

# Optimal investment strategies for district heating plants under prediction uncertainties for cost parameters

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# Overview

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An investment model for district heating generation is developed that particularly concerns prediction uncertainties of cost parameters. It will be based on three different methods:

- ❖ **Generation expansion planning.**

For cost-optimal power plant investments a linear program is well-established in energy economics.

- ❖ **CHP planning.**

A simple model for short-term CHP planning is described that will be used to adapt the standard GEP formulation for district heating investments.

- ❖ **Risk measures for prediction uncertainties.**

The impact of prediction uncertainties on the heat generation costs will be quantified by risk measures that are widely used in financial mathematics.

# Methodolgy

# I. Generation expansion planning

## 1. Hourly generation decisions:

Minimizing the hourly generation costs  $V_{i,h}$  (in Euro/MWh) of the  $i^{\text{th}}$  power plant with generation  $g_{i,h}$  MWh.

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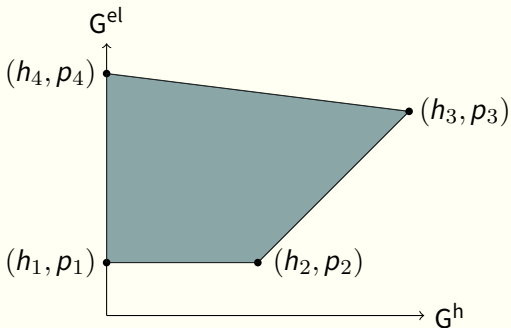
## 2. Yearly investment decisions:

Minimizing the yearly fixed costs  $F_{i,t}$  in Euro/kW with binary investment decisions  $n_{i,t}$  while taking operation costs  $O_t(n_{i,t})$  into account:

$$\min_{n_{i,t}} \sum_{i,t} \sum_{s=1}^t F_{i,t} n_{i,s} + O_t(n_{i,t})$$

## II. CHP planning

The feasible operation region of a CHP plant with power generation  $G^{\text{el}}$  and heat generation  $G^{\text{h}}$  is modelled as a convex polygon with extreme points  $(h_1, p_1), (h_2, p_2), \dots$



Any point in the feasible operation region can be displayed as a convex combination of those four extreme points  $j = 1, \dots, 4$  resulting in the minimum variable costs:

$$\min \sum_i \sum_{j \in J_i} \lambda_{i,j} v_{i,j} \quad \text{st} \dots$$

# III. Risk measures

For measuring the impact of prediction uncertainties of the cost parameters (gas, electricity, CO<sub>2</sub> emissions, ...) on the distribution of the overall heat generation costs risk measures are used. Most common examples include:

- ❖ **Volatility risk measure** ( $\mu + \sigma$ ): classic dispersion based risk measure.
- ❖ **Value-at-risk** ( $\text{Var}_\alpha$ ): maximum costs for heat generation in the best  $\alpha\%$  of all possible cases.
- ❖ **Expected shortfall** ( $\mathbb{E}S_\beta$ ): average costs for heat generation in the worst  $\beta\%$  of all possible cases.



# Optimization program (simplified)

## 1. Hourly generation decisions:

The hourly generation costs  $O_h(n_{i,t}, \omega)$  depend on  $\omega \in \Omega$  and are therefore random variables.

$$O_h(n_{i,t}, \omega) := \min_{\lambda} \sum_{i \in I} \sum_{j \in J_i} \left( V_{i,h,j}(\omega) - g_{i,h,j}^{\text{el}}(\omega) s_h(\omega) \right) \lambda_{i,h,j}(\omega)$$

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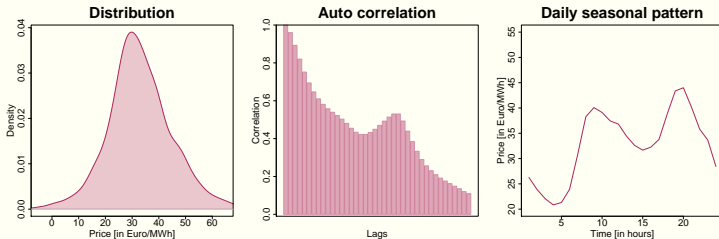
## 2. Yearly investment decisions:

A risk measure  $\mathcal{R}(\cdot)$  is used to include stochasticity of the hourly generation costs  $\sum_h O_h(n_{i,t}, \omega)$  into the investment decisions.

$$\min_n := \sum_{t \in T} \sum_{i \in I} \sum_{s=1}^t F_{i,t} n_{i,s} + \mathcal{R} \left( \sum_{t \in T} \sum_{h \in H_t} O_h(n_{i,t}, \omega) \right),$$

# Prediction uncertainties

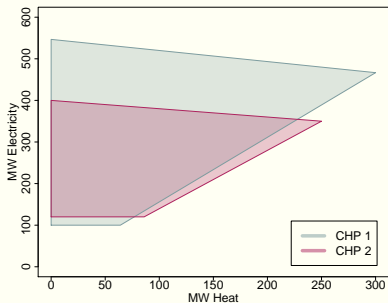
Yearly characteristics (distribution parameters) of all cost data and the district heating load can be given as a stochastic or deterministic process. During the numerical evaluation hourly synthetic profiles are generated based on ARMA-GARCH modelling for the corresponding yearly distributional parameters.



Time series characteristics and distribution of the spot electricity price.

# Results

# Case study portfolio

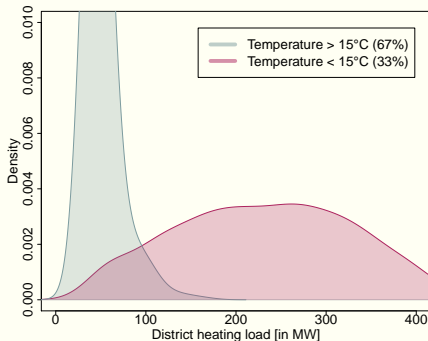


Feasible operation regions of the two CHP plants.

The case study portfolio comprises two CHP plants with a maximum heat generation of 300 and 250 MW (range of  $\eta^{\text{el}}$  of 42.6% to 57% and 49.3% to 58%). For peak loads a gas fired district heating boiler with a maximum capacity of 175 MW and a minimum capacity of 17.5 MW is installed (thermal efficiency  $\eta^{\text{th}}$  of 84% to 88%).

# Case study load

The average load for district heating will be on warm days with a temperature above 15°C at 51 MW, on cold days with a temperature below 15°C at 231 MW. Peak loads will be up to 500 MW.



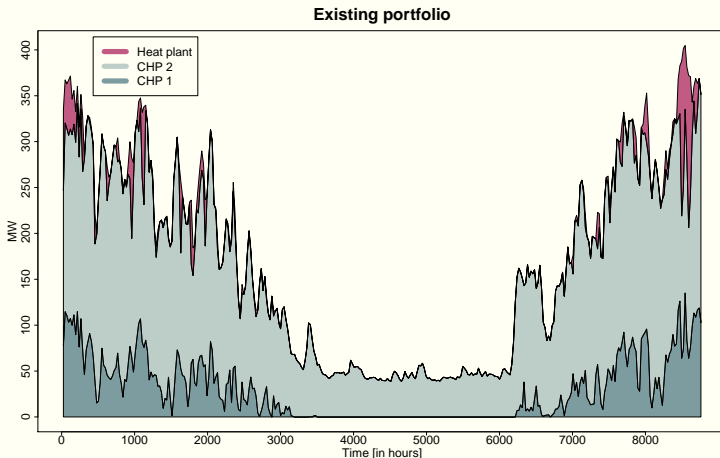
Density conditional on the outside temperature for the corresponding district heating load.

# Optimization

Possible additional technologies include heat pumps (25 MW each), electric boilers and solar district heating. For the analysis the development of some cost parameters is uncertain for two different cases:

- ❖ **Case 1:** The gas price has an uncertain development with its mean remaining at 22 Euro/MWh with a standard deviation of one Euro/MWh. The spot electricity price rises up to 35 Euro/MWh in mean (no uncertainties).
- ❖ **Case 2:** In addition to case 1 also the development of the mean spot electricity price is uncertain with a standard deviation of one Euro/MWh.

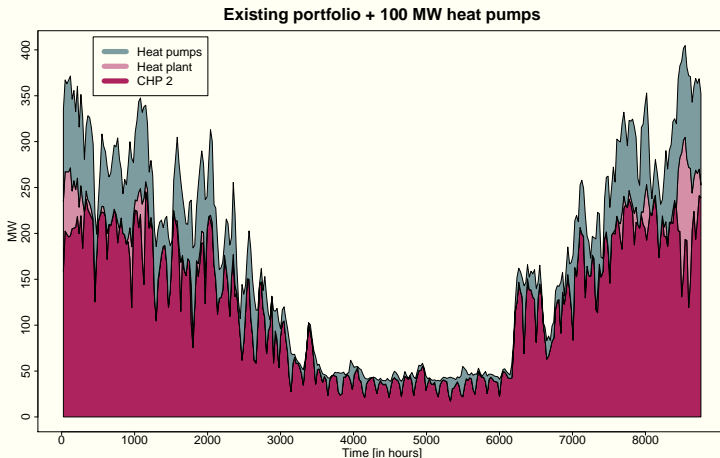
# Existing generation portfolio



Shares of districting heating supply for the existing generation portfolio for one reference year.

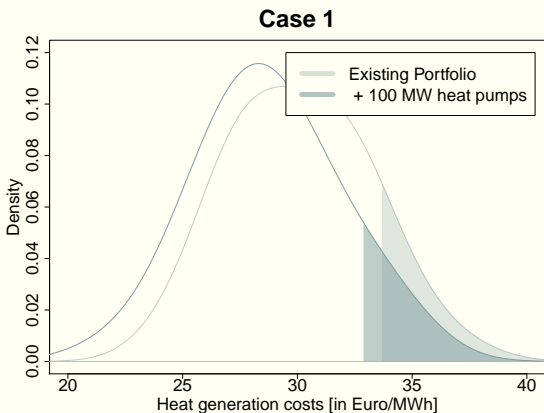


# ... and portfolio after optimization.



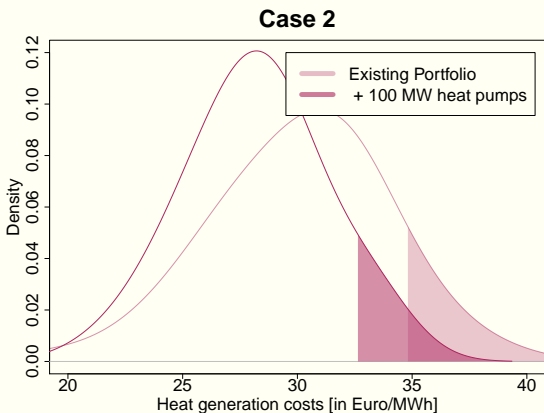
Shares of districting heating supply for the optimized portfolio with 100 MW additionally installed heat pumps (optimal for both cases).

# Heat generation costs (Case 1)



|                     | $\mu$ | $\mu + \sigma$ | $\text{VaR}_{10\%}$ | $\text{ES}_{10\%}$ |
|---------------------|-------|----------------|---------------------|--------------------|
| Existing portfolio  | 30.06 | 32.98          | 33.67               | 35.19              |
| + 100 MW heat pumps | 28.72 | 31.60          | 32.85               | 33.99              |

# Heat generation costs (Case 2)



|                     | $\mu$ | $\mu + \sigma$ | VaR <sub>10%</sub> | ES <sub>10%</sub> |
|---------------------|-------|----------------|--------------------|-------------------|
| Existing portfolio  | 30.08 | 33.76          | 34.76              | 36.09             |
| + 100 MW heat pumps | 28.18 | 31.05          | 32.61              | 33.29             |

# Conclusion

# Concluding remarks

- ❖ Uncertain developments of several costs parameters have a strong influence on the composition of the optimal district heating generation portfolio.

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- ❖ Using only deterministic scenarios neglects the uncertainty nature of the GEP problem. The resulting scenario specific portfolios aren't very useful for investment decisions.

# Concluding remarks

- ❖ Uncertain developments of several costs parameters have a strong influence on the composition of the optimal district heating generation portfolio.
- ❖ Using only deterministic scenarios neglects the uncertainty nature of the GEP problem. The resulting scenario specific portfolios aren't very useful for investment decisions.
- ❖ Prediction uncertainties of cost parameters influence the expected heat generation costs as well as the risk exposure towards cost parameter changes. Risk measures (in particular value-at-risk and expected shortfall) allow for a suitable consideration of these down-side risks.

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