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Abstract

The shift from centralized to decentralized energy provision has created an opportunity for a wide range of distributed energy resources. In deciding how to best serve their long-term energy needs, end consumers face a plethora of investment options together with complex regulatory instruments as well as growing uncertainty regarding, e.g. techno-economic and political developments. Optimization models using linear programming methods are one option to help shed light on possible technology combinations and the economic consequences for end consumers. Yet the existing literature indicates a clear lack of models capable of accounting for high technical, regulatory and economic detail while optimizing investments in multiple future years. Therefore, within this paper, the mixed-integer linear programming model COMODO (Consumer Management of Decentralized Options) is developed to determine the cost-minimal energy provision for end consumers. The model uses its extensive technology catalog to perform an investment and dispatch optimization for multiple years, minimizing total costs over a long-term time horizon while accounting for developments in techno-economic data, regulatory frameworks and energy market conditions. Furthermore, piecewise-linear functions are created to represent costs and subsidies for different systems sizes and for future years. In order to demonstrate the capabilities of the model developed, an exemplary application is presented to investigate the energy provision of four single-family homes in Germany for the years 2025 to 2045. Three scenarios are designed that build upon each other regarding the amount of information available to consumers and their decentralized energy technologies. The results show a clear preference for gas boilers as a base technology coupled with electric heaters to cover demand peaks. Households with higher demand levels invest in PV systems in 2025, while other households with lower demands either wait until 2040 or do not invest. A sensitivity analysis then examines the effects of higher carbon pricing in the German building sector on the consumer's energy provision. The subsequent increase in the retail gas price leads to households choosing to fully electrify their heat provision, i.e., installing a heat pump combined with thermal storage, PV and an electric heater. On average, these households experience an increase in total costs ranging from 3.5% to 5.4% over the complete time horizon and realize a long-term decrease in annual carbon emissions of up to 80% compared to the analysis with lower carbon pricing. Lastly, this work also presents a novel method of analyzing the marginal costs of electricity and heat provision, revealing a strong correlation between the implicit marginal costs of energy provision and the assumptions on retail energy prices.

Keywords: Distributed energy resources, mixed-integer linear programming, consumer investment behavior, consumer modeling, heating, electricity, techno-economic optimization, energy system design

JEL classification: C26, C53, D11, D13, D15, H20

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1. Introduction

1.1. Motivation and Research Objective

The energy landscape for end consumers has undergone a massive transformation in recent years. In many developed countries, the standard means of energy provision have historically consisted of a centralized electricity supplier paired with decentralized heat generation, typically using a gas or oil boiler. Yet the range of distributed energy resources (DER) available to end consumers has widened over the past decade not only due to technological advancements but also as a result of economic, social and political movements. In Germany, for example, DER such as photovoltaics (PV), micro combined-heat-and-power (CHP) systems as well as heat pumps have been subject to incentive mechanisms, which have in turn driven down the total costs of ownership and increased their market visibility. In addition to a larger selection of affordable technologies, consumers as well as policy-makers have become more aware of the individual carbon footprints associated with energy provision, creating a social and economic pressure to move away from carbon-emitting fossil fuels. As such, consumers may no longer choose the least-cost option based on today's total costs of ownership but may have to also account for uncertainties regarding future energy policies on, e.g., the pricing of different energy carriers or carbon emissions.

Needless to say, the plethora of investment options combined with complex regulatory instruments and growing uncertainty make it difficult for end consumers to decide how to best serve their long-term energy needs. To better understand this conundrum, one method often seen in the existing literature is the use of linear programming methods to identify a least-cost solution over a defined time horizon. Although many of such optimization models have been developed, very few are capable of considering a high level of technological diversity and granularity while also accounting for future economic, regulatory and technical elements. Furthermore, the majority of such models are focused on the investment and operational decisions of today rather than considering how these may change over time. As such, the paper at hand seeks to address the following research questions: (i) How can linear programming methods be used to optimize the investment in and operation of distributed generation and storage technologies for end consumers, (ii) what technological, economic and regulatory aspects must be accounted for in order to model the decisions surrounding end consumers' energy provision, and (iii) how may end consumers design and manage their DER systems to minimize the costs of energy provision over longer time horizons, especially when subject to changes in the technological, economic and regulatory landscape?

Within the scope of this paper, the model "Consumer Management of Decentralized Options", referred to as COMODO, is developed to determine the cost-minimal energy provision for an end consumer or consumer group according to each energy use type (EUT), i.e., electricity, water heating and space heating. The model uses mixed-integer linear programming (MILP) to perform a partial-equilibrium investment and dispatch optimization, accounting for a wide range of distributed generation as well as storage technologies. Apart from a large technology catalog, COMODO is able to account for an extensive amount of policy instruments and financial incentives to more precisely valuate the costs of certain technologies or energy carriers. One unique characteristic of COMODO compared to the existing literature is how the total costs are minimized over the complete, long-term time horizon via a so-called 'dynamic anticipative optimization' (Cuisinier et al. (2021)). As such, investments in DER technologies are not restricted to one single year but rather are able to be made in multiple model years subject to developments in, e.g., techno-economic data, regulatory frameworks and energy market conditions. In doing so, COMODO not only serves to analyze the profitability of distributed generation and storage technologies but may also help to understand the key economic and regulatory drivers affecting the end consumer's energy investment choices.

In order to demonstrate the capabilities of the model developed, an exemplary application is presented to investigate the investment and energy use decisions of four single-family homes in Germany for the years 2025 to 2045. Three scenarios are considered and then compared: Status Quo, Smart Tech and Smart Market. The scenarios build upon each other sequentially, with the first scenario seeking to resemble current technological and regulatory conditions, i.e., limited information on future weather, demand, costs or price developments. The Smart Tech scenario, on the other hand, allows for technologies to receive information about weather conditions (e.g., renewable generation potential) and demand profiles as well as energy prices and technology costs in future years, which allows technologies to better optimize their sizing and operation as well as the interactions between generators and storages. The Smart Market scenario extends the amount of information available to include transparency regarding current and future electricity market conditions via hourly retail electricity prices. The results show a clear preference for gas boilers as a base technology coupled with electric heaters to cover demand peaks. Households with higher demand levels invest in PV systems in 2025, while other households with lower demands either wait until 2040 or do not invest at all.

A sensitivity analysis then examines the effects of higher carbon pricing in the German building sector on the consumer's energy provision. The subsequent increase in the retail gas price leads to households choosing to fully electrify their heat provision, i.e., installing a heat pump combined with thermal storage, PV and an electric heater. On average, these households experience an increase in total costs ranging from 3.5% to 5.4% over the complete time horizon and realize a long-term decrease in annual carbon emissions of up to 80% compared to the analysis with lower carbon pricing. Lastly, the paper at hand also presents a novel method of analyzing the marginal costs of electricity and heat provision, revealing a strong correlation between the implicit marginal costs of energy provision and the assumptions on retail energy prices.

1.2. Literature Review

There exists a large body of literature that develops mathematical models to optimize decentralized energy supply, consumption and storage for single or aggregated consumers. The MILP approach, in particular, has established itself as the method of choice due to its both discrete and continuous nature, allowing for technologies to be selected, sized and switched on/off using binary variables. Table 1 gives an overview of reviewed publications that develop or methodologically extend MILP models to optimize the investment in as well as the sizing and operation of decentralized generation and storage technologies.[1] All sources presented in Table 1 include objective functions that seek to minimize the total or annual costs of energy provision, which in this case includes at least[2] both electricity and heating.

As illustrated in Table 1 and in McKenna et al. (2017), one key difference among the literature is the technology catalog considered in the respective models and the selected applications. While a handful of papers focus on one specific technology (e.g., Cano et al. (2014), Merkel et al. (2015)) or on the dynamics between two technologies such as PV and heat pumps (e.g., Beck et al. (2017), Schwarz et al. (2018)), the majority of the publications seek to advance the number of DER types. As is the case with any investment model, the optimal solution depends on the technology options available. As such, one major challenge of modeling DER systems in an economic model lies with the definition of which technologies to consider and how the operation of these technologies can be simulated with high technical complexity, all within computational limits. Ashouri et al. (2013) and Liu et al. (2020) are examples of studies that have an unusually vast amount of DER investment options with high levels of technical detail. In particular, the models used in these studies, as well as in others such as Zhang et al. (2018) and Rikkas and Lahdelma (2021), include a dynamic coefficient of performance (COP) function to account for the variable technical efficiency of heat pumps, which is a key factor effecting their economic feasibility.

Alongside the technological scope and technical complexity exists another key distinction between publications: the ability of the models to consider regulatory aspects. Although this highly depends on the country considered, the inclusion of incentive mechanisms in the objective function can greatly affect the profitability of certain technologies. As can be seen in Table 1, the majority of publications in this field only

[1] Papers that optimize the investment in electricity grids (e.g., microgrids) and/or district heating pipelines have been omitted from this literature review as well as from Table 1. Furthermore, papers that do not include an investment decision, i.e., papers that only optimize the operation of DER systems, are also not considered.

[2] Some papers in Table 1 also consider cooling; however, for the literature selection, it is required that the provision of both electricity and heat are optimized.

Table 1: Overview of reviewed publications

Source	Energy Use[a]				Investment Technology[b]										COP[c]		Regulation[d]								CF[e]		IOS[f]		GS[g]
	EL	SH	HW	CL	PV	BS	CHP	GB	ST	BIO	EH	HP	TS	OT	C	V	FIT	EMS	OVM	CP	HPT	IS	CO_2	PC	L	PW	1Y	MY	
Ren and Gao (2010)	x	x	x	x	x	x	x	x				x	x	x				x				x	x	x		x	x		JP
Buoro et al. (2012)	x	x	x	x	x		x	x	x			x	x	x	x		x	x	x							x	x		IT
Ashouri et al. (2013)	x	x	x	x	x	x	x	x	x		x	x	x	x		x	x	x				x		x	x		x		CH
Cano et al. (2014)	x	x	x		x												x								x			x	ES
Stadler et al. (2014)	x	x	x	x	x	x	x	x	x				x	x				x							x		x		AT
Merkel et al. (2015)	x	x	x				x	x					x				x		x							x	x		UK
Steen et al. (2015)	x	x	x	x	x	x	x	x	x			x	x	x	x			x							x		x		US
Beck et al. (2017)	x	x	x		x	x					x	x	x			x	x							x		x	x		DE
McKenna et al. (2017)	x	x	x		x	x	x	x					x				x		x							x	x		DE
Schütz et al. (2017)	x	x	x		x	x	x	x	x		x	x	x	x		x	x	x	x		x	x			x		x		DE
Acha et al. (2018)	x	x	x	x	x	x	x	x						x			x		x				x	x	x		x		UK
Gabrielli et al. (2018)	x	x	x		x	x		x	x			x	x	x		x	x	x								x	x		CH
Ma et al. (2018)	x	x	x	x	x	x		x					x	x	x								x		x		x		CN
Mavromatidis et al. (2018)	x	x	x		x	x	x	x		x		x	x			x	x									x	x		CH
Schwarz et al. (2018)	x	x	x		x	x						x	x			x	x			x				x	x		x		DE
Zhang et al. (2018)	x	x	x		x	x					x	x	x			x		x						x	x		x		SE
Huang et al. (2019)	x	x	x	x	x	x	x	x			x	x	x	x	x										x		x		CN
Kannengießer et al. (2019)	x	x			x	x	x	x				x	x		x		x	x							x		x		DE
Alabi et al. (2020)	x	x	x	x	x	x	x	x				x	x	x	x										x			x	HK
Liu et al. (2020)	x	x	x	x	x	x	x	x	x			x	x	x		x									x		x		CN
Mavromatidis and Petkov (2021)	x	x	x		x	x	x	x		x		x	x		x			x							x			x	CH
Rikkas and Lahdelma (2021)	x	x	x	x	x	x						x	x	x		x		x						x	x		x		FI
Petkov et al. (2022)	x	x	x	x	x	x	x	x		x		x	x	x	x			x							x			x	CH
This study	x	x	x		x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x		x		x	DE

[a] EL: Electricity, SH: Space Heating, HW: Hot Water Heating, CL: Cooling

[b] PV: Photovoltaic, BS: Battery Storage, CHP: Combined Heat and Power Gas Engine, GB: Gas Boiler/Gas Condensing Boiler, ST: Solar Thermal, BIO: Biomass Boiler/Stove, EH: Electric Heaters, e.g., Heating Rod or Electric Boiler, HP: Heat Pump, TS: Thermal Storage, OT: Other Technologies that are not listed in the table, which may include, e.g., wind turbines, electrolyzers, fuel cells, flow heaters and/or absorption/electric cooling systems

[c] COP: Coefficient of Performance of Heat Pumps (hourly), C: Constant, V: Variable

[d] FIT: Feed-In Tariff, EMS: Electricity Market Sales, OVM: Other Variable Mechanisms (e.g., market premium, self-consumption fees), CP: Capacity Pricing, HPT: Heat Pump Tariff, IS: Investment Subsidies, CO_2: Carbon Tax, PC: Price Components

[e] CF: Cost Function, L: Linear, PW: Piecewise (considered for at least one technology)

[f] IOS: Investment Optimization Strategies, 1Y: Single-Year (static investment optimization), MY: Multi-Year (dynamic anticipative optimization)

[g] GS: Geographic Scope, JP: Japan, IT: Italy, CH: Switzerland, ES: Spain, DE: Germany, AT: Austria, UK: United Kingdom, US: United States, CN: China, SE: Sweden, HK: Hong Kong, FI: Finland

consider variable remuneration such as, e.g., feed-in tariffs or direct electricity sales, and ignore the possibility of subsidies or other cost savings via, e.g., alternative tariffs or carbon abatement. Schütz et al. (2017) is one of the few papers examined that actively investigate the effect of the regulatory environment on the optimal design of DER systems. In doing so, the authors extend an existing MILP model to include a wide range of German legislation and market characteristics including subsidies for CHP and PV as well as heat pump tariffs. However, the authors provide little information on the assumptions regarding the individual price components assumed for the gas and electricity tariffs. In Germany, for example, retail electricity prices are constructed based on the average spot market bids, grid fees, renewable surcharge and other taxes and fees. By breaking the retail prices down to the individual components, alternative tariff structures such as capacity pricing can be considered. Furthermore, assumptions on the future developments in, for example, the renewable surcharge or carbon taxes can be accounted for in the tariff predictions. As shown in Table 1, few studies offer information on price components, with only Schwarz et al. (2018) including the option of capacity-based pricing in the model.

A third characteristic that varies across the presented literature is the design of the cost function implemented in the model. As is often the case in MILP models, the investment in a technology may not be linear but rather stepwise, as a certain technology may only be available in predefined sizes (e.g., a battery may be bought with 3 kWh or with 7 kWh but not in between). Some of the studies shown in Table 1 use a piecewise-linear cost approximation approach to allow for each step to have their own linear cost function. Ren and Gao (2010), Buoro et al. (2012) and Merkel et al. (2015) are often cited as some of the first to apply a piecewise-linear cost approximation to DER systems in MILP models. More recently, papers such as Gabrielli et al. (2018) and Mavromatidis et al. (2018) have increased the level of detail in the cost function, accounting for both fixed (i.e., installation) and variable (i.e., material) investment costs in the piecewise approximation. Yet with the introduction of greater technical complexity, multi-stage investment decisions and higher temporal resolutions, the use of piecewise-linear cost functions may lead to computational issues. As such, many of the most recent publications assume linear capital costs regardless of a technology's size, ignoring effects such as economies of scale. Furthermore, none of the other studies shown in Table 1 transfer the concept of piecewise-linear approximation to fixed operation and maintenance (FOM) costs or subsidies, which may also vary non-linearly according to a technology's installed capacity.

Another trend that stands out in Table 1 is the general lack of papers that optimize investments over multi-year stages, i.e., such that the consumer may invest in technologies over multiple future time periods. Cuisinier et al. (2021) refer to this type of optimization as "dynamic anticipative", meaning the model jointly optimizes investment decisions successively for the complete time horizon (i.e., perfect foresight) over evolving data. Although many studies optimize the system costs over the complete system lifetime, the majority of the papers considered perform what Cuisinier et al. (2021) call "static investment optimization" in which the investment decision occurs in a single stage (e.g., one single year). In fact, only three of the reviewed publications shown in Table 1 develop models capable of dynamic-anticipative investments, the earliest of which being Cano et al. (2014). In their paper, the authors develop a MILP model to optimize the energy planning in buildings and seek to complement an existing decentralized heating system with PV, with the results showing endogenous investments in PV capacity in three out of the five future years considered. More recently, Mavromatidis and Petkov (2021) and Petkov et al. (2022) address this research gap in the development of their models MANGO and MANGOret, capable of performing dynamic-anticipative investments for a large technology catalog. The former, in particular, optimizes the design of an energy system for a hypothetical urban area assuming a 30-year planning period with six investment stages. However, at the time of this research, the MANGO model omits the possibility of regulatory instruments and their development over time, which may greatly impact future investment decisions.

Lastly, although Table 1 highlights the methodological variations in the selected literature, the sources can also be characterized by the unique case studies or scenario analyses that are performed to demonstrate the models' abilities. Yet one interesting finding is the homogeneity of the economic analyses performed. In fact, of the papers that provide economic results, their findings are based on the level values of the output variables, e.g., total annual costs, total investment costs, total operational costs, etc.. Marginal values in the form of implicit or shadow prices, on the other hand, have yet to be evaluated, most likely due to the non-linear nature of MILP models. However, following the methodology provided in Williams (1989) and Williams (2013), the marginal values of MILP models may be interpreted as shadow prices as long as the optimal MILP solution is then linearized, i.e., the binary variables are set to the optimal solution. In doing so, it is possible to determine the implicit prices for decentralized electricity and heat provision — a task that has yet to be done in the reviewed literature.

1.3. Contribution and Paper Structure

In light of the existing literature, the paper at hand seeks to both (i) advance the individual criterion outlined in Section 1.2 as well as (ii) offer a unique combination of these criteria not previously seen, emphasized by the distinct combination of x's in the last line of Table 1. As such, this work offers several significant contributions within the methodology developed as well as the application performed, in particular:

- The model includes an extensive technology catalog with a comparably large number of generation and storage technologies for space and water heating as well as electricity. The DER systems are modeled with a great deal of technical detail, including the design of an hourly COP profile for heat pumps dependent on regional temperature profiles.
- The cost minimization in COMODO takes into account a wide range of incentive mechanisms including variable remunerations such as feed-in tariffs, market premiums and direct electricity sales as well as investment subsidies. Due to the detailed depiction of the individual price components for electricity and gas, further regulatory aspects such as capacity pricing, heat pump tariffs and carbon taxes may also be considered.
- The ability of the model to optimize investments in multiple future years, i.e., perform a dynamic anticipative optimization, is a unique characteristic of COMODO. The model therefore requires that assumptions for techno-economic input data be made for each model year for the complete model horizon. This includes detailed assumptions on regulatory and market developments.
- Although several studies have designed piecewise-linear functions for the investment costs of DER for static, single-year optimization, the study at hand uses learning rates to create piecewise-linear cost functions for all future model years. Furthermore, the piecewise-linear approximation approach is also applied to FOM costs as well as investment subsidies, which has also yet to be performed in the reviewed literature.
- To the best of the authors' knowledge, the paper at hand is the first to analyze the future marginal costs of decentralized heat and electricity provision for individual exemplary households in Germany based on a MILP optimization.

The remainder of the paper is structured as follows: Section 2 presents a detailed explanation of the methodology and the model equations. The scenario application and optimization results are given in Section 3, including a description and evaluation of the marginal costs of energy provision. The assumptions as well as findings of the sensitivity analysis are also included in Section 3. Section 4 concludes.

2. Model Description

2.1. Model Overview

The COMODO model is a mixed-integer problem that uses linear programming methods to minimize the total system costs of supplying energy to a specific consumer or consumer group. Consumers are defined according to criteria such as building type (e.g., single-family home, multi-family home, industry building, etc.), building age, modernization standard, living area, available roof space, number of inhabitants, inhabitants' working schedules and building location. These key criteria, in turn, determine how the consumers are parameterized according to, e.g., their energy demand levels, load profiles, investment options, generation potentials as well as economic and regulatory conditions. The model developed then determines the consumer's private economic optimum in satisfying its electricity as well as space and water heating demands using a partial-equilibrium investment and dispatch optimization. In doing so, COMODO is able to determine the cost-minimal energy provision for a consumer class according to each energy use type (EUT), i.e., electricity, water heating and space heating, over a predefined period of time. Although the model considers individual years, the optimization takes place over the complete time horizon.[3]

In order to cover the consumer's energy needs, COMODO may choose one or multiple investment objects from its extensive DER catalog or may purchase electricity or district heat[4] from the grid. Figure 1 gives a schematic overview of the investment objects, available fuels and energy flows that are currently accounted for in the model COMODO, with yellow boxes and lines indicating electricity flow and red indicating heat flows for both space and water heating.

The current DER catalog accounts for 18 distributed generation and storage technologies[5], represented by the grey boxes in Figure 1.[6] All technologies are subject to their specific investment and installation costs, operating costs and other fixed costs as well as technical specifications such as efficiency, lifetime and generation potential. Several investment objects require natural gas, oil or wood pellets as input, which can be bought at the local commodity price (see the boxes and arrows in green, black and brown in Figure 1, respectively). Others require electricity, which can either be produced and supplied by the

[3]In other words, the model benefits from perfect foresight.

[4]Although the functional layout of COMODO is designed to include district heat, it is not considered in this analysis and therefore omitted from Figure 1.

[5]Currently, these include PV, solar thermal (hot water, combined hot water and space heating), micro-CHP (gas, diesel), fuel cell CHP (gas), gas condensing boiler, gas-fired boiler, gas flow heater, oil condensing boiler, pellet stove, thermal storage, battery storage, electric heater, heat pump (air-to-water, water-to-water, geothermal) and power flow heater. Electric networks and pipelines are not included in the technology catalog as these are excluded as investment objects within the work at hand. This also holds true for investments in building envelope refurbishment.

[6]The model structure allows for the technology catalog to be expanded to include additional electricity or heat production, storage and/or consumption technologies and is in no way limited to the technologies shown in Figure 1.

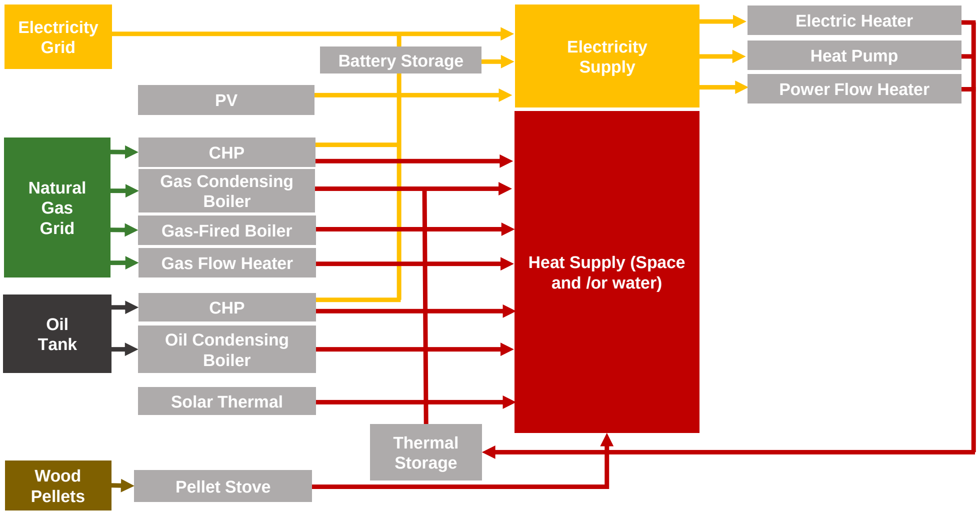

Figure 1: Overview of the energy supply flows and DER systems in the model COMODO, with the yellow boxes and lines indicating electricity, the red boxes and lines indicating heating and grey boxes indicating technologies

consumer or bought from the electricity market at the retail price. In the case of PV and solar thermal, the energy input is solar irradiation[7] and depends on the weather conditions in the consumer's region. Weather conditions may also affect other technologies such as heat pumps, whose efficiency may, e.g., decrease in colder temperatures (see Section 2.4). Three types of heat pumps are considered in COMODO, namely air-to-water, water-to-water[8] and geothermal[9].

Next to the investment decision, the model also optimizes the resulting consumption, generation and storage-use profiles of the chosen DER systems in order to satisfy demand of all EUTs at each point in time. For example, the decision of the consumer to, e.g., directly consume her own production, store her own production and/or immediately feed-in her own production is simultaneously optimized against the consumer's load, weather conditions, regulatory framework and market signals until the cost-minimizing solution is found. For electricity, demand may be both exogenous and endogenous as the consumer's immediate electricity needs —the exogenous part— may be accompanied by an endogenously-determined heat-driven demand for electric power from, e.g., an electric heater. Space and water heating demands, on the other hand, are defined completely exogenously.[10] The standard temporal resolution of the model is hourly but can be adjusted to account for more (e.g., quarter-hourly) or fewer (e.g., via clustering) time slices.

As emphasized in Sections 1.2 and 1.3, the model is also able to accommodate current as well as planned or hypothetical regulatory frameworks and energy market conditions relative to the location of the consumer.

[7]Not pictured in Figure 1.
[8]I.e., including a ground collector
[9]I.e., including vertical drilling
[10]In other words, it is assumed that no technology uses heat as an input energy source. The thermal storage systems are an exception to this assumption, as heat losses can lead to an additional endogenous heat demand.

These include, among others, remuneration mechanisms such as investment subsidies, feed-in tariffs, market premiums and direct sales of distributed generation as well as transparent market signals via, e.g., variable electricity prices. The tariff structure may also be adjusted for either energy (€/kWh) or capacity (€/kW) prices. Further constraints to account for, e.g., emission reduction targets may also be applied. The model can be used to examine future years by adjusting, among others, the regulatory and market conditions as well as the economic and technical assumptions. In doing so, COMODO provides the opportunity to analyze the diffusion of DER systems over time for specific consumer classes or accumulated consumer groups.

2.2. Minimizing Total Costs of Meeting Demand

The objective function in COMODO is a minimization of the sum of the individual cost components that consumers[11] face when satisfying their energy needs over a predefined period of time.[12] As shown in Equation (1a), these can be broken down into fixed costs ($\boldsymbol{FC}$) and variable costs, which may either be energy-based ($\boldsymbol{EBC}$) and[13]/or capacity-based[14] ($\boldsymbol{CBC}$), for each year y. Furthermore, certain technologies used to supply certain energy use types (EUT) may also be eligible for an energy-based remuneration[15] ($\boldsymbol{EBR}$) via incentive programs, which dampen the consumer's variable costs.[16] Before summing over all modeled years, the annual costs are discounted according to an interest rate i and the starting year y_0.

$$min!\boldsymbol{TC} = \sum_{y} \left[\frac{1}{(1+i)^{(y-y_0)}} \cdot \Big(\boldsymbol{FC}_y + \boldsymbol{EBC}_y + \boldsymbol{CBC}_y - \boldsymbol{EBR}_y \Big) \right] \tag{1a}$$

$$\text{s.t.} \quad d_{y,t,EUT} + \sum_{x} \Big[\boldsymbol{XFI}_{y,t,x,EUT} + \boldsymbol{GFI}_{y,t,x,EUT} \Big] = \sum_{x} \Big[\boldsymbol{XS}_{y,t,x,EUT} + \boldsymbol{GS}_{y,t,x,EUT} \Big] + \boldsymbol{GS}_{y,t,EUT=EUT_{demand}} \tag{1b}$$

$$\boldsymbol{Q}_{y,x} \geq \boldsymbol{XS}_{y,t,x,EUT} \tag{1c}$$

$$q_{grid,EUT} \geq \sum_{x} \Big[\boldsymbol{GS}_{y,t,x,EUT} \Big] + \boldsymbol{GS}_{y,t,EUT=EUT_{demand}} \tag{1d}$$

$$cap_{CO_2,y} \geq \sum_{t,f_x,EUT} \left[\left(\sum_{x} \Big[\frac{\boldsymbol{XS}_{y,t,x,EUT}}{\eta_{t,x,EUT}} \Big] + \boldsymbol{GS}_{y,t,EUT=EUT_{demand}} \right) \cdot factor_{CO_2,t,f_x/EUT} \right] \tag{1e}$$

[11] It is important to note that, in order to simplify the nomenclature, the dependence on the consumer definition has been excluded from the equations. In other words, all the equations shown in Sections 2.2, 2.3, and 2.4 apply to a single or an aggregated group of consumers. More information on the consumer definition may be found in Section 3.1.1.

[12] The period of time is usually defined to be anywhere from a 10-year to 30-year interval.

[13] Both may be possible if, for example, a combination of multiple fuels with different price structures are consumed or if the retail price of an energy use type is made up of a combination of energy-based and capacity-based price components.

[14] Capacity-based costs depend on the size of the consumer's connection to the grid. Per definition, this depends on the energy use type or on the fuel being transported, as infrastructure costs differ for, e.g., electricity or gas (see Equation (5)).

[15] Energy-based remuneration is awarded according to energy units (kWh), e.g., feed-in tariffs (see Equation (6)).

[16] A complete list of the notations used for all model sets, parameters and variables can be found in Appendix A. Unless otherwise noted, optimization variables are indicated using bold, uppercase letters.

Equations (1b) - (1e) summarize the main constraints of the minimization problem. The first of these equations requires that equilibrium between demand and supply be maintained in every time slice t. In addition to an exogenously-defined energy demand d for each y, t and EUT, an endogenous energy demand may arise from feeding an EUT into a technology ($\boldsymbol{XFI}$) or feeding an EUT into the grid[17] ($\boldsymbol{GFI}$). The exogenous and endogenous demand may be supplied by a decentralized technology x ($\boldsymbol{XS}$) and/or by an energy provider via the grid[18] ($\boldsymbol{GS}$), which may be directly consumed to meet exogenous demand d of an EUT (indicated by the subscript $EUT = EUT_{demand}$[19]) or fed into a technology to store or transform the EUT (indicated by the subscript x). Equation (1c) shows the capacity constraint for the DER systems, meaning that the supply $\boldsymbol{XS}$ can not exceed the installed capacity $\boldsymbol{Q}$ of a certain technology x for every time slice t and year y.[20] Similarly, Equation (1d) limits the amount of energy that can be supplied from the grid ($\boldsymbol{GS}$)[21] according to the size of the connection capacity (q_{grid}) for the corresponding EUT, which may vary strongly depending on the consumer definition. The last constraint shown, Equation (1e), is only included in the model if a carbon emission reduction target is considered. In this case, total emissions of a single consumer or consumer group are determined by adding the energy consumption of decentralized generation technologies ($\frac{\boldsymbol{XS}_{y,t,x,EUT}}{\eta_{t,x,EUT}}$)[22] to the energy consumed directly from the grid ($\boldsymbol{GS}_{y,t,EUT=EUT_{demand}}$) and then multiplying by the corresponding CO_2 factor. If the energy source of technology x is a fuel f_x[23] such as gas or oil, then the CO_2 factor is equal to the combustion emissions factor ($factor_{CO_2,f_x}$)[24]; however, in the event that an EUT is bought from an energy provider to be used directly ($EUT = EUT_{demand}$) or as an input energy source for technology x, then the CO_2 factor is equal to an average emissions factor of the generation technologies used to produce the respective EUT ($factor_{CO_2,t,EUT}$).[25] The total CO_2 emissions emitted by the consumer are then limited by an exogenously-given target value $CO_{2,cap}$ for year y.

[17] Grid feed-in is only possible if a suitable bidirectional grid connection is available to the consumer. Currently, this is most commonly the case for electricity. However, from a technical standpoint, grid feed-in may also be possible for heat.

[18] In this case, grid supply pertains solely to the buying of an EUT, namely electricity or heat, from an energy provider to cover a consumer's energy demand. Grid supply is only possible if a suitable grid connection is available to the consumer.

[19] The subscript $EUT = EUT_{demand}$ is necessary for the notation of variables that describe a direct energy consumption without conversion in a technology x.

[20] Equation (1c) holds for $y \in [y_x^*, y_x^* + lt_x]$, where y_x^* indicates the installation year and lt_x the technical lifetime of technology x. If the model chooses to remove the technology before the end of its technical lifetime, $\boldsymbol{XS}$ would then be equal to zero.

[21] Analogous to Equation (1b), grid supply is separated into two variables depending on whether it is stored or converted by a technology x or if it is directly used to cover the exogenous demand d, the latter indicated by the subscript $EUT = EUT_{demand}$.

[22] The technical efficiency included in Equation (1e) depends not only on the technology x but also on the time slice t and the EUT. The temporal differentiation is important for heat pumps, whose efficiency may differ over time due to changes in the source temperature (e.g., outside air temperature), whereas the dependence on EUT is essential for technologies such as micro-CHP, whose efficiency depends strongly on the type of energy being produced.

[23] The subscript f_x denotes the matching between the input fuel f and technology x.

[24] This factor represents the carbon intensity of the fuel emitted in combustion, i.e., according to the chemical composition. Any emissions arising in the construction and decommissioning of energy systems are not taken into account.

[25] The parameter $factor_{CO_2,t,EUT}$ depends on the time slice t as the amount of CO_2 emitted during the energy conversion to the EUT may be variable depending on, e.g., the electricity generation mix.

The fixed costs ($\boldsymbol{FC}$) in year y include the annualized investment costs ($\boldsymbol{AIC}$) and fixed operation and maintenance costs ($\boldsymbol{FOMC}$), summed over all technologies installed x,

$$\boldsymbol{FC}_y = \sum_x \Big[\boldsymbol{AIC}_{y,x} + \boldsymbol{FOMC}_{y,x}\Big], \tag{2}$$

with

$$\boldsymbol{AIC}_{y,x} = \frac{j_x}{1-(1+j_x)^{-w_x}} \cdot \big(\boldsymbol{IC}_{y^*,x} - \boldsymbol{S}_{y^*,x}\big). \tag{3}$$

The investment costs ($\boldsymbol{IC}$), which are discussed in detail in Section 2.3, may be partly compensated by a subsidy $\boldsymbol{S}$ in the event that a subsidy program for the technology exists. Both the investment costs and subsidy amounts depend on the year in which the technology is installed (y^*). Using a financing rate j, the remaining investment costs are then annualized over a financing period w, which may vary according to technology x. As such, Equation (3) holds for $y \in [y_x^*, y_x^* + w_x]$; however, the fixed costs in Equation (2) may hold for $y \in [y_x^*, y_x^* + lt_x]$, where lt_x indicates the technical lifetime of technology x and $lt_x \geq w_x$.[26] In other words, the fixed operation and maintenance costs may extend past the financing period, as long as the technology is still installed and the technical lifetime has not been reached.

In addition to the fixed costs, a significant share of the consumer's energy expenses result from the variable costs that arise from purchasing either an energy use type from an energy provider or a fuel to be consumed by a DER system. Currently, it is most common to see these costs defined according to energy units, i.e., kWh. Within the scope of this paper, these are referred to as energy-based costs ($\boldsymbol{EBC}$) and are defined in Equation (4),

$$\begin{aligned}\boldsymbol{EBC}_y = \sum_{t,EUT} \Big[\boldsymbol{GS}_{y,t,EUT=EUT_{demand}} \cdot \sum_{epc} \big[ep_{y,t,EUT,epc}\big]\Big] \\ + \sum_{t,f_x,EUT} \Big[\sum_x \big[\frac{\boldsymbol{XS}_{y,t,x,EUT}}{\eta_{t,x,EUT}}\big] \cdot \sum_{epc} \big[ep_{y,t,f_x/EUT,epc}\big]\Big].\end{aligned} \tag{4}$$

The energy price ep can be defined either for an energy use type, e.g., electricity, or for a fuel, e.g., gas (indicated by the subscript f_x/EUT). In both cases, the retail price for the consumer is made up of energy price components (epc) such as acquisition, taxes and grid fees, which may vary over time slice t and year y. The corresponding energy price is then used to determine the annual costs arising from consuming energy use types directly from the grid ($\boldsymbol{GS}_{y,t,EUT=EUT_{demand}}$) as well as the transformation or storage of

[26] It should be noted that, by definition, the model may choose to remove a technology before the end of its technical lifetime or even before the end of the financing period if it leads to an overall decrease in the total costs.

an energy use type or fuel by a technology ($\frac{\boldsymbol{XS}_{y,t,x,EUT}}{\eta_{t,x,EUT}}$).

As the regulation of energy prices in future years remains uncertain, COMODO allows for prices as well as individual price components of energy use types to be defined according to capacity (kW) rather than energy units.[27] In this case, the consumer pays a capacity price (cp) for the grid capacity relative to the maximum[28] amount of energy use type needed to be supplied by the grid over time slices t in year y, referred to in Equation (5) as capacity-based costs ($\boldsymbol{CBC}$):

$$\boldsymbol{CBC}_y = \sum_{EUT} \Bigg[\frac{max_t \Big(\sum_x \big[\boldsymbol{GS}_{y,t,x,EUT}\big] + \boldsymbol{GS}_{y,t,EUT=EUT_{demand}} \Big)}{t} \cdot \sum_{cpc} \big[cp_{y,t,EUT,cpc} \big] \Bigg]. \tag{5}$$

The variable costs $\boldsymbol{EBC}$ and $\boldsymbol{CBC}$ may be reduced if a consumer's DER system is eligible to benefit from incentive programs offering energy-based remuneration ($\boldsymbol{EBR}$). Classic examples include compensation for feeding-in energy to the grid via, e.g., feed-in-tariffs or market premiums; however, certain technologies may also be eligible for remuneration for self-consumption, i.e., if an energy use type is locally generated and then consumed on site. On the other hand, some technologies are restricted as to how much they are allowed to produce and self-consume, paying a fee for each kilowatt-hour over the limit. The yearly amount of variable remuneration[29] a consumer may receive is calculated according to Equation (6),

$$\boldsymbol{EBR}_y = \sum_{t,x,EUT} \Big[\boldsymbol{GFI}_{y,t,x,EUT} \cdot er_{y,t,x,EUT} + \Big(\boldsymbol{XFI}_{y,t,x,EUT} - \boldsymbol{GS}_{y,t,x,EUT} \Big) \cdot \Big(scr_{y,x,EUT} - scf_{y,x,EUT} \Big) \Big], \tag{6}$$

such that the amount of energy fed into the grid $\boldsymbol{GFI}$ is compensated according to a energy remuneration er, and the amount of energy fed into technology x that does not come from the grid ($\boldsymbol{XFI}$-$\boldsymbol{GS}$) is rewarded or penalized according to a self-consumption remuneration scr or self-consumption fee scf, respectively.

2.3. Piecewise Linearization of Costs for Current and Future Years

Investment costs are equal to the capital costs that must be paid to install a certain decentralized energy technology, as introduced in Equation (3). These include not only the costs for the technology itself but also for additional hardware or labor costs that are needed for the technology to run. Investments in decentralized

[27] Technically speaking, although only energy use types are mentioned here, Equation (5) could also be applied to a grid-supplied fuel such as gas. This is, however, omitted to simplify the explanation.

[28] It should be noted that Equation (1d) still holds for Equation (5). In other words, $max_t\Big(\sum_x \big[\boldsymbol{GS}_{y,t,x,EUT}\big] + \boldsymbol{GS}_{y,t,EUT=EUT_{demand}}\Big)$ would be equal to $q_{grid,EUT}$ if the maximum amount demanded by the consumer over time slice t reached the size of the connection capacity. Furthermore, it is also possible to allow for time-variable capacity prices by calculating the maximum of a subset of time slices, e.g., in the case of peak pricing.

[29] As opposed to investment subsidies, which are accounted for in Equation (3).

technologies are done linearly, meaning the consumer may install the exact capacity (kW) that is optimal for the individual or communal energy system.[30] As explained in Section 1.2, many existing studies using MILP methods assume linear, capacity-specific investment costs for each technology. Capacity-specific investment costs (€/kW), however, may vary drastically depending on the total size of the technology installed: For example, a larger system may benefit from lower costs per kW due to, e.g., economies of scale or a decrease in the specific installation costs. Especially for very small systems (e.g., less than 5 kW), the cost difference from one kW to the next may be substantial.

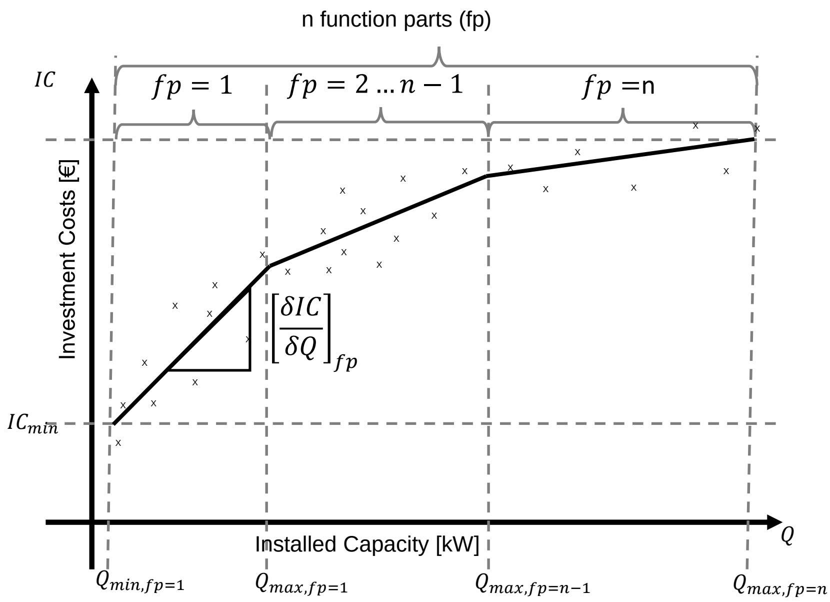

Figure 2: Graphical example of the piecewise-linear function used to determine investment costs

In order to mimic this non-linear cost structure in a linear model, a piecewise-linear cost function is built for each technology's investment costs.[31] In doing so, individual linear costs functions (so-called 'function parts') for different system sizes are joined together to create a curve-like form similar to a logarithmic growth function for each DER technology.[32] Figure 2 presents an illustrative example for a technology with a minimum achievable capacity $Q_{min,fp=1}$ and maximum achievable capacity $Q_{max,fp=n}$. As shown in

[30]Restrictions limiting the minimum size of the investment object are taken into account, as many decentralized technologies are only available starting from, e.g., 2 kW.

[31]Although the description presented focuses on the investment costs, a piecewise-linear function is also used to determine the capacity-specific FOM costs as well as the capacity-specific subsidy values, as these may also greatly depend on the system size. See Appendix C for a graphical overview of the piecewise-linear functions assumed for the investment and FOM costs in the application in 3, as well as a thorough presentation of the subsidies included in COMODO.

[32]The cost functions for some technologies, such as thermal storage and solar thermal, do not display a logarithmic curve. In fact, the capacity-specific costs may increase once the systems size exceeds a certain capacity. The additional costs result from technical requirements in scaling-up system size, e.g., construction, system control or design.

the figure, each function part has a minimum[33] and maximum capacity, which defines the range of system sizes that are assumed to exhibit the same capacity-specific investment costs. For example, all systems with installed capacities that fall between the minimum ($Q_{min,fp=1}$) and maximum ($Q_{max,fp=1}$) of the first function part are assumed to have the same marginal costs, which is determined by the linear slope of the first function part, $\frac{\delta IC}{\delta Q}_{fp=1}$. A decrease in the slope from one function part to the next reveals how the capacity-specific investment costs may be reduced by an increase in total installed capacity.

The corresponding equation for determining the investment costs $\boldsymbol{IC}$ in year y for technology x using the piecewise-linear function shown in Figure 2 can be seen in Equation (7),

$$\begin{aligned}\boldsymbol{IC}_{y_x,x} = IC_{Q_{min},x} \cdot \gamma_{y_x,x,fp_x=0} + \sum_{fp_x=1}^{\boldsymbol{N}} \left[(Q_{max,y_x,x,fp_x} - Q_{max,y_x,x,fp_x-1}) \cdot \left[\frac{\delta IC}{\delta Q}\right]_{x,fp_x} \cdot \gamma_{y_x,x,fp_x} \right] \\ - \left[(Q_{max,y_x,x,fp_x=\boldsymbol{N}} - \boldsymbol{Q}_{y_x,x}) \cdot \left[\frac{\delta IC}{\delta Q}\right]_{x,fp_x=\boldsymbol{N}} \cdot \gamma_{y_x,x,fp_x=\boldsymbol{N}} \right], \qquad (7)\end{aligned}$$

with $\boldsymbol{N} \leq n$, where n is the maximum number of function parts and $\boldsymbol{N}$ indicates the function part in which the total installed capacity $\boldsymbol{Q}_{y_x,x}$ falls on the x-axis, i.e.,

$$Q_{max,y_x,x,fp_x=\boldsymbol{N}-1} \leq \boldsymbol{Q}_{y_x,x} \leq Q_{max,y_x,x,fp_x=\boldsymbol{N}}. \qquad (8)$$

and

$$Q_{max,y_x,x,fp_x=0} = Q_{min,y_x,x,fp_x=1}. \qquad (9)$$

As illustrated in Equation (7), the investment costs for a system with installed capacity $\boldsymbol{Q}_{y_x,x}$ are determined by first taking the investment costs of the minimum achievable capacity Q_{min} ($IC_{Q_{min},x}$) and then adding the investment costs of each additional unit of capacity until the full system size has been reached. As shown in Figure 2, this is done piecewise for each function part according to the capacity increase from one function part to the next, namely the difference between the maximum capacity of the current function part and of the previous function part (Q_{max,y_x,x,fp_x} - Q_{max,y_x,x,fp_x-1}), multiplied by the slope of the linear cost function for the current function part ($\frac{\delta IC}{\delta Q}_{x,fp_x}$). This is done up until the $\boldsymbol{N}$th function part containing $\boldsymbol{Q}_{y_x,x}$, as shown in Equation (8). As the total installed capacity may not be equal to the maximum capacity of the $\boldsymbol{N}$th function part, the investment costs must be "corrected" for the difference in capacity, $Q_{max,y_x,x,fp_x=\boldsymbol{N}} - \boldsymbol{Q}_{y_x,x}$. The decision whether to install the technology as well as

[33] The minimum capacity of a function part is equal to the maximum capacity of the previous function part, with the exception of the first function part where a starting value ($Q_{min,fp=1}$) is given (see Equation (9)).

the navigation of the function parts are imposed using binary variables.[34]

A learning rate γ is included in Equation (7) to account for changes in the investment costs that may occur over future time periods. In addition to the investment year y and the technology x, the learning rate may also differ according to each function part as systems of varying sizes may be subject to different cost degressions over time.[35]

2.4. Technology Specifics

In addition to designing the objective function and building the piecewise cost function, another major contribution of the paper at hand is the modeling of complex decentralized energy technologies. As discussed in Section 2.1, COMODO can optimize both investment and dispatch decisions simultaneously. In doing so, additional constraints must be included for certain DER systems to ensure technical accuracy of the model.

Generation from solar technologies, which include PV for electricity and solar thermal for space and water heating, is subject to a modified version of the capacity constraint shown in Equation (1c), i.e.,

$$\boldsymbol{XS}_{y,t,x=PV/ST,EUT=elec/heat} \leq G_t \cdot \eta_{t,x=PV/ST,EUT=elec/heat} \cdot \boldsymbol{Q}_{y,x=PV/ST}, \tag{10}$$

where G_t represents the global solar irradiation on a tilted area measured in kW/m^2. The parameter G_t is determined not only relative to the orientation and tilt angle of the solar system itself but also according to the direct and indirect solar radiation at the location at a specific time, the latter depending on both the solar altitude and azimuth.[36] The global solar irradiation on a tilted area is then multiplied by the technology-specific efficiency $\eta_{t,x=PV/ST,EUT=elec/heat}$, which represents the ability of the system to transform the solar energy into the desired EUT. For PV systems, the factor $\eta_{t,x=PV,EUT=elec}$ is equal to $\frac{\alpha_0}{spacefactor_{PV}}$, where α_0 represents the optical efficiency[37] and $spacefactor_{PV}$ is equal to the maximum amount of PV capacity per square meter[38]. For the case of solar thermal, the efficiency is determined by a quadratic function

$$\eta_{t,x=ST,EUT=heat} = \alpha_1 - \alpha_2 \cdot \frac{T_{collector,t} - T_{ambient,t}}{G_t} - \alpha_3 \cdot \frac{(T_{collector,t} - T_{ambient,t})^2}{G_t}, \tag{11}$$

[34] Binary variables are excluded from the equations to increase readability.

[35] In Equation (7), the learning rate corresponding to the investment costs for the minimum installed capacity ($IC_{Q_{min},x}$) is shown using the subscript $fp = 0$. As there is no function part equal to zero, this should be understood as the learning rate for the starting (i.e., minimum) capacity Q_{min}.

[36] The global solar irradiation on a tilted area may also be influenced by the building characteristics specific to the consumer, e.g., roof construction, surrounding topography, etc. The global solar irradiation on a tilted area is calculated according to Eicker (2012). See Appendix C.8 for more information.

[37] The optical efficiency accounts for losses due to, e.g., reflection, shade, heat or residue on the PV panels. Although these conditions may vary from one time slice to the next, the optical efficiency within the model is assumed to be an average value held constant over time.

[38] This assumption is based on the current PV module types available.

as recommended by the European Solar Thermal Industry Federation (2007). In this case, α_1 describes the technical efficiency of the system, accounting for optical efficiency losses. The remaining part of Equation (11) accounts for any heat loss due to the radiation and convection of the heat transfer medium used in the collector. The quadratic function contains two heat-loss coefficients, α_2 and α_3, multiplied by the temperature difference between the mean collector temperature $T_{collector,t}$ and ambient temperature $T_{ambient,t}$.

Furthermore, as the roof size for a single consumer or consumer group is limited, rooftop installations of PV and ST systems must compete for the available roof space rs,

$$rs \geq \boldsymbol{Q}_{y,x=ST} + \frac{\boldsymbol{Q}_{y,x=PV}}{spacefactor_{PV}}, \tag{12}$$

where the optimal installed capacity of PV in kW ($\boldsymbol{Q}_{y,x=PV}$) is converted to area according to the parameter $spacefactor_{PV}$.[39]

Next, additional technology-specific equations must be included in COMODO to account for battery and thermal storage. In particular, storage technologies introduce a temporal shift into the model, allowing for energy to be consumed or transformed at a different point in time than it was generated or purchased. In other words, the amount of energy that can be injected into or discharged from the storage in time slice t depends on the storage level, $\boldsymbol{SL}$, which is relative to the storage level in the previous time slice $t-1$,

$$\begin{aligned} \boldsymbol{SL}_{y,t,x=storage,EUT} &= \boldsymbol{SL}_{y,t-1,x=storage,EUT} \cdot (1-\beta_{t,x=storage,EUT}) - \boldsymbol{XS}_{y,t,x=storage,EUT} \\ &+ \Big(\sum_{x_1 \neq storage} \Big[\boldsymbol{XFI}_{y,t,(x_1 \rightarrow x_2=storage),EUT} \Big] + \boldsymbol{GS}_{y,t,x=storage,EUT} \Big) \cdot \eta_{t,x=storage,EUT}. \end{aligned} \tag{13}$$

The temporal shift between $t-1$ and t results in storage losses equal to β, while the injection of energy either from a technology other than storage ($\boldsymbol{XFI}_{y,t,(x_1 \rightarrow x_2=storage)}$), in this case x_1[40], or from the grid ($\boldsymbol{GS}_{y,t,x=storage,EUT}$) must be corrected for the storage's technical efficiency η. The amount of energy discharged from the storage ($\boldsymbol{XS}_{y,t,x=storage,EUT}$) can then be used either directly by the consumer in its current energy use type or fed into another technology to be transformed to another energy use type.

Similar to the investment costs discussed in Section 2.3, the available storage volume (in kWh) for technology x in year y is calculated using piecewise-linear functions according to an installed storage capacity (in kW). Therefore, storage level $\boldsymbol{SL}$ in time slice t must be less than or equal to the available storage volume $\boldsymbol{SV}$ for technology x, energy use type EUT and year y, i.e., $\boldsymbol{SL}_{y,t,x,EUT} \leq \boldsymbol{SV}_{y,x,EUT}$.

[39] For solar thermal, the installed capacities, e.g., $\boldsymbol{Q}_{y,x=ST}$ in Equation (12), are given in square meters.
[40] The subset (x_1, x_2) is included in Equation (13) to specify that, in this case, the energy flows from one technology x_1 into a storage technology x_2.

Furthermore, technologies that handle multiple energy use types, such as CHP or power-to-heat (PtH) systems, require additional mathematical constraints. For example, CHP systems may consume gas, diesel or even hydrogen to produce both electricity and heat according to a power-to-heat ratio $\eta_{EUT=elec}/\eta_{EUT=heat}$,

$$\boldsymbol{XS}_{y,t,x=CHP,EUT=elec} = \frac{\eta_{t,x=CHP,EUT=elec}}{\eta_{t,x=CHP,EUT=heat}} \cdot \boldsymbol{XS}_{y,t,x=CHP,EUT=heat}, \tag{14}$$

where $\boldsymbol{XS}$ indicates the amount of energy production by the CHP system for the energy use type electricity ($EUT = elec$) and heat ($EUT = heat$) in time slice t. PtH technologies, which include electric heaters and heat pumps, consume electricity either produced by another technology ($\boldsymbol{XFI}$), in this case x_1[41], or purchased from the electricity grid ($\boldsymbol{GS}$) to generate heat supply ($\boldsymbol{XS}$), as shown in Equation (15):

$$\boldsymbol{XS}_{y,t,x=PtH,EUT=heat} = \eta_{t,x=PtH,EUT=heat} \cdot \left(\sum_{x_1} \left[\boldsymbol{XFI}_{y,t,x_1,x_2=PtH,EUT=elec} \right] + \boldsymbol{GS}_{y,t,x=PtH,EUT=elec} \right). \tag{15}$$

Whereas the efficiency η of an electric heater (e.g., a heating rod or electric boiler) tends to be less than one and remain constant for every time slice t, the efficiency of heat pumps not only reaches levels at least 3x higher but also fluctuates from one time slice to the next. The performance of electric heat pumps, i.e., the COP, is highly dependent on the temperature delta between the source temperature and the desired flow temperature of the heating system. In order to determine the temperature-dependent, variable COP of electric heat pumps, the following equation is developed[42],

$$COP_t = \eta_t = 0.0016(T_{flow} - T_{source,t})^2 - 0.2058(T_{supply} - T_{source,t}) + 8.7302 \tag{16}$$

where T_{flow} indicates the desired flow temperature, $T_{source,t}$ the outside source temperature in time slice t and COP_t the resulting COP in time slice t. A larger delta between the outside source temperature and the desired flow temperature leads to lower COPs, i.e., colder days lead to lower efficiency levels. The flow temperature for the heating system is assumed to depend on the technical construction of the heating system and, in turn, on the modernization standard of the building considered.[43]

[41] The subset (x_1, x_2) is included in Equation (15) to specify that in this case, the energy flows from one technology x_1 into a PtH technology x_2.

[42] The construction of the equation is based on data from Ruhnau (2019), Bundesamt für Wirtschaft und Ausfuhrkontrolle (2019) and industry data.

[43] For example, it is assumed that an existing building has a flow temperature of 50°C and newly-built buildings a flow temperature of 35°C.

3. Application

To demonstrate the capabilities of the model developed, three scenarios are defined and examined using COMODO. The Status Quo, Smart Tech and Smart Market scenarios as well as the corresponding assumptions pertaining to the consumer types, market conditions and DER systems are explained in Section 3.1. Section 3.2 presents and compares the scenario results with regards to investment behavior, energy generation and consumption as well as the costs for each household. The next subsection, Section 3.3, investigates the yearly and hourly marginal costs of energy provision. Finally, a sensitivity analysis is performed in Section 3.4 to explore the impact of higher carbon prices on the choices of the households considered.

3.1. Scenario Definition

Three scenarios are constructed that vary according to their technical and regulatory frameworks. More specifically, the scenarios aim to depict a progression in the amount of information available to consumers and their DER systems. Figure 3 shows an overview of the scenario definitions and corresponding attributes.

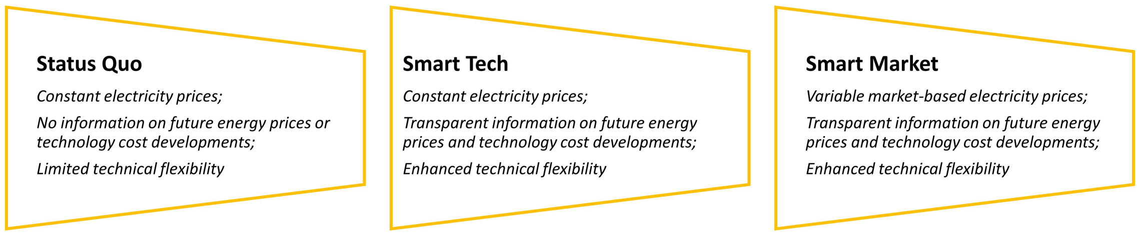

Figure 3: Overview of the scenario definitions

The first scenario, a so-called Status Quo scenario, assumes that the technologies receive no information regarding electricity market conditions, i.e., consumers see only a constant retail price. Furthermore, the consumers' investment decisions are made based on the data for only one model year rather than the entire time horizon. As such, it is assumed that consumers have no knowledge of how investment costs, remunerations, heat and electricity demand as well as weather profiles and retail prices will develop and therefore assume that all future model years will be identical to the first model year, in this case 2025.[44] The operation of the DER systems, however, is optimized on a daily basis, meaning the technologies themselves are only capable of forecasting weather and demand patterns for a single day. As a result, the optimization strategy is limited in its ability to plan generation and storage flows, similar to the current status quo.

[44] Although the consumer can not see future price or costs developments at the time of the investment decision, the consumer will still pay the, e.g., retail price that is assumed for the model year according to Figure 4 in Section 3.1.2. This is done ex-post in order to normalize the results shown in Section 3.2.

The second scenario, referred to as the Smart Tech scenario, assumes that DER systems are capable of receiving information on the demand and weather conditions for all time steps in all model years. In terms of operation, this means that technologies can better manage their energy provision by, e.g., using storage to optimize generation and consumption over a single week rather than a single day.[45] Furthermore, households are exposed to forecasts on energy price developments as well as expected changes in investment costs and subsidy values for decentralized energy technologies. In other words, investment decisions can be made with knowledge on future economic and regulatory conditions.

The third scenario, i.e., the Smart Market scenario, builds upon the Smart Tech scenario and allows for additional information on the current and future electricity market to be available to consumers and their technologies. In this scenario, the constant retail electricity price is replaced with a variable tariff to reflect changes in electricity supply and demand occurring in the market.[46] As a result, the profitability of decentralized electricity generators, storages as well as electricity-based heaters may increase as these technologies seek to optimize operation according to the hourly variations in electricity prices.

3.1.1. Defining the Consumer

COMODO is particularly well designed for analyzing the energy provision of privately-owned single-family homes in which the owner is also the resident of the house. In this case, the investment decision lies solely with one party such that a cost minimization can be performed without a mismatch in the incentives between investor and technology user.[47] Therefore, within each of the three scenarios, four privately-owned, single-family household types are considered, two with four residents and two with two residents. Table 2 shows the assumptions on the key consumer characteristics of each household type.[48] All consumers considered are assumed to live in Cologne, Germany.

Each household type is defined by individual load profiles for electricity and heat consistent with the annual demand values shown in Table 2. For electricity, the hourly demand for lighting, information and communication technology as well as household appliances is determined using a tool[49] developed in Pflugradt (2016). In doing so, an individual load profile is generated for each household type according to the

[45]At the time of this paper, the standard setting in COMODO is that the storage technologies are able to shift energy consumption within a time frame of one week. Other storage systems would have to be considered to expand this time frame.
[46]It should be noted that the electricity market price is assumed to be unaffected by the electricity consumption and generation behavior of the individual consumer. In other words, the variable tariff is not endogenously coupled with the single consumer's energy provision and is handled rather as an exogenously-defined input parameter.
[47]Especially for multi-family homes, the landlord/tenant dilemma distorts the incentives for investment: While the landlord bears the investment costs, the tenant may financially profit from using certain technologies.
[48]The key characteristics are defined in line with Shamon et al. (2021), with the household types presented being closely linked to the household types $HH1b\_A\_t3$ (HH1), $HH2b\_A\_t3$ (HH2), $HH1b\_N\_t1$ (HH3) and $HH2b\_N\_t1$ (HH4).
[49]Load profiles are derived using the *Loadprofilegenerator* (Version 7.2): `https://www.loadprofilegenerator.de/`.

	HH1	HH2	HH3	HH4
number of residents	4	2	4	2
share of residents employed	25%	100%	25%	100%
building age	existing	existing	new	new
living space [m^2]	122.4	96.0	122.4	96.0
roof size [m^2]	60	60	60	60
appliance type	standard	standard	efficient	efficient
annual electricity demand [kWh_{el}]	5674	3414	3723	2469
annual heat demand [kWh_{th}]	18051	14158	8849	6940
peak electricity demand [kW_{el}]	4.7	4.8	4.1	3.7
peak heat demand [kW_{th}]	15.4	12.1	15.6	12.2
financing rate [%]	5	5	5	5
financing period* [a]	15	15	15	15

*Financing period holds as long as the technical lifetime is exceeded

Table 2: Consumer characteristics of each household type based on Shamon et al. (2021)

consumer characteristics affecting electricity consumption behavior such as, e.g., location, number of residents, appliance efficiencies, working hours[50] and vacation periods[51]. The sum of the hourly load profiles results in the annual electricity demand shown in Table 2. For heat, on the other hand, first the annual heat demand is estimated before being broken down into an hourly consumption profile. The demand is assumed to be for both space and water heating, i.e., via a central heating system. As can be seen in Table 2, the annual heat demand varies with living space and building age, with the latter being indicative of the insulation status: While existing buildings are assumed to have a specific heat demand of 147.5 $\mathrm{kWh_{th}/(m^2a)}$, newly built homes are assumed to require 72.3 $\mathrm{kWh_{th}/(m^2a)}$. The annual heat demand is transformed into daily values following the concept of heating degree days[52] based on temperature profiles taken from 2015 weather data measured at the Cologne Airport location.[53] The daily values are then converted into hourly profiles using the structures of the typical days described in the German engineering guidelines.[54]

All consumers are assumed to make an energy investment in the year 2025, installing either the first system in a new building or a replacement system in an existing building. In other words, for households

[50]The share of residents employed indicated in Table 2 are assumed to work for eight hours per day, five days a week during daytime hours at a location other than the residence.

[51]It is assumed that each household type is on vacation for two weeks in July.

[52]The heating degree days are calculated according to Alt (2013). In line with the assumptions in Verein Deutscher Ingenieure (2019), it is assumed that the heating is turned on once the daily average outside temperature goes below 15°C for existing buildings and below 12°C for newly-built buildings.

[53]The weather data published by Deutscher Wetterdienst can be found at `ftp://opendata.dwd.de/climate_environment/CDC/observations_germany/climate/10_minutes/air_temperature/historical/`, `ftp://opendata.dwd.de/climate_environment/CDC/observations_germany/climate/10_minutes/solar/historical/` and `ftp://opendata.dwd.de/climate_environment/CDC/observations_germany/climate/10_minutes/wind/historical/`

[54]The German engineering guidelines "Verein Deutscher Ingenieure" (VDI) provide profiles for 15 different so-called "typical regions" in Germany, with Cologne falling under Region 5. The daily profiles from the VDI are constructed based on measurements taken from the existing German building stock and therefore account for building-specific (e.g., absorption of heat from building materials) as well as inhabitant-specific (e.g., opening/closing of windows) characteristics. Ten "typical days" are given for each region, differentiated by criteria such as summer/winter/between seasons, workday/Sunday and cloudy/sunny. These typical days are matched to the heating degree days using the limit values given by Verein Deutscher Ingenieure (2019).

with existing technologies, it can be assumed that any technology installed beforehand will no longer be able to operate in the year 2025, requiring a new investment. The time period considered in the optimization runs up to 2045, with 2040 being the last possible year for investment. Investments in solar systems are limited to the roof size, which is assumed to be equal for each household type regardless of the living space. Furthermore, it is assumed that each household type is equipped with the necessary infrastructure to allow for an investment in any of the DER systems considered. In other words, sufficient electric grid capacity[55] as well as a connection to the gas grid is implicitly assumed.

3.1.2. Defining the Market

A cornerstone of the scenario definition are the assumptions regarding future energy prices, as the minimization of variable costs is a key component of determining the least-cost energy provision. As described in Section 2.2, energy prices for private consumers consist not only of the day-ahead (i.e., spot) market bids but also include a wide range of taxes, surcharges and fees. The left-hand side of Figure 4 presents an overview of the retail price structures assumed for the year 2025, i.e., the first year of investment, for electricity, wood pellets and gas.[56] This is complemented by the line graph in the middle of Figure 4, which depicts the development of the retail prices between 2025 and 2040, i.e., the last year of investment considered in the scenarios. As shown in the bar graph, the retail prices in Germany are composed of a combination of four main cost components: grid fees, acquisition, renewable surcharge and concession and taxes. The future retail prices are determined by making assumptions on the developments of these individual energy price components, which are then summed up for each fuel type. The assumptions on the price components and their developments are made according to the regulatory state of affairs in Germany as of November 2021. Additional details on the fuel prices and individual price components can be found in Appendix B.

As per Figure 3 and explained in the scenario description, the Smart Market scenario allows for end consumers and their technologies to receive transparent market signals in the form of variable electricity prices. The box plot on the right-hand side of Figure 4 summarizes the data set for the hourly acquisition prices assumed in the Smart Market scenario between 2025 and 2040.[57] The boxes specify the interquartile ranges, whose height grows significantly between 2025 and 2040. The lines in the boxes on the right-hand

[55]An upper limit for the size of the electricity grid connection is included in the model.

[56]Only the energy carriers shown in Figure 4 are considered in the scenario analysis. Further energy carriers such as oil, hydrogen and steam (i.e., district heating) are omitted from the application.

[57] The hourly acquisition prices for future years are taken from the study Gierkink et al. (2021), which was completed at the Institute of Energy Economics at the University of Cologne (EWI). The prices can be understood as the marginal costs of electricity generation in Germany, which are estimated using the energy system model DIMENSION. DIMENSION is a European investment and dispatch model that accounts for, e.g., national and European decarbonization targets. For more information about the DIMENSION model, see Helgeson and Peter (2020).

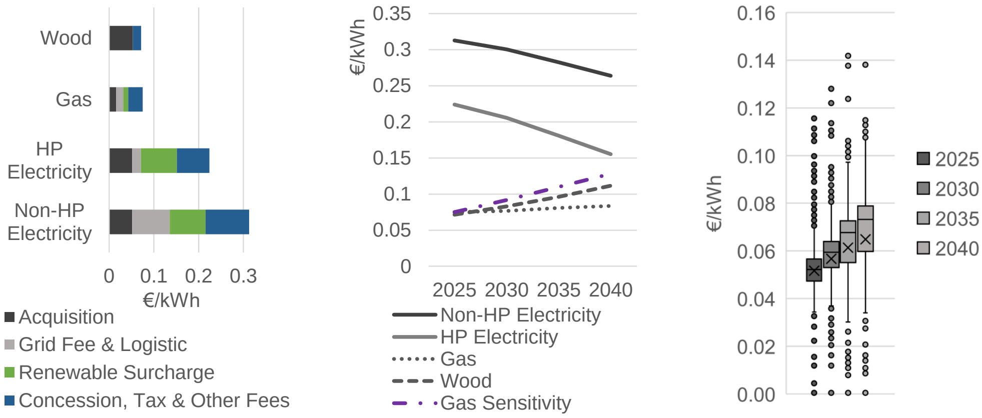

Figure 4: Assumptions on fuel prices including the individual price structures in 2025 (left) and developments in the retail prices up to 2040 (middle) for all three scenarios as well as the variance of the hourly electricity acquisition prices assumed in the Smart Market scenario (right)

side of Figure 4 indicate the average of the acquisition price over each year. These are then used in the Status Quo and Smart Tech scenarios as the constant yearly acquisition price, consistent with the dark grey area in the graph on the left-hand side of Figure 4. The retail price is then calculated by taking the hourly acquisition prices and adding the other price components (i.e., grid fees, renewable surcharge and concession, taxes and other fees), which are assumed to remain constant for every hour within a single year.

Unlike the other fuels, electricity is separated into two categories in Figure 4, namely "Heat-Pump Electricity" and "Non-Heat-Pump Electricity". Whereas the latter indicates the price for "typical" electricity consumption for, e.g., lighting and appliances, the former refers to a lower electricity tariff that is solely available for heat pump operation as imposed by German energy regulation at the time of this analysis (see Mailach and Oschatz (2021)). On average, the retail electricity price decreases from 31.2 €-ct./kWh_{el} in 2025 to 26.3 €-ct./kWh_{el} in 2040 for non-heat-pump electricity use and from 22.4 €-ct./kWh_{el} in 2025 to 15.5 €-ct./kWh_{el} for heat-pump electricity use.

Furthermore, as of the year 2021, the use of fossil fuels such as natural gas in Germany requires that consumers pay a price for the resulting carbon emissions. In Figure 4, this is indicated in the gas price by the renewable energy surcharge shown in green, equal to 1.1 €-ct./kWh_{th} in 2025 and 1.8 €-ct./kWh_{th} in 2040.[58] Since German policymakers have yet to define the mid- to long-term carbon pricing strategy for the residential and commercial building sector, an alternative gas price labelled "Gas Sensitivity" in Figure 4 is used in the sensitivity analysis in Section 3.4, which assumes a higher carbon price in 2030 (2.5 €-ct./kWh_{th}),

[58]These values are calculated based on a carbon price of 55 €/t_{CO_2} in 2025, as set by the German federal government (see `https://www.bundesregierung.de/breg-en/issues/nationaler-emissionshandel-1685054`). For the remaining years up to 2040, the carbon price is determined endogenously by the energy system model DIMENSION (see Footnote 57) based on the scenario examined in Gierkink et al. (2021), equal to 61 €/t_{CO_2} in 2030, 78 €/t_{CO_2} in 2035 and 89 €/t_{CO_2} in 2040. These are then converted to €/kWh based on the carbon emissions factor of natural gas.

2035 (4.0 €-ct./kWh$_{th}$) and 2040 (5.5 €-ct./kWh$_{th}$).[59] In sum, the energy price components for gas add up to an overall price of 7.5 €-ct./kWh$_{th}$ in the main and sensitivity analyses in 2025 and rise to 8.4 €-ct./kWh$_{th}$ in the main analysis in 2040 and to 12.8 €-ct./kWh$_{th}$ in 2040 in the sensitivity analysis.

3.1.3. Techno-Economic and Regulatory Assumptions for DER Systems

As explained in Section 1.3, key contributions of this work include the high level of technical as well as regulatory detail for a wide range of technologies together with the piecewise linearization of investment costs, FOM costs and subsidies for multiple future years. Appendix C provides an overview of the techno-economic and regulatory assumptions for each technology considered in the application. More specifically, technical descriptions including assumptions on, e.g., efficiencies and lifetimes are presented in individual subsections for condensing boilers, micro-CHP, electric heaters, electric heat pumps, pellet stoves, solar thermal systems, thermal storage, PV and battery storage. Moreover, graphical overviews of the piecewise-linear investment and FOM costs are shown for each technology, derived from an extensive data set collected from a wide range of industry and academic sources based on values for the year 2020. In order to determine the future investment costs for each investment year between 2025 and 2040, technology-specific learning rates are derived and used to scale the 2020 values (see Table D.5 in Appendix D). All investment costs are assumed to decrease over time, with some newer technologies reaching reductions of 50% by 2040.

The subsections in Appendix C also provide details on the regulatory assumptions on investment subsidies as well as variable remunerations and fees specific to the respective technologies. Incentive programs that exist in Germany as of November 2021 are accounted for in this analysis. The households considered are therefore eligible to receive investment subsidies for heat pumps, solar thermal systems and pellet stoves.[60] With the revision of the subsidy program in 2021, compensation that was historically set as a fixed amount per technology was replaced with a percentage of the capital (i.e., investment plus installation[61]) costs that were to be refunded. As such, the piecewise-linear investment costs determine the magnitude of the subsidy, which then decrease according to the same learning rates. Furthermore, electricity feed-in from a PV system is assumed to be remunerated according to the hourly acquisition price, as summarized on the right-hand side of Figure 4, plus a market premium (see Appendix C.8). CHP systems, on the other hand, receive a fixed feed-in tariff for electricity supplied to the grid and are also subject to remuneration for any electricity generation that is self-consumed (see Appendix C.2).

[59] The carbon prices used in the sensitivity analysis are taken from Repenning et al. (2021) and are calculated in the same manner as described in Footnote 58.
[60] As outlined in Bundesamt für Wirtschaft und Ausfuhrkontrolle (2021a).
[61] See Bundesamt für Wirtschaft und Ausfuhrkontrolle (2021b)

3.2. Results of the Household Optimization

The results of the investment decisions as well as the subsequent total annual costs (TAC), CO_2 emissions levels, volumes of electricity and gas consumption, the self-consumption shares of PV systems and the yearly averages of the marginal costs for electricity and heat provision for each household type within each model year and scenario are shown in Table 3. The TAC are equal to the sum of the annualized investment costs (AIC), variable costs and FOM costs corrected by the remuneration for a single year, as shown in Table E.6 in Appendix E.[62] The total costs, i.e., the objective values of the optimization variable **TC** given in Equation (1a) in Section 2.2, are presented in Table E.7 in Appendix E for each household type and scenario.[63]

HH		Status Quo 2025	Status Quo 2030	Status Quo 2035	Status Quo 2040	Smart Tech 2025	Smart Tech 2030	Smart Tech 2035	Smart Tech 2040	Smart Market 2025	Smart Market 2030	Smart Market 2035	Smart Market 2040
1	GB [kW]	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.4	8.4	8.4	8.4
	PV [kW]	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
	EH [kW]	6.9	6.9	6.9	6.9	6.9	6.9	6.9	6.9	7.0	7.0	7.0	7.0
	BS [kW]	-	-	-	-	-	3.6	3.6	3.6	-	3.6	3.6	3.6
	TAC [€/a]	4054	4035	4040	2251	4054	4052	4091	2024	4054	4045	4082	2013
	CO_2 [t/a]	4.0	3.9	3.7	3.6	4.0	3.7	3.6	3.6	4.0	3.7	3.6	3.6
	EG [$\frac{kWh}{a}$]	3091	3091	3091	3091	3088	1282	1282	1282	3104	1299	1311	1316
	GG [$\frac{kWh}{a}$]	16020	16510	16447	16443	16023	17275	17241	17207	16005	17256	17222	17188
	PVSC [%]	52.7	47.7	48.4	48.4	52.7	62.8	63.2	63.5	52.7	62.9	63.3	63.6
2	GB [kW]	7.1	7.1	7.1	7.1	6.8	6.8	6.8	6.8	6.8	6.8	6.8	6.8
	PV [kW]	-	-	-	-	-	-	-	10.0	-	-	-	10.0
	EH [kW]	5.0	5.0	5.0	5.0	5.3	5.3	5.3	5.3	5.3	5.3	5.3	5.3
	TAC [€/a]	2906	2885	2877	2413	2904	2882	2873	2386	2902	2880	2872	2397
	CO_2 [t/a]	3.7	3.5	3.3	3.2	3.7	3.5	3.3	2.7	3.7	3.5	3.3	2.7
	EG [$\frac{kWh}{a}$]	3605	3605	3605	3605	3658	3658	3658	2168	3668	3668	3668	2172
	GG [$\frac{kWh}{a}$]	14362	14362	14362	14362	14309	14309	14309	12378	14299	14299	14299	12372
	PVSC [%]	-	-	-	-	-	-	-	35.7	-	-	-	35.7
3	GB [kW]	4.7	4.7	4.7	4.7	4.6	4.6	4.6	4.6	4.5	4.5	4.5	4.5
	PV [kW]	5.3	5.3	5.3	5.3	-	-	-	10.0	-	-	-	10.0
	EH [kW]	10.8	10.8	10.8	10.8	10.9	10.9	10.9	10.9	11.0	11.0	11.0	11.0
	TAC [€/a]	2655	2636	2626	1466	2492	2456	2416	1967	2484	2446	2403	1975
	CO_2 [t/a]	2.2	2.1	2.0	1.9	2.7	2.4	2.2	1.8	2.7	2.4	2.2	1.8
	EG [$\frac{kWh}{a}$]	2309	2309	2309	2309	4067	4067	4067	2136	4082	4082	4082	2151
	GG [$\frac{kWh}{a}$]	8007	8238	8212	8181	8682	8682	8682	7863	8667	8667	8667	7848
	PVSC [%]	48.1	43.4	44.0	44.7	-	-	-	29.1	-	-	-	29.1
4	GB [kW]	3.7	3.7	3.7	3.7	3.6	3.6	3.6	3.6	3.6	3.6	3.6	3.6
	EH [kW]	8.5	8.5	8.5	8.5	8.6	8.6	8.6	8.6	8.6	8.6	8.6	8.6
	TAC [€/a]	1886	1864	1841	1549	1886	1863	1840	1552	1882	1860	1837	1548
	CO_2 [t/a]	2.0	1.8	1.7	1.6	2.0	1.8	1.7	1.6	2.0	1.8	1.7	1.6
	EG [$\frac{kWh}{a}$]	2737	2737	2737	2737	2755	2755	2755	2755	2771	2771	2771	2771
	GG [$\frac{kWh}{a}$]	6833	6833	6833	6833	6815	6815	6815	6815	6797	6797	6797	6797

GB: Gas Condensing Boiler Capacity, PV: Photovoltaic Capacity, EH: Electric Heater Capacity, BS: Battery Storage Capacity, TAC: Total Annual Costs, CO_2: Annual Carbon Dioxide Emissions from Gas and Electricity Consumption, EG: Annual Electricity Grid Consumption, GG: Annual Gas Grid Consumption, PVSC: PV Self-Consumption Share

Table 3: Results of the main analysis

[62] The values for TAC given in the tables are not discounted but rather the present value. As such, summing the TAC over the complete time horizon will not equal the total costs shown in Table E.7 in Appendix E.

[63] The total costs are calculated assuming an interest rate (i.e., i in Equation (1a)) equal to 3%.

The installed capacities in all three scenarios shown in Table 3 present a clear trend for gas-driven solutions. Households combine gas boilers for base generation together with electric heaters to cover any demand peaks. All households install a cumulative capacity equal to their heat peak as given in Table 2 in Section 3.1.1. As the information available in each of the scenarios becomes more complex, the size of the gas boilers decreases by 0.1 kW while the electric capacity rises by 0.1 kW. In the Smart Market scenario, in particular, the opportunity of low electricity prices in certain hours creates an incentive for some households to slightly increase their electricity-consuming capacities. However, as can be seen by cross-referencing Table 3 with Table E.6 in Appendix E, variable costs remain more or less unchanged between the Smart Tech and Smart Market scenarios despite the small shift from gas to electricity grid consumption found in the latter. As such, it may be concluded that the simultaneity of hours with higher heat demand and high retail electricity prices prevents the electric heater from taking full advantage of low retail electricity prices. Surprisingly, the variable electricity prices in the Smart Market scenario do not create an incentive for the endogenous investment in a thermal storage, which would be a logical decision if households could financially benefit via arbitrage. The lack of thermal storage prevents the decoupling of generation and consumption such that heat must be used directly at the time of production, regardless of the electricity price.

Nevertheless, the model results reveal that installed capacities vary stronger across household types than across scenarios. While the heat demand peaks of HH1 and HH2 resemble those of HH3 and HH4, respectively, the annual heat demands differ for each household type (see Table 2 in Section 3.1.1). Existing buildings, i.e., HH1 and HH2, are assumed to have higher annual heat demands and are found to install larger gas boilers compared to the newly-built buildings, i.e., HH3 and HH4, who demand less heat over the year. The latter two household types choose to combine smaller gas boilers with larger electric heaters, using electricity to cover their absolute peak heat demand. As such, it may be lucrative for consumers to invest in larger gas capacities, despite higher specific investment costs compared to electric heaters, as long as a certain number of full-load hours can be reached.[64]

Furthermore, high energy demand is found to be a key driver for decentralized PV electricity generation and consumption. Household types HH1 and HH3 have comparatively high electricity and heat demands as these household types are assumed to have four, as opposed to two, residents (see Table 2 in Section 3.1.1). In fact, as can be seen in Table 3, the substantial energy demand of HH1 triggers an investment in a 10 kW PV system (i.e., the largest capacity possible given the assumed roof size) across all scenarios immediately in the first year 2025. In doing so, HH1 is able to consume more than 50% of the generated

[64]Full-load hours of the gas boilers lie between 1675 (HH3, Status Quo) and 2092 (HH2, Smart Market) per year.

electricity directly via, e.g., the electric heater as well as for other appliances. In 2030 of the Smart Tech and Smart Market scenarios, HH1 decides to complement its PV system with a battery storage to further increase the self-consumption share to 63%. Following a similar logic, the relatively high energy demand of HH3 drives an investment in a 5.3 kW PV system in 2025 in the Status Quo scenario; however, in the other two scenarios, the transparency of future reductions in investment costs and electricity prices results in the installation of a 10 kW PV system being delayed until 2040.[65] The larger capacities in the Smart Tech and Smart Market scenarios, in turn, yield a lower self-consumption share of roughly 30% compared to 50% in the Status Quo scenario. For the other two-person households, the lower energy demand appears to hinder the investment in a PV system: HH2 only installs a PV system in 2040 in the Smart Tech and Smart Market scenarios for reasons analogous to those discussed above for HH3. For HH4, the energy needs of the household are too low to reach the self-consumption shares large enough to justify the capital costs.

As is to be expected, the installation of a PV system reduces the annual electricity consumption from the grid, as shown in Table 3. Moreover, the amount of gas that is consumed from the grid is also reduced, e.g., in HH2 and HH3, as a greater amount of heat is provided by the electric heater using PV electricity. In turn, these households are able to lower their CO_2 emissions more effectively than households without PV systems who only benefit from the predefined reduction in the carbon intensity of the German power mix.

For each household type, a drop in the TAC can be observed in Table 3 in 2040 as investments made in 2025 have reached the end of their financing period, thus strongly decreasing the AIC (see Table 2 in Section 3.1.1 and Table E.6 in Appendix E).[66] As is to be expected, the similarities in the investment decisions lead to very little discrepancies in the TAC across scenarios.[67] In fact, just looking at the annual costs, it may appear that the Status Quo scenario is more economical than the other, more efficient scenarios. However, when considering the discounted total costs over the complete time horizon shown in Table E.7 in Appendix E, the increase in the amount of information available tends to have a positive effect on cost savings, especially for households with larger energy demands (i.e., HH1 and HH3).[68] It is also worth noting that neither gas boilers nor electric heaters benefit from governmental funding. In other words, under the

[65] In the Status Quo scenario, the consumer believes that the relatively high electricity prices in 2025 will remain constant for the complete time horizon, making self-consumption from a PV system more attractive. On the other hand, in the scenarios with foreseeable price reductions, HH3 abstains from an investment in a PV system in 2025; however, by 2040, the capital costs of the PV system have decreased such that an investment is economical despite the lower retail electricity price.

[66] As electric heaters have a technical lifetime of fifteen years, systems that are built in 2025 must be replaced in 2040. As such, households who only invest in 2025 (e.g., HH4) will have paid off all of their annualized investment costs by 2040, yet will begin a new financing period for the replacement electric heater in 2040. This is equal to roughly 24-27 €/a, depending on the thermal capacity (see Table E.6 in Appendix E).

[67] The one noteworthy exception is the difference between the Status Quo scenario and the Smart Tech and Smart Market scenarios for HH3 due to the difference in the investment decisions, as explained below.

[68] It should be noted that any additional costs associated with a technology's ability to handle increased amounts of information (e.g., software, digital infrastructure, hardware accessories) are not considered in this analysis.

assumptions outlined in Section 3.1, the incentive mechanisms offered for other heating technologies such as heat pumps and micro-CHP are not effective in instigating investment for the household types considered.

3.3. Investigating the Marginal Costs of Energy Provision

As explained in Sections 1.2 and 1.3, one key contribution of this work is the evaluation of the implicit shadow prices for each EUT, referred to in this paper as the marginal costs of energy (i.e., heat or electricity) provision. Generally speaking, an interpretation of the shadow prices in MILP models is not possible due to their non-linear nature. However, in this analysis, the technique outlined by Williams (1989) and Williams (2013) is used such that a second model run is performed for each household type and scenario in which all binary variables are set equal to the values found in the first unrestricted optimization. In doing so, the non-linear model is then linearized, allowing for the marginal values of the equilibrium constraint (i.e., the first-order condition of Equation (1b)) to be interpreted as the marginal costs of heat or electricity provision. Simply put, the marginal costs of energy provision reveal the price that the consumer pays for the energy used, which is estimated by the model as the change in the total costs (i.e., the objective value) if the consumer were to demand an additional kWh of energy. As such, the marginal costs depend strongly on the options available to the consumer to supply or generate energy at each point in time.

		Status Quo				Smart Tech				Smart Market			
HH		2025	2030	2035	2040	2025	2030	2035	2040	2025	2030	2035	2040
1	HM [$\frac{\text{€-ct}}{kWh}$]	5.4	5.5	5.7	5.8	5.4	5.6	5.8	5.9	5.4	5.6	5.8	5.9
	EM [$\frac{\text{€-ct}}{kWh}$]	22.9	22.3	21.1	20.1	22.9	17.9	17.3	16.7	22.9	17.6	17.1	16.4
2	HM [$\frac{\text{€-ct}}{kWh}$]	5.5	5.5	5.8	5.9	5.6	5.6	5.9	5.6	5.6	5.6	5.8	5.6
	EM [$\frac{\text{€-ct}}{kWh}$]	31.3	30.1	28.2	26.4	31.3	30.1	28.2	19.3	31.2	29.9	28.1	19.4
3	HM [$\frac{\text{€-ct}}{kWh}$]	4.6	4.7	4.8	4.9	4.7	4.8	5.0	4.9	4.8	4.8	5.0	4.9
	EM [$\frac{\text{€-ct}}{kWh}$]	23.1	22.4	21.2	20.1	31.3	30.1	28.2	19.2	31.2	29.9	28.1	19.4
4	HM [$\frac{\text{€-ct}}{kWh}$]	4.7	4.7	4.9	5.0	4.7	4.8	5.0	5.1	4.7	4.8	5.0	5.1
	EM [$\frac{\text{€-ct}}{kWh}$]	31.3	30.1	28.2	26.4	31.3	30.1	28.2	26.4	31.2	29.9	28.1	26.2

HM: Average Marginal Cost for Heat Provision, EM: Average Marginal Cost for Electricity Provision

Table 4: Marginal costs of energy provision for each household type, year and scenario in the main analysis

The results of the marginal costs of electricity provision as well as as the marginal costs of heat provision averaged over all hours of each model year are shown in Table 4 for each household type and scenario. To aid in the understanding of the marginal costs, Figure 5 shows the electricity provision and demand, the heat provision and demand as well as the marginal costs of energy provision for HH1 (left) and HH3 (right) for the second and first weeks in February[69] 2040, respectively, in the Smart Tech scenario. Looking first at

[69]These weeks were chosen because these include the hour in which the household's heat demand is at its absolute peak.

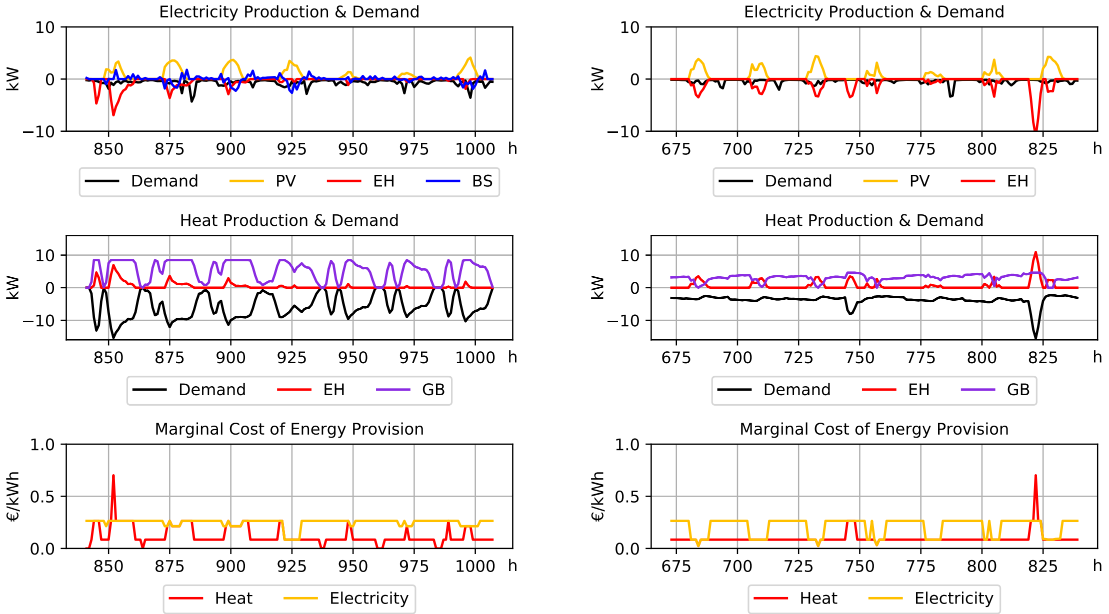

Figure 5: Hourly supply, demand and marginal costs of electricity and heat provision in the second week of February 2040 for HH1 (left) and first week of February 2040 for HH3 (right) in the Smart Tech scenario in the main analysis

the marginal cost of electricity provision depicted by the yellow line in the bottom graph in Figure 5, the profile frequently flattens at a level equal to the retail electricity price (i.e., 26.4 €-ct./kWh$_{el}$ in 2040) for both household types. In these hours, an additional kWh of demand would be covered by electricity from the grid, hence the marginal cost equaling the retail price. For households without PV installations, this holds true in every hour, as depicted by similarities in the average marginal costs of electricity provision in Table 4 for HH2 (i.e., Status Quo scenario as well as 2025-2035 of the Smart Tech and Smart Market scenarios), HH3 (i.e., 2025-2035 of the Smart Tech and Smart Market scenarios) and HH4.[70]

However, in hours in which PV generation is consumed, the marginal costs of electricity provision sink. In fact, in hours in which solar irradiation coincides with low energy demand, the marginal costs of electricity provision approach zero as excess PV electricity is fed into the grid. In this case, PV electricity would hypothetically be available if demand were to increase, hence the marginal costs undercutting the retail electricity price.[71] This can be seen for example, on the right-hand side of Figure 5 via the dips in the yellow line in the bottom graph (i.e., the marginal costs of electricity provision) that coincide with the peaks of the yellow line in the top graph (i.e., PV electricity generation), with the yellow line in the bottom graph

[70] The values in the Smart Market scenario listed here may deviate slightly (i.e., $< 1\%$) from the constant retail electricity prices seen in the Smart Tech scenario results due to minor shifts in the operation of the electric heater in response to hours with lower electricity prices.

[71] The self-consumption of decentralized PV electricity presents consumers with an indirect financial incentive by facilitating the evasion of taxes, levies and surcharges that are charged when consuming electricity from the grid, as explained in Jägemann et al. (2013).

meeting the x-axis in the 757$^{\text{th}}$ hour when the black lines in the top and middle graphs (i.e., electricity and heat demand, respectively) are at their weekly lows. As a result of the PV self-consumption, the average marginal costs of electricity provision for HH2 and HH3 in 2040 in the Smart Tech and Smart Market scenarios as well as HH3 in the Status Quo scenario drop significantly (i.e., $> 24\%$) compared to the retail electricity price (see Table 4). For HH1, high energy demand drives an investment in battery storage in the Smart Tech and Smart Market scenarios to shift the consumption of PV generation to cover demand in, e.g., peak evening hours, which can be seen in the structure of the blue line in the top graph on the left-hand side of Figure 5. The battery storage coupled with a PV system, in turn, leads to HH1 being able to decrease its electricity supplied from the grid. In fact, as can be seen in Figure E.11 in Appendix E, HH1 is able to reduce it's electricity consumption from the grid to zero in many more hours in the Smart Tech and Smart Market scenarios compared to the Status Quo scenario.[72] These effects, in turn, drive down the average marginal costs of electricity provision even further, reaching a lowest average value of 16.4 €-ct./kWh$_{\text{el}}$ in 2040 in the Smart Market scenario (see Table 4).

The marginal costs of heat provision follow a similar trend as electricity, with the majority of hours following the gas price corrected by the boiler efficiency (e.g., reaching 8.5 €-ct./kWh$_{\text{th}}$ in 2040). However, unlike with electricity, heat demand may drop to zero in certain hours, causing the marginal costs of heat provision to also fall to zero — an effect that can clearly be seen for HH1 when examining the middle and lower graphs on the left-hand side of Figure 5.[73] On the other hand, contrary to what is seen with the marginal costs of electricity provision, the marginal costs of heat provision spike upwards in moments of higher heat demand. For the majority of these peaks, the household would be able to ramp up the production from the electric heater, which results in a marginal cost of heat provision equal to the marginal cost of electricity provision (see, e.g., the meeting of the red and yellow lines in the lower graphs of Figure 5 coinciding with times of electric heater production, indicated by spikes in the red line in the middle graphs of Figure 5). However, as heat can not be bought from a central supplier, it must be able to be generated by the household, which in turn requires sufficient generating capacity. Yet the investment decision in the peak technology of the households is based on the absolute peak heat demand, which in the case of HH1 occurs in the 852$^{\text{nd}}$ hour and for HH3 in the 822$^{\text{nd}}$ hour. Therefore, the marginal costs of heat provision in these

[72] This effect can be profitable for more than just the household. Smart technologies can strongly influence the consumers grid consumption pattern, therefore potentially reducing the expansions to the distribution grid.

[73] It should be noted that the two household types shown in Figure 5 have very different hourly demand structures due to the difference in building age. HH3 is a newly-built building that is equipped with, e.g., floor heating, which is rarely turned on or off and thus creates a small amount of base demand. HH1, on the other hand, is an existing building with radiatiors and a central heating system, which can be adjusted as need be. This creates a more volatile demand structure that may reach a higher level but also drop to zero during, e.g., nighttime hours. A strong peak is given in both profiles, which are constructed based on Verein Deutscher Ingenieure (2019) (see Section 3.1.1).

peak hours not only reflect the increased variable costs but also the additional investment costs needed to provide the extra kW of heat.[74]

The average marginal costs of heat provision shown in Table 4 reflect the combination of the effects discussed above. All values are significantly under the gas price, indicating the frequency of hours with zero heat demand, i.e. 2996h/a for existing buildings and 3956h/a for newly-built buildings. The high share of hours in which zero demand occurs in the latter drastically reduces the average marginal costs of heat provision. Furthermore, the newly-built HH3 and HH4 cover a larger share of their heat demand with gas, which also helps to lower the average marginal costs compared to existing buildings HH1 and HH2, who use their electric heater more frequently.

3.4. Sensitivity Analysis

3.4.1. Motivation and Design of the Sensitivity Analysis

A common challenge associated with the modeling of future energy systems is the inability to predict the unpredictable. In fact, a large body of literature is dedicated to assessing uncertainty and its effect on MILP optimization results (e.g., Mavromatidis et al. (2018)). Estimating future energy prices based on today's information is particularly precarious, as unforeseen shifts in, e.g., regulation, geopolitics or market dynamics may significantly effect price developments. Nevertheless, studies such as the IEA's World Energy Outlook (International Energy Agency (2020)) have emerged as standard sources for commodity price predictions. Yet for the end consumer, it remains unclear how the different price components will evolve over time.

This is especially true when considering the fee for CO_2 emissions that was just recently introduced by the German government. Currently, CO_2 emissions in Europe are priced according to a European certificate trading system known as the EU-ETS. At the time of this paper, emissions arising from end energy use in residential and commercial buildings are not included in the EU-ETS. Therefore, German policymakers have introduced an independent pricing system for the buildings sector, setting a price of 55 €/t_{CO_2} in 2025; however it is unclear how this price will develop in the longer term.

In the main analysis, the CO_2 price post-2025 is set equal to the EU-ETS price, which is determined endogenously by the energy system model DIMENSION. However, studies such as Repenning et al. (2021) have suggested that the carbon price in the building sector will far exceed the certificate price, reaching levels equal to 125 €/t_{CO_2} (i.e., 2.5 €-ct./kWh_{th}) in 2030, 200 €/t_{CO_2} (i.e., 4 €-ct./kWh_{th}) in 2035 and 275 €/t_{CO_2} (i.e., 5.5 €-ct./kWh_{th}) by 2040. In order to examine the consequences of alternative carbon price

[74]Supplementary model runs with increased peak demand indicate that the marginal costs of energy provision in the peak hours shown in Figure 5 reflect the investment in one additional kW of electric heater capacity.

pathways, a sensitivity analysis is performed for the Smart Tech and Smart Market scenarios in which the values from Repenning et al. (2021) are assumed for the CO_2 prices in the German buildings sector.[75] In doing so, the long-term retail gas price is increased significantly compared to the main analysis, reaching 9.2 €-ct./kWh$_{th}$ in 2030 and 12.8 €-ct./kWh$_{th}$ in 2040 (see Figure 4 in Section 3.1.2).[76]

3.4.2. Key Findings of the Sensitivity Analysis

Analogous to the results of the main analysis, the results of the sensitivity analysis are presented in Table 5, with a detailed overview of the annual cost results shown in Table E.8 and the total costs shown in Table E.7 in Appendix E. As expected, the increase in the long-term retail gas price leads to significant changes in the investment decisions in all four household types in the Smart Tech and Smart Market scenarios. Below, the key findings of the sensitivity analysis are outlined and compared to the results of the main analysis.

Sensitivity Finding #1: Electric heat pumps replace gas boilers as the base heating technologies, which drastically reduces the emissions of the households considered

The increase in the retail gas price leads to higher variable costs for gas boilers, making the investment unattractive for three out of four household types. Instead, electric heat pumps emerge as the base technology, once again combined with an electric heater to cover hours of peak heat demand. Just as in the main analysis, the model chooses to cover a large share of the heat demand with the more capital-intensive technology, while the more inexpensive technology is built to be turned on in select hours when consumption spikes.[77] Whereas, HH1, HH3 and HH4 cover their heat demand completely with electricity, HH2 installs a gas boiler to be used in the first fifteen years before switching over to an electric heat pump in 2040. The delay in investment can be attributed to the assumptions regarding the building characteristics: HH2, just like HH1, is assumed to be an existing building, which means that a radiator heating system is assumed. In this case, heat pumps require higher flow temperatures to reach the same target room temperature, which in turn decreases the COP (see Section 2.4).[78] Since HH2 only has two residents, the lower annual heat demand

[75]The Status Quo scenario is not included in the sensitivity analysis as, by definition, the investment decision is unaffected by future price developments, i.e., the consumer sees only the retail gas price in 2025. Although the AIC remain unchanged between the two scenarios, the variable costs increase in the sensitivity analysis due to the higher carbon prices. Therefore, for completeness, the total costs of the Status Quo scenario in the sensitivity analysis are included in Table E.7 in Appendix E.

[76]Although the sensitivity analysis is centered around a scenario with higher CO_2 prices, it should be noted that a more expensive retail gas price may in reality be due to increases in any of the price components including, e.g., the costs of gas acquisition. In other words, the results presented in Section 3.4.2 may be more generally interpreted as a consequence of rising retail gas prices in the German building sector.

[77]Similar to the main analysis, information gains tend to decrease the capacity of the base technology while the capacity of the peak technology slightly increases.

[78]New buildings, on the other hand, are often heated with floor heating systems, which can process lower flow temperatures.

HH		Smart Tech 2025	Smart Tech 2030	Smart Tech 2035	Smart Tech 2040	Smart Market 2025	Smart Market 2030	Smart Market 2035	Smart Market 2040
1	HP [kW]	6.0	6.0	6.0	6.0	5.9	5.9	5.9	5.9
	TS [kW]	49.1	49.1	49.1	49.1	51.6	51.6	51.6	51.6
	PV [kW]	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
	EH [kW]	4.6	4.6	4.6	4.6	4.5	4.5	4.5	4.5
	TAC [€/a]	4479	4358	4189	1847	4467	4350	4178	1817
	CO_2 [t/a]	1.8	1.3	1.0	0.8	1.8	1.3	1.0	0.8
	EG [$\frac{kWh}{a}$]	7558	7578	7599	7607	7571	7602	7625	7642
	PVSC [%]	53.4	52.9	52.6	52.5	53.7	53.1	52.9	52.6
	HM [$\frac{\text{€-ct}}{kWh}$]	5.2	4.9	4.4	4.0	5.2	4.9	4.4	3.8
	EM [$\frac{\text{€-ct}}{kWh}$]	24.3	23.3	21.9	20.6	24.2	23.3	22.0	20.6
2	GB [kW]	6.7	6.7	6.7	-	6.6	6.6	6.6	-
	HP [kW]	-	-	-	4.4	-	-	-	4.4
	TS [kW]	-	-	-	34.2	-	-	-	34.1
	PV [kW]	-	-	-	10.0	-	-	-	10.0
	EH [kW]	5.4	5.4	5.4	4.1	5.4	5.4	5.4	4.2
	TAC [€/a]	2906	3101	3289	2762	2903	3098	3286	2748
	CO_2 [t/a]	3.7	3.5	3.3	0.6	3.7	3.5	3.3	0.6
	EG [$\frac{kWh}{a}$]	3685	3685	3685	5377	3701	3701	3701	5416
	GG [$\frac{kWh}{a}$]	14281	14281	14281	-	14266	14266	14266	-
	PVSC [%]	-	-	-	39.2	-	-	-	39.3
	HM [$\frac{\text{€-ct}}{kWh}$]	5.7	6.7	7.8	4.1	5.7	6.7	7.7	4.0
	EM [$\frac{\text{€-ct}}{kWh}$]	31.3	30.1	28.2	19.9	31.2	29.9	28.1	20.0
3	HP [kW]	3.0	3.0	3.0	3.0	3.1	3.1	3.1	3.1
	TS [kW]	31.9	31.9	31.9	31.9	28.0	28.0	28.0	28.0
	PV [kW]	6.8	6.8	6.8	6.8	-	-	-	10.0
	EH [kW]	7.8	7.8	7.8	7.8	8.1	8.1	8.1	8.1
	TAC [€/a]	2868	2808	2726	972	2749	2652	2511	1574
	CO_2 [t/a]	1.0	0.7	0.5	0.4	1.4	1.0	0.7	0.4
	EG [$\frac{kWh}{a}$]	3891	3888	3888	3884	6390	6393	6398	3694
	PVSC [%]	39.1	39.3	39.4	39.6	-	-	-	29.0
	HM [$\frac{\text{€-ct}}{kWh}$]	4.0	3.8	3.4	3.1	4.5	4.2	3.8	2.9
	EM [$\frac{\text{€-ct}}{kWh}$]	23.2	22.5	21.2	20.0	31.2	29.9	28.1	19.5
4	HP [kW]	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7
	EH [kW]	9.5	9.5	9.5	9.5	9.5	9.5	9.5	9.5
	TAC [€/a]	2098	2030	1931	1305	2085	2018	1918	1286
	CO_2 [t/a]	1.1	0.8	0.6	0.5	1.1	0.8	0.6	0.5
	EG [$\frac{kWh}{a}$]	4715	4715	4715	4715	4726	4726	4726	4726
	HM [$\frac{\text{€-ct}}{kWh}$]	4.5	4.3	3.8	3.4	4.5	4.2	3.8	3.4
	EM [$\frac{\text{€-ct}}{kWh}$]	31.3	30.1	28.2	26.4	31.2	29.9	28.1	26.2

GB: Gas Condensing Boiler Capacity, HP: Heat Pump Capacity, TS: Thermal Storage Capacity, PV: Photovoltaic Capacity, EH: Electric Heater Capacity, TAC: Total Annual Costs, CO_2: Annual Carbon Dioxide Emissions from Gas and Electricity Consumption, EG: Annual Electricity Grid Consumption, GG: Annual Gas Grid Consumption, PVSC: PV Self-Consumption Share, HM: Average Marginal Cost for Heat, EM: Average Marginal Cost for Electricity

Table 5: Results of the sensitivity analysis

compared to HH1 causes the investment in a heat pump to be uneconomical as the full-load hours can not be reached that would justify the lower efficiency gains. By 2040, significant reductions in the investment costs of heat pumps combined with the increased retail gas price drive HH2 to modify their heating system.

The change in the main source of energy from gas in the main analysis to electricity in the sensitivity analysis leads to a drastic change in carbon emissions, as can be seen by comparing Table 3 with Table 5.

High efficiencies of electric heat pumps combined with the avoided fossil fuel consumption lead to a reduction of emissions by at least 45% in 2025 for the case in which the household does not install a PV system (i.e., HH4, Smart Market). This emission reduction is then increased as soon as households begin covering shares of their electricity consumption using a PV system, and even more so when introducing a thermal storage. By maximizing the self-consumption share of PV electricity in both heat generation as well as direct electricity use, consumers are able to reduce their consumption of carbon-intensive electricity from the grid. In doing so, emissions can be reduced in 2025 by up to 64% (HH3, Smart Tech) compared to the main analysis, reaching up to 80% in 2040 depending on the household type. As such, it can be concluded that the increase in the carbon price in the German building sector assumed in the sensitivity analysis would be effective in incentivizing investments in renewable generators and lowering the emissions of the household types considered.[79]

Aggregated over the entire time horizon, up to an additional 50 tonnes of CO_2 can be avoided in the sensitivity analysis compared to the main analysis, as shown in Table E.9 in Appendix E. The decrease in carbon emissions increases the households' total costs, which vary according to the timing and the type of new investments. Additional abatement costs arising from the deeper decarbonization in the sensitivity analysis compared to the main analysis are found to be highest for HH2 at 293 €/tCO_2 in the Smart Tech Scenario, as shown in Table E.9 in Appendix E. All other households exhibit lower carbon abatement costs, ranging between 36 €/tCO_2 (HH3, Smart Tech Scenario) and 56 €/tCO_2 (HH1, Smart Tech Scenario). These households experience earlier investments in lower-carbon technologies, which result in a greater amount of emissions savings over time combined with lower gas consumption and, in turn, CO_2 levies.

Sensitivity Finding #2: Increase in electricity demand via heat pumps makes investments in PV systems even more attractive

As explained in Section 3.2, PV systems are only lucrative if a certain self-consumption share can be reached. In the sensitivity analysis, HH2 and HH3 achieve even higher self-consumption shares by using PV electricity to run their heat pumps. Furthermore, contrary to the Smart Tech results of the main analysis, the increased electricity demand drives HH3 to invest in a PV system in 2025 rather than waiting until 2040. This is not seen in the Smart Market scenario, as dips in the electricity price during daytime hours tend to negate the benefits of distributed PV generation. Lastly, even with complete electrification, the low electricity and heat demands assumed for HH4 do not exceed the threshold to make an investment in a PV system economical.

[79] It should be noted that this analysis only accounts for the carbon emissions resulting from the final energy consumption of the households. There is no crediting for emissions reduction that may arise in the German power sector due to the household's feed-in of renewable electricity.

Sensitivity Finding #3: Investments in thermal storage emerge to help manage heat demand peaks as well as increase self-consumption of PV generation and maximize heat pump efficiency

As can be seen in Table 5, both four-person households, i.e., HH1 and HH3, choose to install thermal storage in the first year of investment (i.e., 2025) in the sensitivity analysis with higher retail gas prices. In fact, the results show a clear preference to couple thermal storage with investments in heat pumps and PV systems. In doing so, the heat pump is able to maximize the use of PV electricity generation by supplying heat into the thermal storage during sunny periods and discharging the storage, e.g., during heat demand peaks in evening hours. In other words, thermal storage is able to alleviate the mismatch in hours with strong solar irradiance and high heat consumption. HH2, for example, switches from a gas boiler/electric heater system to a heat pump/thermal storage/PV/electric heater system in 2040. As a result, HH2 reaches a self-consumption share of 39.2% in the sensitivity analysis compared to 35.7% in the main analysis despite significantly larger electricity demand. Furthermore, thermal storage create an opportunity for heat pumps to adjust their operation to make the most of their COP profile, i.e., by ramping-up production in hours with high efficiencies and ramping-down in hours with low efficiencies, independent of demand. This is particularly clear when looking at the hourly production and consumption profiles, as discussed below. Finally, thermal storage systems allow the household to install heat pumps and electric heaters with lower capacities, with the cumulative capacity sized to cover roughly 70% of the heat demand peak. Households without a thermal storage system install heating capacity up to their heat peak, similar to the main analysis.

Sensitivity Finding #4: Stricter emission pricing increases total costs of households' energy provision

The increased carbon price for the German building sector in the sensitivity analysis drives the households to spend more on their energy provision than in the main analysis. This comparison holds true for all household types and for each scenario. As explained above, the higher retail gas price leads to three out of four households avoiding gas investments completely, choosing a more capital-intensive investment in 2025 compared to the main analysis, as can be seen by comparing the AIC in Table E.8 with Table E.6 in Appendix E.[80] For example, HH4 faces in both the Smart Tech and Smart Market scenarios of the sensitivity analysis AIC that are twice as high compared to the main analysis. An even more extreme example is HH3, whose early investment in PV in the Smart Tech scenario of the sensitivity analysis leads to nearly five times higher yearly capital costs than in the Smart Tech scenario of the main analysis. For HH1, the difference in the AIC between analyses is not as pronounced due to the investment in a capital-intensive battery

[80] It should be noted that the AIC shown in Table E.8 in Appendix E have already been corrected for the heat pump subsidy, consistent with Equation (3) in Section 2.2.

storage seen in the main analysis. However, in electrifying their heating systems in the sensitivity analysis, household types HH1, HH3 and HH4 are able to benefit from lower heat pump tariffs together with higher efficiency levels of the heat pump and increased self-consumption shares of the PV system. This results in an immediate reduction in the variable costs in the first year of investment, i.e., 2025, for the households with fully electric heating systems by 3% (HH4, Smart Tech) up to 44% (HH3, Smart Tech). By 2040, decreasing electricity prices continue to lower variable costs, achieving a 14% (HH1, Smart Tech, 2040) up to a 34% (HH2, Smart Market, 2040) reduction compared to the main analysis.

These counteracting effects result in HH1, HH3 und HH4 in the sensitivity analysis increasing their TAC anywhere from 10% (HH1, both scenarios) to 15% (HH3, Smart Tech) in 2025 and decreasing their TAC by 9% (HH1, Smart Tech) to 51% (HH3, Smart Tech) in 2040 compared to the main analysis.[81] All in all, these household types see a rise in total costs in the sensitivity analysis ranging from 3.5% (HH3, Smart Market) to 5.4% (HH1, Smart Tech) over the complete time horizon (see Table E.7 in Appendix E). For HH2, as explained above, an early investment in a gas boiler remains the least-cost option in the sensitivity analysis despite higher retail gas prices. As a result, total costs increase by 8.2% in the Smart Tech scenario compared to the main analysis, which is the greatest discrepancy seen across all household types. Consistent with the results of the main analysis, the total costs across the scenarios of the sensitivity analysis also decrease as more information becomes available to the households and their DER systems.

Sensitivity Finding #5: Electrification of heat production increases marginal costs of electricity provision and decreases marginal costs of heat provision

Contrary to the presentation of the main results, the average marginal costs of electricity and heat provision for the sensitivity analysis are included with the other results in Table 5. In addition, Figure 6 shows the retail energy prices, the electricity provision and demand, the heat provision and demand, the thermal storage levels, the COP of the heat pump as well as the marginal costs of energy provision for HH1 for the second week in February 2040 in the Smart Tech (left) and Smart Market (right) scenarios.

The trends described in Section 3.3 hold true for the marginal costs of electricity provision found in the sensitivity analysis. As such, the average values for households without PV systems are found to be equal to the retail electricity prices and are thus identical to the results of the main analysis (i.e., the values for HH2 in years 2025-2035 of the Smart Tech and Smart Market scenarios, HH3 in years 2025-2035 of the Smart Market scenario and HH4). Furthermore, similarities can also be seen in the results for HH2 and HH3 in 2040, with decentralized generation of PV systems once again driving down the marginal costs of electricity provision

[81] By 2040, decreases in variable costs outweigh increases in AIC as the financing period for investments from 2025 has ended.

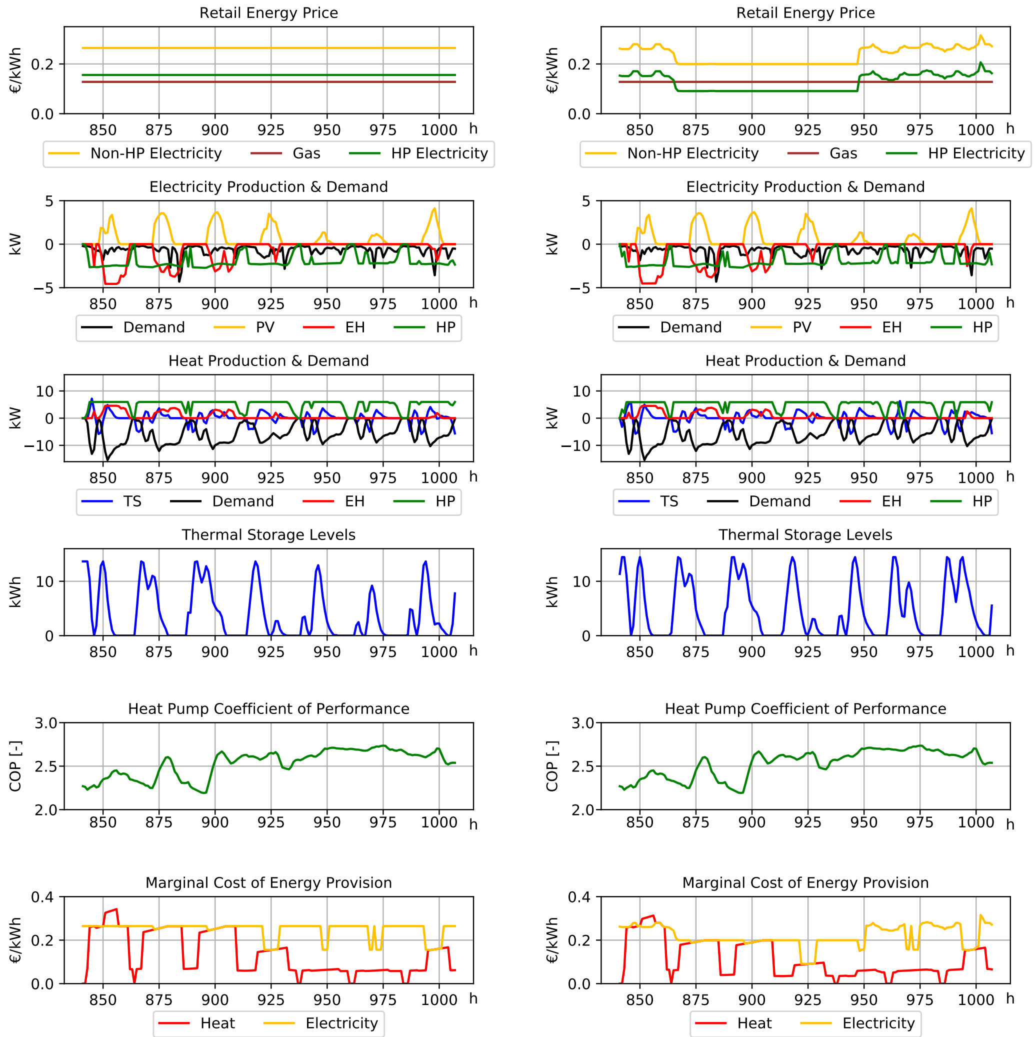

Figure 6: Hourly results of the sensitivity analysis for HH1 in the second week of February 2040 for the Smart Tech scenario (left) and the Smart Market scenario (right)

in certain hours. In the sensitivity analysis, however, slightly higher average values arise as the increase in electricity demand via the heat pumps drives a higher amount of grid consumption (see Tables 3, 4 and 5). Nevertheless, two distinct anomalies stand out when comparing the average marginal costs of electricity provision in the two analyses: First, an earlier investment in a PV system in the Smart Tech scenario of the sensitivity analysis leads to HH3 reducing their marginal costs of electricity provision in all model years rather than just in 2040. Second, the lack of battery storage together with the increased electricity demand result in HH1 facing higher average marginal costs for electricity provision in the sensitivity than in the main analysis. As a result, the average marginal costs of electricity provision increase by up to 30% in the years 2030-2040 in both scenarios of the sensitivity analysis.

For the marginal costs of heat provision, the shift in the investment decision away from gas and towards a fully electric energy provision has some interesting consequences. Contrary to the main analysis, marginal costs of heat provision shown in Table 5 decrease over time as the fuel prices, in this case the retail non-heat-pump and heat-pump electricity prices, also decline. As explained in Section 3.3, the marginal costs of heat provision may equal the marginal costs of electricity provision in times when electricity could be consumed to ramp up heat production. In this case, two electricity-consuming technologies are available yet are subject to different tariffs. Looking at Figure 6, the marginal costs of heat provision and the marginal costs of electricity provision (i.e., the red and yellow lines, respectively, in the bottom graphs) meet at a level equal to the retail non-heat-pump electricity price (i.e., the yellow line in the top graphs) in several instances during the first three days of the week (i.e., hours 841-912). Here, it can be concluded that the electric heater fueled with electricity from the grid would be the next least-cost option.[82]

The heat pump, on the other hand, is designed as a base generator and is therefore limited in its ability to increase production due to capacity constraints. Nevertheless, the combination with thermal storage allows heat pumps to play a crucial role in driving down the marginal costs of heat provision by (i) ramping down production despite higher demand levels to evade lower COPs, no PV generation and/or high retail electricity prices, and (ii) continuing to run in times of low or no demand to benefit from strong COPs, PV generation and/or low retail electricity prices. Examples of the second effect can be seen by looking at Figure 6: Marginal costs of heat provision remain below the marginal costs of electricity provision for most of the second half of the week, e.g., hours 933 to 994. During this time, heat demand drops below the levels of the previous days, which in turn allows HH1 to avoid using the electric heater (see the black and red lines in third graphs from the top). As such, heat demand is covered by the heat pump together with thermal storage, who optimize the charging and discharging of the storage to minimize the costs of heat provision. In doing so, the heat pump uses the correlation between PV generation and high COPs to continue generating heat in times of zero heat demand in order to feed heat into the thermal storage, e.g., in hours 937-938, 960-962 and 984-986 in the Smart Tech scenario. Heat produced from the heat pump is then supplied by the thermal storage in hours with higher heat demands, resulting in the marginal costs of heat provision staying between 3.5 and 6.6 €-ct./kWh$_{\text{th}}$ over this time frame.

In the 852$^{\text{nd}}$ hour, i.e., the hour of peak heat demand for HH1, the marginal costs of heat provision also reach their maximum value, as can be seen in Figure 6. Whereas the marginal costs of heat provision in the

[82] It is interesting to note that the curves of the marginal costs of heat provision discussed here do not plateau at the level equal to the retail price, as seen with the marginal costs of electricity provision, but rather have a slightly increasing slope. This is due to the hourly losses of the thermal storage that occur over time, referred to as β in Equation (13) in Section 2.4.

peak demand hour in the main analysis include the investment costs for 1 kW of additional heating capacity, the availability of thermal storage offers a less capital-intensive option.[83] In this case, the storage could, e.g., shift one unit of heat discharge from the previous hour to the peak hour, using an electric heater in the previous hour to supply the missing kW. Comparing Figures 5 and 6, this effect leads to the maximum value for HH1 decreasing from 0.70 €-ct./kWh_{th} in the main analysis to about 0.33 €-ct./kWh_{th} in the sensitivity analysis. All in all, the flexibility introduced via thermal storage leads to significant reductions in the yearly averages of the marginal costs, as can be seen in Table 5. In fact, the absolute values of the average marginal costs of heat provision are found to be up to 38% lower than those seen in the main analysis.

Sensitivity Finding #6: Variable electricity prices have little effect on the costs of energy provision for the households considered

The main analysis and the sensitivity analysis present different investment strategies for the household types to cover their energy demands. Nevertheless, in both cases, the investment decisions appear to be unaffected by the differences in the definitions of the Smart Tech and Smart Market scenarios. In other words, the introduction of hourly, market-based variable electricity prices does not drive a major change in the cost-minimizing technology mix for the households considered. Yet the presence of a thermal storage coupled with electricity-consuming heating technologies in the sensitivity analysis creates an opportunity for households to take advantage of the variable electricity price structure. For example, comparing the Smart Tech (left) and the Smart Market (right) scenarios in Figure 6, the heat pump in the Smart Market scenario ramps up in times of lower electricity prices (e.g., in hours 961-963 and 985-987) to deliver larger heat volumes to the thermal storage. The thermal storage can then be discharged to relieve the heat pump in hours with unfavorable electricity prices (i.e., in hours 967/968 and 983). Moreover, dips in the electricity price also incentivize the electric heater to increase production compared to the Smart Market scenario, as seen in hour 996 in Figure 6. In this case, the peak heating technology is activated in addition to the baseload electric heat pump, increasing electricity consumption. This effect leads to a slight increase in the maximum amount of electricity consumed from the grid in a single hour in the Smart Market scenario, which occurs in times of low electricity prices and high thermal storage feed-in (see Tables E.10 and E.11 in Appendix E).[84]

[83] In fact, additional model runs of the sensitivity analysis show that an increase in the peak demand by 1 kW leads to only a 0.1 kW increase in the capacity of the electric heater, with the capacities of all other technologies remaining unchanged.

[84] Though the model results reveal a minimal effect between scenarios, alternative "smart" price signals that account for, e.g., grid conditions or grid availability could support the technologies in exploiting their flexibility potential. Furthermore, it should be noted that households do not pay or redeem compensation for changes in grid connection size as the costs of electric networks are not considered within this analysis.

Surprisingly, however, neither the variable costs nor the marginal costs of energy provision presented in Table E.8 in Appendix E and Table 5, respectively, differ significantly across scenarios.[85] This insinuates that (i) the thermal storage is limited in its ability to benefit from arbitrage and (ii) households in the Smart Tech and Smart Market scenarios optimize operation, for the most part, according to the same criteria: maximizing of the use of PV electricity in the heat production of heat pumps and using thermal storage to shift the consumption of this heat to hours with demand peaks. Because both the solar irradiation and demand profiles are identical across scenarios, the possibilities for discrepancies in the operation of the technologies are limited, leading to similar costs despite different price structures.

4. Conclusion

Within this paper, the mixed-integer linear programming model COMODO is developed to determine the cost-minimal energy provision for an end consumer or consumer group accounting for electricity, water heating and space heating. The model uses its extensive technology catalog to perform an investment and dispatch optimization for multiple years, minimizing total costs over a long-term time horizon in a dynamic anticipative optimization. Developments in techno-economic data, regulatory frameworks and energy market conditions are taken into account to help understand the key drivers affecting the end consumer's energy investment choices. Furthermore, piecewise-linear cost functions are developed to more accurately represent the technology investment costs, FOM costs and subsidies for different systems sizes and for future years. In order to demonstrate the capabilities of the model developed, an exemplary application is presented to investigate the investment and energy use decisions of four single-family homes in Germany for the years 2025 to 2045. Three scenarios are designed that build upon each other regarding amount of information available to consumers and their decentralized energy technologies. Finally, a sensitivity analysis then examines the effects of higher carbon pricing in the German building sector on the consumer's energy provision.

The results reveal the investment and operational strategies as well as the energy costs of the households under changing technical, market and regulatory conditions. The Status Quo scenario, which is meant to resemble the technical and regulatory standard of today, shows a clear preference for gas boilers as a base technology coupled with electric heaters to cover demand peaks. The inability of households to receive forecasts on future developments in technology costs, energy prices or demand structure leads to households deviating from the long-term, cost-minimal investment and therefore spending more on their energy provision

[85] This comparison holds true as long as the installed capacities are the same across scenarios. For HH3, for example, differences in the investment decision between 2025-2035 lead to cost deviations, as explained above.

compared to the other two scenarios. The introduction of transparent information on future costs, prices and demand in the Smart Tech scenario affects each household type differently, with the energy demand levels playing a central role. Households with higher demand levels invest in PV systems immediately in 2025, while other households with lower demands either wait until 2040 (i.e., the last year of investment) or do not invest at all. The household with the highest energy demand invests in a battery storage in 2030 to maximize the self-consumption of PV electricity. The choice of heating technologies, however, remains unchanged compared to the Status Quo scenario. These results also hold for the Smart Market scenario, which extends the Smart Tech scenario such that households are exposed to variable retail electricity prices. While the opportunity of hourly retail electricity prices does not have a strong effect on the investment decision or household expenditures, increases in carbon pricing is found to play a significant role. When subject to higher carbon prices, the retail gas price increases to the point where most of the households choose to fully electrify their heat provision, i.e., installing a heat pump combined with thermal storage, PV and an electric heater. With this alternative technology mix, households on average experience an increase in total costs ranging from 3.5% to 5.4% over the complete time horizon and realize a long-term decrease in annual carbon emissions of up to 80% compared to the analysis with lower carbon pricing.

The paper at hand also presents a novel method of analyzing the marginal costs of electricity and heat provision, i.e., the shadow prices of the model's equilibrium constraints. The results reveal a strong correlation between the implicit marginal costs of electricity provision and the retail electricity price in all scenarios and both analyses (i.e., with lower and higher carbon pricing). As such, the decrease in the retail electricity price that is assumed for future years drives the yearly average of the marginal costs of electricity provision downwards over time. Deviations are found to occur in hours with PV electricity generation or during peak demand. The self-consumption of PV electricity, in particular, is identified to have significant potential in reducing marginal costs. Similarly, the marginal costs of heat provision are also found to be linked to the fuel price: If gas-fired technologies are used, as is the case in the analysis with lower carbon pricing, the average marginal costs increase over the years following the upwards trend in the gas price development. However, if electricity-consuming technologies are used, the average as well as hourly marginal costs of heat provision tend to equal the marginal costs of electricity provision. The use of electricity generated by decentralized PV systems via electric heat pumps coupled with thermal storage yields drastic reductions in the marginal costs of heat provision.

As is the case in any model-based analysis, this research is subject to several limitations. First, the proposed model assumes perfectly rational behavior and perfect foresight over the full model horizon. Although this assumption is typical for MILP energy models, the information on future developments may result in more capital-intensive technologies being selected than would be chosen under real-world conditions. Second, consumers may make decisions on their energy provision based on additional non-monetary preferences or risk assessments, which are difficult to include in a cost-minimizing model.[86]

The model COMODO presented in this paper offers a wide range of opportunities for future research. For example, in this analysis, only single-family homes are considered. However, COMODO is designed to be able to optimize any consumer type or group. As such, additional analyses examining, e.g., larger living complexes, industry consumers or other non-residential buildings could be an interesting extension of this work. Increasing the heterogeneity of the consumer types could allow for a larger pool of consumers to be considered, e.g., on a neighborhood, national or even multi-country level.[87] Furthermore, although the technology catalog developed is already relatively extensive, investment objects could be added to allow for a more realistic depiction of the current scope of installed and available decentralized technologies (e.g., air conditioning, gas heat pumps, electric vehicles, electrolyzers, etc.) as well as building retrofits (e.g., insulation improvements). Additional options for energy supply such as district heating or hydrogen could also be implemented; however, uncertainty regarding aspects such as prices and pipeline accessibility may pose challenges. Investigating the marginal costs of heat provision, as done in this work, offers a promising research avenue for understanding the costs of decentralized heat supply and the competitiveness to centralized heat providers. Moreover, the input data used in the application could be increased in complexity to account for, e.g., weather phenomena or smaller (<1h) time steps to improve the accuracy on generation, grid consumption and storage cycles. Lastly, research questions surrounding shifts in the regulatory landscape could be complementary extensions to the sensitivity analysis performed in this work. Topics such as the consequences of capacity pricing, carbon reduction targets or restrictions on fossil fuel use could provide valuable insights for, e.g., policymakers.

[86]The concept of including preferences in MILP models is addressed in Shamon et al. (2021).
[87]For example, the German residential building stock is examined using COMODO in Arnold et al. (2023).

Appendix A. Nomenclature and Abbreviations

Throughout the paper, notation as listed in Tables A.1 and A.2 is applied. Unless otherwise noted, optimization variables are indicated using bold, uppercase letters.

Sets		
y	-	year
x	-	technology
f	-	fuel
EUT	-	energy use type
fp	-	function part
t	-	time resolution
cpc	-	capacity price components
epc	-	energy price components
Parameters		
i	-	interest rate
j_x	-	financing rate of technology x
w_x	a	financing period of technology x
y	a	year
y_0	a	start year
y_x^*	a	installation year of technology x
lt_x	a	technical lifetime of technology x
γ_x	-	learning rate of technology x
$IC_{x,min}$	€	minimal investment costs of technology x
$\delta IC/\delta Q$	€$/kW$, €$/kWh$, €$/m^2$	capacity-specific investment costs
n	-	maximum number of function parts
$d_{y,t,EUT}$	kW	exogenously-defined energy demand for energy use type EUT in time slice t and year y
$cap_{CO_2,y}$	t_{CO_2}	consumer emissions cap in year y
$factor_{CO_2,f_x}$	g/kWh	CO_2 factor of fuel f used in technology x
$factor_{CO_2,t,EUT}$	g/kWh	average CO_2 factor of an energy use type EUT supplied by the grid in time slice t
$\eta_{t,x,EUT}$	-	efficiency of technology x producing energy use type EUT in time slice t
rs	m^2	roof size
$q_{grid,EUT}$	kW	size of the connection capacity for the corresponding EUT
$ep_{y,t,EUT,epc}$	€$/kWh$	energy price
$cp_{y,t,EUT,cpc}$	€$/kW$	capacity price
$er_{y,t,EUT}$	€$/kWh$	energy remuneration
$scr_{y,x,EUT}$	€$/kWh$	self-consumption remuneration
$scf_{y,x,EUT}$	€$/kWh$	self-consumption fee
G_t	kW/m^2	global solar irradiation on a tilted area
α_0	-	optical efficiency
$T_{collector,t}$	K	mean collector temperature
$T_{ambient,t}$	K	ambient temperature
T_{flow}	K	flow temperature
$T_{source,t}$	K	source temperature of heat pumps
rs	m^2	available roof space

Table A.1: Model sets and parameters

$\boldsymbol{TC}$	€	total costs
$\boldsymbol{FC_y}$	€/a	fixed costs in year y
$\boldsymbol{AIC_{y,x}}$	€/a	annualized investment costs in year y
$\boldsymbol{IC_{y_x^*,x}}$	€	investment costs for technology x in the installation year y_x^*
$\boldsymbol{S_{y_x^*,x}}$	€	subsidy allocation for technology x in the installation year y_x^*
$\boldsymbol{FOMC_{y,x}}$	€/a	fixed operation and maintenance costs for technology x in year y
$\boldsymbol{EBC_y}$	€/a	energy-based costs in year y
$\boldsymbol{CBC_y}$	€/a	capacity-based costs in year y
$\boldsymbol{EBR_y}$	€/a	energy-based remuneration in year y
$\boldsymbol{HR_{y,x,EUT}}$	€/a	remuneration received via a time-variable (hourly) compensation for eligible technology x and energy use type EUT in year y
$\boldsymbol{Q_{y,x}}$	kW, kWh, m^2	capacity, storage volume or panel area for technology x in year y
$\boldsymbol{GFI_{y,t,x,EUT}}$	kW	feed-in of energy into grid
$\boldsymbol{XFI_{y,t,x,EUT}}$	kW	feed-in of energy into technology x
$\boldsymbol{GS}_{y,t,EUT=EUT_{demand}}$	kW	energy supply from the grid to cover exogenously-defined energy demand $d_{y,t,EUT}$
$\boldsymbol{GS}_{y,t,x,EUT}$	kW	energy supply from the grid
$\boldsymbol{XS}_{y,t,x,EUT}$	kW	energy supply from a decentralized energy technology
$\boldsymbol{N}$	-	number of the function part comprising the optimal installed capacity of a certain technology
$\boldsymbol{Qmin}$	kW, kWh, m^2	minimum achievable capacity
$\boldsymbol{SL_{y,t,x,EUT}}$	kWh	storage level in time slice t
$\boldsymbol{SV_{y,t,x,EUT}}$	kWh	available storage volume for a certain technology x

Table A.2: Model variables

AIC	annualized investment costs
CHP	combined-heat-and-power
COMODO	consumer management of decentralized options
COP	coefficient of performance (heat pump)
DER	distributed energy resources
el	electric
EU-ETS	European Emissions Trading System
FIT	feed-in tariff
FOM	fixed operation and maintenance
MILP	mixed integer linear programming
PtH	power-to-heat
PV	photovoltaic
TAC	total annual cost
th	thermal

Table A.3: Abbreviations

Appendix B. Additional Information on the Assumptions on Fuel Price Developments

Within this analysis, three energy carriers are available to households: wood pellets, gas and electricity. In the following, the assumptions on the price components and price developments shown in Figure 4 in Section 3.1.2 are explained for each fuel type.

For wood, the price composition is relatively straightforward. Unlike the other energy carriers, the price for wood pellets consists only of acquisition together with concession, taxes and fees. Wood acquisition and processing make up 74% of the overall price of wood pellets.[88] The remaining share of the retail price includes, e.g., the value added tax as well as costs for logistics and storage. Wood pellet prices are assumed to increase drastically by more than 55% from 7.2 €-ct./kWh$_{th}$ in 2025 to 11.1 €-ct./kWh$_{th}$ in 2040 as a result of increasing material costs (Shamon et al. (2021)).[89]

Gas, on the other hand, is made up of all four price components. Generally speaking, grid fees, which are paid by the end consumer to the energy provider, are passed on to grid operators in order to manage, maintain and expand the grid infrastructure. For gas, the grid fee makes up a 21% share of the overall gas price in 2025 and is assumed to stay constant at 1.6 €-ct./kWh$_{th}$ up to 2040. The price for gas acquisition follows the assumptions of the Sustainable Development Scenario in the IEA's World Energy Outlook 2020 (International Energy Agency (2020)) and equals 1.54 €-ct./kWh$_{th}$ in 2025 and increases by a mere 2% by 2040.[90] Furthermore, as explained in Section 3.1.2, end consumers in Germany are now required to pay a price for their resulting carbon emissions from energy provision, assumed to equal 1.1 €-ct./kWh$_{th}$ in 2025 and reach 1.8 €-ct./kWh$_{th}$ by 2040. The higher carbon prices assumed in the sensitivity analysis in Section 3.4 are assumed to equal 2.5 €-ct./kWh$_{th}$ in 2030, 4.0 €-ct./kWh$_{th}$ in 2035 and 5.5 €-ct./kWh$_{th}$ in 2040. Lastly, more than 40% of the retail price in 2025 is composed of payments for concession fees, taxes and other surcharges, which for the most part remain constant over the time period considered. All in all, the energy price components for gas add up to an overall price of 7.5 €-ct./kWh$_{th}$ in 2025 and rise to 8.4 €-ct./kWh$_{th}$ in 2040 in the main analysis and to 12.8 €-ct./kWh$_{th}$ in 2040 in the sensitivity analysis.

Unlike the other fuels, electricity is subject to two separate tariffs, as illustrated in Figure 4 in Section 3.1.2, namely "Heat-Pump Electricity" and "Non-Heat-Pump Electricity". The discrepancy between the two tariffs is primarily due to differences in grid fees: As electricity demand from heat pumps is more predictable due to strong correlations with weather conditions, they tend to provide less strain on the electricity grid.

[88] See `https://gas.info/energie-gas/energie-preisvergleich/preisentwicklung-holzpellets`

[89] See `https://www.depi.de/pelletpreis-wirtschaftlichkeit#dau2v`

[90] It should be noted that the analysis at hand was performed prior to the Russian invasion of Ukraine in February 2022. Any consequential economic developments concerning the gas acquisition costs or supply restrictions are not considered in this work.

As such, heat pumps are subject to lower grid fees, making up 9% of the overall electricity price as opposed to 27% for non-heat-pump electricity use in 2025. The grid fee for both heat-pump and non-heat-pump electricity use is assumed to increase linearly after 2025, reaching 2.4 €-ct./kWh$_{el}$ and 10.5 €-ct./kWh$_{el}$ by 2040, respectively. Furthermore, around 30% of the retail price for both non-heat-pump and heat-pump electricity use is composed of payments for concession, taxes and further fees. These remain mostly constant up to 2040. The third component is the renewable surcharge, as specified in the German Renewable Energies Act from the year 2000. This levy serves to refinance the renewable energy subsidies to support renewable expansion in Germany. In 2025, the renewable surcharge is assumed to reach its peak at 8 €-ct./kWh$_{el}$ for all electricity use before steadily decreasing to zero by 2040.[91] The final price component, i.e., the costs of electricity acquisition, is the only market parameter that differs across scenarios: For the Smart Market scenario, hourly electricity prices are assumed, as shown in the box plot on the right-hand side of Figure 4 in Section 3.1.2. For the Status Quo and Smart Tech scenarios, yearly averages of the hourly variable prices are set as constant electricity prices. At an average of 5.2 €-ct./kWh$_{el}$ in 2025, this cost component makes up the lowest share of the electricity retail price for both heat-pump and non-heat-pump use. By 2040, however, changes in electricity generation and demand in Germany yield an annual average acquisition cost of 6.5 €-ct./kWh$_{el}$. On average, the retail electricity price decreases from 31.2 €-ct./kWh$_{el}$ in 2025 to 26.3 €-ct./kWh$_{el}$ in 2040 for non-heat-pump electricity used and from 22.4 €-ct./kWh$_{el}$ in 2025 to 15.5 €-ct./kWh$_{el}$ for heat-pump electricity use. For the Smart Market scenario, a minimum retail price of 26.2 €-ct./kWh$_{el}$ and a maximum retail price of 37.7 €-ct./kWh$_{el}$ in 2025 and a minimum retail price of 20.0 €-ct./kWh$_{el}$ and a maximum retail price of 33.7 €-ct./kWh$_{el}$ in 2040 are assumed.

[91] Analogous to the carbon prices, the renewable energy surcharge is an endogenous result of the energy system model DIMENSION (see Footnote 57).

Appendix C. Detailed Description of the Economic and Technical Assumptions according to Technology Type

A significant contribution of the paper at hand is the inclusion of a wide range of technologies in the model. Each technology is subject to different technical, economic and regulatory characteristics, all of which must be accounted for in order to determine the cost-minimal energy provision. The following subsections present the technologies that are available to consumers, including a thorough explanation of the techno-economic assumptions. More specifically, the piecewise-linear investment costs, including installation and material costs, as well as the fixed annual operation and maintenance costs are shown in a series of figures.[92] For certain technologies, investment costs may be subsidized via incentive programs offered by the German government (c.f. Bundesamt für Wirtschaft und Ausfuhrkontrolle (2021a) and Bundesamt für Wirtschaft und Ausfuhrkontrolle (2021b)), as long as these fulfill certain technical requirements (see, e.g., Bundesamt für Wirtschaft und Ausfuhrkontrolle (2020)). Furthermore, technologies may also be eligible to receive financial remuneration for, e.g., decentralized electricity generation. Such regulatory aspects are also discussed below as they pertain to the specific technology.

Appendix C.1. Condensing Boilers

Conventional fuels such as natural gas or heating oil can be burned in a condensing boiler, achieving higher efficiencies compared to older non-condensing systems by taking advantage of upper, rather than the lower, heating values.[93] Oil condensing boilers are assumed to have an efficiency of 96% while gas condensing boilers are assumed to have an efficiency of 99%.[94] After installation, the household can use a gas condensing boiler for up to 25 years, while oil condensing boilers can be used for up to 20 years.[95]

[92] It should be noted that the investment costs illustrated in the following subsections do not include fuel storage systems (e.g., pellet or oil tank) or the installation of heating circuits such as radiators.

[93] Condensing boilers withdraw heat from the exhaust gas, causing the water in the exhaust to condense. This is not the case in conventional non-condensing boilers. Non-condensing boilers are not considered in this paper as new investments are assumed to be fully focused on the state-of-the art technology.

[94] Both assumptions are based on Fleiter et al. (2016) and Energinet.dk and Energi Styrelsen (2012).

[95] The lifetime of gas condensing boilers is based on a life span of 17 to 30 years (see Fleiter et al. (2016), Energinet.dk and Energi Styrelsen (2012), Bettgenhäuser and Boermans (2011), Palzer (2016), Hedegaard and Münster (2013), Heinen et al. (2016), Brown et al. (2018), Omu et al. (2013), Gerhardt et al. (2015) and Kemna et al. (2007)). The lifetime of oil condensing boilers is taken from Fleiter et al. (2016), Energinet.dk and Energi Styrelsen (2012), Bettgenhäuser and Boermans (2011), Kemna et al. (2007) and Palzer (2016).

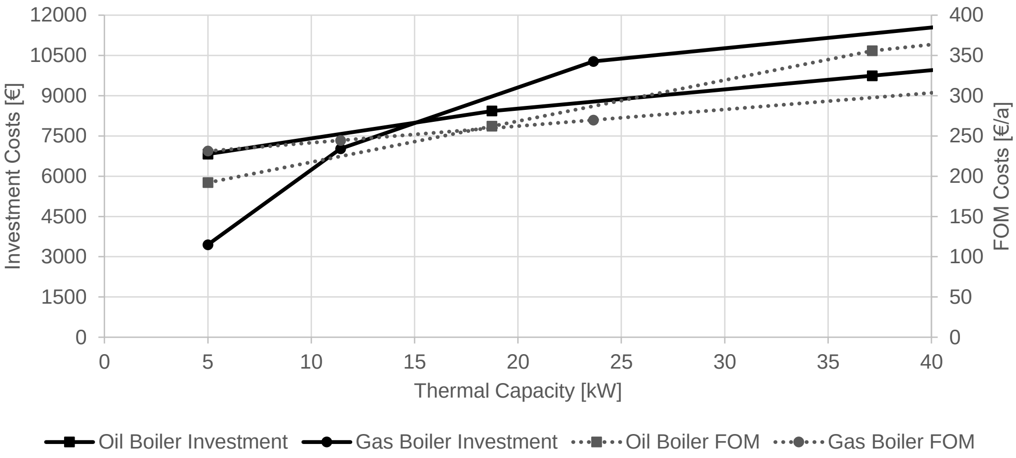

Figure C.1: Investment and FOM costs of condensing boiler systems in 2020

Condensing boilers have the lowest specific investment costs compared to the other base heating technologies considered in this analysis. An exception are electric heaters, which are typically used as peak technologies. Investment costs for oil and gas condensing boilers are shown in Figure C.1 and are calculated based on Mailach and Oschatz (2016), Mailach and Oschatz (2017) and Energinet.dk and Energi Styrelsen (2012). Further data from Adolf et al. (2013) and Fleiter et al. (2016) as well as additional industry sources were used for the investment cost analysis for gas boilers. The FOM costs are based on Bettgenhäuser and Boermans (2011), Fleiter et al. (2016) and Energinet.dk and Energi Styrelsen (2012) and are depicted in Figure C.1 by the dotted lines.

The costs of storage systems for fuels, e.g., the construction of an oil or gas tank, are not included in these costs. As such, it is assumed that adequate storing options either already exist or are not needed, i.e., a grid connection is readily available. Furthermore, it is assumed that condensing boilers are already at an advanced development state and are therefore subject to only minimal reductions in investments costs in the coming years (see Table D.5 in Appendix D).

Moreover, it is assumed that no government-funded subsidies or other variable remunerations are available for condensing boilers at the time of this paper.[96]

[96] In reality, gas-condensing boilers could potentially qualify for subsides: According to Bundesamt für Wirtschaft und Ausfuhrkontrolle (2021a), 20% of the full investment costs (including installation (see Bundesamt für Wirtschaft und Ausfuhrkontrolle (2021b))) would be refunded if the system is "renewable ready" within two years after installation. In other words, a renewable energy heating system would have to be integrated into the the system and be able to supply a specific share of the energy demand (Bundesamt für Wirtschaft und Ausfuhrkontrolle (2020)). Technically speaking, the condensing boilers considered in this analysis could easily be combined with a renewable system, e.g., a solar heating system. Nevertheless, subsidies are modeled in COMODO according to the individual, as opposed to coupled, technology investment.

Appendix C.2. Combined-Heat-and-Power Systems

Combined-heat-and-power (CHP) systems allow for the simultaneous generation of both thermal and electrical energy, with natural gas or oil being converted into electricity and heat according to a so-called 'power-to-heat' ratio.[97] As such, the systems can achieve a high total efficiency by making use of the energy which may have been lost as heat. The consumer can choose between three CHP systems, namely an oil- or gas-fired motor or a gas-fueled fuel cell. The three systems do not only vary with respect to the fuel used but also according to their technical build, which leads to differences in the power-to-heat ratios and, in turn, the electric and thermal efficiencies, which are shown in Table C.4 for the CHP systems modeled.

CHP System Type	**Electric Efficiency** $\eta_{t,x=CHP,EUT=elec}$	**Thermal Efficiency** $\eta_{t,x=CHP,EUT=heat}$	**Selected Sources**
Gas CHP	30%	61%	Klotz et al. (2014), Verbraucherzentrale Nordrhein-Westfalen Energieberatung (2013), Wünsch et al. (2011), Bürger et al. (2016), Energinet.dk and Energi Styrelsen (2012), Diefenbach et al. (2017), Björnebo et al. (2018), Hamzehkolaei and Amjady (2018), Karmellos and Mavrotas (2019), Klein et al. (2014), Fleiter et al. (2016)
Oil CHP	32%	57%	Verbraucherzentrale Nordrhein-Westfalen Energieberatung (2013), Wünsch et al. (2011)
Fuel Cell	40%	52%	Klotz et al. (2014), Verheyen (2011), Wünsch et al. (2011)

Table C.4: Efficiencies of CHP systems

Figure C.2 shows the assumed gas, oil and fuel cell CHP investment costs.[98] The graph clearly shows that fuel cells have higher costs than the other technologies, which is due to the difference in technical complexity as well as maturity of fuel cells compared to motor CHP systems. Motor CHP systems are typically modular such that higher capacities may be achieved by installing multiple motors. Therefore, the scaling effect is rather limited. Moreover, the assumed learning rates show that costs for fuel cells are expected to be reduced by 50% while costs for gas- and oil-fired motor CHPs see cost reductions of 23% by 2040 (see Table D.5). Furthermore, the assumptions for the FOM costs are depicted in Figure C.2.[99]

[97]The CHP systems in the model are assumed to have a constant power-to-heat ratio. Larger CHP plants may run flexibly and, as such, have varying power-to-heat ratios.

[98]The investment costs for gas-fired CHP are based on Bürger et al. (2016), Energinet.dk and Energi Styrelsen (2012), Mailach and Oschatz (2016), Adolf et al. (2013) and Klein et al. (2014); for oil-fired CHP based on Verbraucherzentrale Nordrhein-Westfalen Energieberatung (2013),Wünsch et al. (2011); and for fuel cells based on Verbraucherzentrale Nordrhein-Westfalen Energieberatung (2013), Klotz et al. (2014), Pehnt et al. (2012), Ammermann et al. (2015), Verheyen (2011) and industry data.

[99]The FOM costs for gas-fired CHP are based on Klotz et al. (2014). Because of the technical similarities, it is assumed that the FOM costs of oil-fired CHP make up the same percentage share of investment costs as the FOM costs of gas-fired CHP. The FOM costs for fuel cells are based on Klotz et al. (2014), Pehnt et al. (2012), Ammermann et al. (2015) and Battelle Memorial Institute (2017).

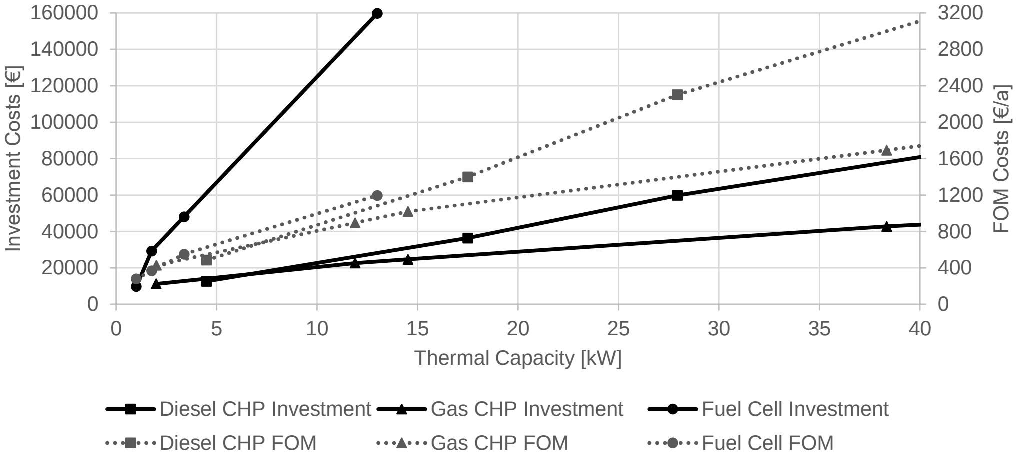

Figure C.2: Investment and FOM costs of CHP systems in 2020

Electricity generation via CHP systems up to a capacity of 50 kW_{el}[100] is promoted with a feed-in tariff of 16 €-ct./kWh_{el} for electricity fed into the grid and a remuneration of 8 €-ct./kWh_{el} for all electricity which is not (see Bundesamt für Justiz (2020a)). Both are granted for up to 30,000 full-load hours (see Bundesamt für Justiz (2020b)).[101] Once installed, technical lifetimes of 15 years for motor CHP systems and 10 years for fuel cell systems are assumed [102]

Appendix C.3. Electric Heater

The simplest form of power-to-heat technologies is the electric heater. This heating system is able to convert electricity into heat with near-zero energy losses.[103] Figure C.3 shows the assumed power to heat system investment costs based on Beck et al. (2017) and Bechem et al. (2015). Electric heaters are usually used in combination with other heating technologies such as condensing boilers, CHP or electric heat pumps. In multi-technology systems, electric heaters typically supply heat in times of peak demand, i.e., serve as a peak technology. It is assumed that electric heaters are not subject to FOM costs. According to Beck et al. (2017), investments must be renewed every 15 years due to limited technical lifetimes.

[100]The restriction on electric capacity of 50 kW_{el} is equal to about 101 kW_{th} for gas-fired CHP, 89 kW_{th} for oil-fired CHP and 65 kW_{th} for fuel cells.

[101]For simplicity, it is assumed in the model that the remuneration of 8 €-ct./kWh_{el} for 30,000 full-load hours of electricity generation is directly redeemed at the time of investment. Because of this one-time compensation, the feed-in tariff is then corrected to 8 €-ct./kWh_{el}.

[102]The assumption for motor CHP is based on Ren and Gao (2010), Mailach and Oschatz (2016), Diefenbach et al. (2017),Björnebo et al. (2018), Hamzehkolaei and Amjady (2018),Energinet.dk and Energi Styrelsen (2012) and Fleiter et al. (2016). For fuel cells, see Ren and Gao (2010), Fleiter et al. (2016), Verheyen (2011) and Brandoni and Renzi (2015).

[103]An efficiency of 100% is assumed.

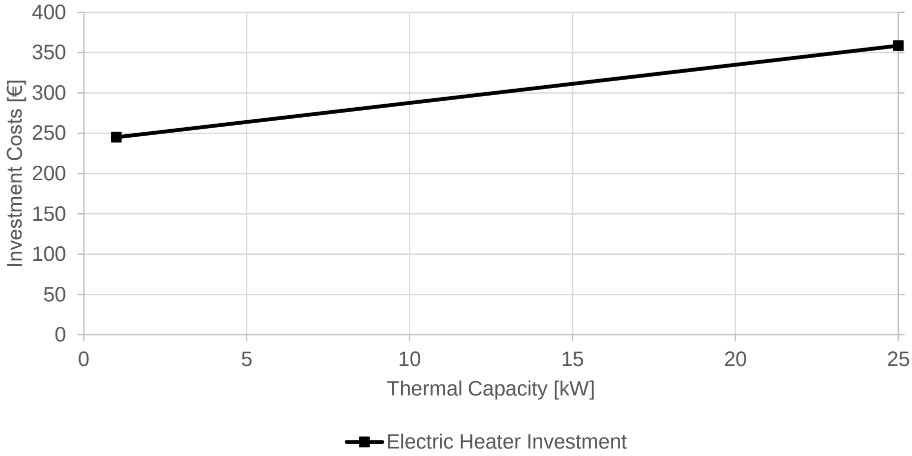

Figure C.3: Investment costs of electric heaters in 2020

Appendix C.4. Electric Heat Pumps

Electric heat pumps use the enthalpy of an electricity input to extract energy from low-temperature energy sources in order to generate high-temperature space and warm water heating. Possible energy sources for this technology are ambient air (air-to-water), ground (water-to-water) or geothermal energy.

Figure C.4 shows the investment costs for the three different electric heat pumps included in COMODO: air-to-water, water-to-water (also known as collector) and geothermal.[104] The costs presented include the construction of the system to retrieve the source energy (e.g., collector or drilling). For water-to-water and geothermal systems, high investment costs are strongly driven by construction costs in order to access the energy source. Geothermal systems, in particular, have high installation costs due to the need for vertical drilling. Furthermore, FOM costs are also depicted in Figure C.4 for each heat pump type.[105] Once installed, electric heat pumps are assumed to have a technical lifetime of 20 years. [106]

[104]The investment costs for air-to-water electric heat pumps are based on Beck et al. (2017), Bettgenhäuser and Boermans (2011), Bürger et al. (2016), Henning and Palzer (2013), Petrović and Karlsson (2016), Pfnür et al. (2016), Brown et al. (2018), Mailach and Oschatz (2016), Mailach and Oschatz (2017), Omu et al. (2013),Herkel et al. (2018), Palzer (2016), Adolf et al. (2013), Heinen et al. (2016), Hedegaard and Münster (2013), Karmellos and Mavrotas (2019) and industry data; for water-to-water electric heat pumps based on Bettgenhäuser and Boermans (2011), Bürger et al. (2016), Henning and Palzer (2013) and Petrović and Karlsson (2016); and for geothermal electric heat pumps based on Hardy et al. (2016) and industry data.

[105]The FOM costs assumed for air-to-water electric heat pumps are based on Beck et al. (2017), Bettgenhäuser and Boermans (2011), Henning and Palzer (2013), Petrović and Karlsson (2016), Pfnür et al. (2016), Heinen et al. (2016), Brown et al. (2018), Hedegaard and Münster (2013), Mailach and Oschatz (2016), Mailach and Oschatz (2017), Palzer (2016) and Heinen et al. (2016); for water-to-water electric heat pumps based on Bettgenhäuser and Boermans (2011), Henning and Palzer (2013) and Petrović and Karlsson (2016); and for geothermal electric heat pumps based on Brown et al. (2018) and Palzer (2016).

[106]Henning and Palzer (2013), Omu et al. (2013), Palzer (2016), Petrović and Karlsson (2016), Gerhardt et al. (2015), Heinen et al. (2016), Beck et al. (2017), Brown et al. (2018), Herkel et al. (2018), Karmellos and Mavrotas (2019) and Hedegaard and Münster (2013) assume lifetimes in the range of 15 to 30 years.

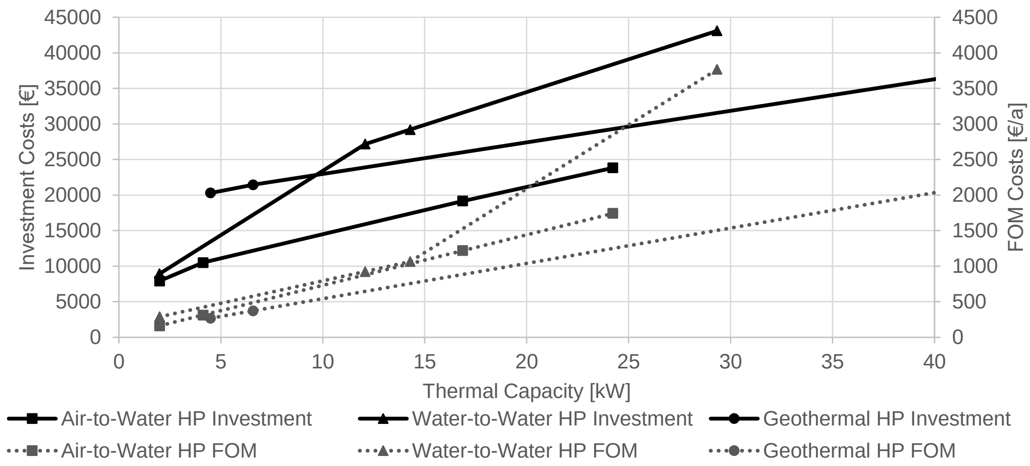

Figure C.4: Investment and FOM costs of electric heat pump (HP) systems in 2020

As explained in Section 2.4, the performance of electric heat pumps is determined according to the COP, a variable efficiency factor that is highly dependent on the temperature delta between the source temperature and the desired flow temperature of the heating system. Whereas the desired flow temperature depends on the consumer preference and building age, the heat source temperature is different for each type of heat pump. For air-sourced heat pumps, the heat-source temperature is the outside temperature. Thus, the temperature delta fluctuates strongly over time, with the COP decreasing when the outside temperature drops and the delta becomes larger. This variance in performance explains the relatively low investments costs shown in Figure C.4 compared to the other heat pump types. For the ground-sourced water-to-water heat pumps, the heat-source temperature at a depth of one meter below surface is calculated according to Benker and Heidt (2000).[107] In a depth of one meter, the temperature still varies with the outside temperature; however, the variance is reduced due to the insulation effect of the ground. This leads to a more stable COP compared to that of the air-to-water electric heat pump. For geothermal heat pumps, a heat-source temperature of 10°C is assumed. As a result, the temperature delta of geothermal heat pumps and the subsequent COP are constant over all time slices. All in all, heat pumps are capable of achieving COPs ranging from 2 and 6.

Electric heat pumps are eligible for subsidies equal to up to 35% of the full investment costs (see Bundesamt für Wirtschaft und Ausfuhrkontrolle (2021a)) including installation costs (see Bundesamt für Wirtschaft und Ausfuhrkontrolle (2021b)), as long as they reach an annual performance factor[108] of 3.5 for air-sourced

[107] Data on the specific heat capacity (1175.75 J/(kg*K), density (1742.25 kg/m^3) and thermal conductivity (1.5025 W/(m*K)) is taken as a mean from Bundesindustrieverband Deutschland Haus-, Energie- und Umwelttechnik e.V. and Bundesverband Wärmepumpe e.V. (2011)
[108] The annual performance factor is equal to the demand weighted average of the COP over the year.

or 3.8 for ground-sourced heat pumps in existing buildings and 4.5 for all heat pumps (i.e., regardless of source) in newly-constructed buildings (see Bundesamt für Wirtschaft und Ausfuhrkontrolle (2020)).

Appendix C.5. Pellet Stove

Renewable heat can be provided by burning wood pellets in a stove. Figure C.5 shows the investment costs assumed for pellet stoves based on Raab et al. (2013). These do not include the costs of storage and transportation of wood pellets. Up to 35% of the costs illustrated in Figure C.5 may be subsidized by the German government (see Bundesamt für Wirtschaft und Ausfuhrkontrolle (2021a) and Bundesamt für Wirtschaft und Ausfuhrkontrolle (2021b)). Furthermore, the FOM costs are also depicted in the figure, calculated as a share of 4.8% of the investment costs.[109] Once installed, wood pellet stoves can provide energy with an efficiency of 92% [110] for a technical lifetime of 20 years (see Raab et al. (2013)).

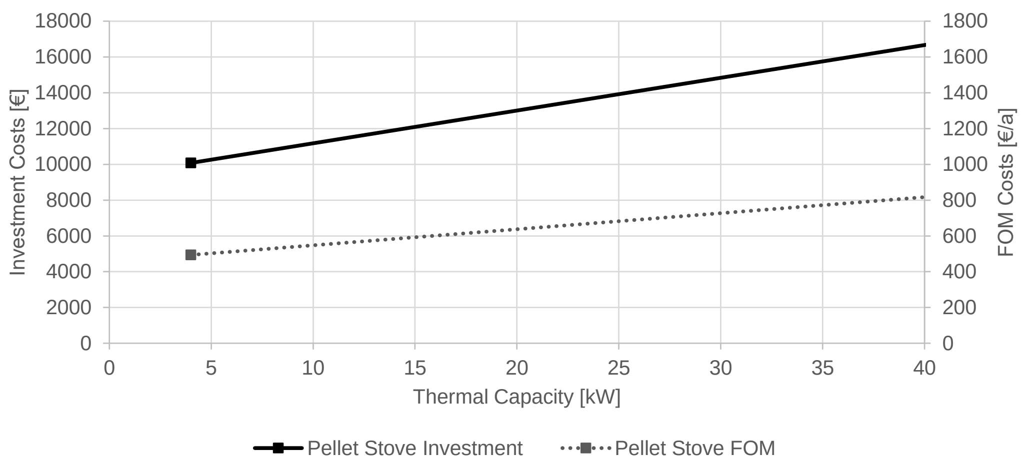

Figure C.5: Investment and FOM costs of pellet stoves in 2020

Appendix C.6. Solar Thermal Plant

Solar thermal plants convert direct and indirect solar irradiation into heat for both space and water heating. Solar thermal systems are typically rooftop installations and thus depend on the solar irradiation on a tilted surface analogous to PV, as described below in Section Appendix C.8. In order to determine the heat production of such a system, the solar irradiation on the tilted surface is adjusted according to the energy losses. Based on European Solar Thermal Industry Federation (2007), these losses can be estimated

[109] The literature states that the annual FOM costs range from 3.2% up to 6% of the investment costs. Sources for the FOM costs are Breitschopf et al. (2010), Bürger et al. (2016), Stuible et al. (2016) and Härdtlein et al. (2016).

[110] This efficiency is a mean between the different manufacturers, models and load levels.

using optical losses, which are included as a percentage, as well as first- and second-order heat losses.[111] The total heat losses then depend on the difference between the mean collector temperature[112] and the outside air temperature. Solar thermal systems are the only systems considered in the model whose size is measured in square meters (i.e., m^2) and not in kilowatts.

Figure C.6 shows the investment costs assumed for solar thermal systems for space and water heating.[113] Furthermore, the FOM costs are also depicted, calculated as a 1.6% share of investment costs.[114] Investments in solar thermal plants may receive subsidies up to 30% (see Bundesamt für Wirtschaft und Ausfuhrkontrolle (2021a)) of the overall investment costs (see Bundesamt für Wirtschaft und Ausfuhrkontrolle (2021b)). Once installed, solar thermal plants can be operated for 20 years.[115]

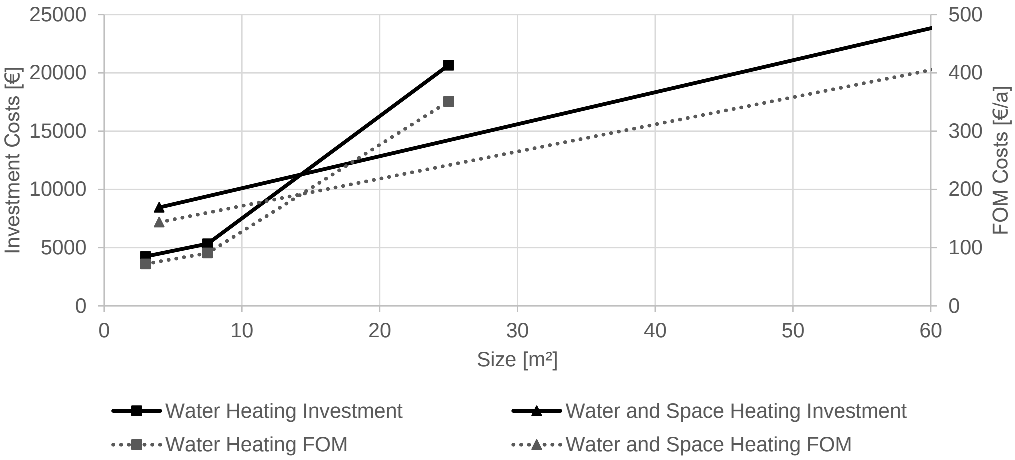

Figure C.6: Investment and FOM costs of solar thermal systems for water and space heating in 2020

Appendix C.7. Thermal Storage

Thermal storage systems can be used in combination with any of the heat generation technologies described in order to decouple the time of heat generation and consumption. The thermal storage assumed in this paper is a sensible heat storage based on the storage medium water. Storage systems are designed according to a storage volume measured in kWh, which in turn defines the maximal amount of storable energy. Moreover, the maximum energy flow that can be fed into or be discharged from the storage system

[111] Within this paper, an optical efficiency of 80%, a first-order heat loss coefficient of approximately 3 W/(m^2K) and a second-order heat-loss coefficient of 0.008 W/(m^2K^2) based on Trier (2012) are assumed.
[112] Mean collector temperatures of 50°C for warm water systems and 60°C for space heating systems are assumed.
[113] The investment costs are based on Thiel and Ehrlich (2012), Gerhardt et al. (2015), Wiemken et al. (2008), Bettgenhäuser and Boermans (2011), Ebert et al. (2011) and industry data.
[114] Brown et al. (2018), Henning and Palzer (2013) and Gerhardt et al. (2015) provide data on the FOM costs as a share of the investment costs ranging between 1% and 2%.
[115] According to the technical lifetimes given in Brown et al. (2018) and Henning and Palzer (2013).

needs to be taken into consideration when designing the system. The maximal flow level is measured in kW. Figure C.7 illustrates the relationship between the maximum flow level and the storage volume.[116] As can be seen in the figure, the maximum flow level rises when the storage volume is increased.

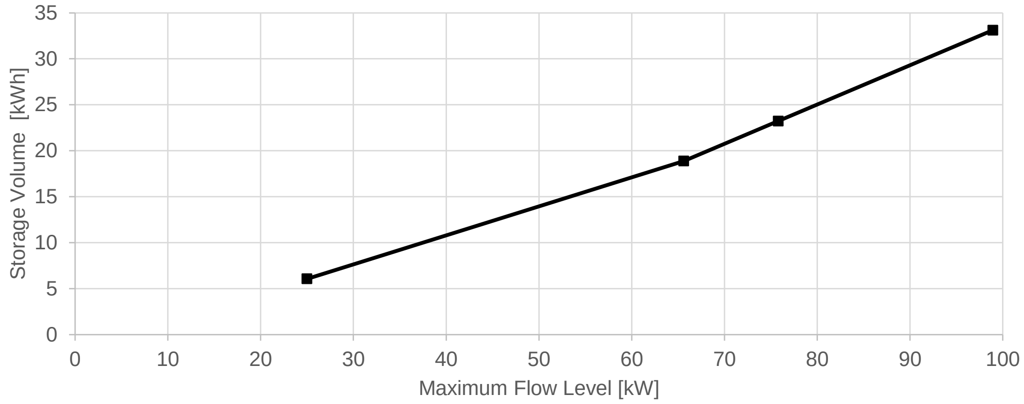

Figure C.7: Relationship between the maximum flow level (kW) and storage volume (kWh) of thermal storage

Although thermal storage systems are not energy generators, they may also experience energy losses. When storing heat in a thermal storage, heat radiates from the storage tank and therefore lost from one point in time to the next.[117]

Figure C.8 shows the investment costs assumed for thermal storage based on industry data. For any storage volume above 76 kWh, specific installation costs increase drastically as a pre-assembling of parts is no longer possible due to the height and width of the larger storage tank. Furthermore, it is assumed that a thermal storage system itself is not subject to any FOM costs; however, it is assumed that the maintenance of the storage is carried out together with the inspection of the heat generating technology and is thus included in the FOM costs of the generating technology. Within this paper, a technical lifetime of 30 years is assumed for a simple thermal sensible heat storage.

[116]The relationship between the maximum flow level and storage volume shown in Figure C.7 was constructed by evaluating the specifications of storage systems from many different manufacturers.

[117]Within this paper, a loss equal to 1% of the stored energy is assumed for each hour in which the energy is stored.

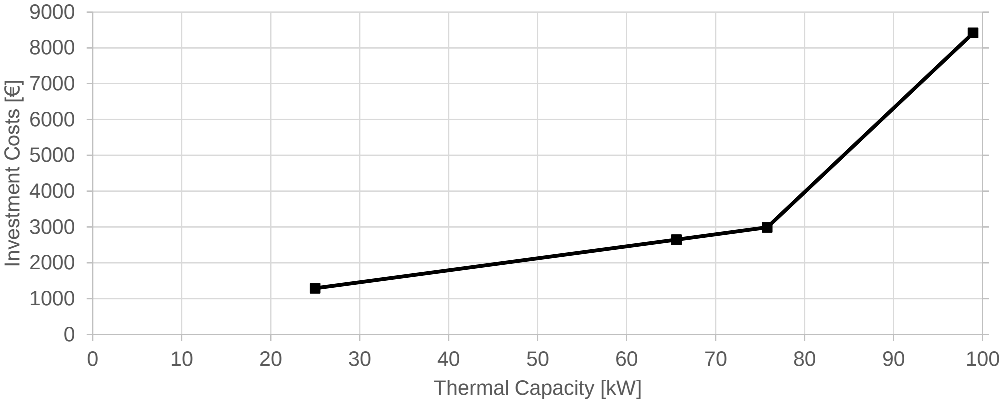

Figure C.8: Investment costs of thermal storage systems in 2020

Appendix C.8. Photovoltaics

Photovoltaic (PV) panels are a renewable energy system used to convert irradiation from the sun into electricity, often installed on rooftops. To determine the amount of electricity produced, the calculation of the global irradiation on the inclined surface follows the functional estimations of the isotropic diffuse irradiation model stated in Eicker (2012). Put simply, the radiation depends on the position of the sun relative to the PV panel and the losses in the atmosphere. The sun's position, in turn, depends on the location of the PV panel as well as the time of day.[118] For the research at hand, all PV systems are assumed to be south-facing[119] with an inclination of 35.5° [120]. Furthermore, a reflection coefficient of 0.2 is assumed in order to calculate the diffused reflection from the ground. Shade as well as other non-optimal conditions for the PV system that may vary according to the individual location of the installation of a specific consumer are ignored, assuming a full conversion of the direct incident sunlight.

Figure C.9 shows the investment costs of the PV system assumed.[121] As PV panels are modular installations, the cost function is almost linear and thus have near-constant specific investment costs. Furthermore, the figure also presents the FOM costs based on Bergner and Quaschning (2019) and industry data.

[118] In order to calculate the solar position, a standard time-meridian (zonal) of 15 and a local meridian of 6.667 are assumed. Germany can be found on latitude 51.

[119] South-facing corresponds to a surface azimuth of 180°.

[120] For the assumptions in this paper, this inclination gives the highest observed generation.

[121] These are based on Balcombe et al. (2015), Beck et al. (2017), Karmellos and Mavrotas (2019), Omu et al. (2013) and industry data.

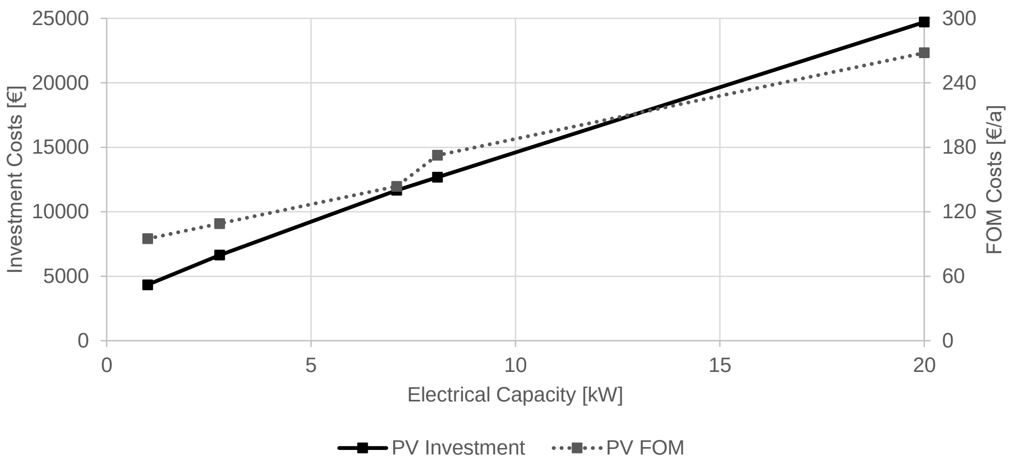

Figure C.9: Investment and FOM costs of photovoltaic systems in 2020

Once installed, it is assumed that the PV system can operate for 25 years [122]. The electricity produced by the PV system can either be used directly to cover the consumer's individual electricity demand or fed into a heat generating technology, battery storage or the electricity grid. If the electricity is fed into the grid, consumers receive a market premium of 2.3 €-ct./kWh_{el} plus the compensation for selling the PV electricity to the market, i.e., the hourly spot-market electricity price at the time of feed in.[123]

Appendix C.9. Battery Storage

In order to allow for the flexible use of electricity, the consumer can choose to invest in an electricity storage system, i.e., a lithium-ion battery storage. With an efficiency of 81%[124], electric energy can be stored and supplied at a later point in time.[125] The installed capacity (kW) of a battery storage defines the installed storage volume (kWh) according to a so-called energy-to-power ratio.[126] Once installed, the

[122]Beck et al. (2017), Brown et al. (2018), Palzer (2016), Omu et al. (2013), Ren and Gao (2010), Henning and Palzer (2013), and Gerhardt et al. (2015) provide operational time frames between 20 and 30 years.

[123]According to German regulation, consumers with rooftop PV systems qualify for so-called "reference values", which are made up of the market premium plus the spot-market electricity price. The German government sets the reference value, which decreases by about 1.4% every month and is guaranteed for 20 years from the time of installation. In order to estimate the market premium in COMODO, the yearly average of the reference values are corrected for the yearly average of the spot-market price assumed in the scenario definition (see Figure 4 in Section 3.1.2) for the future years. For more information, see https://www.bundesnetzagentur.de/EN/Areas/Energy/Companies/RenewableEnergy/RegisterDataTariffs/start.html.

[124]The efficiency is calculated based on Beck et al. (2017), Lazard (2017), Diefenbach et al. (2017), Fisher et al. (2019), Bakhshi Yamchi et al. (2019), Henning and Palzer (2013), May et al. (2018) and Brown et al. (2018). This value represents an efficiency for the storage cycle independent of the duration of storage, i.e., it accounts solely for energy losses resulting from the feeding in and discharging of electricity.

[125]At the time of this paper, the standard setting in COMODO is that a battery storage can be used to shift electricity consumption within a time frame of one week. Longer storing periods are not taken into account.

[126]In line with Tsiropoulos et al. (2018) (see page 21), it is assumed that the storage volume in kWh is twice the amount of the storage capacity in kW.

battery storage can be used for up to 15 years.[127]

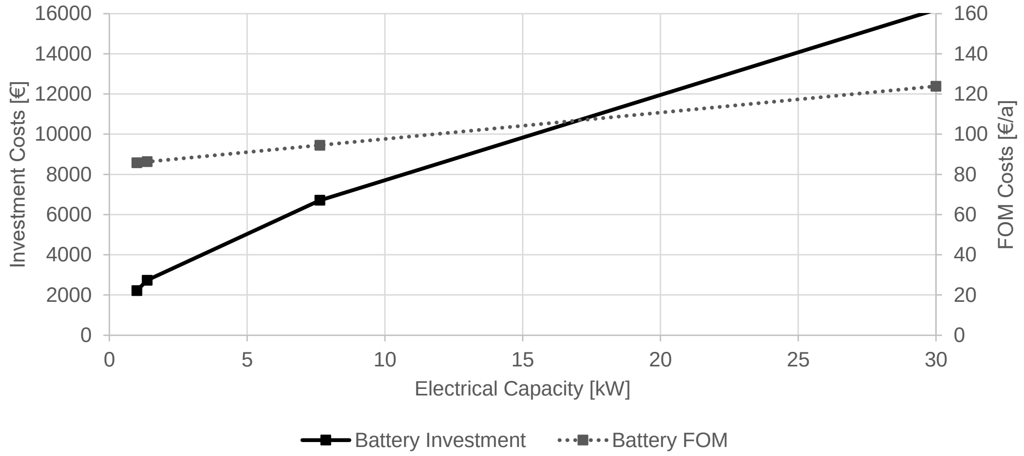

Figure C.10: Investment and FOM costs of lithium-ion battery storage systems in 2020

Figure C.10 shows the investment costs of assumed lithium-ion battery storage systems.[128] The investment costs are assumed to decrease significantly (-50%) by 2040 (see Table D.5 in Appendix D). The FOM costs, based on Lazard (2017) and Diefenbach et al. (2017), are also depicted by the dotted line.

At the time of this research, the purchase of a battery storage is not directly subsidized. Nevertheless, storage can help to reduce variable costs if they are used to optimize the use of decentralized electricity generation from, e.g., PV.

[127]A technical lifetime of 15 years is assumed based on analyses from Fisher et al. (2019), Karmellos and Mavrotas (2019), May et al. (2018), Brown et al. (2018), Diefenbach et al. (2017) and Balcombe et al. (2015).

[128]These are based on Beck et al. (2017), Lazard (2017), Karmellos and Mavrotas (2019), Diefenbach et al. (2017), Fisher et al. (2019), Henning and Palzer (2015) and industry data.

Appendix D. Assumptions on Learning Rates to Approximate Future Investment Costs

Costs for technology investments are assumed to decrease over time. This effect is included in the model via learning rates, consistent with manufacturer data. Technologies that are currently undergoing research are expected to face stronger decreases in costs than more mature technologies. The assumed learning rates are given in Table D.5, which illustrates the percentages of the costs in the specific year compared to the costs in 2020.

Technology	**2025**	**2030**	**2035**	**2040**	**based on**
CHP (Gas and Diesel)	94	89	83	77	Bürger et al. (2016)
Fuel Cell	88	75	63	50	Bürger et al. (2016)
Oil Condensing Boiler	99	98	97	96	own assumption
Gas Condensing Boiler	99	98	97	96	own assumption
Electric Heater	99	98	97	96	own assumption
Air-to-Water Heat Hump	97	93	91	89	Bürger et al. (2016), Palzer (2016), Energinet.dk and Energi Styrelsen (2012), Petrović and Karlsson (2016)
Water-to-Water Heat Pump	97	94	91	88	Bürger et al. (2016), Palzer (2016), Energinet.dk and Energi Styrelsen (2012), Petrović and Karlsson (2016)
Geothermal Heat Pump	98	95	93	91	Bürger et al. (2016), Henning and Palzer (2015)
Photovoltaic	90	79	69	58	Gerbert et al. (2018), Palzer (2016), Bürger et al. (2016)
Lithium-Ion Battery Storage	100	58	54	50	Henning and Palzer (2015), World Energy Council (2016)
Solar Thermal	96	93	89	86	Energinet.dk and Energi Styrelsen (2012), Gerhardt et al. (2015)
Thermal Storage	99	98	97	96	own assumption
Pellet Stove	98	96	94	91	Bürger et al. (2016), Nitsch et al. (2010), Henning and Palzer (2015), Gröger (2016)

Table D.5: Learning rates for technology cost developments in % compared to 2020

Appendix E. Additional Results

		Status Quo				Smart Tech				Smart Market			
HH	[a]	2025	2030	2035	2040	2025	2030	2035	2040	2025	2030	2035	2040
1	AIC [€/a]	1799	1799	1799	25	1800	2111	2111	25	1795	2109	2109	25
	FOM [€/a]	426	426	426	426	426	515	515	515	426	515	515	515
	VC_{tot}[€/a]	2170	2195	2201	2190	2169	1709	1754	1776	2174	1704	1747	1765
	VC_{el}[€/a]	968	931	872	817	967	386	362	339	974	382	356	330
	VC_{gas}[€/a]	1201	1265	1328	1373	1202	1323	1392	1437	1200	1322	1391	1436
	RC[€/a]	231	265	266	272	231	197	205	208	231	197	204	208
	MP[€/a]	110	121	119	119	110	86	85	85	110	86	85	84
	TAC [€/a]	4054	4035	4040	2251	4054	4052	4091	2024	4054	4045	4082	2013
2	AIC [€/a]	464	464	464	24	450	450	450	845	448	448	448	846
	FOM [€/a]	235	235	235	235	235	235	235	423	235	235	235	423
	VC_{tot}[€/a]	2207	2186	2178	2153	2219	2197	2188	1607	2220	2198	2189	1618
	VC_{el}[€/a]	1130	1086	1018	953	1146	1101	1033	573	1148	1102	1034	585
	VC_{gas}[€/a]	1077	1100	1160	1200	1073	1096	1156	1034	1072	1095	1155	1033
	RC[€/a]	0	0	0	0	0	0	0	341	0	0	0	341
	MP[€/a]	0	0	0	0	0	0	0	148	0	0	0	148
	TAC [€/a]	2906	2885	2877	2413	2904	2882	2873	2386	2902	2880	2872	2397
3	AIC [€/a]	1165	1165	1165	27	336	336	336	848	332	332	332	848
	FOM [€/a]	360	360	360	360	230	230	230	418	230	230	230	418
	VC_{tot}[€/a]	1324	1326	1315	1294	1925	1890	1849	1222	1922	1883	1841	1229
	VC_{el}[€/a]	723	695	652	611	1274	1225	1148	565	1272	1219	1141	574
	VC_{gas}[€/a]	723	695	652	611	651	665	701	657	650	664	700	655
	RC[€/a]	131	147	147	147	0	0	0	357	0	0	0	357
	MP[€/a]	63	68	68	67	0	0	0	163	0	0	0	163
	TAC [€/a]	2655	2636	2626	1466	2492	2456	2416	1967	2484	2446	2403	1975
4	AIC [€/a]	288	288	288	26	283	283	283	26	279	279	279	26
	FOM [€/a]	229	229	229	229	228	228	228	228	228	228	228	228
	VC_{tot}[€/a]	1370	1347	1324	1294	1374	1351	1328	1297	1375	1353	1330	1294
	VC_{el}[€/a]	857	824	773	724	863	829	778	728	865	832	781	726
	VC_{gas}[€/a]	512	523	552	571	511	522	550	569	510	521	549	568
	TAC [€/a]	1886	1864	1841	1549	1886	1863	1840	1552	1882	1860	1837	1548

[a] The cost values given are not discounted but the actual payment in the described year. The costs are AIC: Annualized Investment Cost, FOM: Fixed Operation and Maintenance Cost, VC_{tot}: Total Variable Costs, $VC_{el/gas}$: Variable Cost for Electricity/Gas (included in VC_{tot}), RC: Remuneration for Direct Electricity Sales of PV Electricity Feed-In, MP: Market Premium for PV Electricity Feed-In, TAC: Total Annual Costs

Table E.6: Annual costs of energy provision in the main analysis

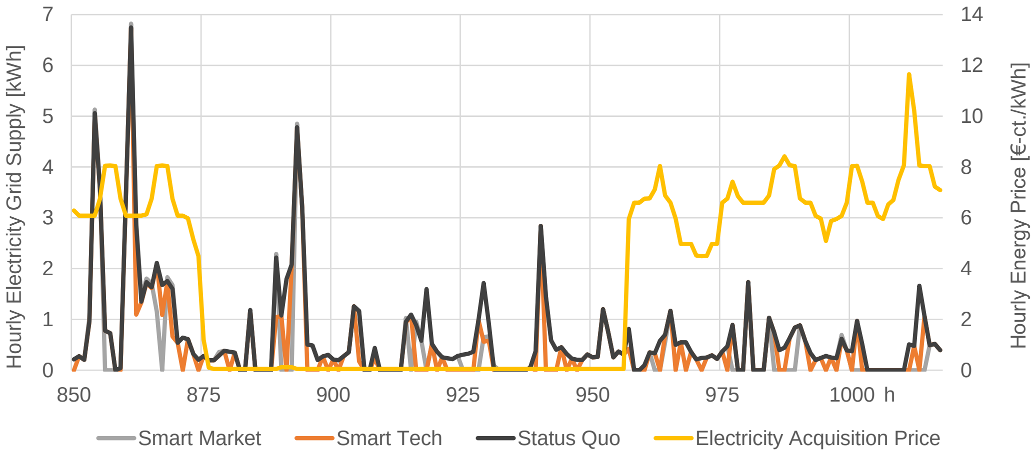

Figure E.11: Electricity supplied from the grid in each of the three scenarios as well as the corresponding electricity acquisition prices of the main analysis for HH1 in the second week of February 2040

	HH	Status Quo	Smart Tech	Smart Market
Main Analysis	1	51690	51295	51210
	2	39176	39077	39087
	3	33745	33082	32993
	4	25268	25265	25220
Sensitivity Analysis	1	56011	54087	53888
	2	43112	42271	42202
	3	35922	34258	34140
	4	27140	26412	26216

Table E.7: Total costs of energy provision in the main and sensitivity analyses

HH	[a]	Smart Tech 2025	Smart Tech 2030	Smart Tech 2035	Smart Tech 2040	Smart Market 2025	Smart Market 2030	Smart Market 2035	Smart Market 2040
1	AIC [€/a]	2196	2196	2196	24	2201	2201	2201	24
	FOM [€/a]	630	630	630	630	624	624	624	624
	VC_{tot}[€/a]	1982	1867	1699	1533	1968	1858	1687	1509
	VC_{el}[€/a]	1004	965	905	848	1008	973	917	856
	VC_{HP}[€/a]	977	901	794	685	960	885	770	653
	RC[€/a]	221	226	226	231	220	225	225	231
	MP[€/a]	108	109	110	110	107	109	109	110
	TAC [€/a]	4479	4358	4189	1847	4467	4350	4178	1817
2	AIC [€/a]	444	444	444	1587	441	441	441	1586
	FOM [€/a]	235	235	235	521	235	235	235	518
	VC_{tot}[€/a]	2227	2422	2610	1093	2227	2422	2611	1084
	VC_{el}[€/a]	1155	1110	1040	621	1158	1112	1043	632
	VC_{HP}[€/a]	0	0	0	472	0	0	0	451
	VC_{gas}[€/a]	1073	1312	1569	0	1070	1310	1568	0
	RC[€/a]	0	0	0	299	0	0	0	299
	MP[€/a]	0	0	0	141	0	0	0	141
	TAC [€/a]	2906	3101	3289	2762	2903	3098	3286	2748
3	AIC [€/a]	1698	1698	1698	26	717	717	717	847
	FOM [€/a]	373	373	373	373	237	237	237	425
	VC_{tot}[€/a]	1087	1030	946	866	1795	1699	1558	811
	VC_{el}[€/a]	752	723	678	635	1337	1281	1197	602
	VC_{HP}[€/a]	335	307	269	231	458	418	361	209
	RC[€/a]	195	197	196	198	0	0	0	345
	MP[€/a]	95	95	95	94	0	0	0	163
	TAC [€/a]	2868	2808	2726	972	2749	2652	2511	1574
4	AIC [€/a]	556	556	556	26	554	554	554	26
	FOM [€/a]	209	209	209	209	207	207	207	207
	VC_{tot}[€/a]	1333	1265	1166	1070	1324	1257	1157	1053
	VC_{el}[€/a]	968	930	872	817	968	930	873	813
	VC_{HP}[€/a]	365	335	294	253	357	327	284	240
	TAC [€/a]	2098	2030	1931	1305	2085	2018	1918	1286

[a] The cost values given are not discounted but the actual payment in the described year. The costs are AIC: Annualized Investment Cost, FOM: Fixed Operation and Maintenance Cost, $\mathrm{VC_{tot}}$: Total Variable Costs, $\mathrm{VC_{el/gas/hp}}$: Variable Cost for Electricity/Heat Pump/Gas (included in $\mathrm{VC_{tot}}$), RC: Remuneration for Direct Electricity Sales of PV Electricity Feed-In, MP: Market Premium for PV Electricity Feed-In, TAC: Total Annual Costs

Table E.8: Annual costs of energy provision in the sensitivity analysis

HH		Smart Tech	Smart Market
1	ATC [€]	2792	2678
	ACA [t_{CO_2}]	50.01	49.88
	ACAC [€/t_{CO_2}]	55.83	53.70
2	ATC [€]	3194	3115
	ACA [t_{CO_2}]	10.89	10.89
	ACAC [€/t_{CO_2}]	293.44	286.06
3	ATC [€]	1176	1147
	ACA [t_{CO_2}]	32.59	27.55
	ACAC [€/t_{CO_2}]	36.09	41.64
4	ATC [€]	1147	997
	ACA [t_{CO_2}]	21.24	21.2
	ACAC [€/t_{CO_2}]	53.98	47.02

[a] ATC: Additional Total Costs, ACA: Additional Carbon Abatement, ACAC: Additional Carbon Abatement Costs

Table E.9: Carbon abatement in the sensitivity analysis compared to the main analysis aggregated over the model years 2025-2045

	Status Quo				Smart Tech				Smart Market			
HH	2025	2030	2035	2040	2025	2030	2035	2040	2025	2030	2035	2040
1	6.75	6.75	6.75	6.75	6.73	6.73	6.73	6.73	6.82	6.82	6.82	6.82
2	5.23	5.23	5.23	5.23	5.49	5.49	5.49	4.10	5.53	5.53	5.53	4.14
3	10.98	10.98	10.98	10.98	11.11	11.11	11.11	11.11	11.18	11.18	11.18	11.18
4	9.26	9.26	9.26	9.26	9.35	9.35	9.35	9.35	9.44	9.44	9.44	9.44

Table E.10: Maximum amount of electricity consumed from the grid in a single hour for each model year and scenario in the main analysis

	Smart Tech				Smart Market			
HH	2025	2030	2035	2040	2025	2030	2035	2040
1	9.81	9.81	9.81	9.81	9.85	9.85	9.85	9.85
2	5.60	5.60	5.60	8.31	5.66	5.66	5.66	8.34
3	9.60	9.60	9.60	9.60	9.81	9.81	9.81	9.81
4	11.18	11.18	11.18	11.18	11.19	11.19	11.19	11.19

Table E.11: Maximum amount of electricity consumed from the grid in a single hour for each model year and scenario in the sensitivity analysis

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