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ZIB-Report (Print) ISSN 1438-0064
ZIB-Report (Internet) ISSN 2192-7782

Long-Term Multi-Objective Optimization for Integrated Unit Commitment and Investment Planning for District Heating Networks

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August 13, 2025

Abstract

The need to decarbonize the energy system has intensified the focus on district heating networks in urban and suburban areas. Therefore, exploring transformation pathways with reasonable trade-offs between economic viability and environmental goals became necessary. We introduce a network-flow-based model class integrating unit commitment and long-term investment planning for multi-energy systems. While the integration of unit commitment and investment planning has been applied to multi-energy systems, a formal introduction and suitability for the application of long-term portfolio planning of an energy provider on an urban scale has yet to be met. Based on mixed integer linear programming, the model bridges the gap between overly detailed industrial modeling tools not designed for computational efficiency at scale and rather abstract academic models. The formulation is tested on Berlin's district heating network. Hence, the challenge lies in a large number of variables and constraints and the coupling of time steps, for example, through investment decisions. A case study explores different solutions on the Pareto front defined by optimal trade-offs between minimizing costs and CO₂ emissions through a lexicographic optimization approach. The resulting solution catalog can provide decision-makers valuable insights into feasible transformation pathways, highlighting distinctions between robust and target-dependent investments.

1 Introduction

While energy providers are urged to decarbonize, current optimization tools for multi-energy systems still fall into two categories: On one hand, detailed industrial modeling tools (e.g., BoFiT by Volue¹, ResOpt by Kisters²) do not allow for an integrated structural optimization for large input data due to the inherent complexity. On the

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¹<https://www.volue.com/products-and-services/volue-bofit-optimisation-chp-sector-coupling-and-industry>

²<https://www.kisters.eu/product/forecasting-and-optimisation/>

other hand, academic models either efficiently solve large-scale systems but lack accuracy (e.g., PyPSA [Brown et al., 2018], REMix [Gils et al., 2017]) or are tailored to small-scale systems (e.g., [Verheyen et al., 2024], [Lambert and Spliethoff, 2024], [Castelli et al., 2024]). Recent developments in the energy modeling community show an increase in integrating network design and operational decisions and apply this approach to micro-grids or short-term scenarios, while a solution for urban areas of large size and long-term scenarios is not available due to efficiency issues. Still, no solution effectively bridges the gap between these industrial and academic tools.

We address the research gap of formally defining the problem class of integrated design and operational optimization for energy providers of large urban areas from a mathematical point of view. To that end, we propose a novel model class in Section 2 that offers the level of detail and flexibility required for industrial usage while being tractable for long-term planning. We demonstrate its effectiveness by presenting a case study on an instance of Berlin’s district heating network, the most complex grid in Western Europe, in Section 3. The study explores a lexicographic bi-objective approach to determine a solution catalog with optimal and relevant trade-offs between cost and environmental targets. We investigate how the conflicting objectives affect the transformation paths and distinguish robust from target-dependent investments.

2 A Multi-Energy Integrated Operation and Design Optimization Problem

We introduce a novel network-flow-based model class integrating operation and design optimization for multi-energy systems. The operation optimization is modeled as a unit commitment problem [Sheble and Fahd, 1994], incorporating a time horizon, a set of generating and storage units, a representation of the topology, and demand/price forecast time series as input. Unit commitment involves three decisions:

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 at a time. Since the model further includes sources (generation units) and sinks (demand), this part represents a network flow problem.

Design optimization or investment planning comprises:

design/investment decisions: whether an investment is selected.

Finally, the integrated problem is formulated as a mixed-integer linear program (MILP).

2.1 MILP

Let R be a set of resources, T the set of time steps, I the set of generating units and K the set of storage units.

2.1.1 Variables:

For resource $r \in R$ and time $t \in T$, we denote as variables by $x_{t,i}^r, x_{t,i}^{out} \in \mathbf{R}_{\geq 0}$ the flow incoming/outgoing flow at unit $i \in I$, by $z_{i,t} \in \{0, 1\}$ the status of unit $i \in I$,

by $s_{i,t} \in \{0, 1\}$ whether the status of unit $i \in I$ changed at t , by $h_{t,k}^r$ the storage level of storage $k \in K$, by $p_t^r, e_t^r \in \mathbf{R}_{\geq 0}$ purchased and sold resource and by $\hat{z}_i \in \{0, 1\}$ whether an investment is selected.

2.1.2 Objectives:

We minimize for costs f_1 , which include investment and operational costs containing fuel and power trading, and for CO₂ emissions f_2 .

2.1.3 Full Program:

For given demand vector d , parameter vectors a and c , and for piecewise linearized characteristic curves φ , the following MILP describes integrated unit commitment and investment planning for multi-energy systems:

$$\begin{aligned}
\min \quad & \left(f_1^{inv}(\hat{z}) + \sum_{t \in T} f_1^{op}(z_t, s_t, h_t, p_t, e_t, x_t), \sum_{t \in T} f_2(p_t, x_t) \right) \\
& \sum_{i \in I} x_{t,i,out}^r + \sum_{k \in K} x_{t,k,out}^r + p_t^r = d^r + \sum_{i \in I} x_{t,i,in}^r + \sum_{k \in K} x_{t,k,in}^r + e_t^r \quad \forall r \in R \quad (1) \\
& x_{t,i,out}^{r_2} = \varphi_{i,t}^{r_1,r_2}(x_{t,i,in}^{r_1}) \quad \forall i \in I, t \in T, r_1, r_2 \in R \quad (2) \\
& s_{i,t} \leq z_{i,t}, s_{i,t} \leq 1 - z_{i,t}, s_{i,t} \geq z_{i,t} - z_{i,t-1} \quad \forall i \in I, t \in T \quad (3) \\
& \sum_{\tau \in T_{i,t}^{up}} (s_{i,t} - z_{i,t}) \leq 0, \sum_{\tau \in T_{i,t}^{down}} (s_{i,t} + z_{i,t} - 1) \leq 0 \quad \forall i \in I, t \in T \quad (4) \\
& x_{t+1,i,out}^r - x_{t,i,out}^r \leq a_i^{up}, x_{t,i,out}^r - x_{t+1,i,out}^r \leq a_i^{down} \quad \forall i \in I, t \in T, r \in R \quad (5) \\
& h_{t+1,k}^r = a_{t,k}^{loss} h_{t,k}^r + a_{t,k}^{load} x_{t,k,in}^r - a_{t,k}^{unload} x_{t,k,out}^r \quad \forall k \in K, t \in T, r \in R \quad (6) \\
& z_{i,t} \leq \hat{z}_i \quad \forall i \in I, t \in T \quad (7) \\
& h, x, p, e \leq c_{max}, \quad h, x, p, e \geq c_{min} \quad (8)
\end{aligned}$$

The main goal is to fulfill the given demand while balancing all resources, represented by Constraint 1. Constraint 2 describes the conversion from one resource to another at a generating unit in form of a piecewise linear characteristic curve. Constraints 3 - 5 incorporate technical constraints such as activation, minimum up and down times, and ramping for generating units. Constraint 6 models the time linking of storage levels. Constraint 7 links investment decisions to the corresponding operation variables. Capacities are set for all non-binary variables by Constraints 8. For an in-depth discussion on the model, we refer to [Clarner et al., 2022].

3 Case Study on Berlin's District Heating Network

3.1 Instance

The effectiveness of the model is demonstrated on an instance of Berlin's district heating network. A simplified structure is depicted in Figure 1.

The initial topology includes heat-generating units with a capacity distribution of 43% from heating stations and 57% from combined heat and power plants (CHP), predominantly fueled by gas (75%) and coal (19%). In addition, the model incorporates various storage units and integration with relevant markets. Beyond the initial grid topology, the model encompasses 38 potential investments with a 25-year depreciation period. These include 11 additional heating stations, five storage units, three heat

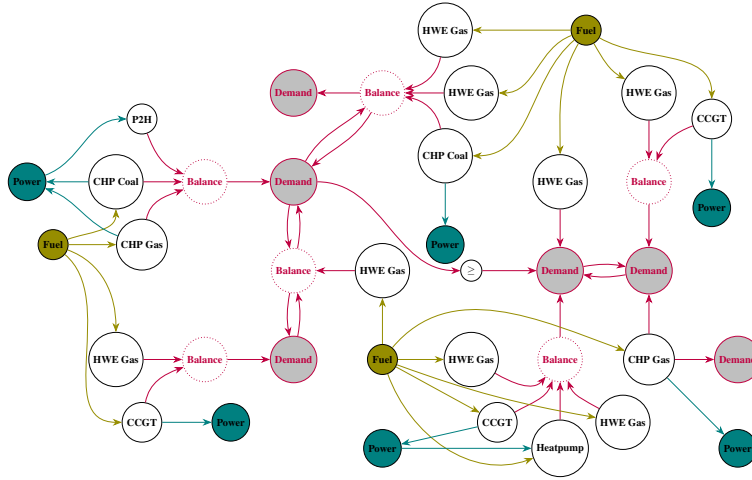


Figure 1: Abstract structure of the Berlin instance

pumps of varying capacities up to 120 MW, four electrical heaters with capacities up to 320 MW, a solar thermal facility, five CHP plants, and nine gas turbines or upgrades to existing gas turbines. The resulting MILP contains approximately 3.6M variables and 3.5M constraints.

3.2 Method

The goal is to explore various transformation pathways to achieve decarbonization targets while maintaining reasonable economic costs. Due to the instance size, finding all Pareto optimal solutions (i.e., solutions that cannot be improved in one objective without worsening another) for two objectives (costs, CO₂ emissions) is intractable. Therefore, we explore a reasonable number of Pareto optimal solutions using a lexicographic optimization approach, prioritizing costs before CO₂ emissions (hierarchical method [Marler and Arora, 2004]). While minimizing CO₂ emissions, the optimal cost value is relaxed in increments of 5%, ranging up to 30% of the cost optimum. The 1% relaxation admits a 2% MIP-gap, the 5% relaxation a 1% MIP-gap, and further relaxations a 0.5% MIP-gap. Our computations were executed on a high-performance Cluster, featuring an Intel(R) Xeon(R) Gold 6342 CPU and comparable CPUs with a memory limit of 100 GB. Each individual solution was processed within a time frame of 1 to 6 hours.

3.3 Computational Results

Adapting the cost tolerance gap significantly impacts CO₂ emissions. The rate of CO₂-savings is particularly rapid for the near-optimal cost solution, gradually diminishing as the tolerance gap widens, as illustrated in Fig. 2.

Table 1 presents the resulting investment solution catalogue. Among the potential investments, 27 investments consistently remain unselected, while 10 emerge as fixed choices, i.e. robust investment decisions. These include an additional heating station, four new CHP plants, and five gas turbines or their upgrades. Three distinct transformation pathways have been identified: The cost-optimal pathway, which includes the

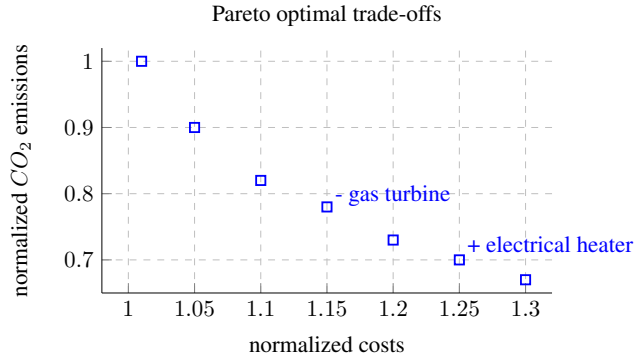


Figure 2: Set of computed points on the Pareto front through an iterative relaxation of the costs with corresponding changes in the selected investments.

Table 1: Selected investments.

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	robust
CHP	1	1	1	1	1	1	1	robust
Block CHP	1	1	1	1	1	1	1	robust
CCGT	1	1	1	1	1	1	1	robust
Heating station (biomass)	1	1	1	1	1	1	1	robust
Gas turbine upgrade	1	1	1	1	1	1	1	robust
Gas turbine	1	1	1	1	1	1	1	robust
Gas turbine	1	1	1	1	1	1	1	robust
Gas turbine	1	1	1	1	1	1	1	robust
Gas turbine	1	1	1	1	1	1	1	robust
Gas turbine	1	1	1	0	0	0	0	target-dependent
Electrical heater (120 MW)	0	0	0	0	0	1	1	target-dependent
Total	11	11	11	10	10	11	11	

robust investments plus an additional gas turbine. Omitting this gas turbine can achieve a CO₂-emission reduction of 22-26%, while introducing an electrical heater results in a CO₂-emission reduction of 30-33%.

Notice that the reduction of CO₂ emissions is not solely dependent on the choice of investments but is also linked to the operation of a given system setup. As a result, identical investment portfolios can produce different CO₂-emission outcomes. For instance, the three scenarios characterized by a cost tolerance gap up to 10% do not differ in investment decisions but show a CO₂-emission reduction of up to 17%. This highlights the importance of integrating investment planning with unit commitment to make well-informed decisions.

4 Conclusion

In conclusion, we formally defined integrated unit commitment and investment planning for multi-energy systems in a mathematical closed form as a MILP. A non-linear formulation of the problem class can be considered by omitting the piecewise linearization of the characteristic curves. In a case study on Berlin's district heating network, we presented a method to efficiently compute bi-objective solutions for the proposed model. The findings of this study highlight the interaction of investment and operational decisions. Exploring trade-offs within relevant parameter ranges through multi-objective optimization offers a detailed understanding of robust and target-dependent

investment decisions and enables stakeholders to make informed decisions for long-term energy portfolio planning.

5 Acknowledgement

The work for this article has been conducted in the Research Campus MODAL funded by the German Federal Ministry of Education and Research (BMBF) (fund numbers 05M14ZAM, 05M20ZBM). The work has been supported by the German National Science Foundation (DFG) Cluster of Excellence MATH+.

References

- [Brown et al., 2018] Brown, T., Hörsch, J., and Schlachtberger, D. (2018). Pypsa: Python for power system analysis. *Journal of Open Research Software*.
- [Castelli et al., 2024] Castelli, A. F., Pilotti, L., Monchieri, A., and Martelli, E. (2024). Optimal design of aggregated energy systems with (n-1) reliability: Milp models and decomposition algorithms. *Applied Energy*, 356:122002.
- [Clarner et al., 2022] Clarner, J.-P., Tawfik, C., Koch, T., and Zittel, J. (2022). Network-induced unit commitment - a model class for investment and production portfolio planning for multi-energy systems. ZIB-Report 22-16, ZIB, Takustr. 7, 14195 Berlin.
- [Gils et al., 2017] Gils, H. C., Scholz, Y., Pregger, T., Luca de Tena, D., and Heide, D. (2017). Integrated modelling of variable renewable energy-based power supply in europe. *Energy*, 123:173–188.
- [Lambert and Spliethoff, 2024] Lambert, J. and Spliethoff, H. (2024). A two-phase nonlinear optimization method for routing and sizing district heating systems. *Energy*, 302:131843.
- [Marler and Arora, 2004] Marler, R. and Arora, J. (2004). Survey of multi-objective optimization methods for engineering. *Structural and Multidisciplinary Optimization*, 26:369–395.
- [Sheble and Fahd, 1994] Sheble, G. B. and Fahd, G. N. (1994). Unit commitment literature synopsis. *IEEE Transactions on Power Systems*, 9:1.
- [Verheyen et al., 2024] Verheyen, J., Schöbel, N., Thommessen, C., Roes, J., and Hoster, H. (2024). Integration of heat pumps and renewable heat suppliers in optimized short-term planning for district heating systems. pages 1419–1430. The 37th International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy, ECOS 2024.