) \qquad \text{s.t.} \quad x \in X$$

1.
$$f_1^{opt} = \min_x \; f_1(x) \quad s.t. \; x \in X$$

2.
$$f_2^{opt} = \min_x \; f_2(x) \quad s.t. \; x \in X, \quad f_1(x) \le f_1^{opt}$$

Lexicographic optimization with iterative relaxation on objective 1

$$\min_x \quad f_1(x), f_2(x) \qquad \text{s.t.} \quad x \in X$$

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$$f_1^{opt} = \min_x \; f_1(x) \quad s.t. \; x \in X$$

2.
$$f_2^{opt} = \min_x \; f_2(x) \quad s.t. \; x \in X, \quad f_1(x) \le (1 + p) * f_1^{opt}$$

$p \in \{0.05, 0.1, 0.15, 0.2, 0.25, 0.3\}$

Design and operation optimization for 2 objectives

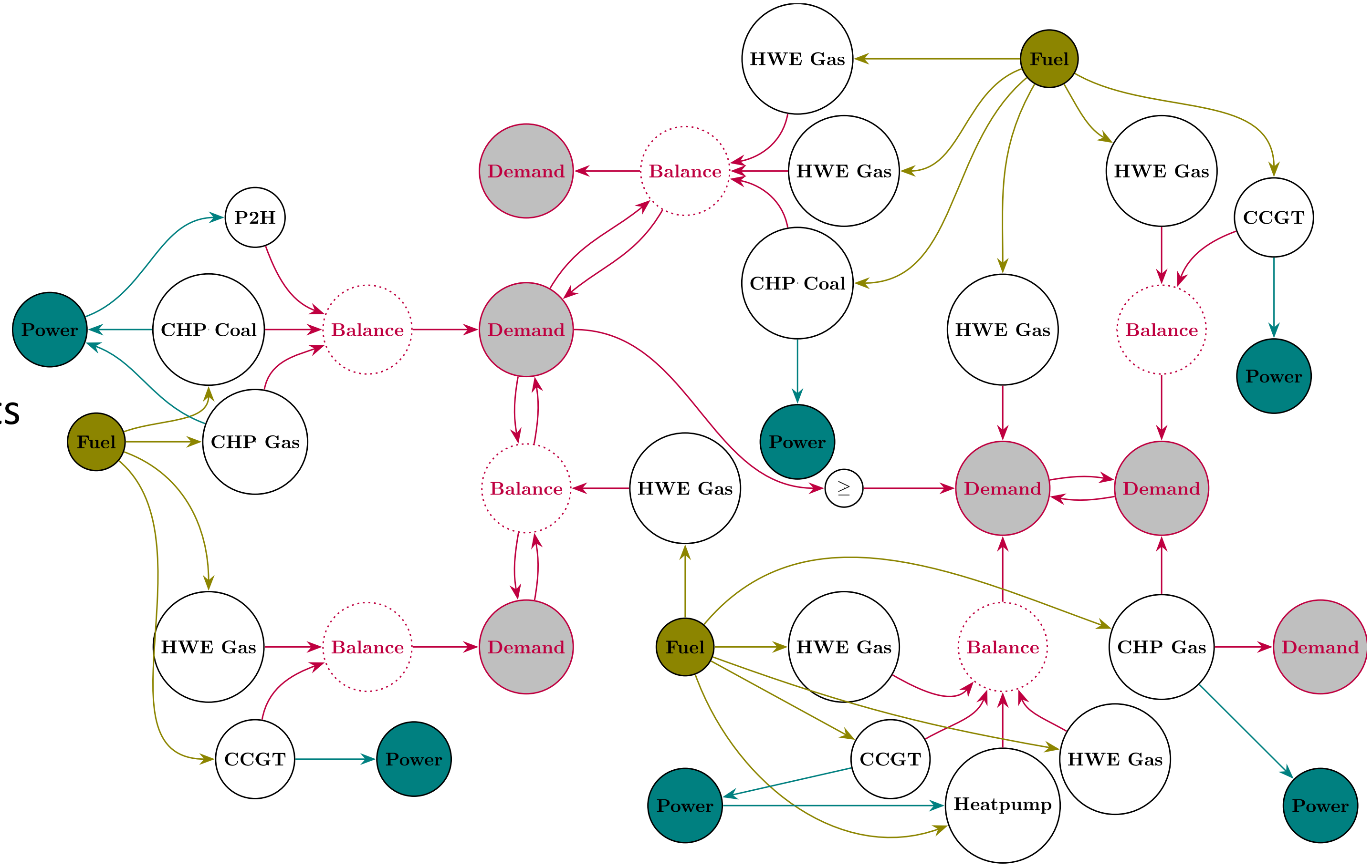
Model: Berlin, Germany

- Heat generation:
  - Gas heating plants (43%)
  - CHP (= combined heat and power plant)
  - CCGT (= combined cycle gas turbine)
  - P2H
  - Heatpump
- heat storages
- + 38 strategically chosen potential investments

Time horizon: 25 years with a 24h time step

Problem	operation + design optimization
Objectives	costs, emissions
Method	lexicographic with iterative relaxations

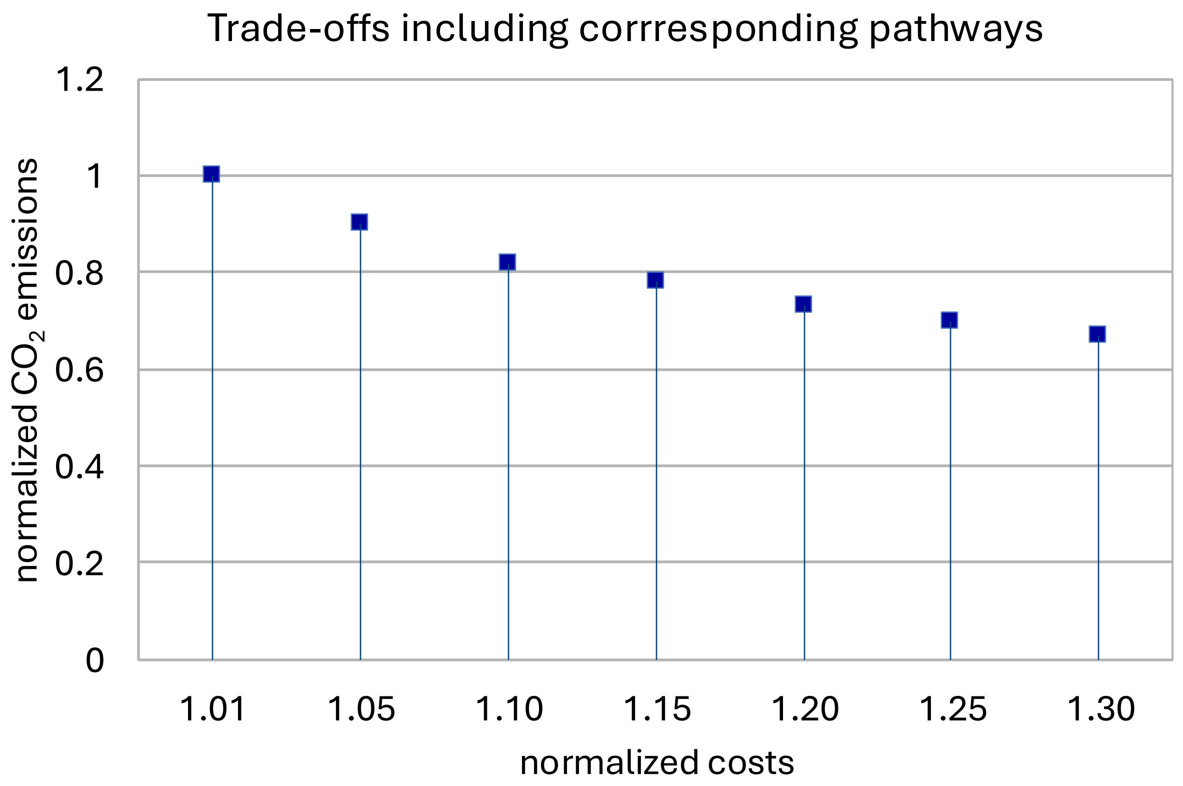
Simplified model structure:



- Graph with 2.9K nodes and 3.8K edges
- 3.6M variables and 3.5M constraints

Design and operation optimization for 2 objectives

Costs	CO_2	No. of Investments
101%	100%	11
105%	90%	11
110%	82%	11
115%	78%	10
120%	73%	10
125%	70%	11
130%	67%	11



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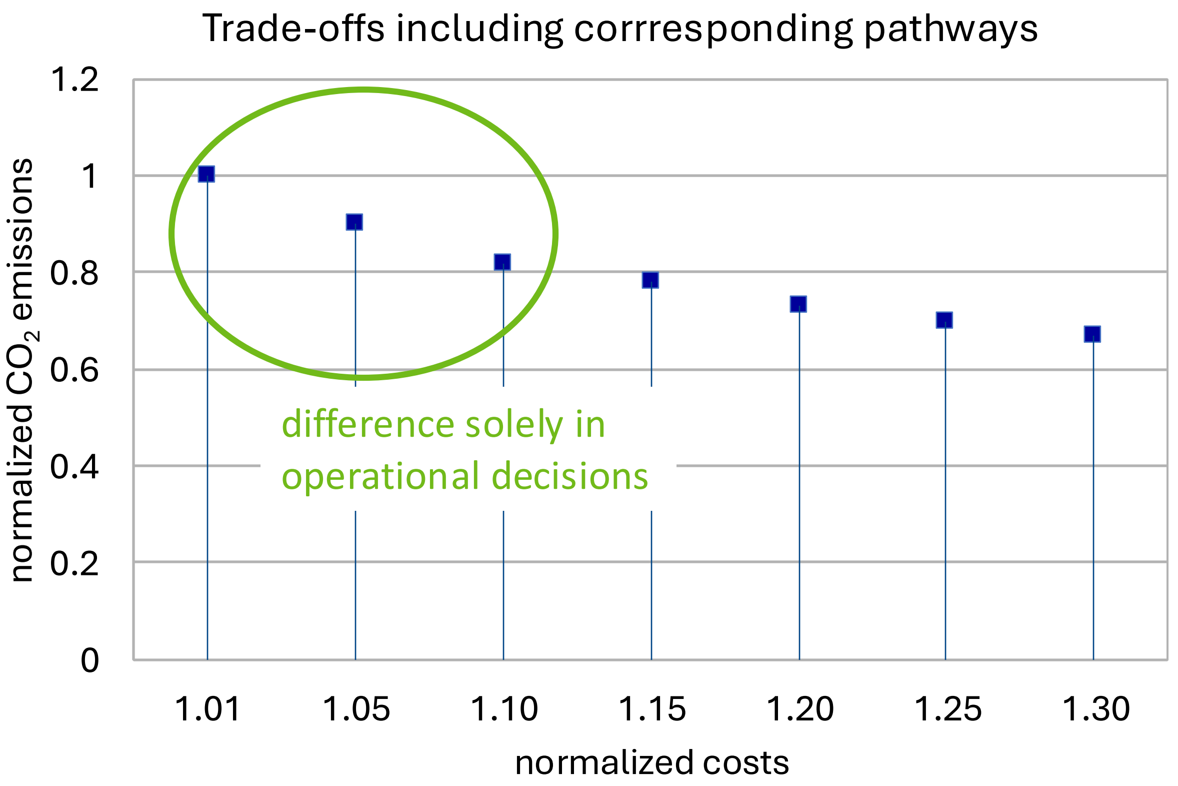


→ Integrating investment planning into unit commitment is important to make informed decisions!

Design and operation optimization for 2 objectives

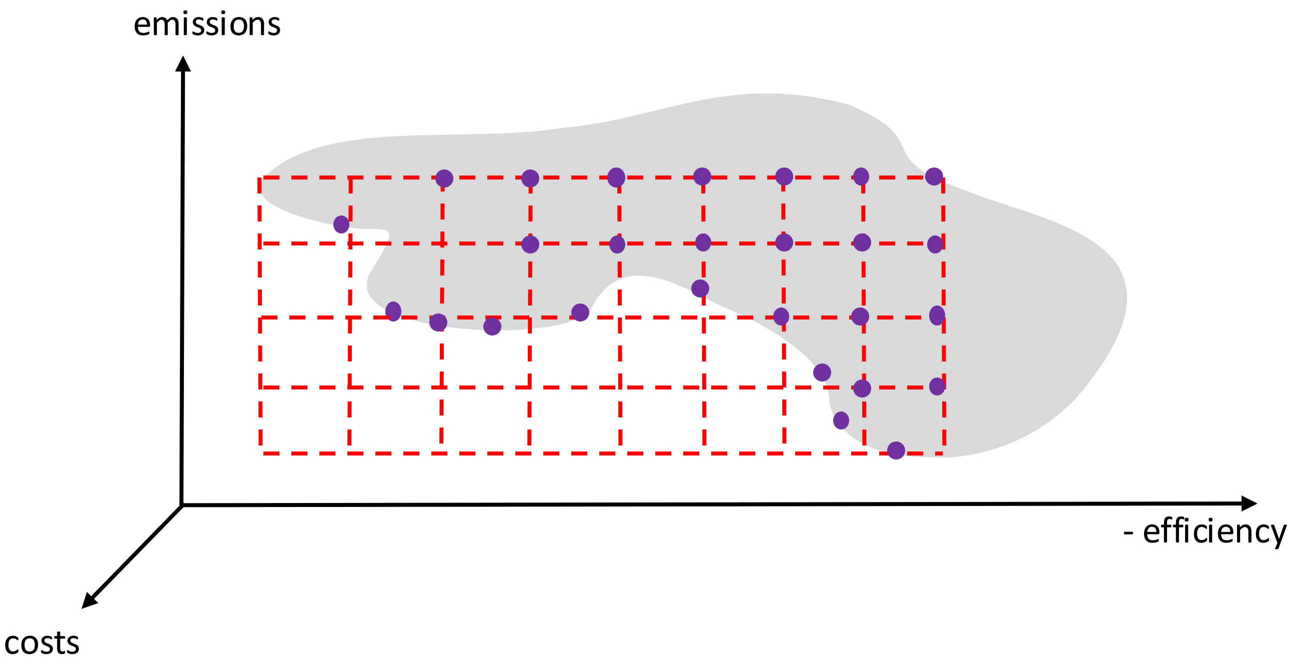
Costs	101%	105%	110%	115%	120%	125%	130%
CO_2	100%	90%	82%	78%	73%	70%	67%
CHP	1	1	1	1	1	1	1
CHP	1	1	1	1	1	1	1
Block CHP	1	1	1	1	1	1	1
CCGT	1	1	1	1	1	1	1
Heating station (Wood)	1	1	1	1	1	1	1
Gas turbine upgrade	1	1	1	1	1	1	1
Gas turbine	1	1	1	1	1	1	1
Gas turbine	1	1	1	1	1	1	1
Gas turbine	1	1	1	1	1	1	1
Gas turbine	1	1	1	1	1	1	1
Gas turbine	1	1	1	0	0	0	0
Electrical heater 120 MW	0	0	0	0	0	1	1
Seasonal Storage, heating station, electrical heater, heat pump, etc.	0	0	0	0	0	0	0

robust investments

target-dependent investments

Operation optimization for 3 objectives

Algorithm 1: Fixed grid epsilon-constraint method
(Mavrotas et al., 2009)

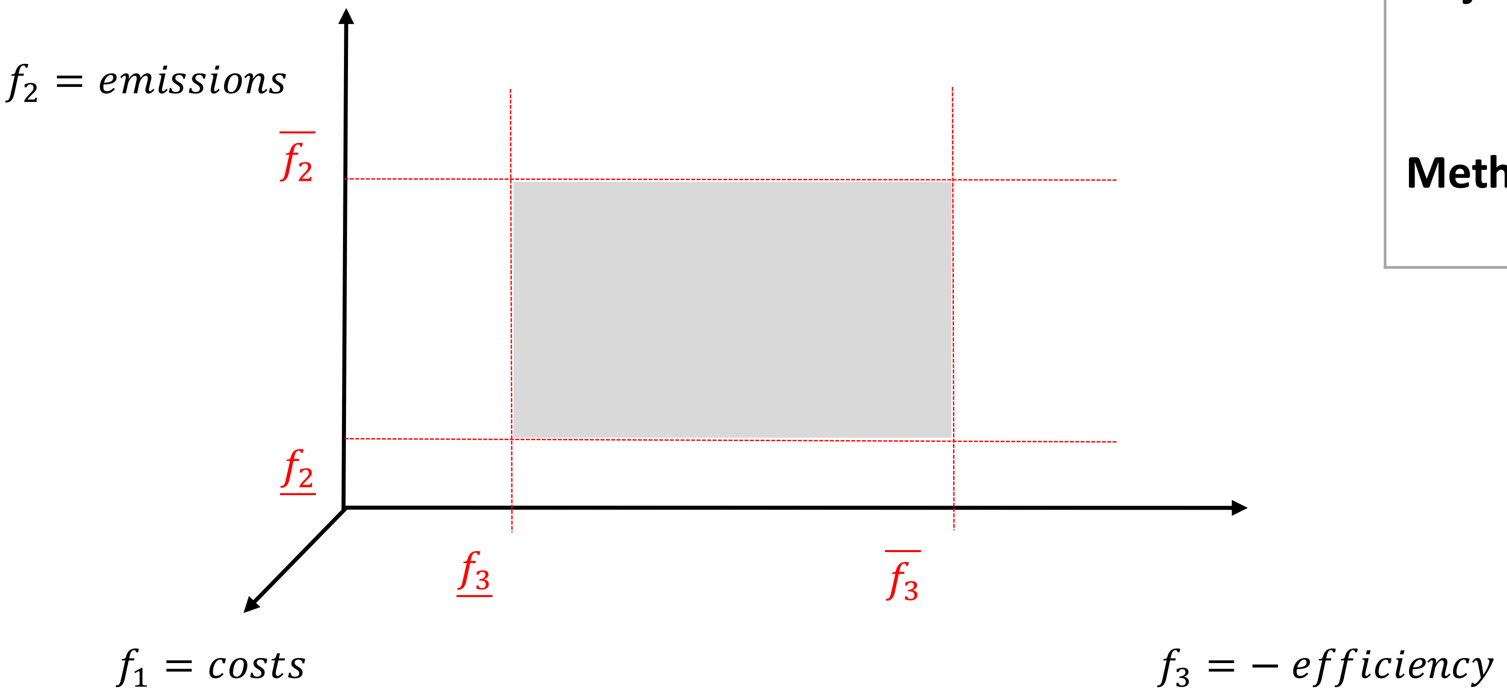


Problem	operation optimization
Objectives	costs, emissions, CHP-heat
Method	epsilon-constraint method (fixed grid)

Operation optimization for 3 objectives

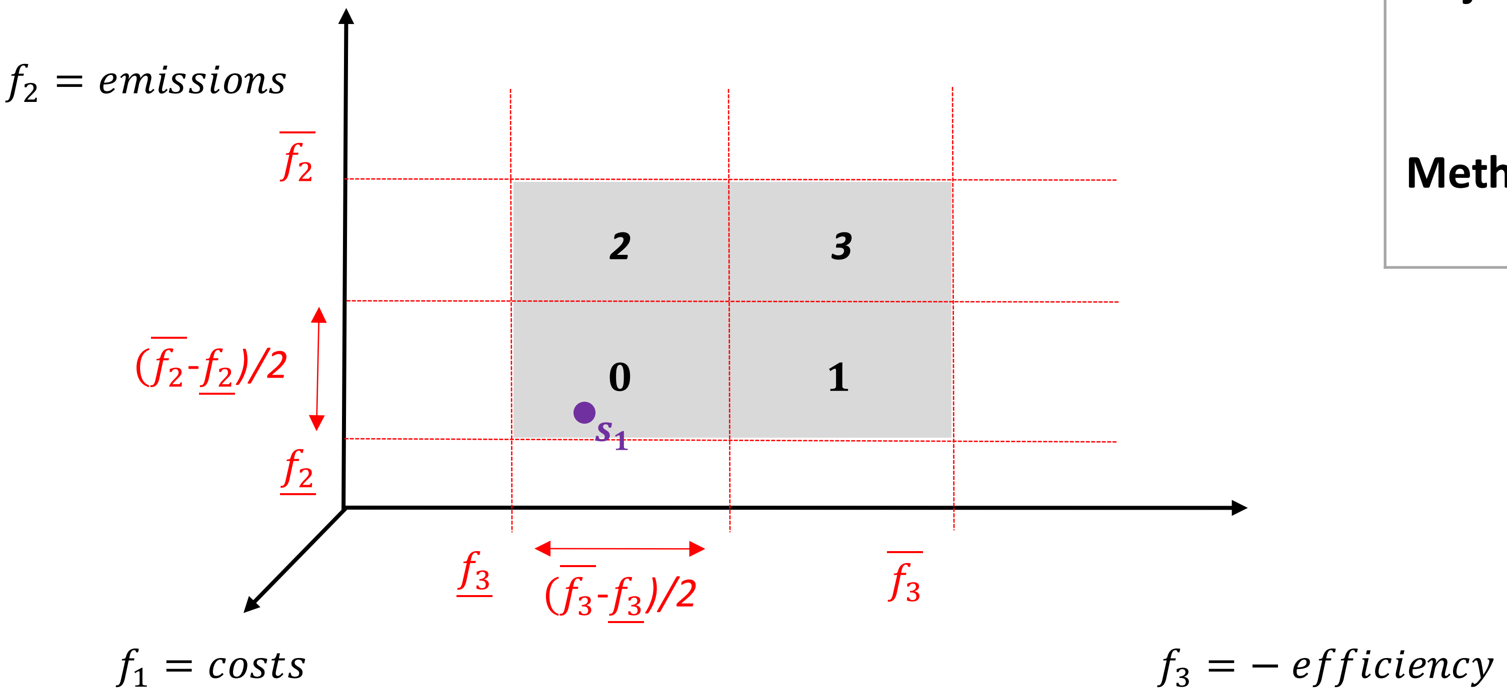
Algorithm 2: Dynamic grid epsilon-constraint method
(Laumanns et al., 2006)

Problem	operation optimization
Objectives	costs, emissions, CHP-heat
Method	epsilon-constraint method (dynamic grid)



Operation optimization for 3 objectives

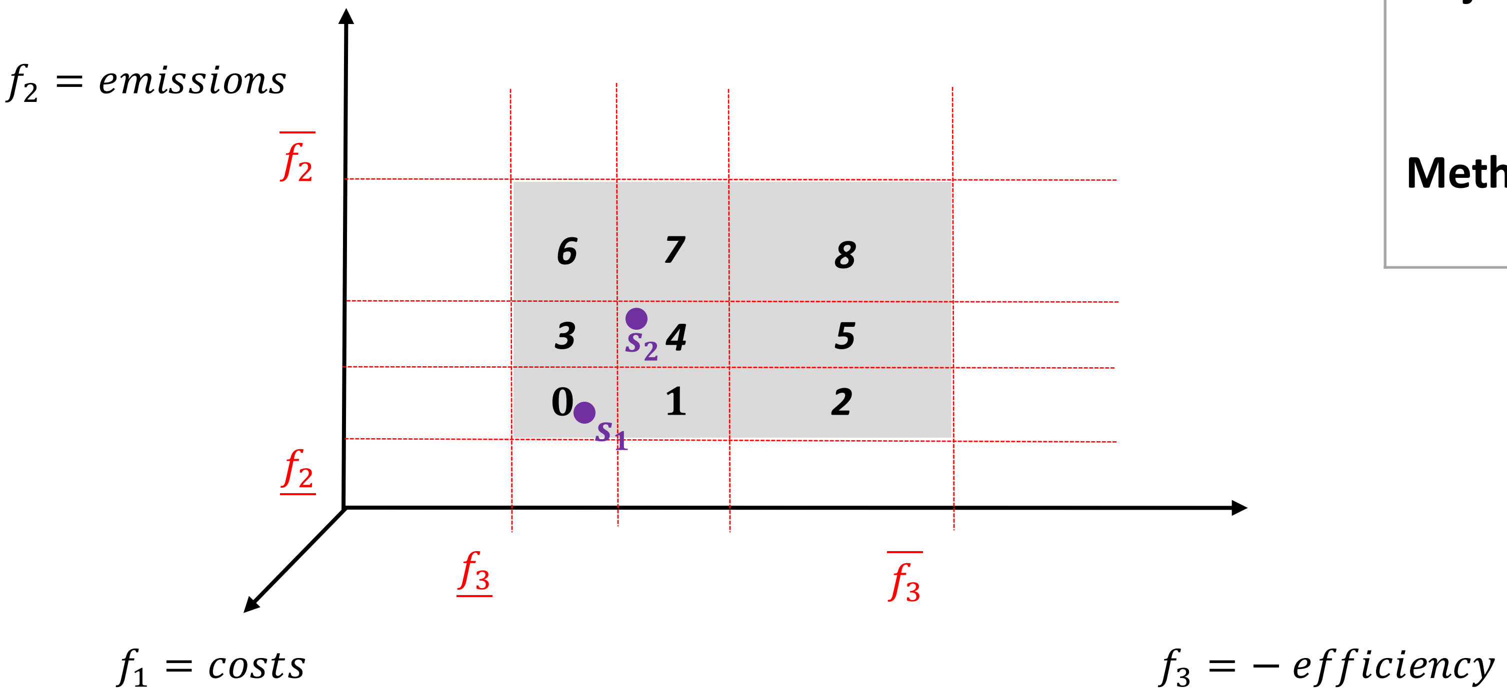
Algorithm 2: Dynamic grid epsilon-constraint method (Laumanns et al., 2006)



Problem	operation optimization
Objectives	costs, emissions, CHP-heat
Method	epsilon-constraint method (dynamic grid)

Operation optimization for 3 objectives

Algorithm 2: Dynamic grid epsilon-constraint method
(Laumanns et al., 2006)



Problem	operation optimization
Objectives	costs, emissions, CHP-heat
Method	epsilon-constraint method (dynamic grid)

Operation optimization for 3 objectives

Model: singular district of Berlin, Germany (about 17,000 connected households)

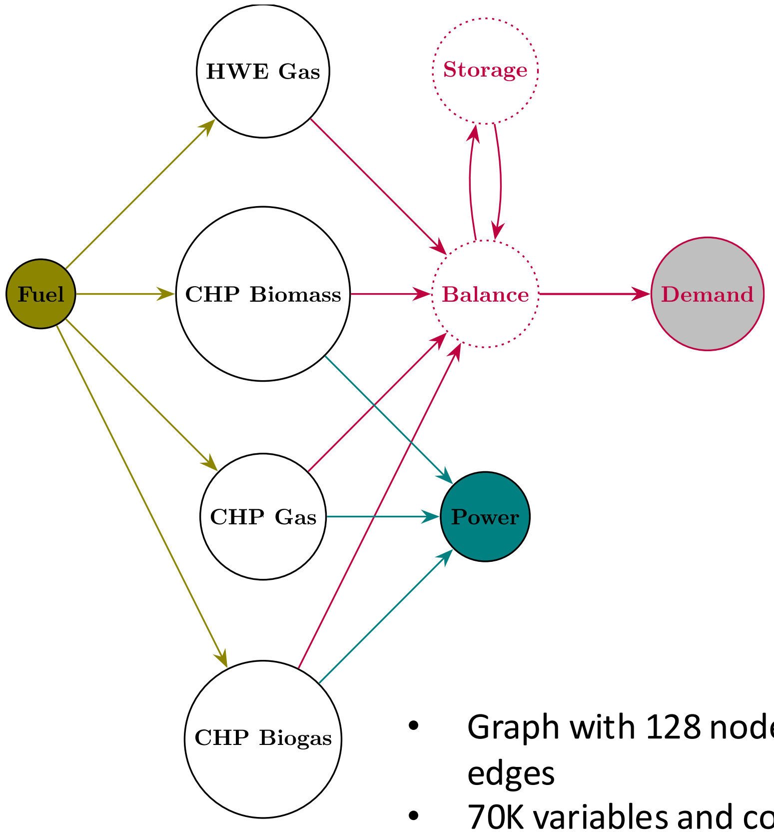
- Heat generation (share of total capacity):
  - Gas heating plant 81.6%
  - Biomass CHP 16.8%
  - Gas CHP (CHP1) 1.3%
  - Biogas CHP (CHP2) 0.2%

  (CHP = combined heat and power plant)
- Small heat storage

Time horizon: 1 month of different heating periods (high season, conclusion) with a 4h time step.

Problem	operation optimization
Objectives	costs, emissions, CHP heat
Method	epsilon-constraint methods (fixed and dynamic grid)

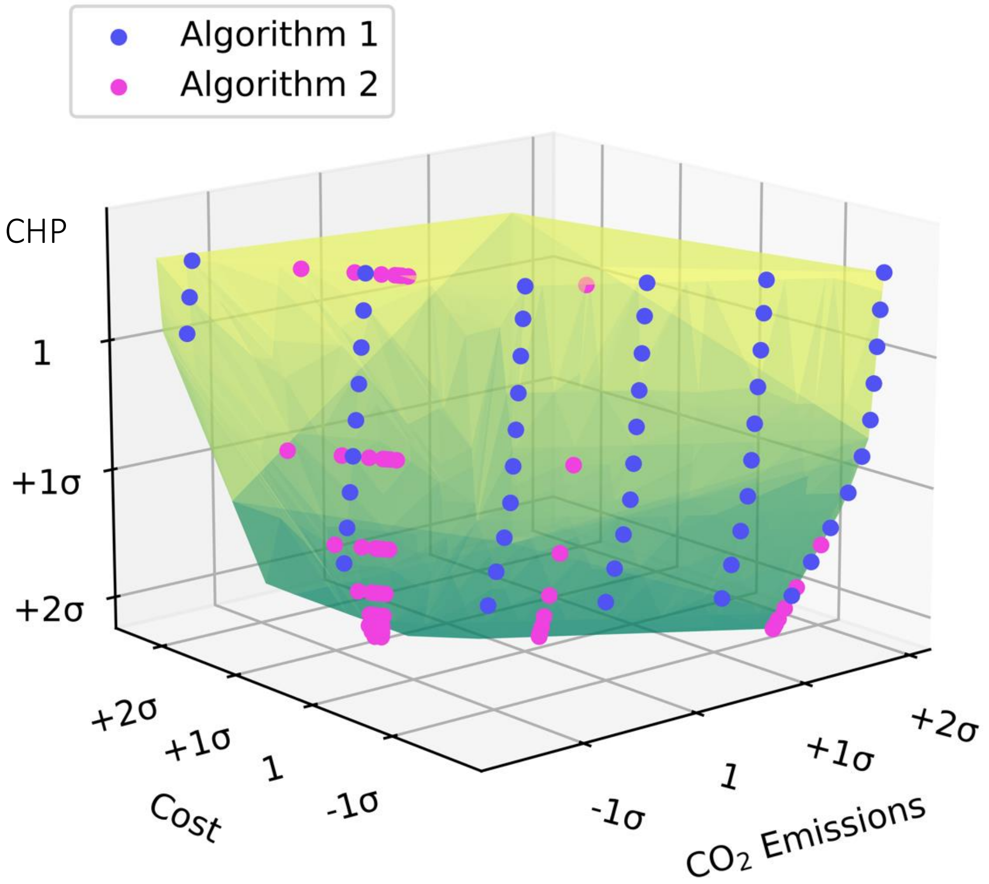
Simplified model structure:



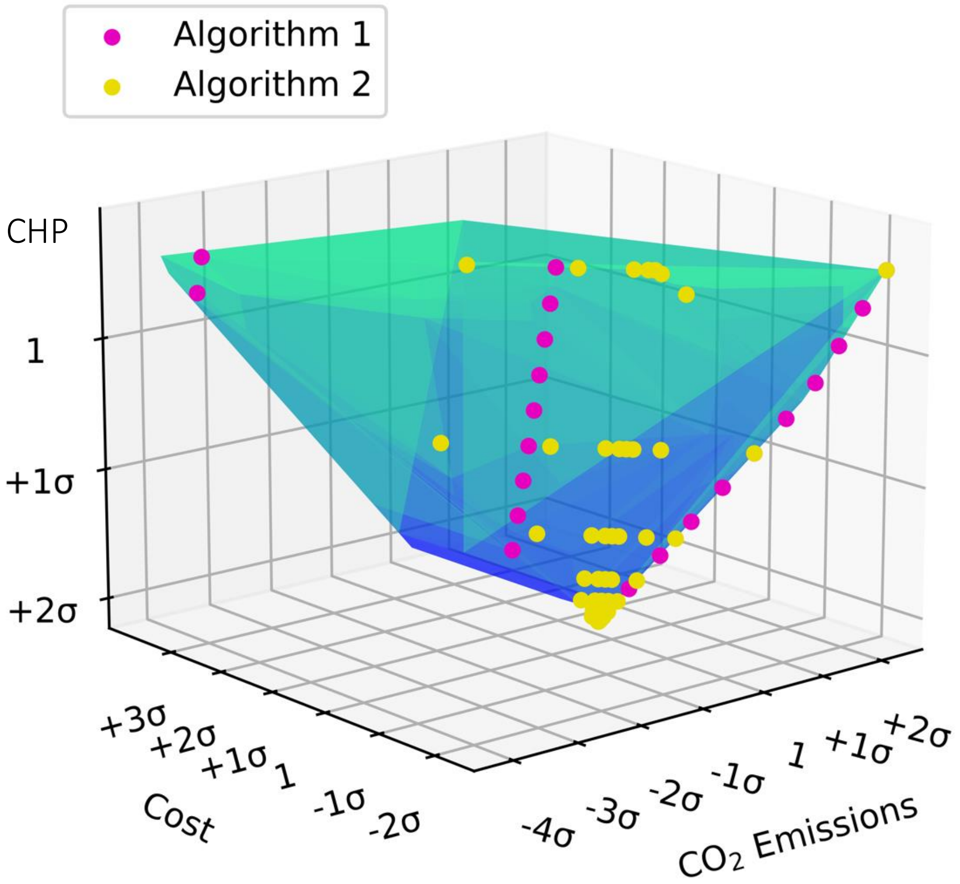
- Graph with 128 nodes and 171 edges
- 70K variables and constraints

Operation optimization for 3 objectives

conclusion month



high season month



Operation optimization for 3 objectives

	fixed grid	dynamic grid
grid	+ − fixed	+ − dynamic + depends on the shape of the feasible space
runtime	+ grid can be adapted to runtime needs	− computational efficiency not known before runtime, depends on feasible space
works best, when the feasible space is …	+ − dense	+ − sparse
coverage	+ overview of the shape of the Pareto front	+ finds solutions clustered in small regions
termination	− after all grid cells have been searched	+ − after given size or number of cells + for large regions when infeasible
parallelization	+ yes	− limited

Operation optimization for 3 objectives

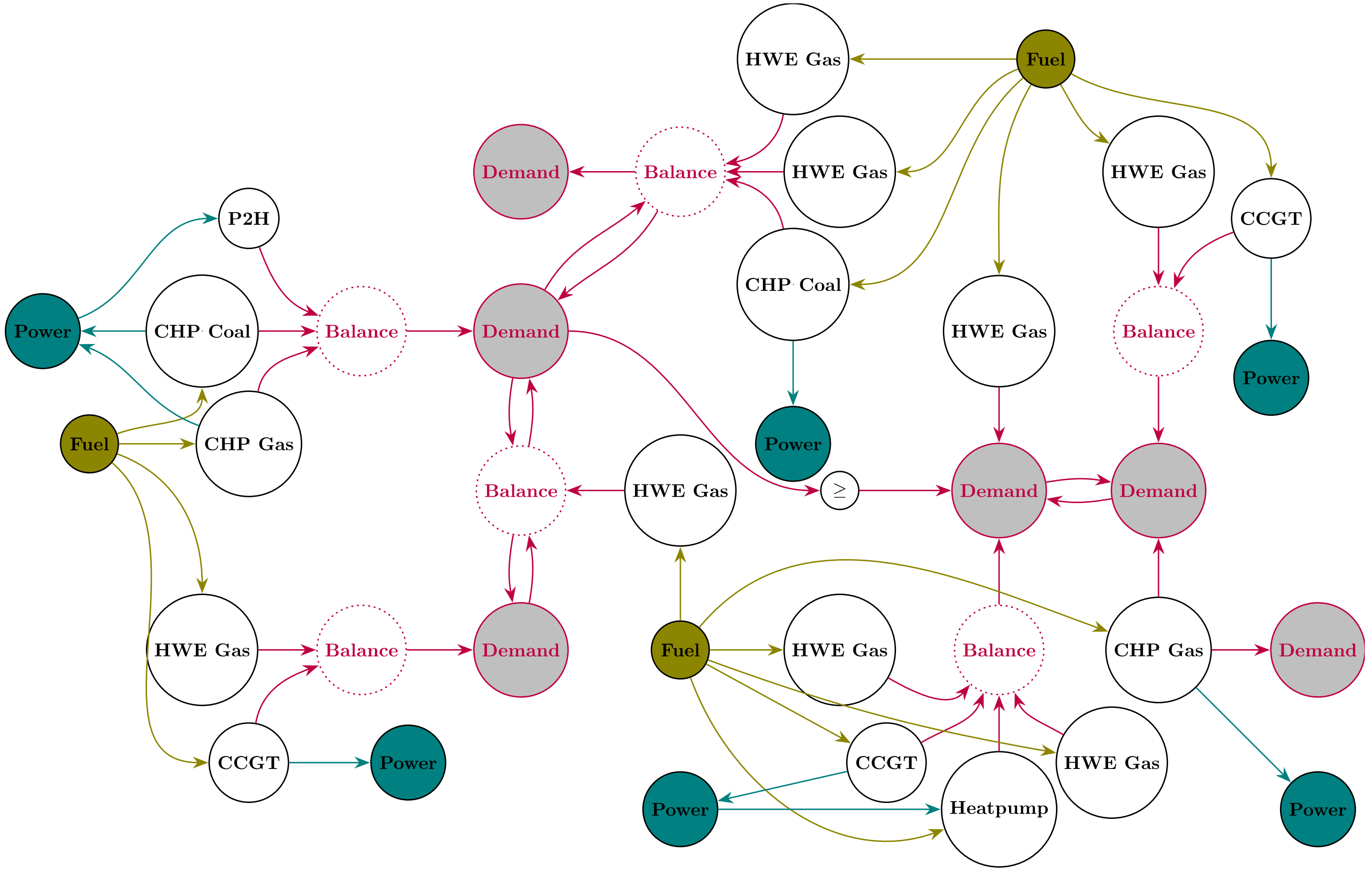
Model: Berlin, Germany

- Heat generation:
  - Gas heating plants (43%)
  - CHP (= combined heat and power plant)
  - CCGT (= combined cycle gas turbine)
  - P2H
  - Heatpump
- heat storages

Time horizon: 1 year with a 24h time step

Problem	operation + design optimization
Objectives	costs, emissions, CHP-heat
Method	epsilon-constraint method (fixed grid)

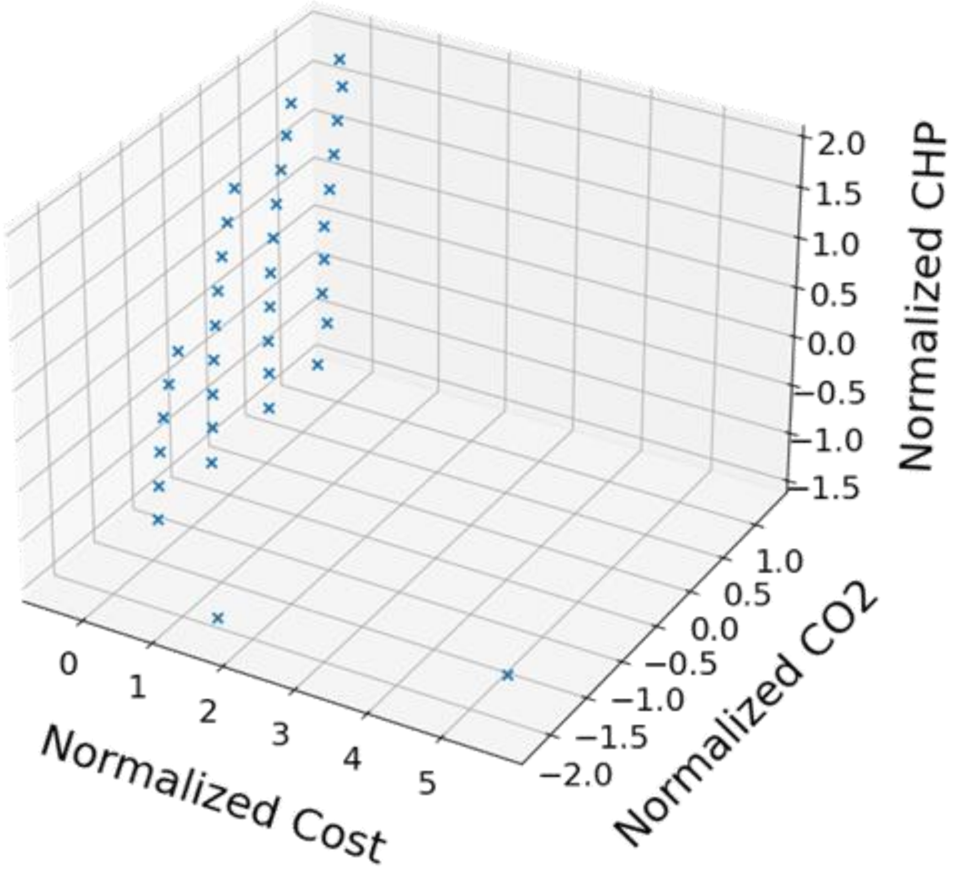
Simplified model structure:

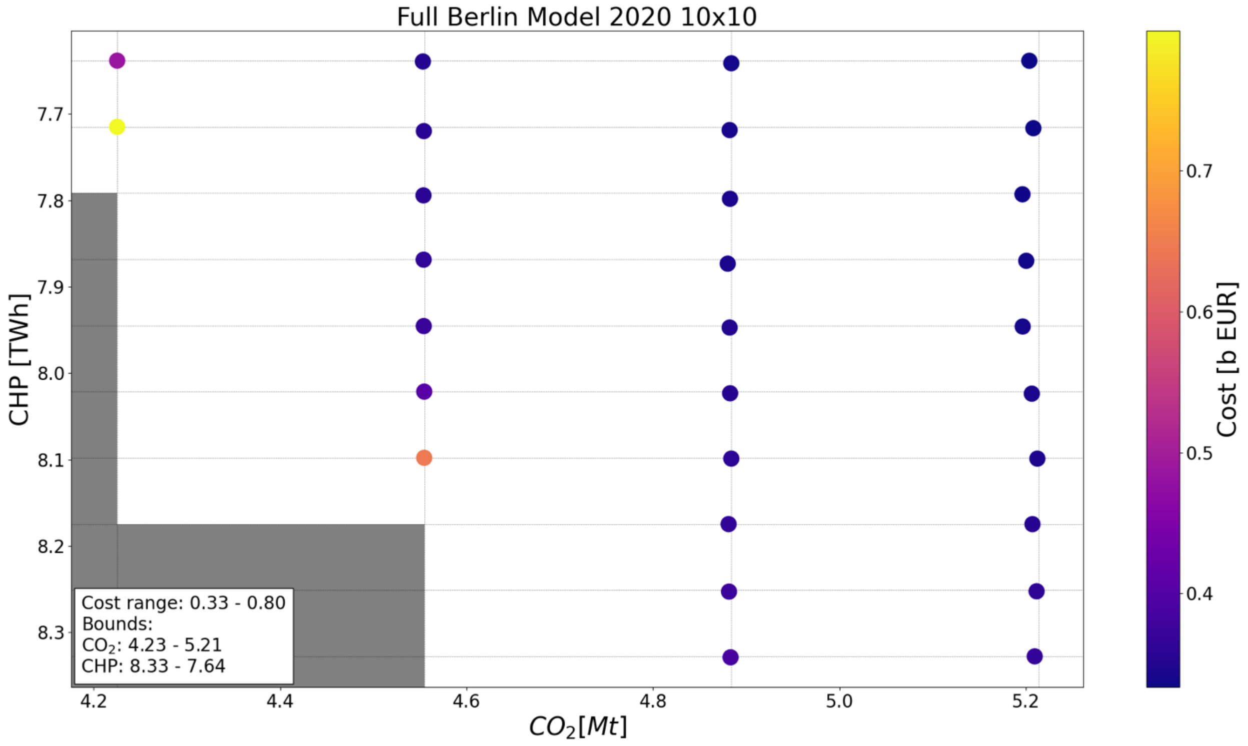


- Graph with 2.9K nodes and 3.8K edges
- 3.0M variables and 2.9M constraints

Operation optimization for 3 objectives

Berlin 2020 Pareto Front - Normalized





Conclusion

✓ formulation of integrated design and operation optimization problem in one mixed integer program

✓ generating solutions with reasonable trade-offs is possible by lexicographic optimization with iterative relaxations

✓ computing a relevant subset of Pareto-optimal solutions for operation optimization is possible by versions of epsilon-constraint method

but:

✗ not efficiently solvable (e.g. the computation of a cost optimal solution takes >50h)

✗ solvable only under restrictions in time granularity and increased MIP-gap

✗ solving integrated design and operation optimization for three objectives for complete Berlin and complete time horizon still open

We‘re on it: TrU-5 Multi-Objective Optimization for Sustainable Energy System Planning