Considering homeowner acceptance of retrofit measures within energy supply network optimization

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Abstract

A key factor towards a low-carbon society is energy efficient heating of private houses. The choice of heating technology as well as the decision for certain energy-efficient house renovations are made mainly by individual homeowners. In contrast, municipal energy network planning heavily depends on and strongly affects these decisions. Further, there are different conflicting objectives for finding optimal network designs, e.g., low carbon emissions opposed to low investment and maintenance costs. This work presents a framework for an energy supply network model that integrates these homeowner micro-decisions in the multi-objective optimization process to aid macro-level decision-making for energy supply network planning. Furthermore, numerical experiments are carried out in order to illustrate our framework.

Keywords. Energy supply networks, mixed-integer nonlinear programming, multi-objective optimization, mathematical modelling.

1. Introduction

Energy used for constructing, heating, cooling, and lighting homes and businesses is responsible for one-third of the global energy consumption and accompanying emissions [20]. Transforming the building sector to low-carbon heating is essential for reaching Net Zero Emissions by 2050, which is formulated into the European Climate Law [30]. This is crucial, as fossil fuels currently dominate, providing nearly two-thirds of heating energy [12, 20]. In [12] two key strategies for that transformation are

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named. Firstly, renewable energy conversion in the sense that one replaces existing fossil fuel heating systems with those utilizing renewable sources. Secondly, energy efficiency improvements by reducing energy demand while maintaining comfort levels, e.g., temperature. Naturally, this can be achieved by various measures [16, 19]. For our work, we use the term energy-efficiency renovations (EER) to refer to and summarize these measures.

The decision to adopt such strategies, including the associated financial investment, ultimately rests with individual homeowners/consumers. Their choices play a vital role in achieving a low-carbon future. Consequently, there is a lot of research about understanding these decisions [12].

In [3, 35] the authors investigate the reasoning behind homeowners' choices regarding EER. Similarly, in [6, 17, 23, 27, 29], the homeowners' reasoning for (not) investing in sustainable heating technologies for their houses is explored for different countries. The authors of [22] examine how renewable heat policies influence homeowners' decisions, while the ones of [28] focus on homeowner satisfaction with low-carbon heating technologies, emphasizing the potential impact of word-of-mouth effects. In [11] potentials for supporting the decision-making processes of homeowners in the direction of EER are studied. For example, this can be done by setting up subsidy programs [8, 15]. Furthermore, in [13, 31] so-called choice experiments are conducted to find out the homeowners' preferences regarding energy retrofits. All of these findings can be used for modeling, predicting, or simulating the homeowners' decision processes. For instance, in [33] the authors set up an agent-based model from an end-user perspective to mimic the behavior of Norwegian homeowners' decisions on heating systems. In [37] the authors model quantitatively why and how homeowners decided for EER. A significant consideration for homeowners is the trade-off between upfront investment costs and anticipated savings from reduced energy consumption [2]. Using such terms and quantitative data one can determine the homeowners' *willingness to pay* (WTP) for EER [34]. All of the above-mentioned research focuses on individual homeowners' choices concerning EER and sustainable heating technologies. Throughout this work, we refer to these individual choices as micro-decisions, emphasizing the individual level at which they are made.

In [7, 14] the authors investigate the potential impact of individual choices (micro-decisions) on achieving the Net Zero 2050 goal. They do this by exploring different scenarios that translate micro-level decisions to their broader (macro-level) effects. The study [14] calculates the potential for carbon reduction achievable through individual actions that are economically feasible. However, the results reveal that these actions alone are insufficient to reach the 2050 target. Accordingly, in [32], the authors claim that „quantification of costs and benefits, from economic, social, and ecological perspectives, is a necessary first step to investment in solutions that take more local and global ecological and economic conditions into account.“ This is in line with the idea of the present paper. We use an energy supply network model [9, 25] designed to find cost-optimal network designs on the district level. In [24], this model was enriched with a second objective function, namely reducing the accompanying carbon emissions of the respective network plans. Having several conflicting objective functions, there is not only one optimal network plan anymore but several so-called optimal compromises (or Pareto optimal points) between the objectives. Proceeding like that and including several objective functions can aid the macro-level decision process in terms of providing (a selection of) optimal compromises.

Although micro-decisions are implicitly included in the model, during the optimization process they are made from the macro-perspective, i.e., these micro-level choices are made which are best for the current macro-preferences. Obviously, by doing so there is no consideration of the homeowners' preferences. As a first step in this direction, we aim to integrate the likelihood of individual homeowners accepting the proposed micro-decisions in this work. We call this *social acceptance* of the proposed network plans. To account for homeowner acceptance, we consider their expected savings and carbon emission reductions as factors influencing their willingness to pay for low-carbon measures. This gives rise to an individual investment budget for each homeowner which we incorporate in two ways into the model. Firstly, as a strict investment cap, i.e., as a constraint, meaning that no micro-decision overrunning the respective investment budget is viable. Secondly, to make the effect of possible subsidies visible, as part of an additional objective function minimizing the overrun of these budgets. Both approaches yield a modeling framework that can be used for an in-depth analysis of the interplay between micro- and macro-level decisions. To the best of the authors' knowledge, this is a novel approach. However, conducting such an analysis is not the goal of the present work as that would require a very careful choice and reasoning of the respective network parameters.

The remainder of this paper is structured in the following way: we introduce the relevant basics of the underlying energy supply network model in Section 2. We give a brief overview of the aspects necessary to the here-discussed extensions of this model. All details regarding the model can be found in [9, 25]. In Section 3, we explain how the notion of homeowner acceptance of the proposed micro-decisions is included in the model. We clarify the notion of willingness to pay and define the individual investment budget for the homeowners. This is then incorporated into the model in two ways: Firstly, a constraint approach yielding a single-objective optimization problem and secondly, an objective approach yielding a multi-objective one. In Section 4 we present some numerical experiments on a given network instance for both of the aforementioned modeling approaches. Finally, in Section 5 we conclude the respective capabilities of the modeling approaches.

2. The decentralized energy supply network problem

In the following, we briefly describe the model of decentralized energy supply networks which is fundamental for considering social acceptance of the proposed network plans. All details regarding the model can be found in [9, 25].

The underlying structure of the model is a directed graph (V, E), where V denotes the set of nodes and E the set of arcs. There is one special node called *source node*, where the energy for the whole network gets injected. The injected energy is then distributed through the network along the arcs. The energy flow along the arcs is modeled using simplified flow equations. One arc $(i, j) \in E$ represents agglomerations of inhabitants like, e.g., residential houses along a street. Thus, an arc is sometimes simply called consumer and/or homeowner in the following. The nodes can then be interpreted as street crossings. With this picture in mind, it is natural to locate energy demand on the arcs. The model considers two energy carriers, electricity and natural gas. For any arc $(i, j) \in E$ the inquired yearly amount of electricity and gas is given by the variables $s^{\mathrm{Esum}}_{i,j}$ and $s^{\mathrm{Gsum}}_{i,j}$, respectively.

The values of these variables can vary depending mainly on two decisions which are made individually for each consumer $(i, j) \in E$ – the so-called micro-decisions in line with [12]. These two individual decisions on the consumer level represent the decentralized character of the model. Firstly, each consumer can decide which energy carrier (electricity or natural gas) is used for heating. Secondly, each consumer can decide to execute energy-efficient renovations (EER) to lower the heating demand.

In the present model, each homeowner can choose between three different *Micro Energy Conversion Technologies* (MECTs). MECTs are local and small-sized energy generators and all of them either convert electricity or natural gas into heat. The details can be seen in Figure 1. Since the so-called *Combined Heat and Power Unit*

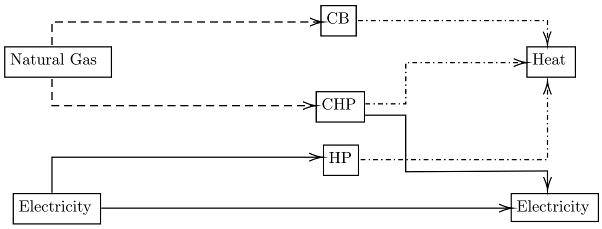

Figure 1: Energy conversion of the three considered MECTs: CB (condensing boilers), CHP (combined heat and power unit) and HP (heating pump), [25, Figure 3.1].

(CHP) uses gas to produce heat and electricity, electrical and gas grids are coupled and cannot be considered separately in the model.

For each consumer $(i, j) \in E$, there are binary variables

$$x^{\mathrm{cb}}_{i,j}, x^{\mathrm{chp}}_{i,j}, x^{\mathrm{hp}}_{i,j} \in \{0, 1\},$$

each of which equals one if technology $t \in T := \{\mathrm{cb}, \mathrm{chp}, \mathrm{hp}\}$ is chosen by consumer (i, j). Naturally, each consumer can only choose one MECT, i.e.,

$$\sum_{t \in T} x^t_{i,j} = 1$$

for each $(i, j) \in E$. As already indicated, the demands for the different energy carriers differ depending on the installed technology. These different yearly demands are given by the model parameters $\mathrm{SUMELOAD}^t_{i,j}$ and $\mathrm{SUMGLOAD}^t_{i,j}$ where $t \in T$ and $(i, j) \in E$. For each $t \in T$, the annualized investment and maintenance cost for a time horizon of 20 years is given by γ^t. Note that all costs occurring in the model are either yearly costs or annualized investments over a time horizon of 20 years. Thus, the technology investment costs for consumer $(i,j) \in E$ are given by

$$C_{i,j}^{\text{tech}} = \sum_{t \in T} \gamma^t x_{i,j}^t, \tag{1}$$

and the one for the whole network is then given by the sum of all consumers.

Another option to change the yearly demand is to carry out EER to reduce the heating demand. For example, one could invest in double-glazed windows or wall insulation. As there are a bunch of possible different measures of energy-efficient renovation [16, 19] and therefore their precise modeling would be very complex, a simplified modeling is chosen. The impact on reducing carbon emissions per invested monetary unit is assumed to be a concave function, i.e., there are several relatively cheap (effective) possibilities to reduce carbon emissions and some relatively expensive (less effective) ones. This concave utility function is then approximated by a piecewise linear function consisting of two line segments. In the model, this leads to a so-called two-stage energy-efficiency renovation, where the first stage consists of the more effective measures and full renovation leads to a heat demand reduction rate of $\mu_1 \in (0,1)$. The second stage instead consists of the less effective measures whose completion results in a reduction of the heat demand of $\mu_2 \in (0, \min\{\mu_1, 1-\mu_1\})$. Note that if suitable data is available, it is possible to individualize the parameters μ_1 and μ_2 to the homeowners $(i,j) \in E$, i.e., for each $(i,j) \in E$ one can choose individual $\mu_1^{i,j}, \mu_2^{i,j}$. In that case, one can also set $\mu_1^{i,j} = \mu_2^{i,j} = 0$ for some homeowner $(i,j) \in E$ for whom one assumes that no EER are carried out – no matter what incentives are present. However, in order to keep the notation as simple as possible, we use uniform μ_1 and μ_2 for the whole network in the present paper. Given the technology $t \in T$ and the consumer $(i,j) \in E$, the progress of the two stages is represented by the variables $x_{i,j}^{1,t}, x_{i,j}^{2,t} \in [0,1]$. Thus, for each consumer $(i,j) \in E$, we obtain

$$s_{i,j}^{\text{Gsum}} = \sum_{t \in T} \text{SUMGLOAD}_{i,j}^t \left(x_{i,j}^t - \mu_1 x_{i,j}^{1,t} - \mu_2 x_{i,j}^{2,t} \right) \tag{2}$$

for the yearly gas demand. Obviously, for the electricity-based technology HP, there is no gas demand at all, and therefore $\text{SUMGLOAD}_{i,j}^{\text{hp}} = 0$. On the other hand, this leads to a higher electricity demand $s_{i,j}^{\text{Esum}}$ for all consumers $(i,j) \in E$ choosing HP. In contrast, for CHP, there is a reduced electricity demand compared to the original one, since electricity is produced during the heat generation from gas. We refer to [9] for the detailed equations covering each case. This gives rise to the energy cost calculation under consideration of the possible EER given by the following formula

$$\begin{aligned} C_{i,j}^{\text{energycost}} &= \left(\alpha_p^e + \beta^e\right) s_{i,j}^{\text{Esum}} \\ &\quad + t_{\text{adv}} \beta^e \left(\text{SUMELOAD}_{i,j} - \text{SUMELOAD}_{i,j}^{\text{chp}}\right) \left(x_{i,j}^{\text{chp}} - \mu_1 x_{i,j}^{1,\text{chp}} - \mu_2 x_{i,j}^{2,\text{chp}}\right) \\ &\quad + \left(\alpha_p^g + \beta^g\right) s_{i,j}^{\text{Gsum}}, \end{aligned} \tag{3}$$

where $s_{i,j}^{\text{Esum}}$ and $s_{i,j}^{\text{Gsum}}$ are the demands of electricity and gas, respectively, according to the proposed micro-decisions as explained before (see, e.g., (2)). The parameters

α_p^e and α_p^g denote the before-tax prices for electricity and gas per kWh, respectively. By β^e and β^g we denote the tax costs for electricity and gas, respectively. Since CHP produces electricity, which equals the difference between the pure electricity demand $\mathrm{SUMELOAD}_{i,j}$ and the one given that CHP is installed, it has to be taxed as well, but with a tax advantage factor $t_{\mathrm{adv}} \in (0,1)$. As before, the variables $x_{i,j}^t \in \{0,1\}$ indicate whether technology t is chosen by consumer (i,j) and the parameters $\mathrm{SUMELOAD}_{i,j}^t$ and $\mathrm{SUMGLOAD}_{i,j}^t$ stand for the technology-dependent demand of electricity and gas, respectively.

The annualized costs per demanded heat unit of first- and second-stage renovation are given by ν_1 and ν_2, respectively, resulting in the renovation cost calculation for a consumer $(i,j) \in E$ given by

$$C_{i,j}^{\mathrm{renovation}} = \sum_{t \in T} \mathrm{SUMHLOAD}_{i,j} \left(\nu_1 x_{i,j}^{1,t} + \nu_2 x_{i,j}^{2,t} \right), \tag{4}$$

where $\mathrm{SUMHLOAD}_{i,j}$ represents the pure heat demand of consumer (i,j).

As there are some real-world limitations regarding the possibility of installing, e.g., heating pumps or laying gas pipes at some places, it is important to consider also grid extensions in the model. It is assumed that the electricity grid is fully available, i.e., there is no need to connect any arc to the electricity grid. In contrast to that, there is no available gas grid yet. Thus, the model has to decide where to build gas pipes to provide the necessary gas to consumers with positive gas demand $s_{i,j}^{\mathrm{Gsum}} > 0$. The incurred costs for such grid extensions are represented by the variable C_g^{grid}. Furthermore, to meet the hourly peak demands of gas and electricity, so-called *allocation costs* $C^{\mathrm{allocation}}$ have to be paid to the public energy supplier.

In [9, 25] all arising costs are summarized in a single so-called cost objective function which is minimized. This function is given by

$$C = C_g^{\mathrm{grid}} + C^{\mathrm{allocation}} + \sum_{(i,j) \in E} \left(C_{i,j}^{\mathrm{energycost}} + C_{i,j}^{\mathrm{renovation}} + C_{i,j}^{\mathrm{tech}} \right). \tag{5}$$

Additionally, as done in [24], the corresponding carbon emissions are shifted to another objective function which is also minimized. By doing so, we enter the setting of multi-objective optimization in terms of multiple conflicting objective functions [10]. The goal of multi-objective optimization is to find the so-called optimal compromises (or nondominated points, Pareto optimal points) between these conflicting objectives. Basic notions of multi-objective optimization are presented in Appendix A.

3. Social acceptance via modeling investment budget

In [9, 25] as well as in [24] the cost optimization process focuses only on the macro decisions, i.e., in the objective function the sum of all appearing costs is minimized. As explained in the previous section, this includes also the investments of the homeowners where the optimization process proposes certain micro decisions. However, while one can quantify the homeowner investments accompanying the proposed optimal network plans, there is no consideration of the respective homeowner acceptance during the optimization process. In the following, we describe a framework that allows us to assess possible network plans based on how likely homeowners are to approve the proposed micro-decisions.

The underlying idea of that framework is the use of utility-based decision theory [5] which has its origins in the seminal work [36]. Expected utility theory assumes that individuals choose one alternative among others that maximizes a certain utility function. In [1], utility theory is related to the cost/investment of certain alternatives resulting in the so-called *willingness to pay* (WTP). For the following, we use the notion of willingness to pay presented in [18]. Let $u(x, y)$ be a utility function where $x \in \mathbb{R}$ represents the wealth and $y \in \{c, d\}$ possible states, namely the current state c and the desired state d with $c \neq d$. In particular, this means $u(x, c) < u(x, d)$ for any wealth $x \in \mathbb{R}$. Then, the WTP according to the utility function u for reaching the desired state d is defined as

$$u(x_0, c) = u(x_0 - \mathrm{WTP}, d),$$

where $x_0 \in \mathbb{R}$ represents the initial wealth. Furthermore, we assume the utility function to be strictly increasing in the wealth variable x, i.e., if $x_1 < x_2$ then also $u(x_1, y) < u(x_2, y)$ for any state y. Following the assumption of individuals choosing the alternative having the higher utility, the above means that given that the desired state d can be reached with some wealth $x' > x_0 - \mathrm{WTP}$, then one decides for action to reach the tuple (x', d) rather than sticking with the current status (x_0, c) due to

$$u(x_0, c) = u(x_0 - \mathrm{WTP}, d) < u(x', d).$$

Applying the described utility theory to the homeowner micro-decisions regarding investments in low-carbon measures, we obtain the following: Homeowner $(i, j) \in E$ decides in favor of investing in retrofits, denoted by the desired state d, if the necessary investment cost is smaller or equal to its WTP for reaching d. If otherwise, the necessary investment cost is larger than its WTP, the homeowner decides against the retrofit. We therefore call the above-described WTP the homeowner's *investment budget*. Note that this allows us to model the homeowner micro-decisions about the – from the optimization process proposed – investments solely knowing the respective investment budget and the necessary investment cost.

For our calculation of the homeowner investment budget, we use two key figures, namely:

- $\iota^{\text{cost save}}$: annualized willingness to pay per saving of one monetary unit regarding the annual energy costs,
- $\iota^{\text{emi save},\rho_1}$, $\iota^{\text{emi save},\rho_2}$: annualized willingness to pay if a reduction of CO_2-emission of at least ρ_1 (or ρ_2, respectively) is realized where $0\% \leq \rho_1 < \rho_2 \leq 100\%$.

Note that ρ_1 and ρ_2 are two parameters of the model that have to be carefully determined when doing a meaningful case study of real-world situations.

To properly model the investment budget of homeowner $(i,j) \in E$ using the data above, we introduce the variables $S_{i,j}^{\text{cost}}$ and $S_{i,j}^{\text{carbon}}$ representing the monetary and emission savings of homeowner (i,j), respectively, after conducted retrofit measures. Naturally, for each homeowner $(i,j) \in E$ the monetary savings are given by

$$S_{i,j}^{\text{cost}} = C_{i,j}^{\text{cost orig}} - C_{i,j}^{\text{cost after}}, \tag{6}$$

where $C_{i,j}^{\text{cost orig}}$ and $C_{i,j}^{\text{cost after}}$ represent the yearly energy costs before and after retrofit measures took place, respectively. Similarly, regarding the annual carbon emissions for homeowner $(i,j) \in E$, we have

$$S_{i,j}^{\text{carbon}} = E_{i,j}^{\text{carbon orig}} - E_{i,j}^{\text{carbon after}}, \tag{7}$$

where $E_{i,j}^{\text{carbon orig}}$ and $E_{i,j}^{\text{carbon after}}$ represent the yearly carbon emissions before and after the retrofit measures took place, respectively. The two variables $C_{i,j}^{\text{cost orig}}$ and $E_{i,j}^{\text{carbon orig}}$ determine the status quo, whereas $C_{i,j}^{\text{cost after}}$ and $E_{i,j}^{\text{carbon after}}$ represent the respective values according to the proposed micro-decisions for homeowner $(i,j) \in E$, i.e., the optimal solution of the optimization problem.

We start by clarifying the status quo variables. In general, having a meaningful status quo depends heavily on the data one has at hand. Here, data means information about the installed heating technologies and the progress of EER for each homeowner considered in the network. Naturally, the developed framework should be able to include such information. On the other hand, we cannot assume that such information is publicly available. In that case, we have to define some more or less meaningful status quo. In the following, we propose a framework that can deal with both situations.

We start with the status quo technology denoted by $t_{i,j}^{\star} \in T$ for homeowner $(i,j) \in E$. If one has information at hand, one simply fixes $t_{i,j}^{\star}$ to be the respective technology. For any homeowner $(i,j) \in E$ with no such information available, we assume that the MECT being the cheapest w.r.t. to both installation costs and ongoing annual energy expenses is installed. Based on (1) and (3) one computes this by

$$t_{i,j}^{\star} = \operatorname*{argmin}_{t \in T} \left\{ C_{i,j}^{\text{tech}} + C_{i,j}^{\text{energycost}} \mid x_{i,j}^{t} = 1,\ x_{i,j}^{t'} = 0\ \forall t' \in T \setminus \{t\} \right\}. \tag{8}$$

Note that (8) can be computed by taking the minimum out of $|T|$ numbers each of which consists of the above-described easily calculated sums. Note further that we have that $x_{i,j}^{t^{\star}} = 1$ and $x_{i,j}^{t} = 0$ for $t \in T \backslash \{t^{\star}\}$ for any homeowner $(i,j) \in E$ independently of information regarding $t_{i,j}^{\star}$ is available. Status quo means that no actions are proposed by the optimization process yet. In particular, this means that for the calculation of $C_{i,j}^{\text{energycost orig}}$ no EER measures are proposed yielding that $x_{i,j}^{t,1} = x_{i,j}^{2,t} = 0$ for any MECT $t \in T$ and any homeowner $(i,j) \in E$. The same holds for the calculations for determining $t_{i,j}^{\star}$ in (8). Consequently, the value of $C_{i,j}^{\text{energycost orig}}$ is computed using

(3) which collapses to

$$\begin{aligned} C_{i,j}^{\text{energycost orig}} &= \left(\alpha_p^e + \beta^e\right) \text{SUMELOAD}_{i,j}^{t_{i,j}^\star} \\ &+ \mathbb{1}_{\{\text{chp}\}}(t_{i,j}^\star) t_{\text{adv}} \beta^e \left(\text{SUMELOAD}_{i,j} - \text{SUMELOAD}_{i,j}^{\text{chp}}\right) \\ &+ \left(\alpha_p^g + \beta^g\right) \text{SUMGLOAD}_{i,j}^{t_{i,j}^\star}. \end{aligned} \tag{9}$$

For two sets A, B with $A \subseteq B$, the characteristic function $\mathbb{1}_A \colon B \to \{0,1\}$ is defined as

$$x \mapsto \begin{cases} 1, & \text{if } x \in A, \\ 0, & \text{otherwise.} \end{cases}$$

Similarly, the status quo carbon emissions are given by

$$E_{i,j}^{\text{carbon orig}} = \kappa^e \, \text{SUMELOAD}_{i,j}^{t_{i,j}^\star} + \kappa^g \, \text{SUMGLOAD}_{i,j}^{t_{i,j}^\star}, \tag{10}$$

Although it does not influence the above computations directly – despite possibly different values for the energy demands –, status quo information regarding the progress of EER also influences the model. The extent of EER measures that can be carried out by homeowner $(i,j) \in E$ starting from the status quo is represented by the parameters $\mu_1^{i,j}$ and $\mu_2^{i,j}$. To integrate possibly available information about the progress of EER, one has to simply adjust these parameters. If, for instance, homeowner $(i,j) \in E$ has carried out all possible EER measures already, we have that $\mu_1^{i,j} = \mu_2^{i,j} = 0$. If otherwise, no such information is available, we assume that no homeowners have carried out any EER, and therefore a reduction in heat demand by the factor $\mu_1 + \mu_2$ is possible for each homeowner.

Next, we examine the calculations used to assess the proposed retrofits. These consist of the proposed micro-decisions for homeowner $(i,j) \in E$, i.e., the proposed heating technology $\bar{t}_{i,j}$ and progress of first and second stage EER $\bar{x}_{i,j}^{\bar{t}_{i,j},1}$ and $\bar{x}_{i,j}^{\bar{t}_{i,j},2}$, respectively. Note that $\bar{x}_{i,j}^{t} = \bar{x}_{i,j}^{t,1} = \bar{x}_{i,j}^{t,2} = 0$ for all $t \in T \setminus \{\bar{t}_{i,j}\}$. Therefore, again using (3) we calculate the after-renovation energycosts by

$$\begin{aligned} C_{i,j}^{\text{cost after}} &= \left(\alpha_p^e + \beta^e\right) s_{i,j}^{\text{Esum}} \\ &+ t_{\text{adv}} \beta^e \left(\text{SUMELOAD}_{i,j} - \text{SUMELOAD}_{i,j}^{\text{chp}}\right) \left(\bar{x}_{i,j}^{\text{chp}} - \mu_1 \bar{x}_{i,j}^{\text{chp},1} - \mu_2 \bar{x}_{i,j}^{\text{chp},2}\right) \\ &+ \left(\alpha_p^g + \beta^g\right) s_{i,j}^{\text{Gsum}}, \end{aligned} \tag{11}$$

and the after-renovation carbon emissions by

$$E_{i,j}^{\text{carbon after}} = \kappa^e s_{i,j}^{\text{Esum}} + \kappa^g s_{i,j}^{\text{Gsum}}. \tag{12}$$

Using (9), (10), (11) and (12), one can compute the respective savings $S_{i,j}^{\text{cost}}$ and $S_{i,j}^{\text{carbon}}$ given by (6) and (7). We are now ready to define the investment budget for homeowner $(i,j) \in E$ as

$$\begin{aligned} B^{\text{inv}}_{i,j} = & \iota^{\text{cost save}}\, S^{\text{cost}}_{i,j}\, \mathbb{1}_{[0,\infty)}\,(S^{\text{cost}}_{i,j}) + \\ & S^{\text{cost}}_{i,j}\, \mathbb{1}_{(-\infty,0)}\,(S^{\text{cost}}_{i,j}) + \\ & \iota^{\text{emi save},\rho_1}\, \mathbb{1}_{[\rho_1,\rho_2)}\left(S^{\text{carbon}}_{i,j}/E^{\text{carbon orig}}_{i,j}\right) + \\ & \iota^{\text{emi save},\rho_2}\, \mathbb{1}_{[\rho_2,1]}\left(S^{\text{carbon}}_{i,j}/E^{\text{carbon orig}}_{i,j}\right). \end{aligned} \tag{13}$$

We now provide a detailed explanation of each component term within (13). The first summand

$$\iota^{\text{cost save}} S^{\text{cost}}_{i,j} \mathbb{1}_{[0,\infty)}(S^{\text{cost}}_{i,j})$$

determines the WTP of homeowner $(i,j) \in E$ expecting savings regarding the annual energy costs of $S^{\text{cost}}_{i,j}$. Note that the summand equals zero if there are no actual savings, i.e., if $S^{\text{cost}}_{i,j} \leq 0$. If the annual energy costs after the proposed retrofits increase compared to the ones of status quo, i.e., if $S^{\text{cost}}_{i,j} < 0$, the second component term becomes non-zero and equals $S^{\text{cost}}_{i,j}$. For instance, such a situation may arise due to the following: assume the status quo technology $t^{\star}_{i,j}$ of homeowner $(i,j) \in E$ is CHP. Then, the electricity demand $\text{SUMELOAD}^{\text{chp}}_{i,j}$ given CHP is installed is smaller than the sole electricity demand $\text{SUMELOAD}_{i,j}$ due to local electricity production of CHP while converting natural gas into heat. Now, if homeowner (i,j) carries out EER, the demand for heat decreases and therefore also the amount of locally produced electricity. In particular, $S^{\text{Esum}}_{i,j}$ increases towards $\text{SUMELOAD}_{i,j}$ – and so do the annual costs for electricity. If these additional costs overrun the savings coming from buying less gas, one ends up with negative energy cost savings $S^{\text{cost}}_{i,j}$. Note that this might lead to a negative investment budget for homeowner $(i,j) \in E$. We will see later on why it makes sense to not exclude such a case.

The third and fourth summand calculate the actual WTP coming from the reduction of carbon emissions. Our model incorporates that homeowners are only motivated by significant reductions in carbon emissions when deciding on retrofits, i.e., carbon emission reduction requires a more significant decrease to incentivize homeowner investments. This contrasts with annual energy cost savings, where each unit saved results in a direct financial benefit. The third term

$$\iota^{\text{emi save},\rho_1} \mathbb{1}_{[\rho_1,\rho_2)}(S^{\text{carbon}}_{i,j}/E^{\text{carbon orig}}_{i,j})$$

is non-zero if and only if there is a reduction in carbon emissions of homeowner (i,j) of at least ρ_1 and below ρ_2. The reduction is calculated by the fraction of the actual emission savings $S^{\text{carbon}}_{i,j}$ over the status quo emissions $E^{\text{carbon orig}}_{i,j}$. Similarly, the fourth summand comes into play if there is a reduction of homeowner (i,j)'s carbon emissions of at least ρ_2. In some cases, choosing a different MECT might lead to higher carbon emissions compared to the status quo. The possible impact of such a situation on the investment budget is not considered in our model. Note further, that one could also use individual WTP-factors $\iota^{\text{cost save}}_{i,j}$, $\iota^{\text{emi save},\rho_1}_{i,j}$ and $\iota^{\text{emi save},\rho_2}_{i,j}$ for each homeowner $(i, j) \in E$ instead of the global ones used above. Doing so would not increase the complexity of the model. However, this requires access to relevant data.

The above demonstrates one approach to model an investment budget for homeowner $(i, j) \in E$, considering the anticipated annual savings in energy costs and carbon emissions resulting from the proposed micro-decisions. We have also seen that – given accurate and reliable data regarding the willingness to pay – according to utility theory the acceptance of the proposed micro-decisions is more likely if the actual investments are smaller than the willingness to pay for the expected outcomes. Subsequently, we propose two ways of including the described concept of social acceptance in the energy supply network model.

We start with the idea of adding social acceptance to the constraints of the model. This means we only consider network plans where the homeowners are likely to accept the respective proposed micro-decisions on retrofits. Therefore, retrofit costs must stay within the designated investment budget. Concretely, this means that for each homeowner $(i, j) \in E$, we add the constraint

$$(C_{i,j}^{\text{tech}} - \gamma^{t_{i,j}^{\star}}) + C_{i,j}^{\text{renovation}} \leq B_{i,j}^{\text{inv}}, \tag{14}$$

where $C_{i,j}^{\text{tech}}$ denotes the installation costs (1) of the proposed MECT, $\gamma^{t_{i,j}^{\star}}$ the MECT installation costs for the status quo technology, and $C_{i,j}^{\text{renovation}}$ the renovation costs (4). Note that this approach goes in the direction of the study [14] where the authors explore the potential carbon reduction achieved only by economically feasible retrofit measures. Instead of the economic feasibility, we use the acceptance of micro-decisions.

A core principle of the above-described constraint approach is strict adherence to individual investment budgets, preventing any cost overruns for retrofits. This approach might overlook opportunities for substantial carbon reduction that could be achieved with a minor increase in investment budgets. Conversely, knowing about such scenarios highlights a potential benefit of implementing subsidies for retrofit measures. By providing financial assistance, such subsidies could help bridge the gap between investment budgets and actual costs. This, in turn, could increase homeowner acceptance of micro-decisions that lead to significant carbon reduction. Making such scenarios visible is the idea of the second approach. Unlike the fixed investment cap, this approach minimizes budget overruns by incorporating them as an additional objective function that needs to be minimized. Therefore, for each homeowner $(i, j) \in E$, we add the variable $F_{i,j}^{\text{inv}}$ representing fantasy money, e.g., possible subsidies. For each homeowner $(i, j) \in E$ we add the constraint

$$(C_{i,j}^{\text{tech}} - \gamma^{t_{i,j}^{\star}}) + C_{i,j}^{\text{renovation}} \leq B_{i,j}^{\text{inv}} + F_{i,j}^{\text{inv}}. \tag{15}$$

The additional objective function is then given by

$$F^{\text{inv}} = \sum_{(i,j) \in E} F_{i,j}^{\text{inv}}. \tag{16}$$

Permitting some flexibility in investment budgets allows for a more nuanced understanding of homeowner acceptance of proposed micro-decisions. Furthermore, one has to keep in mind that the proposed notion of social acceptance relies heavily on the data $\iota^{\text{cost save}}$, $\iota^{\text{emi save},\rho_1}$ and $\iota^{\text{emi save},\rho_2}$. As these are statistical terms, there is inherent uncertainty. One could cope with that by using so-called fuzzy crossover points regarding decision-making [21]. For the sake of model tractability, this work investigates only the scenarios of exceeding the investment budgets. By offering a continuous measure of social acceptance, this approach goes beyond the constraint approach, which only considers network plans, where the costs remain within the budget. This leads to a more comprehensive evaluation of homeowner willingness to participate in various micro-decision scenarios. While having these beneficial aspects, it introduces an additional layer of complexity by transforming the problem into a multi-objective optimization problem, requiring the consideration of multiple goals simultaneously. In the case of using the model from [24], one obtains an additional objective function, namely the reduction of carbon emissions. Basic notions of multi-objective optimization can be found in Appendix A. For a more detailed introduction, we refer to [10].

By incorporating all individual homeowner costs into the investment budget itself, the cost objective function (5) might become redundant with respect to terms like MECT installation costs C^{tech}, renovation costs $C^{\text{renovation}}$, and annual energy costs $C^{\text{energycost}}$. Thus, they can be removed and the cost objective function collapses to only considering public costs, namely

$$C = C_g^{\text{grid}} + C^{\text{allocation}}. \tag{17}$$

4. Numerical experiments

In this section, we present some numerical experiments using the previously introduced notion of social acceptance. For that we use the `pyscipopt`-package [26] relying on the SCIP Optimization Suite [4] on a machine with Intel Core i7-8565U processor and 32GB of RAM.

Note that the upcoming experiments are not intended to provide an in-depth analysis of different scenarios resulting in a meaningful conclusion about real-world situations. To do so, a much more careful discussion of various network parameters and modeling assumptions would have to be done which is not the focus of the present work. Rather, the present work and the upcoming experiments aim to demonstrate the proposed framework's capabilities for incorporating social acceptance. Furthermore, the differences between the single-objective and the multi-objective approach are highlighted.

In general, real-world instances of energy supply networks are large and therefore yield very large-scale models. However, for the following, we restrict ourselves to a small network instance to keep the respective analysis as clear and brief as possible. Figure 2 depicts the graph of the network instance in question. This network is part of a network corresponding to the district *Paradies* in Konstanz, Germany. The source node is the rightmost node, labeled `v24227`. As described before, the energy for the whole network gets injected at this node. For all of the following experiments, we assume an annualized willingness to invest per expected energy cost saving of one

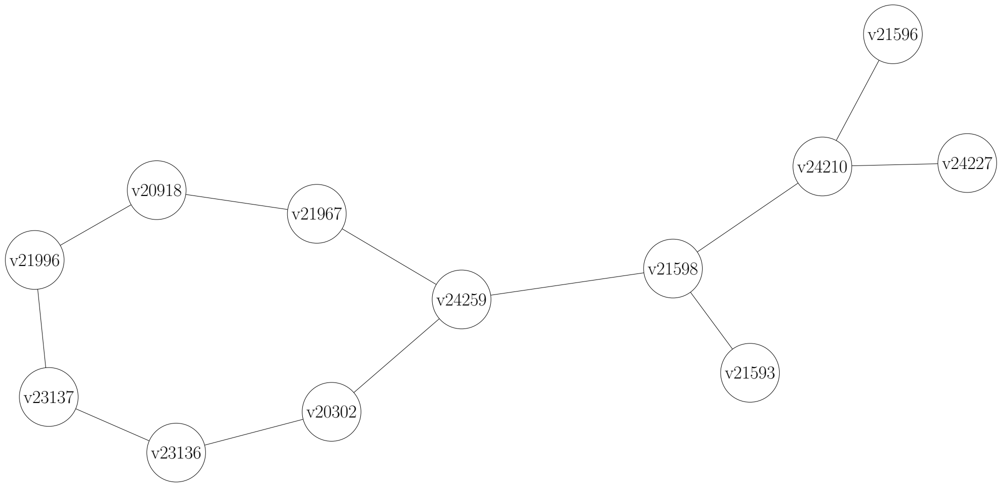

Figure 2: The underlying network graph.

monetary unit of $\iota^{\text{cost save}} = 0.75$. This means that the homeowners balance their investment with the yearly energy cost savings after 15 of the 20 considered years. Further, we assume an annualized willingness to invest for an individual carbon emission reduction of at least $\rho_1 = 20\%$ of $\iota^{\text{emi save},20} = 0.2$ monetary units per demanded heat unit, for at least $\rho_2 = 45\%$ of $\iota^{\text{emi save},45} = 1.5$ monetary units per demanded heat unit. Furthermore, we assume that each homeowner can reduce its heat demand by 80%, where one-half can be achieved by first-stage and one-half by second-stage renovations, i.e., $\mu_1 = \mu_2 = 0.4$. The corresponding renovation costs lie at $\nu_1 = 0.27$, respectively $\nu_2 = 2.7$, monetary units per demanded heat unit. For applying the proposed model to real world situations and deriving substantiated claims, the above parameters are some of the network parameters that require very careful discussions, which goes beyond the scope of this article.

Subsequently, we consider the single-objective approach, i.e., only optimizing public sector costs (17), while not allowing any overrun of the individual investment budgets together with different carbon reduction targets.

We start with a first carbon emission reduction target of at least 20%. Figure 3 depicts the corresponding optimal network plan. We first mention that there is no feasible network plan without any overrun of the investment budget. Consequently, we establish an upper bound on the sum of the granted subsidies written in (16) and increase it successively by $1,000$ until the problem becomes feasible. This is the case when we arrive at an allowed overrun of $10,000$ monetary units.

One can see that on the edges $(\texttt{v21598}, \texttt{v21593})$ and $(\texttt{v24259}, \texttt{v21967})$ there are no heating pumps allowed. This information is provided by the network data and can have, e.g., urban planning reasons. Furthermore, one can see that the edges $(\texttt{v24227}, \texttt{v24210})$, $(\texttt{v24210}, \texttt{v21596})$, $(\texttt{v24210}, \texttt{v21598})$, and $(\texttt{v21996}, \texttt{v23137})$ have no

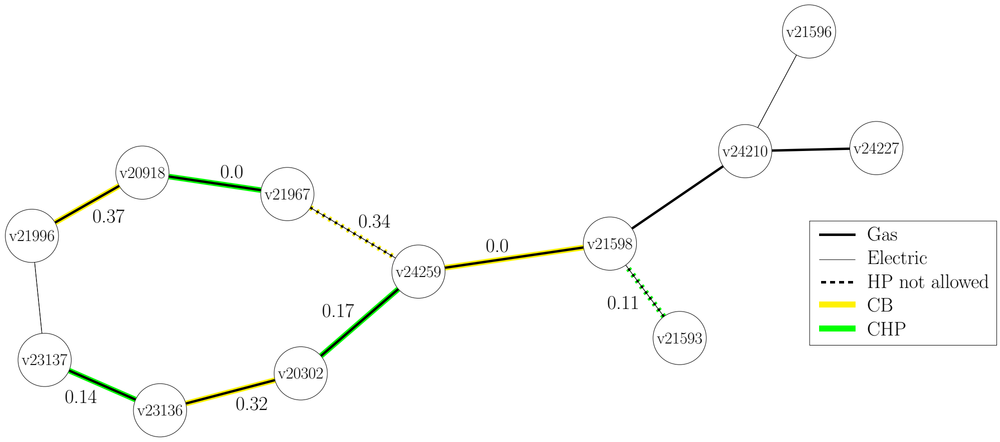

Figure 3: Optimal network plan for a carbon reduction target of 20% and allowed $10,000$ monetary units overrun of investment budgets.

heat demand, i.e., these are just connecting edges where no consumers are located, and therefore no MECT is installed on these edges. All other edges choose gas-fueled MECTs – namely, condensing boilers or combined heat and power units – and therefore have to be connected to the gas grid. There are four homeowners, $(\texttt{v21598}, \texttt{v24259})$, $(\texttt{v24259}, \texttt{v21967})$, $(\texttt{v20918}, \texttt{v21996})$, and $(\texttt{v20302}, \texttt{v23136})$, who stick with the status-quo technology CB. Interestingly, except $(\texttt{v21598}, \texttt{v24259})$, these are the homeowners carrying out more EER – reaching a reduction of the heat demand above 30% – compared to the homeowners who switched to CHP who do not reduce more than 17%. In Table 1, one can see that there are only two homeowners, namely $(\texttt{v21598}, \texttt{v24259})$

homeowner (i, j)	retrofit costs	$B^{\text{inv}}_{(i,j)}$	$F^{\text{inv}}_{(i,j)}$	homeowner share	CO_2 reduction
$(\texttt{v21598}, \texttt{v21593})$	19,029	15,482	3,547	81.4%	$20\% \leq x < 45\%$
$(\texttt{v21598}, \texttt{v24259})$	0	0	0	–	$x < 20\%$
$(\texttt{v24259}, \texttt{v21967})$	25,111	23,718	1,394	94.5%	$20\% \leq x < 45\%$
$(\texttt{v21967}, \texttt{v20918})$	2,855	816	2,039	28.6%	$x < 20\%$
$(\texttt{v20918}, \texttt{v21996})$	27,076	24,056	3,020	88.8%	$20\% \leq x < 45\%$
$(\texttt{v24259}, \texttt{v20302})$	13,136	13,136	0	100%	$20\% \leq x < 45\%$
$(\texttt{v20302}, \texttt{v23136})$	14,409	14,409	0	100%	$20\% \leq x < 45\%$
$(\texttt{v23136}, \texttt{v23137})$	19,971	19,971	0	100%	$20\% \leq x < 45\%$

Table 1: Retrofit cost analysis requiring a reduction network carbon of emissions of 20% allowing a total of $10,000$ monetary units of subsidies.

and $(\texttt{v21967}, \texttt{v20918})$, that do not achieve an individual carbon emission reduction of more than 20%. These are exactly the ones who do not carry out any EER. The remaining homeowners cover a relatively large share of their retrofit costs on their own – some even up to 100% of the arising costs.

In total, this yields a network carbon emission reduction of 20.2% and a cost objective function value of $19,172$ monetary units for the public sector with additional $10,000$ needed subsidies.

We continue with a network carbon emission target of at least 30%. In order to obtain feasibility of the optimization problem one has to set the allowed subsidies to $100,000$ monetary units after increasing it by steps $10,000$. The resulting optimal network plan is depicted in Figure 4. Again, each of the homeowners chooses an MECT

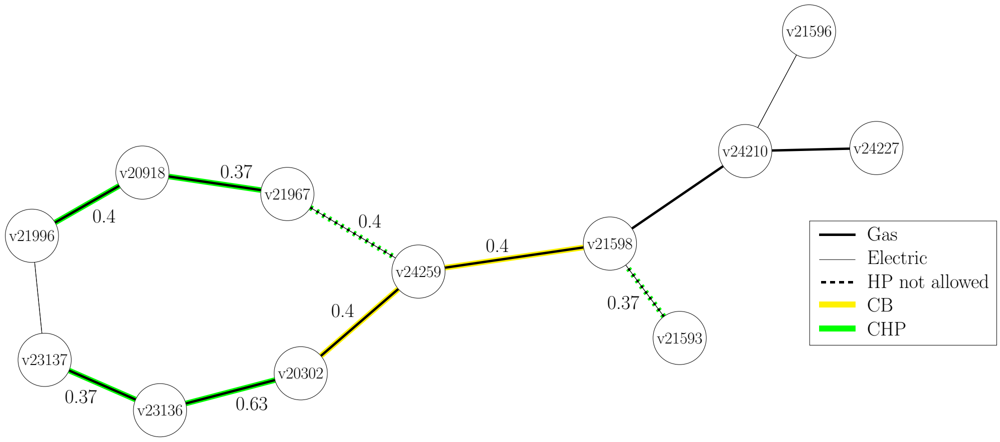

Figure 4: Optimal network plan for a carbon reduction target of 30% and allowed $100,000$ monetary units overrun of investment budgets.

which is fueled by gas but only homeowners (v21598, v24259) and (v2459, v20302) stay with the status quo MECT condensing boiler. Consequently, each consuming homeowner is connected to the gas grid. All homeowners carry out EER at least up to a reduction of the heat demand of around 37%. In contrast to the others, homeowner (v20302, v23136) even starts with second-stage renovation. In contrast to the scenario

homeowner (i,j)	retrofit costs	$B^{\text{inv}}_{(i,j)}$	$F^{\text{inv}}_{(i,j)}$	homeowner share	CO_2 reduction
(v21598, v21593)	30,931	16,150	14,781	52.1%	$20\% \leq x < 45\%$
(v21598, v24259)	1,519	1,198	321	78.9%	$20\% \leq x < 45\%$
(v24259, v21967)	44,848	24,860	19,988	55.4%	$20\% \leq x < 45\%$
(v21967, v20918)	9,431	6,391	3,040	67.8%	$10\% \leq x < 45\%$
(v20918, v21996)	43,720	25,199	18,522	57.6%	$20\% \leq x < 45\%$
(v24259, v20302)	16,051	13,211	2,840	82.3%	$20\% \leq x < 45\%$
(v20302, v23136)	128,998	101,735	27,263	78.9%	$45\% \leq x\%$
(v23136, v23137)	34,053	20,807	13,246	61.1%	$20\% \leq x < 45\%$

Table 2: Retrofit cost analysis requiring a reduction network carbon of emissions of 30% allowing a total of $100,000$ monetary units of subsidies.

before, each homeowner reaches an individual reduction of carbon emissions of at least

20% – homeowner (`v20302`, `v23136`) even above 45% which can be seen in Table 2. Furthermore, no single homeowner covers its retrofit on its own but at least a share of 50%.

In total, this yields a network carbon emission reduction of 30% and a cost objective function value of 18, 019 monetary units for the public sector with additional 100, 000 needed subsidies.

Now, aiming for a network carbon emission reduction of at least 40% the corresponding optimization problem one has to further increase the allowed subsidies. This occurs when reaching an upper bound of 500, 000 monetary units after successively increasing by 100, 000. Figure 5 shows the corresponding optimal network plan. Com-

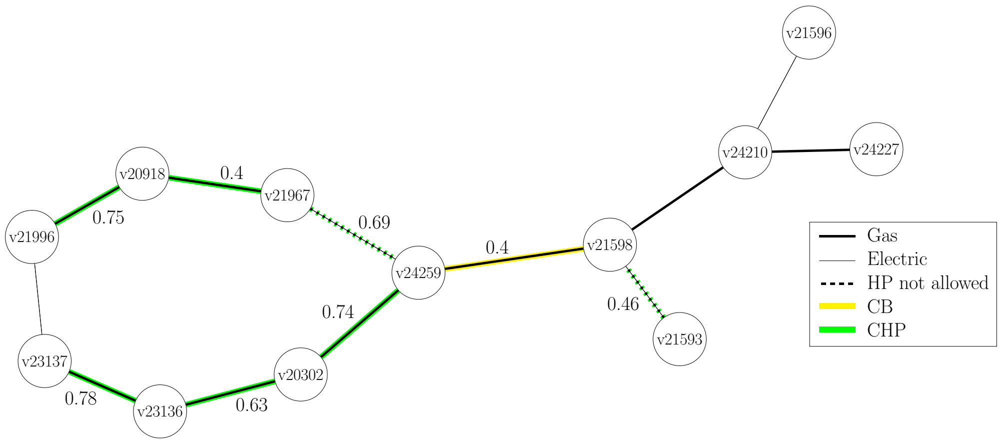

Figure 5: Optimal network plan for a carbon reduction target of 40% and an allowed overrun of investment budgets of 500, 000 monetary units.

pared to the optimal network plan before, we observe that still all homeowners decide for gas-fueled MECTs, but only homeowner (`v21598`, `v24259`) sticks with the status quo MECT whereas all others change to combined heat and power units. Further, there are only two homeowners, namely (`v21598`, `v24259`) and (`v21967`, `v20918`), who complete first-stage renovations but do not start with the second-stage ones. In Table 3, one can see that starting second-stage EER but not reaching a carbon emission reduction above 45% yields a comparably small own contribution to the retrofit costs (see homeowner (`v21598`, `v21593`)). Furthermore, the more of second-stage EER is carried out, the smaller the share of the homeowners' own contribution.

In total, this yields a network carbon emission reduction of 40% and a cost objective function value of 16, 313 monetary units for the public sector with additional 500, 000 needed subsidies.

If now, the public sector has more subsidies available, say an amount of 1, 000, 000 monetary units, one obtains the optimal network plan depicted in Figure 6. Here, only the homeowners who are not allowed to build heating pumps, and the *connecting*

homeowner (i,j)	retrofit costs	$B^{\mathrm{inv}}_{(i,j)}$	$F^{\mathrm{inv}}_{(i,j)}$	homeowner share	CO_2 reduction
(v21598, v21593)	62,634	16,411	46,223	26.2%	$20\% \leq x < 45\%$
(v21598, v24259)	1,519	1,198	321	78.9%	$20\% \leq x < 45\%$
(v24259, v21967)	258,237	166,952	91,285	64.7%	$45\% \leq x$
(v21967, v20918)	10,052	6,414	3,638	63.8%	$20\% \leq x < 45\%$
(v20918, v21996)	301,622	168,649	132,973	55.9%	$45\% \leq x$
(v24259, v20302)	159,795	91,837	67,958	57.5%	$45\% \leq x$
(v20302, v23136)	128,998	101,735	27,263	78.9%	$45\% \leq x$
(v23136, v23137)	270,166	139,826	130,340	51.8%	$45\% \leq x$

Table 3: Retrofit cost analysis requiring a reduction network carbon of emissions of 40% allowing a total of $500,000$ monetary units of subsidies.

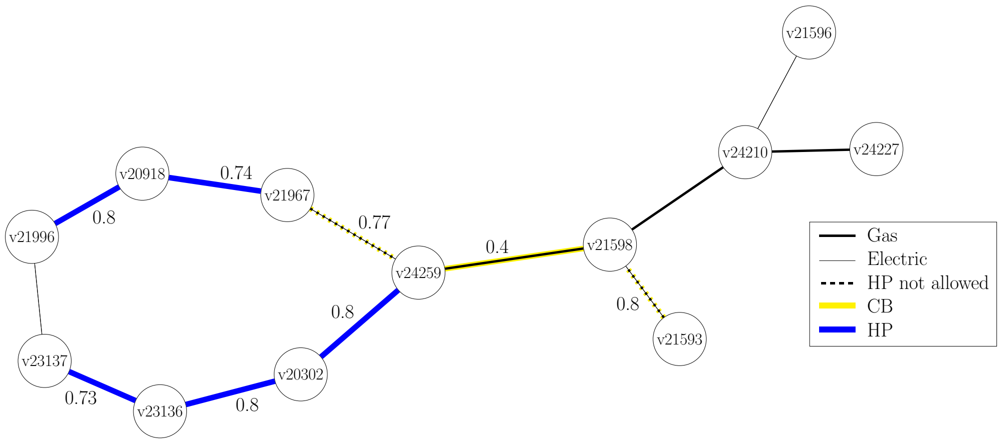

Figure 6: Optimal network plan for a carbon reduction target of 40% and an allowed overrun of investment budgets of $1,000,000$ monetary units.

homeowner decide for condensing boilers whereas the others decide for heating pumps and therefore no gas grid connection is needed there. One can furthermore observe that the *connecting* homeowner (v21598, v24259) is the only one carrying out full first-stage EER but not starting the second-stage ones. For instance, homeowner (v23136, v23137) is one of the homeowners deciding for installing a heating pump. But, compared to the scenario before (cf. Table 3), the share of own contribution to the proposed retrofit measures decreases significantly (cf. Table 4). Firstly, homeowner (v23316, v23137) does not reach carbon emission reduction of at least 45%. Secondly, the energy cost savings decrease compared to the scenario from Table 3. This is due to the fact that the price as well as the carbon emission per unit of electricity is higher than the ones of gas in the used network data. Again, this shows particularly the heavy dependence of the results on the used network data and parameters and therefore motivates a very careful selection of these parameters for a meaningful analysis of such networks.

homeowner (i,j)	retrofit costs	$B^{\text{inv}}_{(i,j)}$	$F^{\text{inv}}_{(i,j)}$	homeowner share	CO_2 reduction
(v21598, v21593)	207,211	17,053	190,158	8.2%	$20\% \leq x < 45\%$
(v21598, v24259)	1,519	1,198	321	78.9%	$20\% \leq x < 45\%$
(v24259, v21967)	301,953	167,028	134,925	55.3%	$45\% \leq x$
(v21967, v20918)	73,793	6,198	67,595	8.4%	$20\% \leq x < 45\%$
(v20918, v21996)	345,614	167,808	177,806	48.6%	$45\% \leq x$
(v24259, v20302)	187,097	91,403	95,694	48.9%	$45\% \leq x$
(v20302, v23136)	210,371	101,656	108,715	48.3%	$45\% \leq x$
(v23136, v23137)	245,723	20,935	224,788	8.5%	$20\% \leq x < 45\%$

Table 4: Retrofit cost analysis requiring a reduction network carbon of emissions of 40% allowing a total of $1,000,000$ monetary units of subsidies.

In total, requiring a network carbon emission reduction of 40% and allowing subsidies up to $1,000,000$ monetary units yields an optimal network plan with a total of $12,033$ monetary units of public costs.

Apart from the difficulty of selecting appropriate network parameters like, e.g., ρ_1 and ρ_2, or the energy prices, we have seen that it is not straightforward to determine a feasible setting in the single-objective case. That means when requiring a certain carbon emission reduction it is not easy to determine an upper bound on the allowed subsidies yielding a feasible problem. Furthermore, in general, the reason for a possible infeasibility of the problem is not clear: Is it just a too-small upper bound on the subsidies or is a certain carbon emission reduction simply unattainable due to technical reasons?

Following a multi-objective approach, some of the above-described issues vanish. For instance, using costs (17), network carbon emissions

$$E^{\text{carbon}} = \sum_{(i,j)\in E} E^{\text{carbon after}}_{i,j}$$

relying on (12), and necessary subsidies (16) as objective functions, among others one obtains the network plans that are the best w.r.t. one of these objectives. In Figure 7 the optimal compromises between these three objectives with a tolerance of 1% are depicted. Details on the corresponding notions are provided in Appendix A. In the visualization of the optimal compromises between the objectives in Figure 7 one can see that the network carbon emissions range from a little over $200,000$ to a little over $120,000$ carbon emission units – resulting in a possible reduction of around 40%. The public sector costs range from a little under $12,000$ to $20,000$ monetary units. The optimum in carbon emissions is attained with public sector costs around $15,000$ monetary units but one can come pretty close with public sector costs of $12,000$ monetary units. However, approaching the optimum of carbon emissions is strongly connected to increasing subsidies. More precisely, one can afford a relatively large carbon emission reduction of around 25% with a comparable small amount of subsidies while reducing carbon emissions more yields a more or less linear increase in necessary subsidies until $1,800,000$ monetary units. These dynamics and relations are way more easier to see using the multi-objective approach than the single-objective one with

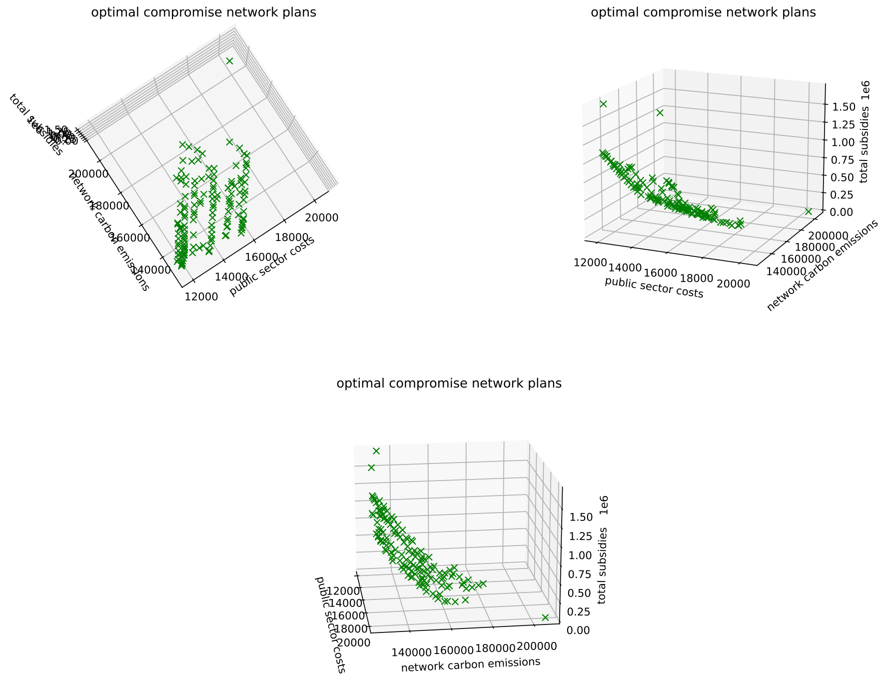

Figure 7: Optimal compromises between three objectives with a tolerance of 1%.

different constraint parameters. However, computing all depicted optimal compromises takes around $1,400$ seconds while each of the three single-objective problems above is solved in at most 20 seconds.

5. Conclusion

In the present paper, we introduce a framework for incorporating a notion of social acceptance into energy supply network optimization. This notion mainly addresses what we call micro-decisions of the individual homeowners, namely choosing a local heating technology and conducting EER measures. Rather than conducting a proper case study that allows to draw conclusions or give answers in one or another direction, we focus on the general framework and the different possibilities of including social acceptance into the model. To this end, we present two different ways – the first one yields a single-objective optimization problem whereas the second one uses multiple objective functions. In Section 4, numerical experiments highlighting the (dis-) advantages of both formulations are discussed. To summarize, one can say that the single-objective approach outperforms the multi-objective one in computational time as well as in clarity. But if one aims to find out the dynamics between the conflicting objectives as well as to end up with a broad overview of the situation one should go for the multi-objective approach.

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A. Basic notions of multi-objective optimization

In the following, we briefly provide basic notions of multi-objective optimization. For a more detailed introduction, we refer to [10] and to [24] for a more concise but still self-contained one. Throughout this section, we write $x \leq y$ for two vectors $x, y \in \mathbb{R}^k$ if for any index $i \in [k] := \{1, \dots, k\}$ we have that $x_i \leq y_i$. A multi-objective optimization problem is given by

$$\min\ f(x) \quad \text{s.t.} \quad x \in S, \tag{MOP}$$

where $f = (f_1, \dots, f_k)^\top$ with $f_i \colon S \to \mathbb{R}$ for every $i \in [k]$, denotes the vector of objective functions and $S \subseteq \mathbb{R}^k$ the feasible set. In general, one cannot assume that there exists $x^\star \in S$ minimizing all k objective functions simultaneously. Hence, one needs a suitable optimality concept, namely so-called *nondominance* or *Pareto dominance*. Given two vectors $x, y \in \mathbb{R}^k$ one says that x dominates y if $x \leq y$. This allows to define the so-called *efficient set* of (MOP) by

$$\mathcal{E} := \{x \in S \mid \text{there exists no } x' \in S \text{ such that } f(x') \text{ dominates } f(x)\},$$

as well as the so-called *nondominated set* or *Pareto front* by

$$\mathcal{N} := \{f(x) \mid x \in \mathcal{E}\}.$$

The nondominated set can be interpreted as the set of optimal compromises. This means that for each feature vector $f(x)$ belonging to the nondominated set, one cannot improve a single feature without worsening another one. In general, multi-objective optimization algorithms aim to compute an approximation of the nondominated set $\mathcal{N}$. For instance, in [24], the authors present an algorithm that computes an approximation of the nondominated set of (MOP) consisting of so-called ε-nondominated points. One calls a point $x \in S$ an ε-nondominated point of (MOP) with respect to a vector $e \in \mathbb{R}^k$, if there exists no $x' \in S$ such that $f(x') + \varepsilon e$ dominates $f(x)$, where $e = (1, \dots, 1)^\top \in$

$\mathbb{R}^k$. Note that one could also use a vector representing the corresponding magnitudes of the different objective functions in order to get a relative tolerance measure. In Section 4 of the present work, we use an algorithm very similar to the one in [24] and therefore also compute so-called ε-nondominated points. Furthermore, we use the relative tolerance measure respecting differences in the magnitude of the objective functions.