Exploring the Near Optimal Solution Space of District Heating in Municipal Heat Planning

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Abstract:
Municipal heating planning is key to transforming urban energy systems and achieving ambitious climate targets, particularly in cities where heating accounts for a large share of energy consumption and greenhouse gas emissions. Effective planning requires decisions on whether to supply heat via district heating networks (DHNs) or building-specific technologies. To address this central question in municipal heat planning the concept of Modeling to Generate Alternatives (MGA) is applied. Robust must-have and must-avoid heating supply technologies are assessed by exploring the near optimal solution space using an extreme min/max MGA approach. The cost-optimal results show that both investigated scenarios rely heavily on DHN supply by large-scale heat pumps or deep-geothermal plants, biomethane boilers, and thermal storage. MGA reveals that DHN expansion remains essential for renewable energy supply even in near-optimal cost scenarios. In the geothermal scenario at least 40 MW of DHN capacity and 20 MW building-specific heat pumps are required within a 10 % cost increase, while PV disappears beyond 5 % higher costs. Overall, MGA provides important insights for robust DHN planning and is therefore a valuable framework for municipal heat planning.

Keywords:
Mixed-Integer Linear Programming, District Heating, Modeling to Generate Alternatives, Energy Planning

1. Introduction

The European building sector is responsible for approximately 35 % of energy-related greenhouse gas emissions, making it a key focus of decarbonization efforts [9]. To address this challenge, European governments are introducing municipal heat planning acts to accelerate the transition towards renewable heat supply. The fluctuating nature of renewable energy sources poses particular challenges when planning future climate-neutral energy systems. In this context, urban energy systems optimization models (UESOMs), defined as "frameworks that provide quantitative, system-level analyses to support local energy strategy development and decision-making" [28], have proven to be an indispensable decision support tool [14]. These models use optimization techniques, such as mixed-integer linear programming (MILP) or linear programming (LP), to determine optimal investment and operational strategies to meet energy demand [13]. Optimization is carried out with respect to a defined objective function, which may include economic or sustainability but rarely social indicators [14]. As Neumann and Brown note, a cost-optimal solution may lack public acceptance, justifying a limited cost increase by, for example, reducing the installed PV capacity. Consequently, it can be preferable to explore multiple alternatives to identify "must-haves" and "must-avoids" rather than providing a single optimal solution to communicate with stakeholders.

1.1. Uncertainty in Urban Energy System

In general, ESOMs have several limitations when applied in practice [8], as they are exposed to both parametric and structural uncertainties [19, 7, 23]. Parametric uncertainty stems from incomplete or unpredictable input data, such as energy prices [19], while structural uncertainty arises from model limitations, including simplifications, idealizations, and the exclusion of difficult-to-quantify real-world aspects. Unmodeled objectives or value-based uncertainties, which influence actual decision-making but are difficult to express mathematically, are a key contributor to structural uncertainty [21, 7]. Additionally, many models also reduce complex decision-making processes to a single objective, typically cost minimization. This approach often results in "flat" objective functions around the optimum, where multiple configurations achieve nearly identical cost performance [29, 6]. Furthermore, most models address uncertainty inadequately; when they do, they generally rely on conventional approaches such as sensitivity analyses, Monte Carlo simulations, stochastic programming, or robust optimization [8, 29], which primarily tackle parametric rather than structural uncertainties.

Only a few studies apply MGA [2] to tackle structural uncertainties in UESOMs [8, 11, 12, 18, 24]. MGA is particularly suitable for municipal heat planning, as it enables the participation of multiple stakeholders and allows the examination of structural uncertainties in DHN expansion. Unlike traditional optimization, which produces a single "optimal" solution that may obscure alternative configurations with comparable cost, MGA systematically explores the near-optimal solution space. By revealing the range of feasible configurations, MGA provides important insights for robust DHN planning and supports participatory municipal heat planning.

[11] applied the Hop-Skip-Jump (HSJ) method and multi-objective optimization with epsilon constraints to a nine-building urban energy system. They compared a mandatory network scenario, in which all buildings were connected via a minimum spanning tree, to a optimal designed network in a baseline scenario, finding the mandatory network to be slightly less favorable economically and environmentally. [8] applied HSJ variations to a university energy system in a distributed configuration, without optimizing network layout or expansion. Similarly, [12, 18, 24] are predefining the DHN expansion. Thus, although MGA has been used to explore various generation and capacity pathways, it has not yet been applied to evaluate the expansion of district heating networks (DHNs) for large-scale urban energy systems. This study addresses this gap by applying the MGA approach to an UESOM with integrated DHN expansion decisions. In doing so, it tackles the central question of municipal heat planning: to what extent should heat be supplied by district heating, and what does the near-optimal solution space look like?

1.2. Modeling to Generate Alternative Method

In [16] the four most established MGA methods are reviewed. The Hop-Skip-Jump (HSJ) method was first proposed by [3] and was subsequently applied to macro-energy system model by [7]. It minimizes the weighted sum of decision variables, with weights based on the number of prior non-zero appearances of each variable in previous solutions. This allows solutions to be found that minimize reliance on previously used variables. Although it is computationally efficient and effective at identifying edge cases, its restrictive formulation that relies on past results, limits its potential for broader explorations. The variable Min/Max approach, first introduced by [27], refers to methods in which a set of variables is randomly or intentionally selected, then minimized or maximized. One special case is the extreme Min/Max variant, in which extreme solutions are systematically explored by assigning weights of 1 to the selected variables and 0 to the others. The random vector method, developed by [1], generates random optimization vectors to sample directions across the feasible space. This method ensures the exploration of a wide range of solutions. However, these vectors rarely align with single-variable axes, which reduces their effectiveness in identifying absolute extremes. The Modeling All Alternatives (MAA) method, first described by [22], identifies the continuum of all near-optimal solutions in convex energy system optimization problems by expanding outward from known solutions. The process begins with at least three initial exterior points, around which a convex hull is built. Then, the outward face-normal vectors are used as new optimization directions to find additional diverse solutions. This process is repeated to identify more extreme points in different directions.

1.3. Research Gap

This paper addresses the following open questions derived from the gaps identified in the existing literature and discussed in Section 1.:

- Which technologies can be considered essential ('must-haves') or unsuitable ('must-avoids') in the design of renewable UES?
- What amount of heat should be supplied via DHN? How robust is the optimal DHN share?
- How can real-world uncertainties, such as geothermal exploration risks, be assessed using MGA?

By answering these questions, the paper contributes to an improved understanding of the role of specific technologies in shaping robust urban energy systems and in exploring the near-optimal solution space for municipal heat planning. Whereas previous studies have mainly emphasized cost-optimal system configurations, this work goes a step further by systematically applying MGA within a UESOM with joint-optimization of DHN expansion and building-specific heat supply. In doing so, it provides insights not only into the existence of multiple near-optimal configurations but also into the identification of technologies that consistently appear as indispensable or, conversely, disadvantageous across these alternatives.

The paper is structured as follows: In Section 2.1., the UESOM model with piecewise linear DHN expansion is introduced. The case study setup is outlined in section 3., followed by results and discussion in Section 4. and 5.. Finally, in Section 6., a summary of the main findings is provided.

2. Methods

In this section, the urban energy system optimization model is first described, emphasizing the joint optimization approach that incorporates DHN expansion into the decision-making process. Secondly, the implemented MGA approach will be introduced.

2.1. UESOM with Detailed Modelling of the Heating Sector

The UESOM model used in this study is described in [26] and was implemented using the open-source Python tool *PyPSA* [25]. The model minimizes total annual energy system costs, including investments and operating expenses, while ensuring that total energy demand is met and that system constraints are satisfied.

The objective function is formulated as:

$$\min_{G_{n,r},F_l,H_{n,s},E_{n,s},g_{n,r,t},f_{l,t},h_{n,s,t}} \Bigg[\sum_{n,r} c_{n,r} \cdot G_{n,r} + \sum_{l} c_l \cdot F_l + \sum_{n,s} c_{n,s} \cdot H_{n,s} + \sum_{n,s} \hat{c}_{n,s} \cdot E_{n,s} + \sum_{n,r,t} o_{n,r} \cdot g_{n,r,t} + \sum_{l,t} o_l \cdot f_{l,t} + \sum_{h,t} o_{n,s} \cdot h_{n,s,t}\Bigg] \tag{1}$$

where $G_{n,r}$, F_l, $H_{n,s}$, and $E_{n,s}$ denote the installed capacities of generators, links, storage units, and energy stores, respectively, indexed by nodes n, generators r, links l, and storage units/stores s. The operational variables include power generation $g_{n,r,t}$, power flow $f_{l,t}$, and storage dispatch $h_{n,s,t}$ across time steps t.

Capital costs are annualized through an annuity factor $A(L, r)$, dependent on component lifetime L and interest rate r:

$$c = A(L, r) \cdot C_{\text{inv}} + FOM, \quad \text{with} \quad A(L, r) = \frac{r(1 + r)^L}{(1 + r)^L - 1} \tag{2}$$

The operational costs o account for fuel prices, CO_2 prices, and variable operation and maintenance (VOM) costs.

A central feature of the model is the integration of DHN expansion decisions into the UESOM. Therefore, the UESOM uses a piecewise-linear approximation of the DHN's investment costs and heat losses, derived through a stepwise sensitivity analysis using topotherm ([15]). The cost curve is implemented using a mixed-integer formulation by introducing i candidate DHN build-out stages, each modeled as a separate DHN link. Where each stage has a capacity variable F_i^{DHN}, which is linked to a binary decision variable b_i^{DHN}. This ensures that capacity is assigned only if the corresponding stage is selected:

$$F_i^{DHN} \leq \text{BigM} \cdot b_i^{DHN} \quad \forall i \tag{3}$$

Additionally, if a DHN link is selected, it must be built with a capacity no smaller than the maximum capacity of the previous stage:

$$F_i^{DHN} \geq F_{i,\max}^{DHN} \cdot b_i^{DHN} \quad \forall i \tag{4}$$

To ensure that no more than one build-out stage is selected at a time, the following constraint is added:

$$\sum_i b_i^{DHN} \leq 1 \tag{5}$$

The model is thus capable of detailed techno-economic optimization of urban energy systems, integrating district heating networks and building-specific supply as well as coupling with the electricity sector. For a comprehensive description of the full model formulation, constraints, and technology implementation, readers are referred to [26].

2.2. Modeling to Generate Alternatives

In [29] MGA is described as "The principle of MGA is to relax the optimal solution, and use a modified model formulation to search the near-optimal solution space for alternative solutions that are maximally different in decision space." Thus, MGA can be broadly interpreted as any systematic method used to explore the near-optimal solution space in search of alternative solutions.

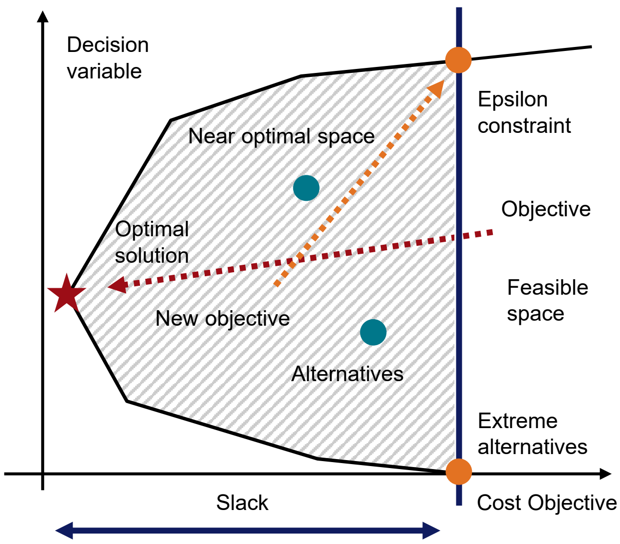

Figure 1: Schematic representation of the MGA approach. (Adapted from [8])

Figure 1 schematically illustrates the MGA concept, where an area of near-equivalent alternatives termed the near-optimal space surrounds the optimal solution. The near-optimal solution space contains solutions that incur only minor additional costs but may differ substantially in system structure. Thereby the slack parameter defines the allowable deviation from the optimal costs to explore alternative configurations. A larger slack increases the near-optimal solution space, allowing more diverse system configurations but also moving further from the original optimum. MGA can generate individual extreme solutions or, via repeated application, produce a comprehensive overview of feasible system structures [1].

The MGA procedure can be summarized in four steps [8, 5]:

1. **Calculate the cost-optimal solution**
   Solve the original optimization problem:
   $$\min_x f(x) = c^\top x \tag{6}$$
   yielding the cost-optimal system configuration. The optimal objective value is denoted by f^*.
2. **Define the cost deviation (slack)**
   Introduce a constraint limiting acceptable cost increase:
   $$f(x) \leq (1+\varepsilon) \cdot f^* \tag{7}$$
   where ε is the slack (e.g., $\varepsilon = 0.01$ for 1% cost increase).
3. **Select a new objective**
   Replace the original cost minimization by maximizing or minimizing an alternative objective, such as the capacity of a specific technology:
   $$\max_x w^\top x \tag{8}$$
   Here, the weights w select which technologies or decision variables to emphasize (e.g., $w_{pv} = 1$ for photovoltaic capacity).
4. **Generate alternative solutions**
   Repeating the process with varying slacks, objectives, and optimization directions (min/max) to generate a set of structurally diverse but near-optimal solutions.

This paper uses the extreme min/max MGA method, which enables the systematic exploration of the near-optimal solution space by pushing each technology to its feasible minimum and maximum. This allows "must-have" and "must-avoid" technologies to be identified, as well as revealing inter-dependencies between different energy system technologies.

3. Case Study

The modeling method of previous work [26], extended by MGA, is re-applied to a district in southern Germany with an area of 28.1 km^2, 17,700 inhabitants, and 3,215 buildings (LoD2 dataset). The year 2022 is chosen as the base year for demand, price, and generation time series, as a validated demand profile is available for this region [4]. A schematic representation of the urban reference energy system is shown in Figure 2. It is important to mention that space-intensive technologies like ST, PV and PTES are constrained by a maximum usable area. Further details can be obtained in the original study.
All models are computed using the commercial solver Gurobi on a Windows 11 workstation (16 GB RAM, AMD Ryzen 5 5625U with Radeon Graphics). The study is conducted as a greenfield planning approach, though brownfield transformation can also be considered by including existing capacities and CO_2 limits or pricing mechanisms.
In this paper, both scenarios with and without a geothermal plant are analyzed with the MGA method to explore the near-optimal solution space. The extreme min–max weighting approach for all capacity variables is applied, considering slack variables of 0.01, 0.02, 0.05, and 0.1 for all technologies. Whereby the building-specific technologies are grouped to "dec heat pump".

4. Results

The results Section 4. is divided into three main parts. First, Section 4.1. provides a brief description of the optimal solution for the two investigated scenarios. Secondly, Section ref near shows the results of the near-optimal solution space, followed by a further investigation of the correlation between separate energy system components in Section 4.3..

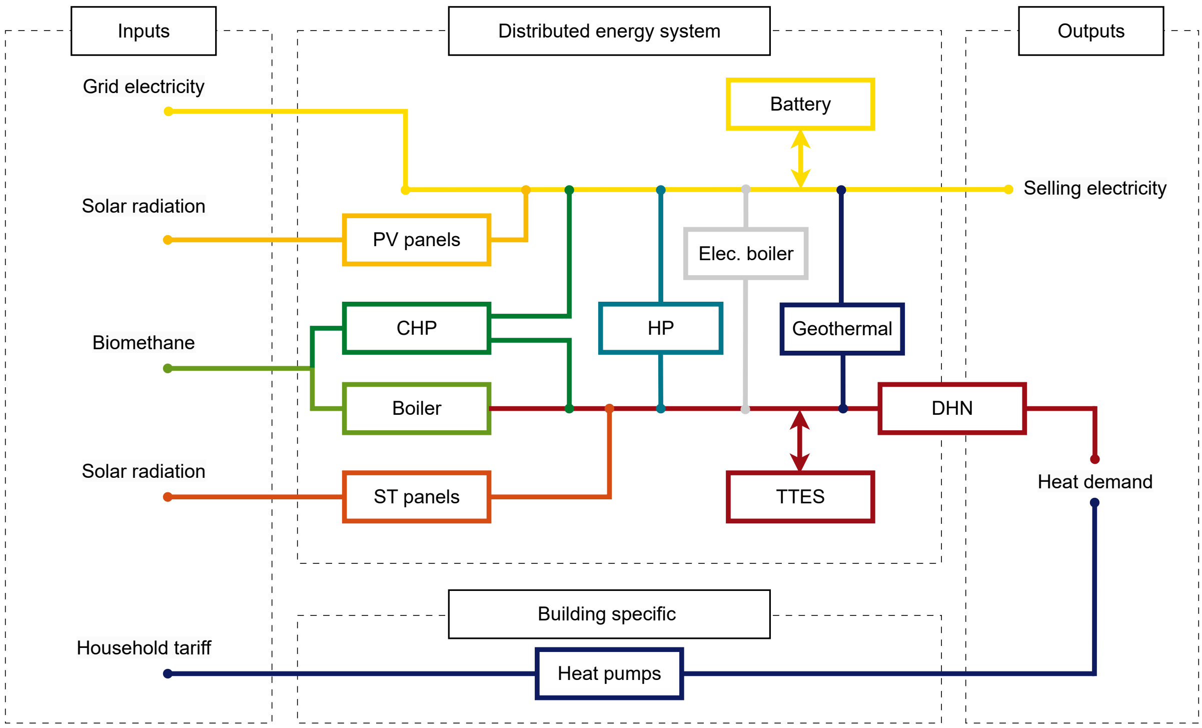

Figure 2: Schematic representation of the urban energy system

4.1. Optimal Solution

In both scenarios, a high district heating share is optimal, relying primarily on a cheap baseload technology, large-scale air-source heat pump in scenario A, and the geothermal plant in scenario B. Peak loads are covered by the biomethane boiler, while TTES provides load shifting and storage capacity to balance demand fluctuations. Both configurations ensure a reliable heat supply and efficient integration of renewable energy sources.
A detailed description of the base scenarios A and B, including assumptions on technology efficiencies and load profiles, is provided in [26], which refers to the 60°C DHN supply temperature scenario. The installed capacities are summarized in Table 1:

Table 1: Installed capacities of cost-optimal solution for Scenario A and Scenario B.

Component	Inst. Capacity in MW/ MWh	
	Scenario A	Scenario B
Dec heat pump	52.01	45.14
Large scale heat pump	72.35	66.54
Biomethane boiler	26.70	20.77
Biomethane CHP	19.44	13.13
Battery storage	4.75	0.84
TTES	150.95	726.23
PV panels	15.58	16.73
ST panels	13.80	0.0
Geothermal plant	0.0	10.89
DHN	92.38	99.37

4.2. Near-Optimal Solution Space

The near-optimal solution space in Figure 3 reveals that the DHN is essential for realizing the potential of the cheap geothermal baseload heat supply and achieving an cost-efficient decarbonization in the hydro-geothermal energy scenario. Even allowing for a 10 % increase in total system cost, a minimum

DHN capacity of 40 MW is built-out for a fully renewable supply, corresponding to over a third of the cost-optimal capacity. In the case without geothermal potential the minimum DHN build-out decreases to 7.5 MW. Relaxing cost constraints further enables flexibility in the choice of supply technologies. For example, in both scenarios, a 10 % cost increase would make it possible to avoid installing large-scale heat pumps and geothermal plants. However, with only a 5 % cost increase, both technologies would remain necessary, with minimum capacities of around 15 to 17 MW (for scenario B and A) and 2.1 MW, respectively.

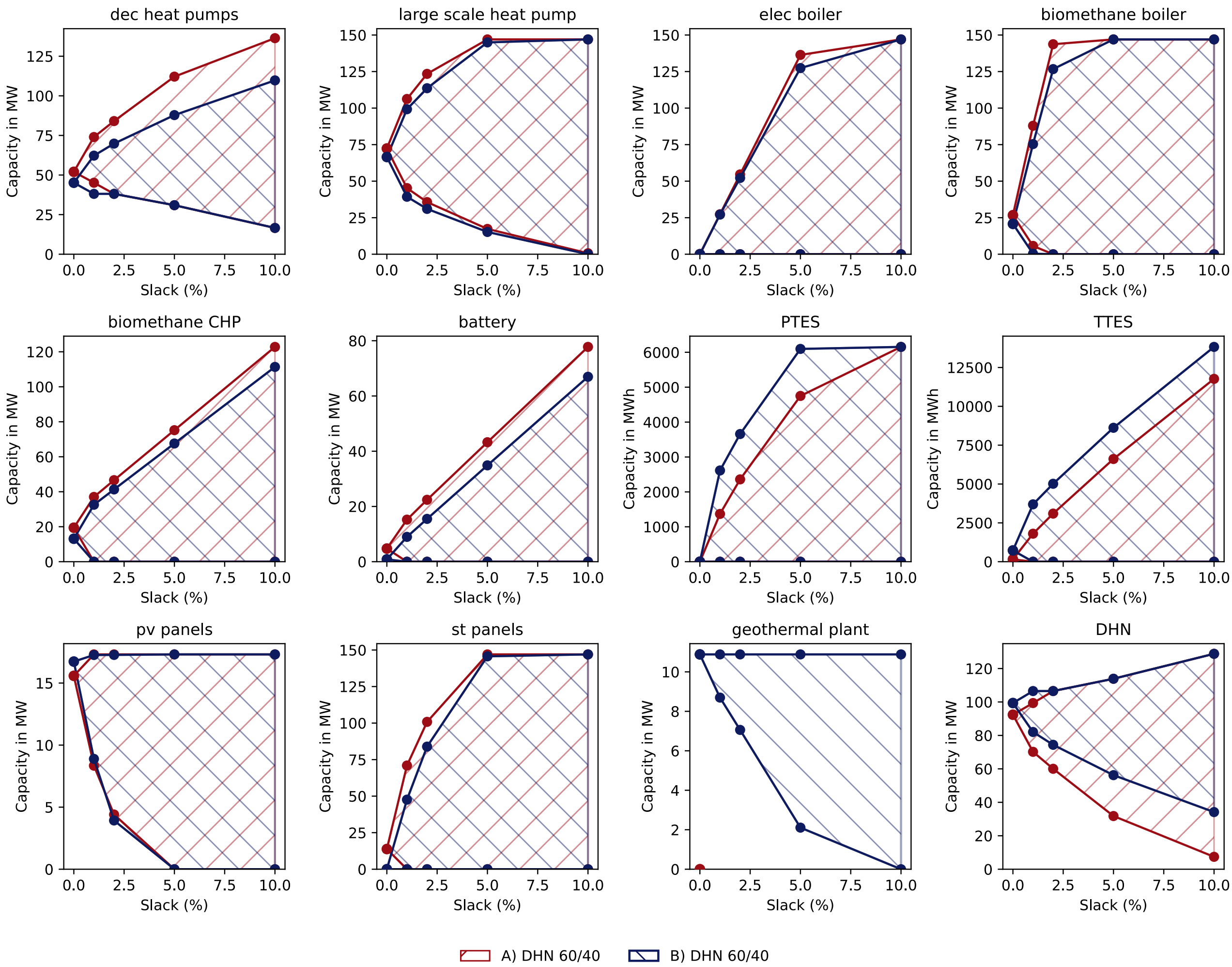

Figure 3: Diversity of technology deployment across near-optimal scenarios with increasing cost slack. Due to the binary variables for piecewise linear capacity investments, the optimization problem is not convex; therefore, not all variable values in the near-optimal solution space are feasible, as indicated by the hatched area.

Photovoltaic (PV) generation emerges as another essential component for cost-effective transformation. Its capacity declines to zero only when cost increases exceed 5 %. Similarly, building-specific heat pumps remain necessary. Within a narrow cost increase range of 1–2 %, DHN capacity varies by approximately 20 MW, corresponding to less than 30 % of the optimal capacity, indicating that the optimal state is relatively robust. Notably, the variation is predominantly a reduction as the DHN capacity is only further extended by 20 to 30 MW when costs increase dramatically by 10 %. So the optimal capacity can be seen as upper limit of cost-efficient DHN-expansion.
Capacity constraints also influence the technology deployment, as geothermal energy and the building-specific ground-source heat pump included in ”dec heat pumps” are limited by maximum capacities, whereas tank thermal energy storage (TES), pit thermal energy storage (PTES), PV, and solar thermal (ST) panels capacities are restricted by the area-constraint.
Figure 4 illustrates how increasing slack in total system cost drives diversity in the energy system configuration. Extremes in the capacity of one technology directly influence the installed capacity of

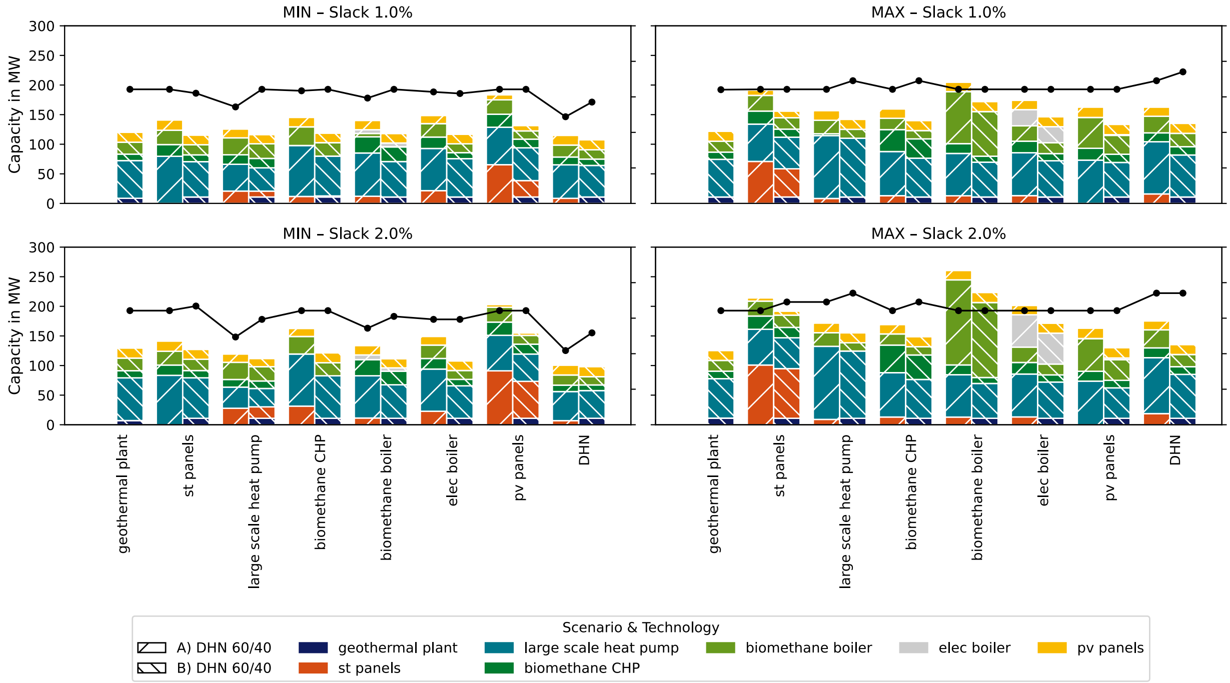

Figure 4: Stacked capacities of key technologies across near-optimal scenarios

others. For instance, the minimum DHN build-out strongly affects the installed capacity of large-scale heat pumps. Similarly, an increase in electric boiler capacity is associated with a lower biomethane boiler capacity and vice versa. In particular, reductions in geothermal and large-scale heat pump capacities are often offset by increased solar thermal deployment, while the capacity of biomethane CHP systems is inversely correlated with battery storage capacity.

4.3. Pearson Correlation

To quantify correlation between technologies across the MGA scenarios, the Pearson correlation coefficients ρ were calculated, following the methodology of [10].

$$\rho(A, B) = \frac{1}{k-1} \sum_{i=1}^{k} \left(\frac{A_i - \mu_A}{\sigma_A} \right) \left(\frac{B_i - \mu_B}{\sigma_B} \right),$$

where A_i and B_i are the values of the compared attributes for solution i, k is the number of solutions considered, μ_A and μ_B are the means of the sets $\{A_i\}$ and $\{B_i\}$, and σ_A and σ_B are their standard deviations.

The pearson coefficient in Figure 5 reveals several interesting patterns of correlation. Building-specific heat pumps and the district heating network exhibit a strong inverse correlation, indicating their mutual substitution. Large-scale heat pumps, CHP plants, and TES positively impact the expansion of the district heating network. Additionally, peak load technologies, such as biomethane, correlate with district heating network expansion. Different correlations can be identified with regard to solar thermal and PV depending on the scenario. Without geothermal energy, a positive correlation is observed between DHN expansion and solar thermal energy, and a negative correlation with PV due to space restrictions. However, scenario B with geothermal energy shows no correlation with these two components. Inverse correlations are observed between PTES and PV, while PTES shows a positive correlation with solar thermal energy use. TES also correlates negatively with PV, albeit less strongly than PTES, as it requires less space. There is also a negative correlation between ST and PV.

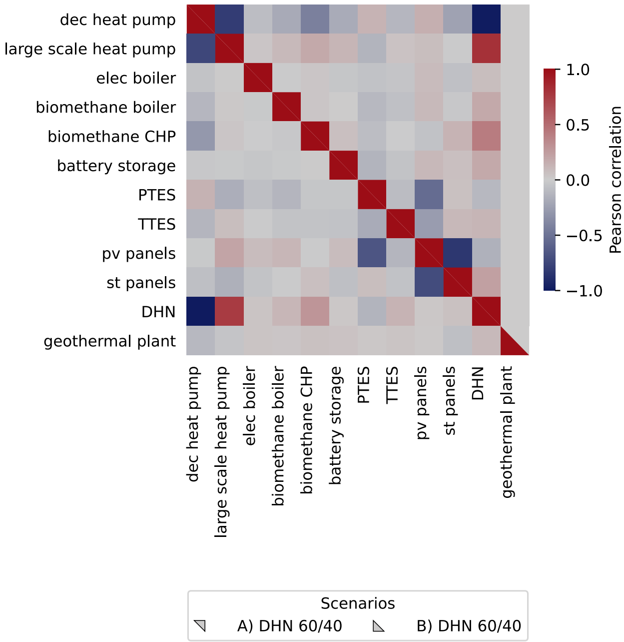

Figure 5: Pearson correlation coefficients between technology capacities across MGA scenarios for the base scenarios A and B

4.4. GIS-based Identification of Heat Supply Areas Based on MGA Results

A buffering algorithms can be used to identify areas where buildings are located at a certain distances from the main DH pipes. As data basis the algorithm uses the with topotherm recalculated DHN topologies of the MGA analysis resulting minimum, optimal and maximum DHN capacity within a 1% cost relaxation. For this study, distances of 25 m, 50 m, and 100 m were considered to estimate the likelihood of a building being connected to the district heating network. As shown in figure 6 darker-colored areas indicate a higher probability of potential DH supply. Whereas gray areas are considered to be very unlikely connected to DH and preferred as building-specific supply areas.

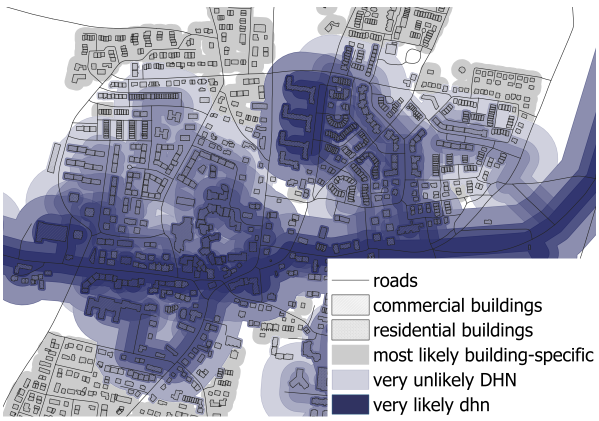

Figure 6: GIS-based evaluation of the near optimal DHN solutions space for 1 % max. and min. slack, with buffer layers of 25, 50 and 100 m of Scenario B for a zoomed in area

5. Discussion

Several key questions arising during municipal heat planning can be effectively addressed with the MGA framework. Firstly, the question of which areas have the potential to be supplied with district heating. What is the optimal level of district heating expansion, and what risks does deep geothermal drilling, for example, entail? Furthermore, MGA's participatory nature makes it easily integrated into the municipal heat planning process. Adapted from [8], MGA can be incorporated into a participatory modeling process with five steps:

1. Involve stakeholders.
2. Jointly define the problem and modeling goals.
3. Develop and validate a simplified but realistic energy system model.
4. Apply MGA and GIS-based algorithms to analyze near-optimal solutions in collaboration with stakeholders.
5. Communicate results to support informed decision-making and revise the model if needed.

[17] propose a five-level "MGA integration ladder" that closely aligns with the participatory MGA approach suggested by [8]. Both emphasize moving beyond pure cost-optimality, validating key modeling assumptions, systematically exploring near-optimal solution space, and ultimately co-developing robust energy strategies with stakeholders.

In municipal heat planning, a central question is whether heat supply should be through district heating networks (DHN) or via building-specific solutions. MGA supports this decision by exploring the near-optimal solution space for DHN expansion and building-specific supply options. By identifying upper and lower bounds of DHN expansion that are associated with a limited increase in total system costs, and by recalculating the corresponding DHN topologies, MGA provides insights into which areas can be robustly classified as either DH-supplied or building-specific.

One key finding is that the near-optimal solution space for DHN expansion is asymmetrically constrained. The maximum capacity of DHN expansion in the near-optimal space appears to be strongly limited: even a small increase beyond the cost-optimal DHN capacity leads to a disproportional increase in total system costs. This suggests that already the 1 % cost relaxed solution can be interpreted as an effective upper bound for a economically reasonable DHN expansion. Consequently, buildings and areas not supplied with district heating in this solution can be interpreted as very likely candidates for a building-specific heat supply option. At the minimum values of the near-optimal solution space, MGA indicates a minimum level of DHN expansion that remains part of a cost-efficient system configurations even for high cost relaxations. However, this lower bound depends strongly on the availability of renewable heat sources. In Scenario B, a minimum DHN capacity of approximately 40 MW is still required even when total system costs are allowed to increase by up to 10 %. This level of DHN expansion can therefore be interpreted as a no-regret or must-have decision within this scenario. By contrast, in the scenario without geothermal energy, the same DHN capacity is already reached with a cost deviation of around 5%, indicating a reduced robustness of DHN expansion in the absence of geothermal heat supply. A similar observation can be made regarding the near-optimal solution space for building-specific heat pumps. Here, the results show that the capacity in the 1 % cost relaxation case remains close to the optimum, while noticeable reductions in building-specific supply only occur when substantially higher cost deviations are permitted. Summarizing these results shows that the DHN expansion identified in the cost-optimal solution is relatively robust. Close to the optimum, an increase in DHN expansion from around 60 to 100 MW is associated with a moderate increase in total system costs of approximately 2.5 %.

Furthermore, the near-optimal solution space from the MGA analysis can provide insights into uncertainties, for example, regarding geothermal exploration risks. In this context, the risk associated with geothermal exploration, such as lower-than-expected yields or temperatures, can be analyzed with the capacity-minimizing scenarios within the MGA framework. The results show that, even when geothermal output is reduced to approximately 8.5 MW, total system costs increase by only about 1 %. By small reductions in thermal capacity, the lower boundary of the near-optimal solution space is relatively steep, suggesting that moderate decreases in geothermal capacity are only associated with a small cost increase. By contrast, scenarios without any geothermal power are associated with a cost increase of 10 %.

In addition, the available and usable space of a municipality plays a decisive role. Depending on this criteria and the acceptance regarding specific technologies, the PV and ST capacities can vary greatly. However, a minimum capacity of 5 MW PV seems to be essential to provide affordable electricity for heating purposes.

6. CONCLUSIONS

This paper applied MGA in the context of municipal heat planning to address whether to supply heat via DHN or building-specify by exploring the near-optimal solution space. By integrating DHN expansion directly into the UESOM and applying an extreme min/max MGA approach, the study identified “must-have” and “must-avoid” technologies under certain cost relaxations. The results show that DHN expansion remains a robust and cost-efficient cornerstone of renewable heat supply, particularly with geothermal energy availability, where a minimum DHN capacity of about 40 MW (27.8% of total peak demand) persists even with 10 % higher system costs. Building-specific heat pumps and PV generation also emerge as essential components within small cost increases of 5 %. MGA further enables the assessment of uncertainties such as geothermal exploration risks and supports spatially explicit planning through GIS-based analysis. The findings highlight the applicability of near-optimal analyses in guiding strategic decisions in a municipal planning process. MGA provides a quantitative assessment of uncertainties, such as geothermal exploration risks and can identify the minimum infrastructure requirements that maintain a reliable and affordable heat supply. Nevertheless, this approach does not yet consider parametric model uncertainties. To achieve a fully robust solution, these should be included in a subsequent modeling step.

NOMENCLATURE

Abbreviations

CHP	Combined heat and power plant
DHN	District heating network
FOM	Fixed operation and maintenance costs
HSJ	Hop-Skip-Jump
LP	Linear programming
MAA	Modeling all alternatives
MGA	Modeling to generate alternatives
MILP	Mixed-integer linear programming
PTES	Pit thermal energy storage
PV	Photovoltaic
ST	Solar thermal
TTES	Tank thermal energy storage
UESOM	Urban energy system optimization model
VOM	Variable operation and maintenance costs

Superscripts and Subscripts

c	Carrier
inv	Investment
l	Links
n	Buses
r	Generators
s	Storage units and stores
t	Snapshots

Latin Symbols

A	Annuity factor
C	Costs
c	Capital costs or cost vector
ϵ	Slack variable
f	Power flow or objective function
g	Power generation
G	Set of generators
h	Storage dispatch
h^+	Charging of storage
h^-	Discharging of storage
H	Set of storage units
k	Number of solutions
L	Links or lifetime
n	Set of buses
o	Marginal costs
r	Interest rate or generator index
ρ	Pearson correlation coefficient
σ	Standard deviation
soc	State of charge
ω	Weighting factor

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