Modelling and optimization of a decarbonized heat supply in suburban areas using the Open Energy Modelling Framework

Shixin Ni[a], Gerrid Brockmann[b], Amin Darbandi[c], Karim Shawky[d], Martin Kriegel[e]

[a] Technical University Berlin, Berlin, Germany, shixin.ni@tu-berlin.de, CA
[b] Technical University Berlin, Berlin, Germany, brockmann@tu-berlin.de
[c] Technical University Berlin, Berlin, Germany, a.darbandi@tu-berlin.de
[d] Technical University Berlin, Berlin, Germany, k.shawky@campus.tu-berlin.de
[e] Technical University Berlin, Berlin, Germany, m.kriegel@tu-berlin.de

Abstract

In Germany, the energy demand for space heating and hot water preparation in the building sector accounts for a substantial part of the total final energy consumption. The energy transition and decarbonization of the building sector are therefore crucial for achieving climate protection goals. District heating is a practical and sustainable technical solution to meet the heat demand of consumers and to reduce greenhouse gas emissions.

The research project SubWW investigates how a future-oriented, decarbonized heat supply can be implemented in suburban areas using the existing suburban area of Leeste near Bremen (Germany) as an example. To evaluate the potential of a district heating system (DHS) to utilize local renewable energy resources and to combine different possible heat generation technologies, the Open Energy Modelling Framework (*oemof*) was used to model the heat generation system of the DHS and to optimize the heat dispatch process. The model was kept as simple as possible and as complex as necessary. The locally available renewable energy, the weather conditions, and the possible funding sources and their requirements were defined as boundary conditions and constraints and taken into account in the optimization process.

The optimization results with the *oemof* tool were evaluated by simulating three nonlinear programming optimization methods under identical conditions. The optimization potential and various advantages and disadvantages of the methods applied are compared and discussed.

1 Introduction

District heating is a practical and sustainable solution for improving resource and energy management and reducing costs and greenhouse gas emissions [1-3]. In addition, such systems are also important solutions for integrating or expanding the use of renewable energies in the building sector [4]. Within the research project SubWW [5], the district of Leeste near Bremen (Germany) is used as an example to investigate how a future-oriented, decarbonized heat supply in suburban areas can be implemented by means of a district heating network. After a thorough analysis of potential local renewable energy sources, a heat plant was designed to optimize the use of renewable energy. The plant consists of a biomass boiler, a natural gas combined heat and power generation (CHP) system, a natural gas condensing boiler, an air source heat pump (ASHP), a wastewater source heat pump (WWSHP), a ground source heat pump (GSHP), a power-to-heat (P2H) system and a photovoltaic (PV) system. The complex structure of the heat generation system presents a challenge for system control and operational optimization.

Mixed-integer linear programming (MILP) is one of the most commonly used optimization techniques for the design, operation and optimization of complex energy systems, as it combines a relatively accurate system description with a reasonable degree of computational complexity [4,6,7]. Various

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decision support tools and frameworks for the control and optimization of multi-generator energy systems have also been developed based on MILP, e.g. [8-15]. This study presents the application of the MILP-based framework Open Energy Modelling Framework (*oemof*) [16] for the dispatch optimization of the multi-generator system designed in the SubWW project. The open source framework *oemof* was implemented in Python with an object-oriented programming method, which enables a universal representation of multi-sector energy systems and ensures flexibility in customization to meet various project-specific requirements.

The behavior of real technical systems often exhibits non-linearities that require linearization for representation in MILP formulations. However, the linearization of system attributes and constraints, such as generator efficiencies, may introduce slight deviations in the optimization problems [7,17]. To investigate the effects of such linearization in the researched system, the optimization results obtained using the *oemof* tool were compared with results of three non-linear programming (NLP) methods:
- Sequential Least SQuares Programming (SLSQP) [18],
- Constrained Optimization BY Linear Approximation (COBYLA) [19], and
- trust-region algorithm for constrained optimization (Trust-Constr) [20].

Further details on the implementation of these three NLP methods can be found in [21].

2 Methodology

2.1 Modeling of the system in *oemof*

The multi-generator heating system was modelled with the open source model library *oemof.solph* [22] on the basis of a linear equation system. The optimization of the target values was carried out using *pyomo* [23] to define the minimization problem and the open source solver *cbc* [24], which is suitable for linear programming and MILP problems.

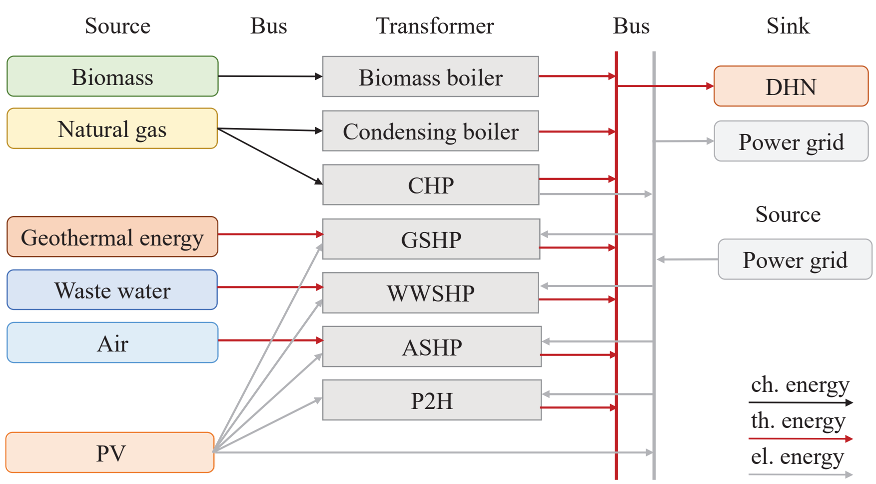

Figure 1: Schematic and simplified representation of the energy system model in *oemof*

Figure 1 shows the structure of the generator park model. The generators, energy sources and carriers as well as grids are defined using the basic components - transformers, sources and sinks - of *oemof.solph*. Each component in the system represents a "node" with input and output flows for which balance equations are calculated over all time steps. The flows between the various components can be chemical, thermal, or electrical. The connections between the components are described by another fundamental component of *oemof.solph*, bus, which links the balance equations of each individual component. Table 1 presents the generator capacities, technically required minimum loads and efficiencies. The efficiencies of CHP and P2H plants are simplified and assumed to be constant. For biomass and natural gas condensing boilers, the efficiencies are linearized over the operation load range.

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The Coefficient of Performance (COP) values for heat pumps are assumed to be 50 % of the efficiency η_{Carnot} in ideal Carnot case, which can be calculated using equation (1), where T_{supply} and T_{source} are the flow and source temperatures of the heat pumps in Kelvin. Partial load effects of the heat pumps are neglected.

$$\eta_{Carnot} = \frac{T_{supply}}{T_{supply} - T_{source}} \tag{1}$$

Necessary model inputs for the optimization are prices and emission factors of the energy sources, demand profile, solar radiation, supply and source temperatures of the heat pumps and the amount of wastewater. The energy prices and CO_2 emission factors used in the simulations are summarized in Table 2. The revenues from the feed-in of self-generated electricity from CHP and PV systems and the subsidy for self-consumption are presented in Table 3. Further boundary conditions are documented in [5] following a detailed analysis of the current situation in the district under investigation. The outputs of the optimization are the dispatch of the generators and the flows between the various system components.

Table 1: Generator properties in system model

Generator	Capacity kW	Minimum load %	Efficiency / COP
Biomass boiler	2594	30	0.80 - 0.85
Condensing boiler	1215	30	0.90 - 0.93
CHP (thermal)	251	50	0.48
CHP (electrical)	214	50	0.41
GSHP	379	20	$0.5 \cdot \eta_{Carnot}$
WWSHP	1045	20	$0.5 \cdot \eta_{Carnot}$
ASHP	1466	20	$0.5 \cdot \eta_{Carnot}$
P2H	1105	5	0.99

Table 2: Prices and CO_2 emission factors of energy carriers

Energy source	CO_2 emission g/kWh	Price ct/kWh
Biomass	0.024 [25]	2.78 [1]
Natural gas	0.201 [26]	6.68 [27]
Grid power (regular)	0.366 [26]	32.63 [27]
Grid power (Heat pump tariff)	0.366 [26]	23.80 [28]

Table 3: Revenues from self-generated electricity

Generator	Self-consumption ct/kWh	Feed-in ct/kWh
CHP	0.00 [2]	15.66 [3]
PV	0.00	18.39 [4]

[1] Average price for wood chips in Germany with 20 % water content in 2021 according to [29].
[2] CHP surcharge for CHP plants > 100 kWel and ≤ 250 kWel according to Combined Heat and Power Act (KWKG)
[3] Sum of the CHP surcharge for CHP plants > 100 kW_{el} and ≤ 250 kW_{el} according to KWKG and the CHP index (average value of the six quarters IV/2020 to I/2022) published by European Energy Exchange AG (EEX)
[4] Average market value from Nov. 2021 to Apr. 2022 according to Federal Network Agency (BNetzA)

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2.2 Mathematical formulation of the optimization problem

For optimization based on the variable cost of the system, the objective function is formulated as (2). The total variable costs for each time step are calculated as the sum of the fuel, electricity, operating, and maintenance costs subtracted by the revenues and savings from the electricity generation through PV and CHP. To simplify the function, the operating and maintenance costs are included in the consumption-related fuel and electricity cost factors c_{fuel} and $c_{el,grid}$ (see Table 2). The heat and electricity generation Q_{gen} and P_{gen}, the efficiency η and the electricity consumption P_{cons} of the generators are functions of the load signals f_{load}. While all partial load efficiencies of the generators are linearized over the operating range for *oemof* with the MILP solver, those of the condensing boiler and the CHP are defined as nonlinear functions for NLP methods, as described in [30]. Additionally, the COP values of the ASHP is calculated according to the performance map in DIN EN 15316-4-2 for NLP methods to account for the efficiency loss due to defrosting at low ambient temperatures. Further boundary conditions and parameters required for the calculation of the efficiencies, such as desired flow temperature and source temperatures of the heat pumps, are documented in [5]. The electricity generation P_{gen} is divided into a self-consumption part $P_{self-cons}$ and a feed-in part $P_{feed-in}$ into public grid, the proportions of which are determined by the optimization algorithms in such a way that the highest revenues and cost savings are achieved.

$$\min \quad \sum_{i \in I} c_{fuel,i} \frac{Q_{gen,i}}{\eta_{th,i}} + c_{el,grid} \left(\sum_{i \in J} P_{cons,j} - \sum_{i \in K} P_{self-cons,k} \right) - \sum_{i \in K} c_{rev,k}\, P_{feed-in,k} \qquad (2)$$

In the case of optimizing according to CO_2 emissions, the objective function is formulated as (3). With self-generated electricity from CHP and PV plants, the consumption of grid electricity can be reduced and a corresponding amount of CO_2 emissions can thus be avoided. The avoided amounts are deducted when calculating the total emissions.

$$\min \quad \sum_{i \in I} CDE_{fuel,i} \frac{Q_i}{\eta_{th,i}} + CDE_{el,grid} \sum_{i \in J} P_{cons,j} - CDE_{el,grid} \sum_{i \in K} P_{gen,k} \qquad (3)$$

Constraints (4) to (7) are applied for both cost and CO_2 emission optimization approaches. Constraint (4) ensures that the heat production must be sufficient to cover the total heat demand of the users. Constraint (5) states that the proportions of self-consumed and grid-fed electricity produced by the system should add up to 100%. Constraint (6) limits the operating range of the generators. Constraint (7) indicates that the maximum heat extraction capacity of the source sides of the heat pumps is limited due to the available wastewater volume and the geothermal probe properties and the maximum load signals for the heat pumps are therefore also limited.

$$\text{s.t.} \quad \sum_{i \in I} Q_{gen,i} - Q_{demand} \geq 0 \qquad (4)$$

$$1 - f_{self-cons,k} - f_{feed-in,k} = 0, \qquad f_{self-cons,k}, f_{feed-in,k} \in [0,1] \qquad (5)$$

$$f_{load,i} \in \{0\} \cup \left[f_{load,min,i}, f_{load,max,i} \right] \qquad (6)$$

$$\dot{Q}_{HP,source} \leq \dot{Q}_{HP,source,max} \qquad (7)$$

The multi-generator heating system is simulated and optimized with *oemof* and the NLP methods under identical conditions for one year in hourly resolution.

As the tested NLP methods only handle real variables in convex feasible areas, the constraint of the minimum loads of the generators is realized by means of NLP-based branch and bound method (NLP-BB). The first step is to solve the NLP relaxation of the original problem, where the loads of the generators can range between 0 and 100%. The solution of the relaxed problem provides a valid lower

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bound of the results. For each load signal that falls between 0 and the minimum load, which violates the constraints for the operational range, the continuous relaxation is divided into new subproblems by adding the constraints load = 0 and load > minimum load to the relaxed problem. New lower bounds can be obtained by solving the new subproblems. If one of the subproblems provides a solution in which all load signals lie within the feasible range, it also provides a valid upper bound. To avoid unnecessary computational effort, the subproblems are not solved if the maximum possible heat production is below the heat demand, with the load signals of certain generators being limited to 0. If the results of the subproblems are infeasible or worse than the upper limit, they are not branched further, since the optimum solution cannot be found in this part of the search space. The optimal results of all searched branches are returned as final control signals.

3 Results and Discussion

The annual specific CO_2 emissions and variable costs of the system in relation to heat production with different operational optimization methods are depicted in Figure 2. Table 4 summarizes the differences in specific emissions and costs between the NLP methods and the MILP method and the simulation times of the different methods.

According to the simulation results, the COBYLA method shows the highest potential for reducing the target value in terms of both CO_2 emissions and cost optimization. The SLSQP and Trust-Constr methods achieved relatively high reductions in one scenario, but only modest ones in the other. The MILP method is not the optimal method in either scenario, but shows relatively high accuracy in both. It is noteworthy that optimizing for one target value can also lead to significant differences in the other target value when using different methods. While the MILP method is not the most effective at improving the current target value, it consistently keeps the other target value low. The COBYLA method is able to prioritize a greater reduction in the current target value by sacrificing the other target value. Conversely, the SLSQP and Trust-Constr methods both lead to a much higher value for the other target, but do not make a significant improvement to the current target value compared to the MILP method.

The average simulation time of the NLP methods is much higher than that of the MILP method. The SLSQP method requires the calculation of the gradient, while the Trust-Constr method requires both the gradient and the Hessian matrix, which leads to an increase in computational complexity and a longer runtime. The gradient-free method COBYLA has the highest convergence speed compared to the other two NLP methods.

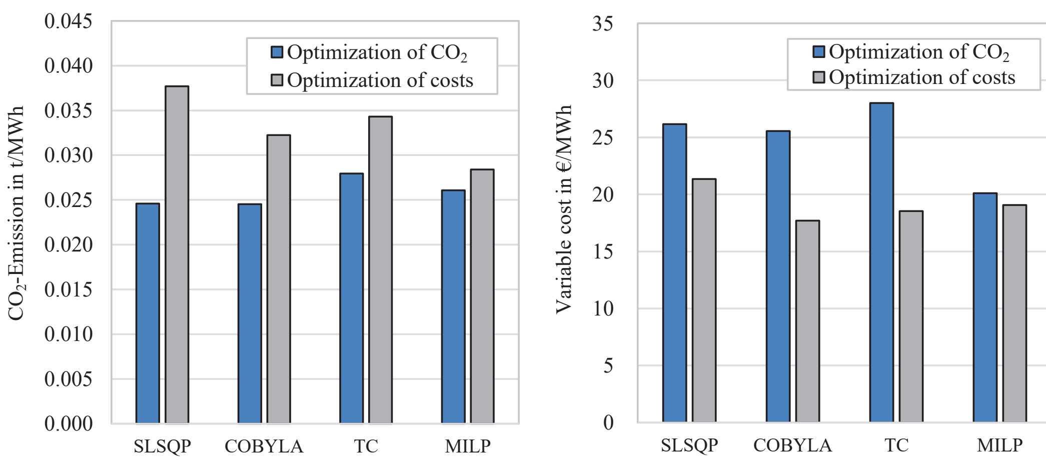

Figure 2: Specific CO_2 emission (left) and variable cost (right) with different control algorithms

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Table 4: Differences in specific CO_2 emissions and variable costs between NLP methods and the MILP method and simulation runtimes

	Reduction of CO_2 emission %	Reduction of variable cost %	Simulation runtime [5] s
Optimization according to CO_2 emission			
NLP 1 - SLSQP	5.6	-30.1	24843.52
NLP 2 - COBYLA	6.0	-27.1	8280.96
NLP 3 - Trust-Constr	-7.2	-39.4	855454.08
MILP (*oemof*)			2179.08
Optimization according to variable cost			
NLP 1 - SLSQP	-32.8	-12.0	17662.72
NLP 2 - COBYLA	-13.6	7.2	25911.04
NLP 3 - Trust-Constr	-20.8	2.8	1248673.92
MILP (*oemof*)			840.25

The main difference in the optimization results of the various methods lies in the ability of the methods to switch on the heat pumps more often at higher source temperatures with higher COP values and thus improve the efficiency of the overall system. The use of more CHP and PV electricity in the heat pumps can also partially avoid the consumption of expensive grid electricity. The coverage shares of the various heat generators are summarized in table 5. Table 6 shows the annual coefficient of performance of the ASHP using different methods. In particular, the NLP methods demonstrated higher efficiency and coverage rate of the ASHP, resulting in a more effective heat generation compared to the MILP method. In terms of CHP electricity, the COBYLA and MILP methods utilized a greater amount of CHP electricity, thereby increasing the income from grid feed-in and the savings in electricity prices for the heat pumps.

Table 5: Annual coverage shares of the heat demand by individual generators in %

	SLSQP	COBYLA	Trust-Constr	MILP
Optimization according to CO_2 emission				
Biomass boiler	63.84	60.32	62.64	69.54
Condensing boiler	3.35	2.19	4.00	4.71
CHP	11.41	13.49	10.60	14.23
ASHP	13.04	14.56	14.65	5.61
WWSHP	1.67	1.67	1.58	1.40
GSHP	6.64	7.24	6.50	4.07
P2H	0.06	0.52	0.03	0.45
Optimization according to variable cost				
Biomass boiler	75.10	74.66	74.27	72.23
Condensing boiler	1.09	0.91	0.83	3.77
CHP	5.39	5.53	5.37	11.99
ASHP	9.40	9.78	11.30	5.95
WWSHP	0.69	0.72	0.66	1.79
GSHP	8.28	8.32	7.55	3.81
P2H	0.03	0.05	0.08	0.46

[5] Intel(R) Core(TM) i5-8500 CPU @ 3.00GHz, 8GB RAM, Windows 10

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Table 6: Annual coefficient of performance of ASHP

	SLSQP	COBYLA	Trust-Constr	MILP
CO_2 optimization	2.724	2.752	2.710	2.206
Cost optimization	4.894	5.176	5.272	4.323

4 Conclusion and future work

In this study, a heating system with multiple generators was modelled and optimized using the open source framework *oemof* and solved using the MILP optimization method. The optimization results were compared with those of three NLP methods under identical conditions. The NLP method COBYLA shows the highest potential for reducing annual CO_2 emissions by 6.0 % and variable costs by 7.2 % compared to the MILP method used by *oemof*. The NLP methods SLSQP and Trust-Constr cannot always achieve satisfactory results and require significantly longer calculation times. Although the MILP method is not the solution with the highest reduction of the objective functions, it is a reasonably accurate alternative with a much shorter computation time.

The system modelled in this study does not incorporate a storage system. As the project is still in the planning phase, the efficiencies of the generators are only theoretical estimates. The boundary conditions and constraints of the optimization problem are limited to an hourly resolution, without considering constraints over a longer time period. Additionally, when optimizing for CO_2 emissions and variable costs, other target values are not taken into consideration by the optimization methods. Potential future work could include modelling and coupling of storage systems, replacing generator characters by more detailed manufacturer data or measurement data, defining long-term constraints, such as funding conditions over one year, and investigating the combination of multiple optimization objectives. For the same use case, open-source global solvers with global convergence guarantees can also be applied and tested. The most appropriate method for system optimization can be identified by simultaneously considering the complexity of defining the system and the optimization problem, the capability of algorithms and solvers to search for global minima, the convergence rate and speed, the computational requirements, and the potential for future adaptations and generalizations.

Nomenclature

Abrevations

ASHP	Air source heat pump
CHP	Combined heat and power
COBYLA	Constrained Optimization BY Linear Approximation
COP	Coefficient of Performance
DHS	District heating system
GSHP	Ground source heat pump
MILP	Mixed-integer linear programming
oemof	Open Energy Modelling Framework
PV	Photovoltaic
P2H	Power-to-heat
SLSQP	Sequential Least SQuares Programming
Trust-Constr	Trust-region algorithm for constrained optimization
WWSHP	Wastewater source heat pump

Symbols

$CDE_{el,grid}$	Carbon dioxide emission factor of electricity consumption, g/kWh
CDE_{fuel}	Carbon dioxide emission factor of fuel consumption, g/kWh

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$c_{el,grid}$	Consumption-related electricity cost, ct/kWh
c_{fuel}	Consumption-related fuel cost, ct/kWh
c_{rev}	Revenue from electricity fed into public grid, ct/kWh
$f_{feed-in}$	Proportion of feed-in to public grid of generated electricity, -
f_{load}	Load signal for generators, -
$f_{self-cons}$	Proportion of self-consumption of generated electricity, -
I	Set of generators with heat production
J	Set of generators that consume electricity
K	Set of generators with electricity production
$P_{feed-in}$	Feed-in of electricity into public grid, kWh
P_{cons}	Electricity consumption, kWh
$P_{self-cons}$	Self-consumption of electricity, kWh
Q_{gen}	Heat production, kWh
Q_{demand}	Heat demand, kWh
$\dot{Q}_{HP,source}$	Heat extraction from heat pump source sides, kW
T_{supply}	Supply temperature of heat pumps, K
T_{source}	Source temperature of heat pumps, K
η_{Carnot}	Carnot efficiency, -
η_{th}	Thermal efficiency of generators, -

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