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# Assessing the conditions for economic viability of dynamic electricity retail tariffs for households

Judith Stute [a,*], Sabine Pelka [b], Matthias Kühnbach [c], Marian Klobasa [b]

[a] Fraunhofer Research Institution for Energy Infrastructures and Geothermal Systems IEG, Breslauer Str. 48, Karlsruhe 76139, Germany
[b] Fraunhofer Institute for Systems and Innovation Research ISI, Breslauer Str. 48, Karlsruhe 76139, Germany
[c] Fraunhofer Institute for Solar Energy Systems ISE, Heidenhofstr. 2, Freiburg 79910, Germany

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ABSTRACT

The success of the energy transition relies on effectively utilizing flexibility in the power system. Dynamic tariffs are a highly discussed and promising innovation for incentivizing the use of residential flexibility. However, their full potential can only be realized if households achieve significant benefits. This paper specifically addresses this topic. We examine the leverage of household flexibility and the financial benefits of using dynamic tariffs, considering household heterogeneity, the costs of home energy management systems and smart meters, the impact of higher electricity prices and price spreads and the differences between types of prosumers. To comprehensively address this topic, we use the EVaTar-building model, a simulation framework that includes embedded optimization designed to simulate household electricity consumption patterns under the influence of a home energy management system or in response to dynamic tariffs. The study's main finding is that households can achieve significant cost savings and increase flexibility utilization by using a home energy management system and dynamic electricity tariffs, provided that electricity prices and price spreads reach higher levels. When comparing price levels in a low and high electricity price scenario, with an increase of the average electricity price by 15.2 €ct/kWh (67 % higher than the average for the year 2019) and an increase of the price spread by 8.9 €ct/kWh (494 % higher), the percentage of households achieving cost savings increases from 3.9 % to 62.5 %. Households with both an electric vehicle and a heat pump observed the highest cost benefits. Sufficiently high price incentives or sufficiently low costs for home energy management systems and metering point operation are required to enable households to mitigate rising electricity costs and ensure residential flexibility for the energy system through electric vehicles and heat pumps.

## 1. Introduction

The recent energy crisis in Europe and in Germany in particular, has had significant impacts on various sectors. Amidst rising electricity prices[1] and the increasing volatility observed on day-ahead spot market prices in Germany in recent months (see Fig. 1), this crisis has not only meant a greater financial burden for households, but has also highlighted the urgent need for sustainable energy solutions. As a result, households are becoming increasingly aware of their energy expenditures.

This crisis has also accelerated the adoption of sector-coupling technologies, such as electric vehicles (EVs) and heat pumps (HPs), but also of PV battery storage systems (PV-BSSs). While these technologies represent a shift towards a more sustainable future, they also lead to an increase in electricity consumption. This surge in electricity demand prompts households to find ways to reduce their overall energy expenditure. Additionally, higher electricity consumption and peak loads due to these technologies and the increasing share of wind and solar power plants in power systems worldwide can pose challenges to local energy infrastructure in the future and requires power systems to become more flexible. In this context, managing high electricity costs and alleviating grid stress become crucial and a key strategy in this regard is the flexible operation of EVs, HPs and PV-BSSs. Assessing the conditions for incentivizing this residential flexibility in an efficient and system friendly manner is relevant in many power systems worldwide with an increasing share of renewable energy sources and sector coupling technologies. Core conditions encompass instruments and enabling technologies for utilizing residential flexibility.

* Corresponding author.
*E-mail address:* judith.stute@ieg.fraunhofer.de (J. Stute).

[1] Average price on the day-ahead spot market for Germany: 96,85 €/MWh in the year 2021 and 235,45 €/MWh in 2022 [1].

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**Nomenclature**

| | |
|---|---|
| $t$ | Time step (h) |
| $\Delta t$ | Difference between two time steps (h) |
| $T$ | Set of all time steps considered |
| $T_{out}$ | Set of time steps where outliers in price time series occur |
| $c_{2019}$ | Electricity price time series for the year 2019 (€ct/kWh) |
| $c_{out,p}$ | Positive outliers of the electricity price time series (€ct/kWh) |
| $c_{scen}$ | Electricity price time series for the specified scenario (€ct/kWh) |
| $C_{sc,min}$ | Minimum price level of a given electricity price scenario (€ct/kWh) |
| $C_{sc,max}$ | Maximum price level of a given electricity price scenario (€ct/kWh) |
| $c_{adj}$ | Adjusted price time series without outliers (€ct/kWh) |
| $c_{out,adj,pos}$ | Adjusted price values for positive outliers (€ct/kWh) |
| $E_{grid,building}$ | Energy drawn from the grid (kWh) |
| $E_{PV,grid}$ | Energy fed into the grid from the PV system (kWh) |
| $E_{H}$ | The household's inflexible energy demand (kWh) |
| $E_{PV,building}$ | Energy supplied to the building by the PV system (kWh) |
| $E_{BSS}$ | Energy supplied to the building by the BSS (kWh) |
| $E_{EV}$ | Energy demand of the EV charging process (kWh) |
| $E_{HP,el}$ | Electrical energy demand of the heating system (kWh) |
| $\alpha_{PV}$ | Binary variable to indicate, if a PV system is available in the building |
| $\alpha_{BSS}$ | Binary variable to indicate if a BSS is available in the building |
| $\alpha_{EV}$ | Binary variable to indicate if an EV is available in the building |
| $\alpha_{HP}$ | Binary variable to indicate if a HP is available in the building |
| $c_{elec.\ price}$ | Electricity unit rate cost (€ct/kWh) |
| $c_{feed-in}$ | Feed-in remuneration (€ct/kWh) |
| $P_{H}$ | Power flow from the building to the household appliances (kW) |
| $P_{PV,grid}$ | Power flow from the PV system to the grid (kW) |
| $P_{PV,building}$ | Power flow from the PV system to the building (kW) |
| $P_{PV,BSS}$ | Power flow from the PV system to the BSS (kW) |
| $P_{PV,generation}$ | Power output of the PV system (kW) |
| $E_{BSS}$ | Energy stored in the BSS (kWh) |
| $P_{BSS}$ | Power flow from the BSS to the building (kWh) |
| $\eta_{BSS,charge}$ | Charging efficiency of the battery |
| $\eta_{BSS,discharge}$ | Discharging efficiency of the battery |
| $q_{losses,BSS}$ | Standby losses of the BSS (%/h) |
| $P_{BSS,max}$ | Maximum charge/discharge power of the BSS (kW) |
| $E_{BSS,max}$ | Usable capacity of the BSS (kWh) |
| $E_{EV}$ | Energy stored in the EV battery (kWh) |
| $P_{EV}$ | Charging power of the EV battery (kW) |
| $P_{EV,max,ch}$ | Maximum charging power of the EV battery (kW) |
| $E_{EV,demand}$ | Energy demand of the EV (kWh) |
| $\eta_{EV,charge}$ | Charging efficiency of the EV battery |
| $q_{losses,EV}$ | Standby losses of the EV battery (%/h) |
| $E_{min,departure}$ | Minimum energy stored in the EV battery at time of departure (kWh) |
| $f_{avail.}$ | Availability of the EV at the home location (binary) |
| $E_{min,charge}$ | Minimum energy level of the EV battery, before charging process starts (kWh) |
| $E_{EV,max}$ | Capacity of the EV battery (kWh) |
| $\dot{Q}_{heat\ demand}$ | Building's thermal heat demand ($kW_{th}$) |
| $\dot{Q}_{HP,building}$ | Thermal power flow from the heat pump to the building ($kW_{th}$) |
| $\dot{Q}_{HS,building}$ | Thermal power flow from the heat storage to the building ($kW_{th}$) |
| COP | Coefficient of performance of the HP (p.u.) |
| $\eta_{COP}$ | Quality grade/scale-down factor of the HP's Carnot efficiency |
| $T_{high}$ | Flow temperature of the heating system (K) |
| $T_{high,max}$ | Technically maximum possible flow temperature of the heating system (K) |
| $T_{amb.}$ | Ambient temperature (K) |
| $T_{amb.,norm}$ | Norm outside temperature (K) |
| $T_{room}$ | Inside temperature (K) |
| $T_{icing}$ | Temperature threshold below which icing occurs ( °C) |
| $f_{icing}$ | Factor of COP reduction due to icing (p.u.) |
| $\dot{Q}_{max,th}$ | Maximum thermal power output of the HP ($kW_{th}$) |
| $COP_{nom}$ | Nominal coefficient of performance (p.u.) |
| $\dot{Q}_{nom,th}$ | Nominal thermal power output of the HP ($kW_{th}$) |
| $P_{HP,el}$ | Power flow from the building to the HP (kW) |
| $\dot{Q}_{HP,th}$ | Thermal power generation of the HP ($kW_{th}$) |
| $\dot{Q}_{HP,HS}$ | Thermal power flow from the HP to the heat storage ($kW_{th}$) |
| $\dot{Q}_{amb,norm}$ | Heat demand at norm outside temperature ($kW_{th}$) |
| $\dot{Q}_{th,20^{\circ}C}$ | Heat demand at ambient temperature of 20°C ($kW_{th}$) |
| $\dot{Q}_{th,min}$ | Heat demand at minimal ambient temperature ($kW_{th}$) |
| $f_{HP,flexibility}$ | Flexibility factor for HP sizing (p.u.) |
| $E_{HS}$ | Energy stored in the heat storage ($kWh_{th}$) |
| $E_{HS,max}$ | Storage capacity of the heat storage ($kWh_{th}$) |
| $q_{losses,HS}$ | Standby losses of the heat storage (%/h) |

### 1.1. Instruments to utilize residential flexibility

A wide range of instruments, so called demand response (DR) mechanisms, are being discussed to incentivize residential flexibility. DR mechanisms are strategies that involve shifting or shedding of electricity demand, providing flexibility to assist in balancing the grid. DR mechanisms can be beneficial for both end-users and utilities as they can increase overall system security and maximize social welfare [2]. DR mechanisms can generally be divided into incentive- or event-driven mechanisms, and price-driven mechanisms [3] with the social context considered critical for successful implementation. Incentive- or event-driven mechanisms include direct load control, emergency demand response programs, capacity market programs, interruptible/curtailable services, demand bidding/buyback programs, and ancillary service market programs [3]. Price-driven DR mechanisms comprise dynamic electricity retail tariffs. These mostly time-variable tariffs incentivize consumers to shift their load from times with higher electricity prices to times with lower ones, thus offering a solution to the challenges posed by the current energy crisis and ongoing energy transition. One advantage of price-driven DR mechanisms is that they are implemented “behind the meter”, on the customer side [4], and, in combination with smart meters, enable end-consumers to make informed decisions about their electricity consumption.

### 1.2. Role of enabling technologies for flexibility utilization in households

Next to DR mechanisms such as dynamic electricity tariffs, enabling technologies play an important role for utilizing flexibility. These enabling technologies, which allow for an automated response to price incentives, are generally classified into three categories: control devices, monitoring systems, and communication systems [5]. Control devices and monitoring systems are combined in home energy management systems (HEMS). A

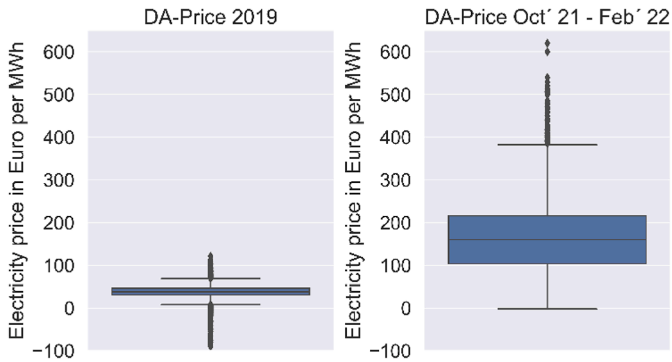


**Fig. 1.** Historical day-ahead spot market electricity prices for the year 2019 and from October 2021 to February 2022.

HEMS within this study is considered to actively manage the household's energy use by implementing control strategies and utilizing optimizing controllers to efficiently operate energy-using equipment including EVs, HPs and PV-BSSs. Together with smart meters acting as communication devices and dynamic electricity prices, these constitute the basic requirements for household customers to be able to operate their flexible assets in an intelligent, cost-optimized manner. A survey described by Buryk et al. [6] indicates that automated load shifting may play a critical role in encouraging customers to transition from a fixed to a dynamic pricing model. According to Parrish et al. [7], automation can simplify the process for households, reducing the complexity and effort required to respond to dynamic tariffs, thus preventing response fatigue and increasing participation. This was shown in a field study in the Flemish region, where after 18 months, no indication of user fatigue was observed [8]. In a field study in the US for households with plug-in hybrid EVs, households with a dynamic electricity tariff preferred managed charging via a programmable smart plug [9]. Another field study in the Netherlands concluded that automatic and smart control of appliances was the most popular strategy amongst the participating households [10].

### *1.3. Effects of the smart operation of flexible technologies on the economic viability of dynamic electricity retail tariffs for households*

If a PV system and a battery storage system (BSS) are combined with a new ToU tariff that varies for different types of day and shows a more extended dependence on energy drawn from the grid, Bignucolo et al. [11] find that applying the enhanced ToU tariff to both the power drawn from and fed into the grid can reduce the daily electricity costs for households in Italy by up to 72 %.

EVs have been discussed as a very promising technology to increase the utilization and financial benefits of dynamic tariffs. Applying the principle of smart charging, Martinenas et al. [12] find that a reduction in charging costs between 48 % and 61 % can be achieved when using a dynamic tariff in Denmark. Bonin et al. [14] study households with an EV, a PV system, and a day-ahead real time pricing (DA-RTP) tariff in Germany and define four charging strategies: direct charging, PV optimized charging, and optimizing electricity costs with the DA-RTP tariff with and without a PV system. The best result in terms of reducing electricity costs is obtained for the PV optimized charging case (35 % cheaper than direct charging), followed by the optimizing electricity costs with the DA-RTP tariff with a PV system case (34.0 % cheaper). A more comprehensive analysis of the change in electricity costs is presented by Kühnbach et al. [15]. Their study shows electricity costs decrease for all residential consumers by up to −3.7 % when EVs in Germany apply controlled charging responding to a price signal derived from the national residual load. The analysis includes the change in electricity procurement costs due to controlled charging and the change in grid charges from the grid expansion needed due to the uptake of EVs. Aguilar-Dominguez et al. [13] investigate different dynamic tariff schemes (time-of-use (ToU), time-of-day, real time pricing (RTP)) for UK households with an EV, a PV system, and a BSS. Their results show a reduction in electricity costs of up to 85 %. Huang et al. [16] find that electricity purchase costs can be reduced by 22.5 % for households with renewable generation, EVs, and air conditioning in Anhui, China, when a HEMS is used. A further reduction of 26.6 % can be achieved if a BSS is included in the system. Lu et al. [17] show similar results. In their setup of a household in Shanghai with an EV, air conditioning and different sizes of PV-BSSs, they obtain a possible cost reduction of up to 71.4 % when using a HEMS and a ToU tariff. Ren et al. [39] find that in households with an EV and a PV-BSS in China, household electricity costs can be reduced by 18 % with an RTP tariff, taking into account uncertainties in forecasting electricity prices and PV output.

According to Pena-Bello et al. [18], households with a HP and a PV system in Switzerland can increase their self-consumption rate and reduce the levelized costs of meeting electricity demand by between 13 % and 26 % if a heat storage is added to the system. Ali et al. [19] show that energy cost savings of up to 40 % are possible from using a DA-RTP with electric space heating and partial thermal storage in Finland. Klaassen et al. [20] assume a DA-RTP tariff for a household in the Netherlands with a HP for floor heating and domestic hot water demand and apply a control algorithm to minimize heating costs. The results show an 8 % reduction in energy heating costs. For a setting in Switzerland applying a DA-RTP tariff, Wilczynski et al. [21] find that households that only have a HP can still achieve cost savings of approximately 1 % attributable to using the HP flexibly.

Looking at households that have both an EV and a HP, and an additional PV system, Yousefi et al. [40] analyze buildings with various energy labels and two different heat emission systems in Denmark. They show possible home energy cost savings between 26 % and 41 %, when a HEMS and a ToU tariff are combined. Yang et al. [41] consider households with an EV, a HP, and a PV-BSS and possible electricity cost savings when a ToU tariff is applied for a household in different climate zones in the US. Results indicate that cost savings ranging from 12 % to 38 % are possible.

A summary of the above presented articles on cost savings through flexibility utilization can be found in Table 1.

### *1.4. Research gap and contribution*

The literature consistently illustrates the positive general impact of dynamic pricing. It effectively reduces procurement costs, particularly when combined with a smart and automated HEMS. However, as a growing proportion of households adopt flexible technologies, our review uncovers significant knowledge gaps that must be bridged in order to evaluate the benefits of dynamic electricity tariffs more comprehensively:

1. **Narrow focus on single technologies:** Predominantly, the existing research concentrates on isolated flexible technologies - such as EVs or HPs, frequently in combination with PV systems or PV-BSSs. These investigations seldom explore the interaction among multiple technologies within a household responding to dynamic electricity prices.
2. **Neglect of household heterogeneity:** The limited variety of load curves considered in these studies overlooks the critical dimension of household heterogeneity, thus limiting the comprehensive understanding and applicability of insights regarding the impact of dynamic electricity prices on households with flexible appliances.
3. **Presumption of HEMS and smart meters:** A common assumption across studies is the pre-existence of HEMS and smart meters. However, the widespread acceptance and implementation of dynamic electricity pricing models and HEMS crucially depend on ensuring that the initial investment costs of such systems are not higher than the financial savings achieved through DR strategies. Therefore, it is essential to incorporate the costs associated with HEMS and smart meters into the analysis.

**Table 1**
Key aspects of the analyzed literature regarding the identified research gaps.

| Ref. | Available technologies | | | | Profile heterogeneity | Tariff scheme | Operating strategies | Included costs | Cost savings |
|---|---|---|---|---|---|---|---|---|---|
| | PV | EV | HP | BSS | | | | | |
| *Bignucolo* et al. [11] | x | | | x | 2 households load profiles, 1 PV generation profile, 24h | ToU, E-ToU | Electricity cost minimization, no flexibility utilization as benchmark | Electricity costs and PV-BSS amortization, no VAT | 37 % with ToU, up to 72 % with E-ToU |
| *Martinenas* et al. [12] | | x | | | 2 load profiles, less than 24h | Dyn. Tariff based on Nord Pool spot, including signals for immediate and predicted grid state | Smart charging (cost optimized), direct charging as benchmark | Unit rate costs without taxes | 48–61 % |
| *von Bonin* et al. [14] | x | x | | | 74 household load profiles, 100 EV profiles, 27 PV generation profiles, 1 year | Static, DA-RTP | PV optimized charging, price optimized charging, price and PV optimized charging, direct charging as benchmark | Total costs of electricity for EV charging | PV optimized charging: 35 %, price optimized charging: 11 %, PV + price optimized charging: 34 % |
| *Kühnbach* et al. [15] | x | x | | | 1 household load profile, 1 PV generation profile, different starting points for EV charging, 1 year | Tariff based on residual load of the system | price optimized charging, direct charging as benchmark | Unit rate costs with all fiscal charges; focus: grid charges & retail & acquisition | Up to 4 % lower electricity unit rate costs for all households |
| *Aguilar-Dominguez* et al. [13] | x | x | | x | 1 household load profile, 1 PV generation profiles, 2 BSS sizes, 2 EV types, 2 weeks | Flat, ToU, ToD, RTP based on energy trade market in the UK | BSS or V2H for electricity bill minimization, no flexibility utilization as benchmark | Total cost of electricity (unit rate costs with taxes) | Up to 85 % |
| *Huang* et al. [16] | x | x | | x | 1 household load profile, 1 PV generation profile, 24 h in summer and transition season | RTP of the power grid | Price optimized scheduling of loads, no flexibility utilization as benchmark | Electricity purchase costs | 23 % without BSS compared to no flexibility utilization, 27 % with BSS compared to flexibility utilization without BSS |
| *Lu* et al. [17] | x | x | | x | 1 household load profile, different combinations of PV and BSS sizes, 24h | ToU | Combined price & peak load optimized scheduling of loads, no flexibility utilization as benchmark | Electricity purchase costs | Up to 71 % |
| *Ren* et al. [39] | x | x | | x | 1 household load profile, 1 PV generation profile, 24h | RTP | Electricity cost minimization while ensuring user's demand, no flexibility utilization as benchmark | Electricity purchase costs | 18 % |
| *Pena-Bello* et al. [18] | x | | x | x | 549 household load profiles, 3 different heat demands, 1 PV profile, 1 year | ToU, + capacity based grid charge | Electricity cost minimization, no flexibility utilization as benchmark | Levelized cost of meeting electricity demand | 13–26 % for households with PV + HP + heat storage |
| *Ali* et al. [19] | | | x | | 1 household load profile, 1 heat demand, different heat storage sizes, 1 day in winter | DA-RTP | Electricity cost minimization, no flexibility utilization as benchmark | Wholesale energy costs | Up to 40 % |
| *Klaassen* et al. [20] | | | x | | 1 household load profile including heat demand, 1 year | DA-RTP | Electricity cost minimization, no flexibility utilization as benchmark | Energy heating costs | 8 % |
| *Wilczynski* et al. [21] | | | x | | 2 building archetypes, 1 year | Flat, ToU, DA-RTP, DA-RTP for a system with full HP penetration | Electricity cost minimization, no flexibility utilization as benchmark | Cost savings attributable to HP flexibility | Approximately 1 % |
| *Yousefi* et al. [40] | x | x | x | | 7 buildings with different energy labels, 2 heat emission systems, 1 household load profile, 1 EV profile, 1 PV generation profile, heat demand depending on building type, 1 week in winter | ToU | Electricity cost minimization, no flexibility utilization as benchmark | Home energy costs | 26–41 % |
| *Yang* et al. [41] | x | x | x | x | 1 household load profile, 1 EV profile, 3 climate zones for PV generation & heat demand, 1 year | ToU | Electricity cost minimization, conventional control strategy as benchmark | Electricity costs | 12–38 % |

4. **Need for comprehensive comparisons:** It is vital to benchmark the performance of flexible technologies under dynamic electricity pricing not merely against scenarios with no explicit flexibility utilization, but also against setups aimed at optimized self-consumption.

The main research question stems from these identified gaps and the recent developments on electricity markets and digital advancements:

- **Under what conditions are dynamic electricity retail tariffs the most economically viable option for households?**

To systematically address this question, we pose several sub-questions related to the identified research gaps:

- How does flexibility utilization[2] via a HEMS in households under dynamic electricity tariffs compare with self-consumption in households equipped with a PV system?
- How are the economic benefits of dynamic electricity tariffs for households influenced by the interaction of multiple flexible technologies, different average electricity prices and different price spreads[3]?
- Do the potential cost savings offset the additional costs of metering point operation and the HEMS?

To address these questions, we introduce the *EVaTar-building* model - a simulation framework featuring embedded optimization designed to simulate household electricity consumption patterns under a HEMS or in response to dynamic tariffs. We explore three cases: households not explicitly utilizing their flexibility, households employing a HEMS to enhance self-consumption via a PV system or a PV-BSS, and households utilizing a HEMS alongside a smart meter, adopting a dynamic electricity tariff based on the day-ahead spot market price. The model's outputs enable a thorough economic analysis considering the investments in a HEMS and metering point operation costs. Furthermore, an analysis on changes in annual electricity consumption per household, and the resulting changes to the load curves is carried out, thereby providing a comprehensive picture of the scenarios.

The study is organized as follows: Section 2 describes the methodological approach, the data used, the electricity price scenarios, and the underlying assumptions of the case study. Section 3 provides an overview of the study results. Section 4 discusses the results, and the study closes with the summary and conclusion (Section 5).

## 2. Material and methods

Our methodology is divided into two parts: the generation of external price signals and the description of consumer flexibility utilization in response to these signals. First, we discuss the methodology developed to generate electricity price signals relevant to the purchase of electricity. In addition, we explain the calculation of the market value that serves as a proxy for the PV feed-in tariff. These price signals are central to our analysis, as they allow for seamless comparison between different scenarios. We then describe the *EVaTar-building* model, which illustrates three different operational strategies for different household types and their flexible technologies, such as EVs, HPs, and PV-BSSs. Finally, we outline the characteristics of the flexible technologies and time series data used in our study.

### 2.1. Preparation of price signals

For households using a HEMS, two price signals are important: the price per kilowatt-hour of electricity purchased from the grid, and the feed-in tariff paid for each kilowatt-hour generated by their PV system and fed back into the grid.[4]

#### 2.1.1. Manipulating electricity price time series to create dynamic electricity retail tariffs

To ensure broad applicability of our findings, we examine dynamic electricity tariffs across diverse price scenarios. For ease of comparison, we have selected the year 2019[5] and modify the price time series to create price scenarios while retaining its intrinsic structure.

In a first step, given the presence of hours within the year characterized by relatively high and low prices, we define the 1 % percentile of all electricity prices in the time series as outliers (ct). This identification yields a set of time steps, $T_{\text{out}}$, during which these outliers are observed. We then recalibrate the mean value and standard deviation of the remaining data set to match the intended scenarios in accordance with Eq. (1).

$$c^t_{\text{adj}} = \frac{c^t_{2019} - \overline{c^t_{2019}}}{\sigma(c^t_{2019})} \cdot \sigma_{\text{scen}} + \varnothing_{\text{scen}}, \quad \forall t \notin T_{\text{out}} \tag{1}$$

In this context, $c^t_{2019}$ represents the electricity price at each time step $t$, excluding instances identified as outliers within this time series. $\sigma_{\text{scen}}$ denotes the standard deviation, and $\varnothing_{\text{scen}}$ signifies the mean value of the electricity price for the specified scenario. $c^t_{\text{adj}}$ stands for the adjusted time series, which omits the outliers.

In the subsequent step, we modify the outliers so that they fall within the bounds defined by the minimum and maximum values of the chosen price scenario ($C_{\text{sc,min}}$ and $C_{\text{sc,max}}$) as well as the minimum and maximum values of the adjusted time series ($\min c^t_{\text{adj}}$ and $\max c^t_{\text{adj}}$). This adjustment is carried out separately for positive and negative outliers. Eq. (2) provides an example for handling positive outliers ($c^t_{\text{out}}, p$).

$$c^t_{\text{out,adj,pos}} = \begin{cases} \dfrac{c^t_{\text{out,p}} - \min c^t_{\text{out,p}}}{\max c^t_{\text{out,p}} - \min c^t_{\text{out,p}}} \cdot \left(C_{\text{sc,max}} - \max c^t_{\text{adj}}\right) + \max c^t_{\text{adj}}, & \forall c^t_{\text{out,p}} \geq c^t_{\text{adj}}, \quad \forall t \in T_{\text{out}} \\ \max c^t_{\text{adj}}, & \forall c^t_{\text{out,p}} < c^t_{\text{adj}}, \quad \forall t \in T_{\text{out}} \end{cases} \tag{2}$$

[2] Utilization of flexibility in the context of this study means the implementation of a HEMS facilitating the load shifting of flexible technologies such as EVs, HPs or PV-BSSs.

[3] A price spread is defined as the difference between the minimum and maximum value of a price time series over a predefined period of time.

[4] This assumes the current regulatory framework in Germany, where electricity is paid in €ct/kWh without any costs for the capacity used.

[5] The choice of 2019 as the base year allows for the creation of a consistent scenario, particularly in combination with available data for weather, temperature etc., for the flexible consumers. This decision was driven by the lack of comprehensive data for more recent years accessible to the authors.

Upon finalizing the manipulation of the distinct datasets $c^t_{\text{adj}}$, $c^t_{\text{out,adj,pos}}$, and $c^t_{\text{out,adj,neg}}$, they are consolidated into a single time series, $c^t_{\text{scen}}$, which represents the electricity price scenario.

#### 2.1.2. Calculating PV market values for the feed-in tariff

As prices in the day-ahead spot market are different for each price scenario, so are the market values of electricity generated from PV systems. To account for this variability in the different price scenarios, we assume a constant feed-in tariff for electricity generated by rooftop PV systems. For easy comparison between scenarios, we derive a PV market value, $\text{MV}_{\text{solar}}$, based on the day-ahead spot market prices. The electricity price $c^t_{\text{electricity}}$ is weighted by the amount of electricity generated by PV systems $E^t_{\text{PV}}$ for each hour $t$, as shown in Eq. (3).

$$\text{MV}_{\text{solar}} = \frac{\sum_{t=0}^{8760} E^t_{\text{PV}} \cdot c^t_{\text{electricity}}}{\sum_{t=0}^{8760} E^t_{\text{PV}}}, \quad \forall t \in T \tag{3}$$

### 2.2. Modeling flexible consumers: EVaTar-building model

Our computational framework integrates various elements, including inflexible household demand, battery storage operations, and the demand response capabilities of EVs and heating systems. This model allows the representation of three different operating strategies for households:

- **No-flex case**: This serves as the baseline case, representing the status quo where households have flexible technologies but do **not explicitly** utilize their flexibility. Households are further subjected to a static tariff.
- **SC-flex case**: In this case, households aim to increase their **self-consumption** through the use of a HEMS, thereby minimizing their electricity purchase costs under a static tariff.
- **DT-flex case**: This case introduces a **dynamic electricity tariff** and a smart meter into the household, allowing a more strategic use of flexibility to take advantage of periods with low electricity prices.

For the no-flex case, a simulation model illustrates the absence of explicit flexibility utilization. For the SC-flex and DT-flex cases, a mixed integer linear programming (MILP) optimization represents operation of the HEMS, providing detailed and efficient strategy for managing household energy consumption.

The following sections outline the general implementation approach for each technology, followed by specific implementations for both inflexible (no-flex case) and flexible (SC-flex and DT-flex cases) behaviors of households.

#### 2.2.1. Building representation and household appliances

*Building representation.* The model represents each building as a household, which may have additional technologies such as EVs, PV systems, BSSs, and heating systems that include both a HP and a heat storage tank. Connected to a low-voltage grid, each building can either withdraw electricity from or feed electricity generated by the PV system back into the grid. Fig. 2 shows the basic structure and energy flows of a flexible consumer in the *EVaTar-building* model.

For the SC-flex and DT-flex cases, it is assumed that each household can be equipped with a HEMS that operates with perfect foresight. To address uncertainties in load and generation forecasts, the model uses a rolling horizon scheme. This scheme considers a 3-day planning horizon with a control horizon of 24 h. The HEMS is responsible for actively optimizing building operations to minimize electricity purchase costs, as stated in Eq. (4):

$$\text{minimize} \sum_{t=0}^{t_{\max}} E^t_{\text{grid,building}} \cdot c^t_{\text{elec. price}} - E^t_{\text{PV,grid}} \cdot c_{\text{feed-in}}, \quad \forall t \in T \tag{4}$$

Here, $E^t_{\text{grid,building}}$ represents the amount of energy drawn from the grid during time step $t$, while $c^t_{\text{elec. price}}$ denotes the applicable electricity price during this time unit. $E^t_{\text{PV,grid}}$ signifies the energy fed back into the grid from the PV system during time step $t$, and $c_{\text{feed-in}}$ is the time-independent feed-in remuneration. The energy drawn from the grid $E^t_{\text{grid,building}}$ is specified as follows:

$$\begin{aligned} E^t_{\text{grid,building}} = \; & E^t_{\text{H}} - \alpha_{\text{PV}} \cdot E^t_{\text{PV,building}} - \alpha_{\text{BSS}} \cdot E^t_{\text{BSS}} \\ & + \alpha_{\text{EV}} \cdot E^t_{\text{EV}} + \alpha_{\text{HP}} \cdot E^t_{\text{HP,el}}, \end{aligned} \quad \forall t \in T \tag{5}$$

In this context, the variable $\alpha$ is binary and indicates the presence of a particular technology in a household. $E^t_{\text{H}}$ refers to the household's inflexible electricity demand during time step $t$. $E^t_{\text{PV,building}}$ signifies the amount of energy supplied to the building from the PV system during time step $t$. $E^t_{\text{BSS}}$ denotes the energy provided to the building by the battery storage system in time step $t$. $E^t_{\text{EV}}$ represents the energy requirements of the EV charging process during tiem step $t$. Finally, $E^t_{\text{HP,el}}$ specifies the electrical energy demand of the heating system during tiem step $t$.

*Household appliances.* This study considers the electricity demand of household appliances as inflexible and defines it exogenously through household load profiles.

#### 2.2.2. PV systems

The PV system can supply power to various applications in the building, charge a BSS, and feed electricity into the grid. To represent this, the power output from the PV system $P^t_{\text{PV,generation}}$ for a given time step $t$ is divided into three different power flows (as shown in Eq. (6)).

$$P^t_{\text{PV,grid}} + P^t_{\text{PV,building}} + P^t_{\text{PV,BSS}} = P^t_{\text{PV,generation}}, \quad \forall t \in T \tag{6}$$

The power flow from the PV system to the grid is represented by $P^t_{\text{PV,grid}}$, while $P^t_{\text{PV,building}}$ represents the power flow from the PV system to the building, and $P^t_{\text{PV,BSS}}$ is the power flow from the PV system to the BSS. Buildings that consist solely of a household and a PV system, without any of the flexibility options presented below, are considered inflexible.

#### 2.2.3. Battery storage systems

The building's BSS can be charged with electricity generated by the PV system and it can provide power to the various technologies available in the building.

The energy stored in the battery, $E^t_{\text{BSS}}$, at a given time step $t$ is defined as follows:

$$\begin{aligned} E^t_{\text{BSS}} = \; & \left(1 - q_{\text{losses,BSS}}\right) \cdot E^{t-1}_{\text{BSS}} + P^t_{\text{PV,BSS}} \cdot \eta_{\text{BSS,charge}} \cdot \Delta t \\ & - P^t_{\text{BSS}} \cdot \frac{1}{\eta_{\text{BSS,discharge}}} \cdot \Delta t, \end{aligned} \quad \forall t \in T \tag{7}$$

With:

$$0 \le P^t_{\text{PV,BSS}} \le P_{\text{BSS,max}}, \quad \forall t \in T \tag{8}$$

$$0 \le P^t_{\text{BSS}} \le P_{\text{BSS,max}}, \quad \forall t \in T \tag{9}$$

$$0 \le E^t_{\text{BSS}} \le E_{\text{BSS,max}}, \quad \forall t \in T \tag{10}$$

$P^t_{PV,BSS}$ represents the power flow from the PV system to the BSS. $P^t_{\text{BSS}}$ denotes the power flow from the battery to the building. $P_{\text{BSS,max}}$ is the maximum charge/discharge power of the BSS, and $E_{\text{BSS,max}}$ is its maximum usable capacity. The charging and discharging efficiency factors are represented by $\eta_{\text{BSS,charge}}$ and $\eta_{\text{BSS,discharge}}$, respectively. $q_{\text{losses,BSS}}$ depicts the standby losses.

*BSS operation strategy in the no-flex case.* The operating strategy for

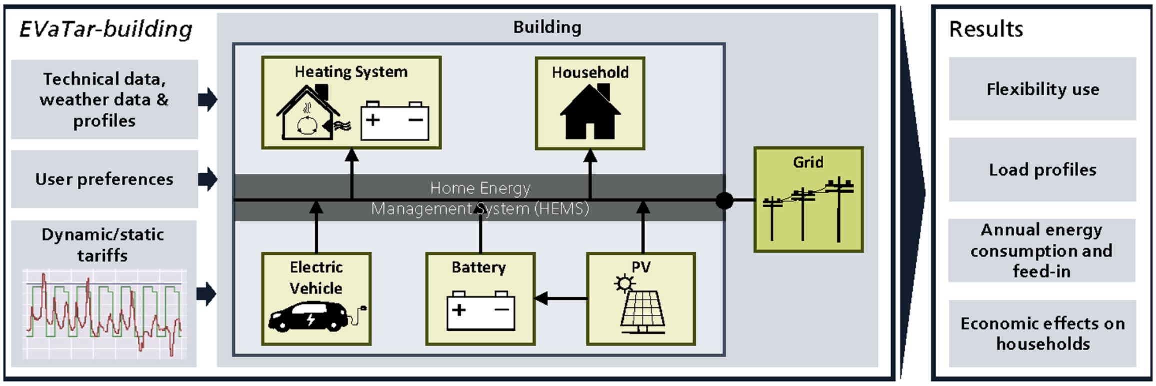


**Fig. 2.** Schematic overview of the flexible consumer model *EVaTar-building*. The figure details the input data, the modeled energy flows within the building and to and from the grid, and the derived results.

inflexible behavior represents the prevalent mode of operation for residential PV-BSS, functioning independently of the tariff system and typical for households without a HEMS. This strategy prioritizes the use of PV generated electricity to meet the building's demand, including EV and HP demands. Any excess generation charges the battery, and any further surplus is fed into the grid. Conversely, when the building's electricity demand exceeds the PV output, the system draws electricity from the battery to supply the household's energy demand.

*BSS operating strategy in the SC-flex and DT-flex cases.* With the introduction of a smart operating strategy, BSSs undergo a transformation to support flexible and predictive functioning, especially under dynamic tariffs. This advanced strategy integrates the BSS within the building's HEMS, aiming to minimize the overall energy procurement costs (as detailed in Eq. (19)) .[6] A key constraint of this strategy is the requirement for the state of charge (SOC) of the BSS at the beginning of the planning horizon to match the SOC at the end, ensuring energy continuity and system integrity. Moreover, it is specified that the battery cannot be simultaneously charged and discharged, reflecting the physical limitations of battery technology.

### 2.2.4. Electric vehicles

EVs are implemented as mobile battery storage units within the model, implying that the EV battery's availability as a flexibility resource is not constant but varies over time. Driving profiles with the corresponding energy demand, $E^t_{\mathrm{EV,demand}}$, are allocated to the households under study. The allocation is based on the socio-demographic metadata of the households and the driving profiles. This method ensures a realistic representation of EV usage and its impact on household electricity demand. Furthermore, the hourly availability of a vehicle at the home location, represented by $f^t_{\mathrm{avail.}}$ is exogenously specified.

The energy currently stored in the EV battery $E^t_{\mathrm{EV}}$ is defined as follows (Eq. (11)):

$$E^t_{\mathrm{EV}} = \left(1 - q_{\mathrm{losses,EV}}\right)\cdot E^{t-1}_{\mathrm{EV}} + P^t_{\mathrm{EV}}\cdot\eta_{\mathrm{EV,charge}}\cdot\Delta t - E^t_{\mathrm{EV,demand}}, \quad \forall t \in T \tag{11}$$

Here $\eta_{\mathrm{EV,charge}}$ represents the efficiency of the charging process and $P^t_{\mathrm{EV}}$ depicts the charging power at a time step $t$, and $q_{\mathrm{losses,EV}}$ stands for the standby losses of the EV battery.

The maximum charging power for the EV battery is limited to $P_{\mathrm{EV,max,ch}}$ (Eq. (12)). Similarly, the total amount of energy that the EV battery can store is constrained by its maximum usable capacity $E_{\mathrm{EV,max}}$ (Eq. (13)).

$$0 \le P^t_{\mathrm{EV}} \le P_{\mathrm{EV,max,ch}}, \quad \forall t \in T \tag{12}$$

$$0 \le E^t_{\mathrm{EV}} \le E_{\mathrm{EV,max}}, \quad \forall t \in T \tag{13}$$

*Uncontrolled charging of EVs in the no-flex case.* The operating strategy involves continuous charging of the EV upon arrival until a state of charge of 100 % is reached or the EV starts driving again.

*Controlled charging of EVs in the SC-flex and DT-flex cases.* The smart operating strategy for EVs involves controlled charging, where the EV is integrated into the building's HEMS. EV owners can input their preferences into the HEMS. This includes the minimum range and minimum energy stored in the battery at the time of departure $E_{\mathrm{min,departure}}$ (Eq. (14)), as well as the latest minimum energy level $E_{\mathrm{min,charge}}$ at which they want to start charging their vehicle, (Eq. (15)).

$$E^t_{\mathrm{EV}} \ge E_{\mathrm{min,departure}}, \quad \forall t \in T \quad \text{where } f^{t-1}_{\mathrm{avail.}} = 1 \wedge f^t_{\mathrm{avail.}} = 0 \tag{14}$$

$$E_{\mathrm{min,charge}} \le E^t_{\mathrm{EV}} \le E_{\mathrm{EV,max}}, \quad \forall t \in T \tag{15}$$

Where $E_{\mathrm{EV,max}}$ represents the maximum capacity of the EV battery.

### 2.2.5. Heating systems

The heating system of a building consists of an air-to-water HP and a heat storage tank (HS). The HP can supply energy to both the building ($\dot{Q}^t_{\mathrm{HP,building}}$) and the heat storage tank ($\dot{Q}^t_{\mathrm{HP,HS}}$). The heat storage tank can only supply the building ($\dot{Q}^t_{\mathrm{HS,building}}$). The building's heat demand $\dot{Q}^t_{\mathrm{heat\ demand}}$ must be met for each time step $t$ (Eq. (16)).

$$\dot{Q}^t_{\mathrm{heat\ demand}} = \dot{Q}^t_{\mathrm{HP,building}} + \dot{Q}^t_{\mathrm{HS,building}}, \quad \forall t \in T \tag{16}$$

The flow temperature of the heating system $T_{\mathrm{high}}$ follows a heating curve and is, therefore, dependent on the ambient temperature. It is calculated as follows (Eq. (17)):

$$T^t_{\mathrm{high}} = T_{\mathrm{room}} + \left(T_{\mathrm{high,max}} - T_{\mathrm{room}}\right)\cdot\left(\frac{T_{\mathrm{room}} - T^t_{\mathrm{amb.}}}{T_{\mathrm{room}} - T_{\mathrm{amb.,norm}}}\right)^{1/n}, \quad \forall t \in T \tag{17}$$

where $T_{\mathrm{room}}$ is the inside temperature, which is considered to be held constant by the HP system, $T_{\mathrm{high,max}}$ represents the technically maximum possible flow temperature of the HP, T depicts the ambient temperature at a given time step $t$, $T_{\mathrm{amb.,norm}}$ is the norm outside temperature for the given location and $n$ is the radiator exponent which is set to $n = 1.33$ for wall mounted radiators.

[6] Battery-to-grid power supply is not included in our analysis. This exclusion is based on the fact that the battery can only be charged via the PV system, and given the constant feed-in remuneration, employing the battery would merely result in additional energy losses.

Furthermore, a temperature-dependent coefficient of performance $COP^t$ is assumed for the air/water HP. In addition, we account for efficiency losses due to icing at ambient temperatures below 2°C ($T_{icing}$) by reducing the COP for low temperatures by a factor of $f_{icing} = 0.2$. With a typical quality grade for air-to-water HPs of $\eta_{COP} = 0.4$ [22], the COP at time step t is calculated as follows (Eq. (18)):

$$COP^t = \begin{cases} \eta_{COP} \cdot \frac{T_{high}}{T_{high} - T^t_{amb.}}, T^t_{amb.} > T_{icing} \\ \eta_{COP} \cdot \frac{T_{high}}{T_{high} - T^t_{amb.}} \cdot (1 - f_{icing}), T^t_{amb.} \leq T_{icing} \end{cases}, \quad \forall t \in T \tag{18}$$

where $T_{high}$ represents the flow temperature of the heating system.

With the time-dependent $COP^t$, the nominal $COP_{nom}$ and the nominal power output $\dot{Q}_{nom,\ th}$ of the HP, the maximum possible power output $\dot{Q}^t_{max,th}$ at time step $t$ can be calculated for each time step:

$$\dot{Q}^t_{max,\ th} = \frac{COP^t}{COP_{nom}} \cdot \dot{Q}_{nom,th}, \quad \forall t \in T \tag{19}$$

The necessary electric power consumption from the building to the HP $P^t_{HP,el}$ is defined as the ratio of the thermal power generation $\dot{Q}^t_{HP,th}$ of the HP and the COP:

$$P^t_{HP,el} = \frac{\dot{Q}^t_{HP,th}}{COP^t} = \frac{\dot{Q}^t_{HP,building} + \dot{Q}^t_{HP,HS}}{COP^t}, \quad \forall t \in T \tag{20}$$

The sizing of the HP is endogenously calculated using data on the building's annual heating demand per square meter, its living space, and the norm outside temperature. Initially, the heat demand at norm outside temperature, denoted as $\dot{Q}_{amb,norm}$, is established using the derived heat demand curve and the time series of the ambient temperature (Eq. (21)).

$$\dot{Q}_{amb,norm} = (T_{amb,norm} - T_{20^\circ C}) \cdot \frac{\dot{Q}_{th,20^\circ C} - \dot{Q}_{th,T_{min}}}{T_{20^\circ C} - T_{min}} \tag{21}$$

Where $\dot{Q}_{th,20^\circ C}$ depicts the heat demand at an ambient temperature of 20°C and $\dot{Q}_{th,T_{min}}$ stands for the heat demand at the minimal ambient temperature of the underlying time series.

The HP's maximum thermal power output is then set using a flexibility factor $f_{HP,flexibility}$. This factor enables more flexible use of the HP, even during periods of low ambient temperatures.

The heat storage tank is used to make the heating system more flexible. Its storage capacity $E^t_{HS,max}$ is defined so that it can store the energy of two hours of the maximum power output of the HP.[7]

The energy currently stored $E^t_{HS}$ in the heat storage is defined as (Eq. (22)):

$$E^t_{HS} = (1 - q_{losses,HS}) \cdot E^{t-1}_{HS} + \dot{Q}^t_{HP,HS} \cdot \Delta t - \dot{Q}^t_{HS,building} \cdot \Delta t, \quad \forall t \in T \tag{22}$$

Here $q_{losses,HS}$ represents the factor of the standby losses of the heat storage tank.

*Inflexible operation of the heating system in the no-flex case.* The heating system follows the heat demand. To guarantee heating availability even in the event of a blackout or technical problems, the heat storage tank is maintained at full charge during the entire heating period.

[7] This corresponds to a typical design parameter for heat storage tanks in Germany. Heat storage tanks of this size are compact enough to be retrofitted into most single-family homes. At the same time, they allow for the bridging of restricted periods as per §14a of the German Energy Act (EnWG).

*Flexible operation of the heating system in the SC- and DT-flex cases.* When the flexibility of the HP is utilized, the heating system is integrated into the HEMS. This implies that the heat storage tank plays a crucial role in managing the household's heat supply. By utilizing the tank, we can strategically shift when the HP is operated while still meeting the household's heat demand.

### 2.3. Input data

In this section, we present the data and assumptions for our analysis, starting with the characteristics of the two price signals relevant to the approach: the electricity price scenarios used for the assessment of dynamic electricity retail tariffs and the PV feed-in tariffs used for these scenarios. We then present a comprehensive overview of data used to represent the households and their flexible and inflexible technologies.

#### 2.3.1. Electricity price scenarios of the dynamic electricity retail tariffs

We define three scenarios:

- a **low price scenario** that corresponds to the 2019 day-ahead spot market price time series for Germany,
- a **high price scenario** that uses statistical values of the day-ahead spot market price time series from October 2021 to February 2022[8] (see Fig. 1),
- and a **medium price scenario** that lies between these two.

Statistical values for the resulting time series after the electricity price time series manipulation are listed in Table 2.

Fig. 3(a) shows average prices for each hour of the day seen by a household (including taxes, levies, and surcharges), broken down by season and the range from minimum to maximum value for all three price scenarios. The prices are seasonally dependent, particularly in the range between the minimum and maximum values. For all seasons the lowest prices can be seen in the early morning hours and – to some extent – in the early afternoon. Fig. 3(b) shows the intraday and intraweek price spreads, which exhibit a clear seasonal difference in the intraweek spreads, with smaller differences in the intraday spreads.

To provide a basis for comparison, a static tariff for each price scenario is defined, which corresponds to the level of the mean value of the dynamic tariff (see Table 2). In the context of electricity pricing structures in Germany, static tariffs exhibit a higher average value compared to dynamic tariffs. However, utilizing the mean value of dynamic tariffs as proxy for static tariffs serves as a worst-case scenario from the standpoint of flexibility utilization.

**Table 2**
Mean values, standard deviation, and minimal and maximal values of the electricity price scenarios used.

| | *Mean* in €ct/kWh | *Standard deviation* in €ct/kWh | *Minimal value* in €ct/kWh | *Maximal value* in €ct/kWh |
|---|---|---|---|---|
| *Low price scenario* | 22.6 | 1.8 | 7.4 | 32.6 |
| *Medium price scenario* | 30.2 | 6.2 | 4.4 | 48.3 |
| *High price scenario* | 37.8 | 10.7 | 1.5 | 91.9 |

[8] Values from October 2021 to February 2022 are used, as data for a time period beyond February 2022 was not available at the point of the creation of this study and the sharp increase in spot market prices was seen approx. from October 2021.

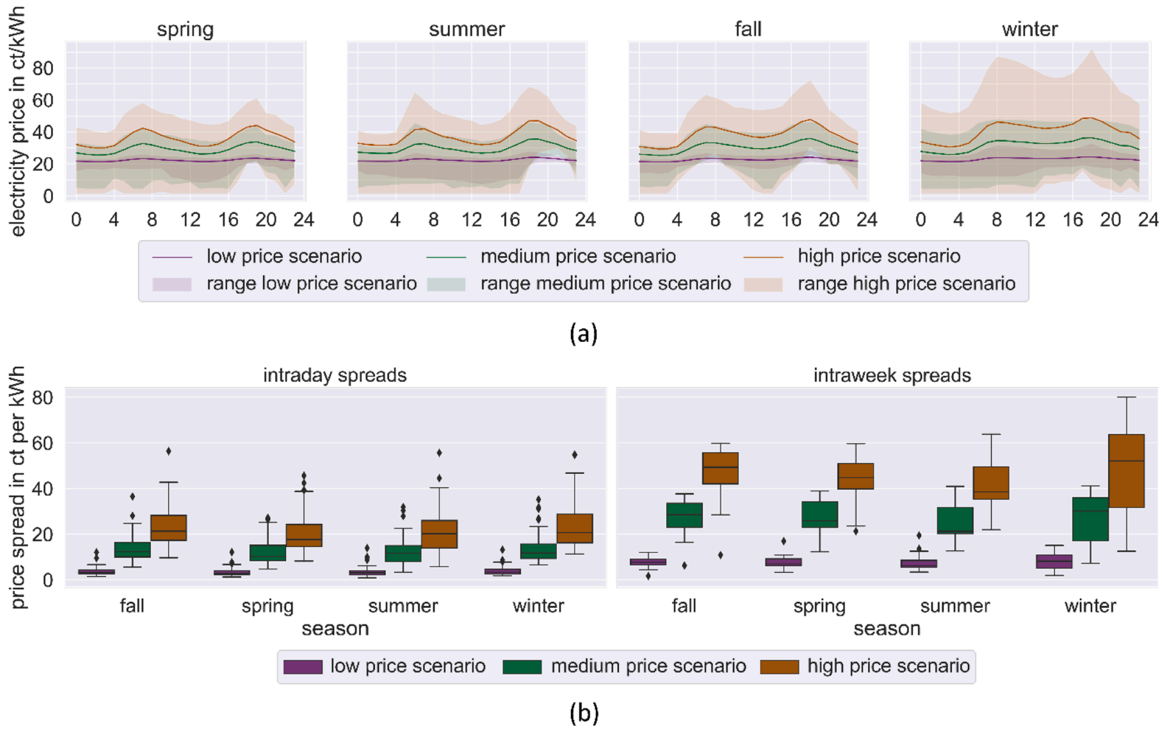


**Fig. 3.** (a) Average prices and range for each hour of the day broken down by season for the three price scenarios; (b) Intraday and intraweek price spreads for the three price scenarios.

**Table 3**
PV market values for the three electricity price scenarios.

| *Electricity price scenario* | *PV market value $MV_{solar}$* |
|---|---|
| *Low price scenario* | 3.62 €ct/kWh |
| *Medium price scenario* | 9.71 €ct/kWh |
| *High price scenario* | 15.81 €ct/kWh |

**Table 4**
Technology specific parameters for the underlying case study.

| *Technology* | *Parameter* | *Value* |
|---|---|---|
| *Battery storage system* | C-Rate | 1 |
| | Round-trip efficiency | 0.95 |
| | Standby losses | 0.01 %/h |
| *Electric vehicle* | Energy consumption while driving | 0.15 to 0.20 kWh/km |
| | Usable battery capacity | 34.2 to 90.0 kWh |
| | $E_{\min,\mathrm{departure}}$ | 80 % of maximum range |
| | $E_{\min,\mathrm{charge}}$ | 20 % of maximum range |
| | Charging power | 11 kW |
| | Standby losses | 0.01 %/h |
| *Heating system* | $T_{\mathrm{high,max}}$ | 50 °C |
| | $\eta_{\mathrm{COP}}$ | 0.4 |
| | Standby losses | 0.2 %/h |

### *2.3.2. Resulting PV feed-in tariff for each electricity price scenario*

The feed-in from PV systems will be remunerated with the market value of the underlying price scenario (see Table 3) .[9] The market value is obtained as described in Section 2.1.2.

### *2.3.3. Load and generation data, and technology specific parameters of buildings*

Building data includes load and generation profiles, temperature profiles, and further technology specific parameters. General information on data sources is given below. Technology specific parameters are shown in Table 4.

*Household load profiles.* To cover the heterogeneity of household load profiles, we use residential load profiles of 316 households from a smart meter field study carried out in Austria and Germany [23]. An overview of the households' annual electricity consumption can be found in Fig. Annex 1(a).

*PV generation profile and design.* For buildings with a PV system, we adjust the installed capacity to the annual electricity consumption of each household. We do this by using information from [24]. For an overview of the installed capacity for all PV systems considered, see Fig. Annex 3(a). The PV generation profile is taken from renewables.ninja[10] for the year 2019 and the city of Karlsruhe.

*Battery storage system design.* To determine the usable battery capacity of the BSS for each household with a PV system, we consider two factors: the household's annual electricity consumption and the installed capacity of their PV system. The correlation between these factors and the usable battery capacity is obtained from [24]. The resulting distribution of usable battery capacity for the households considered can be found in Fig. Annex 3(b).

*Electric vehicle's driving and availability profiles.* The availability at the home location and the power output while driving EVs are taken from

[9] A constant value is selected because time-varying remuneration is generally not observed for smaller photovoltaic systems installed in single-family homes in Germany.

[10] Renewables.ninja is an open-source tool that considers historical weather characteristics and technical parameters to calculate supply profiles. For PV, we use an azimuth angle of 180° and a tilt of 35°. Provided by [25] and described in [26] and [27].

**Table 5**
Overview of the nine combinations of operational strategy cases for flexibility utilization and electricity price scenarios considered within the study.

| *Operational strategy case* | *Electricity price scenario* |
|---|---|
| No-flex | Low |
| | Medium |
| | High |
| SC-flex | Low |
| | Medium |
| | High |
| DT-flex | Low |
| | Medium |
| | High |

Ref. [28]. The data is computed with the vehicle diffusion model ALADIN,[11] which uses vehicle usage data from Ref. [32]. Fig. Annex 2(c) gives an overview of the yearly mileage of all EVs considered. The EV profiles are mapped to the households using socio-demographic data.

*Heating system design and temperature profile.* To determine the appropriate size of the HP for each building, we use the living space of the building, which was obtained from the aforementioned smart meter field study [23] .[12] The HP is sized according to the heating demand of the building, which is assumed to be 100 kWh/m$^2$/a. The heat demand profile is obtained from HotMaps [33] for the city of Karlsruhe (DE12). For consistency, the ambient temperature for the same year (2019) and location is obtained from the Climate Data Center of the German Weather Service (Deutscher Wetterdienst) for Station ID 4177 [34].

The heat storage is designed to meet the maximum heat demand for two consecutive hours.

### 2.4. Case study

We consider different technology combinations, operational strategies, and electricity price scenarios. By this, we address the research gap of possible interactions between multiple flexible technologies within one household. We examine three different cases regarding the utilization of flexibility in households, which are described in detail in Section 2.2: the no-flex case, the SC-flex case, and the DT-flex case. Each case is simulated for each electricity price scenario described in Section 2.3.1, resulting in nine observations (see Table 5). For each observation, results are analyzed for the 316 households and nine technology combinations to account for heterogeneity in households, which sums up to 2,844 profiles for each observation. The technology combinations considered are shown in Fig. 4.

To thoroughly investigate the research questions introduced in Section 1, we have structured our analysis in a logical sequence:

- **Load curve analysis and analysis of electricity draw and self-consumption:** We analyze the difference in flexibility utilization via HEMS in households under dynamic electricity tariffs and households which increase self-consumption. We first examine the impact of HEMS utilization on household load curves, focusing on how and when the load is shifted. Subsequently, we investigate the variations in electricity drawn from the grid and self-consumption rates.
- **Economic benefits of dynamic electricity tariffs:** The financial implications of dynamic electricity pricing for households are evaluated. The effects on annual unit rate costs are examined. The focus lies on the interaction of multiple flexible technologies and the impact of varying average electricity prices and price spreads.

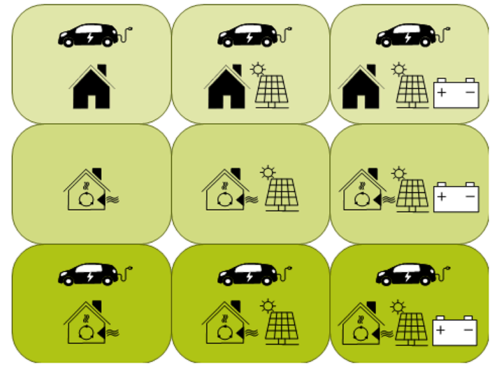

**Fig. 4.** Technology combinations of EVs, HPs, PV systems, and PV-BSS considered within the study.

- **Cost-benefit analysis:** We evaluate whether the potential cost savings outweigh the additional costs of HEMS in the SC-flex case and HEMS and metering point operation in the DT-flex case. We also assess the maximum tolerable costs for enabling technologies (HEMS, smart meter), that would allow at least 75 % of the households considered to still realize financial benefits from flexibility utilization, in either the SC-flex or the DT-flex case.

## 3. Results

### 3.1. Comparing flexibility utilization: dynamic electricity tariffs vs. self-consumption optimization

#### 3.1.1. Impact assessment: flexibility utilization and its influence on load curve dynamics

When analyzing the introduction of a HEMS in the SC-flex and DT-flex cases, significant shifts in the households' electricity consumption patterns can be observed, as shown in Fig. 5.

For households with an EV, the DT-flex case shows a notable change in the average hourly load curves, with the peak load shifting from evening hours to early morning hours, which is a result of the strategic use of lower electricity prices available during these times. The presence of a PV system or a PV-BSS reduces this effect, as households can leverage self-generated electricity for EV charging, reducing their dependency on electricity from the grid during high-cost periods. The load curves remain relatively consistent across the three electricity price scenarios.

The SC-flex case shows a distinct shift in load from evening to morning hours, with EV charging taking place later than in the no-flex and DT-flex cases, close to the daily departure time of the EVs. This is due to the HEMS's operation considering the self-discharge rates of EV batteries, optimizing charging times for energy efficiency.

For households with a HP, the DT-flex case shows a clear shift in load to the early morning hours, when electricity prices are at their lowest, and the afternoon. This shift is significantly influenced by the interplay between electricity prices and the temperature-dependent COP alongside the heating curve. During the day, when outside temperatures are higher, the HP operates more efficiently due to a higher COP. The load shift to the afternoon due to this efficiency gain is more noticeable in the low price scenario as price spreads are lower. This means that if the price spreads are higher, it is more likely that a lower COP can be compensated for and the load is shifted to times with the lowest electricity prices.

The incorporation of a PV system or a PV-BSS into households with a HP enables the use of self-generated electricity to power the heating system, which can be observed in the SC-flex case. However, in the DT-flex case, there is still an observed increase in load during the early morning hours, indicating a responsive behavior to dynamic electricity prices. The use of a HP has a more significant impact during winter

[11] For more information on the ALADIN model, we refer to [29,30], and [31]
[12] An overview on the living space of all households considered is given in Fig. Annex 1(b).

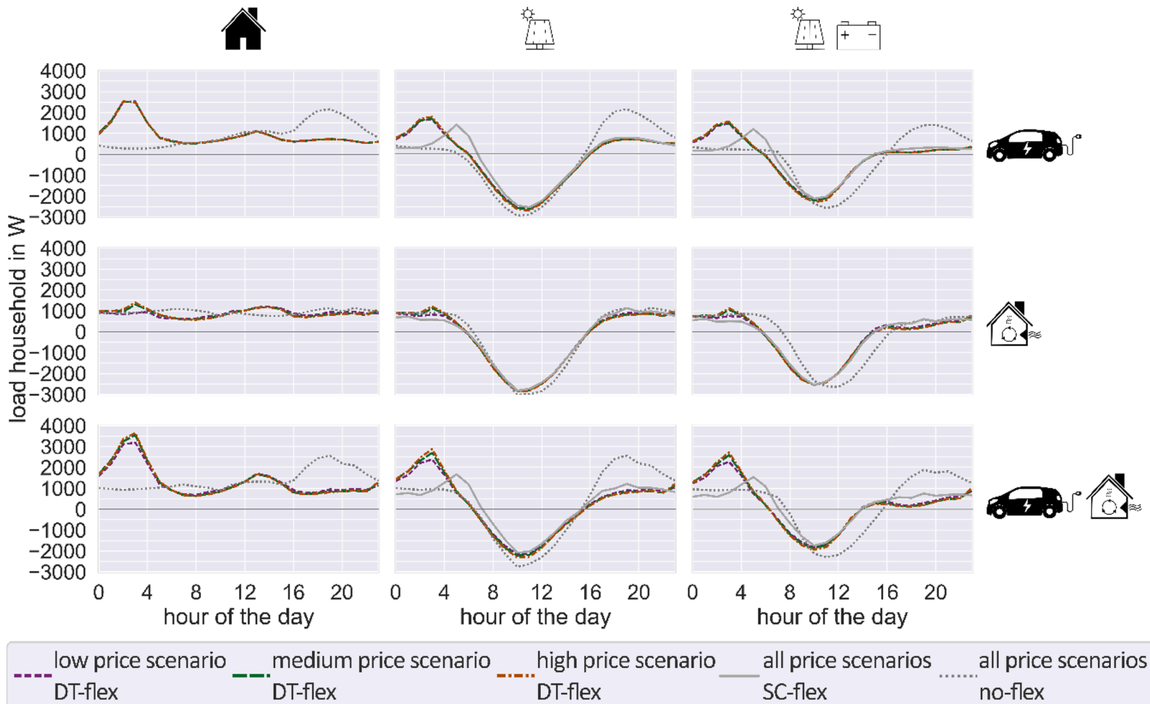


**Fig. 5.** Yearly average household load for each hour of the day including all households considered for the defined cases and scenarios.

**Table 6**
Time of day of the occurring load peaks for the technology combinations broken down by cases considered.

| *Available technologies* | *Load peaks no-flex case* | *Load peaks SC-flex case* | *Load peaks DT-flex case* |
|---|---|---|---|
| *EV* | Evening | – | Early morning |
| *EV + PV or PV-BSS* | Evening | Morning | Early morning |
| *HP* | Morning/ evening | – | Early morning/ afternoon |
| *HP + PV or PV-BSS* | Morning/ evening | Evening | Early morning |
| *EV + HP* | Evening | – | Early morning/ afternoon |
| *EV + HP + PV or PV-BSS* | Evening | Morning | Early morning |

months when the demand for heating is higher due to lower outside temperatures.

For households that have both an EV and a HP, the effects described above are combined. However, we observe a stronger impact from the EV effects.

For a comprehensive analysis, please refer to Fig. Annex 1, which provides a seasonal evaluation of the effect for each technology combination. Table 6 presents a summary of the time of day when load peaks most likely occur across the technology combinations and operational strategy cases.

### *3.1.2. Analyzing the impact on electricity draw and self-consumption rates*

The analysis of load curves showed the effective use of flexibility provided by the HEMS in managing HP operations. This is further demonstrated by the reduction in annual electricity draw from the grid. In the DT-flex scenario, a significant decrease in annual electricity draw ranging from 2.4 % to 10.9 % across all households is observed, highlighting the HEMS's ability to optimize energy efficiency by leveraging hours with higher COP values to operate the heating system.

When comparing households with a PV system or a PV-BSS to the no-flex case, both the SC-flex and DT-flex cases show improvements in self-


**Fig. 6.** Average self-consumption rate for the SC-flex and DT-flex case for all three price scenarios.

consumption rates in all price scenarios, with rates reaching up to 62.1 % (as shown in Fig. 6). This maximum improvement is observed for households with an EV, a HP, and a PV-BSS. In the low price scenario, self-consumption rates are similar across the SC-flex and DT-flex cases for all technology combinations. However, in scenarios with higher electricity prices, the DT-flex case exhibits lower self-consumption rates because the HEMS shifts the load towards hours with lower electricity prices, rather than solely focusing on increasing self-consumption.

### *3.2. Evaluating economic benefits of dynamic electricity tariffs: analysis of multiple flexible technology combinations and price scenarios*

The households' annual unit rate costs are impacted by the changes


**Fig. 7.** Annual unit rate costs for the no-flex, SC-flex, and DT-flex cases for all three price scenarios (average over all households).

benefit the most, with potential savings of up to 821 %[13] (for households with an EV and a PV-BSS). However, households with a HP and a PV system experience lower cost savings on average in the DT-flex case compared to the SC-flex case in terms of annual unit rate costs, as the HEMS is not able to shift the load of HPs as freely as the load of EVs. This is because HPs must follow a relatively steady heat demand of the household with a comparably small storage capacity. As a result, electricity consumption cannot be completely shifted away from hours with high prices, especially in the evening hours. This results in higher overall costs as the unit rate for the dynamic tariff during peak hours can exceed the rate offered by the static tariff.

### *3.3. Assessing the cost-effectiveness of HEMS and smart meters: do savings outweigh additional expenses?*

#### *3.3.1. Evaluating the financial attractiveness of HEMS and smart meter integration*

Assuming an investment of €1500 in the HEMS, the estimated annualized costs are 167 €/yr.[14] Additionally, the metering point operation costs of 7.5 €/month result in annual costs of €90. Fig. 8 shows the distribution of the most financially attractive option for households in each price scenario, considering these additional costs.

The analysis shows that higher price scenarios make it more financially attractive to adopt a HEMS and a dynamic tariff. It is important to note that households with an EV benefit more from dynamic tariffs than

**Table 7**
Relative change in unit rate costs averaged over all households for the SC-flex and DT-flex cases, reference case: no-flex case.

| *Available technologies* | *SC-flex case* | | | *DT-flex case* | | |
|---|---|---|---|---|---|---|
| | Low price scenario | Medium price scenario | High price scenario | Low price scenario | Medium price scenario | High price scenario |
| *EV* | – | – | – | −4 % | −11 % | −15 % |
| *EV + PV* | −29 % | −44 % | −72 % | −33 % | −61 % | −112 % |
| *EV + PV-BSS* | −43 % | −175 % | −404 % | −51 % | −272 % | −821 % |
| *HP* | – | – | – | −6 % | −5 % | −5 % |
| *HP + PV* | −25 % | −38 % | −103 % | −23 % | −35 % | −97 % |
| *HP + PV-BSS* | −30 % | −116 % | −400 % | −30 % | −126 % | −485 % |
| *EV + HP* | – | – | – | −7 % | −12 % | −14 % |
| *EV + HP + PV* | −26 % | −29 % | −52 % | −28 % | −37 % | −72 % |
| *EV + HP + PV-BSS* | −27 % | −44 % | −70 % | −30 % | −60 % | −114 % |

in self-consumption, annual electricity drawn from the grid, and the use of dynamic tariffs. Fig. 7 shows that the annual unit rate costs averaged across all households differ significantly across the three price scenarios and the three operational strategy cases considered. Table 7 presents the average cost savings for all households between the SC-flex and no-flex cases, as well as between the DT-flex and no-flex cases.

The SC-flex case demonstrates a reduction in annual unit rate costs across all price scenarios when compared to the no-flex case, ranging from 25 % to 404 % depending on the available technologies and price scenario. In the low and medium price scenarios, households with an EV benefit more than those with a HP. However, in the high price scenario, households with a HP and a PV system benefit more.

The introduction of a dynamic tariff in the DT-flex case results in further cost reductions in almost all cases. Households with an EV

those with a HP, due to annual unit rate cost savings being lower for households with a HP, and therefore the additional metering point operation costs for the DT-flex case not being easily offset. Therefore, the SC-flex case is more financially attractive for households with a HP. In the high price scenario, 85.4 % of households that own an EV choose the DT-flex case, while only one household with a HP would choose this option. When a PV system is incorporated, the SC-flex case becomes the most financially attractive option for all households equipped with a HP in the medium and high price scenarios. For households that have both an EV and a HP, the dynamic tariffs under the DT-flex case offer even greater financial benefits. In the medium price scenario, 93.7 % of these households consider the DT-flex case to be the financially most attractive option, increasing to 99.4 % in the high price scenario. Finally, the financial attractiveness of the DT-flex and the SC-flex cases for

[13] For households equipped with a PV-BSS or a PV system, the percentage change in costs can be significantly high, particularly since overall electricity expenses are relatively low in the no-flex scenario.

[14] With an assumed lifetime of 10 years and an interest rate of 2 %

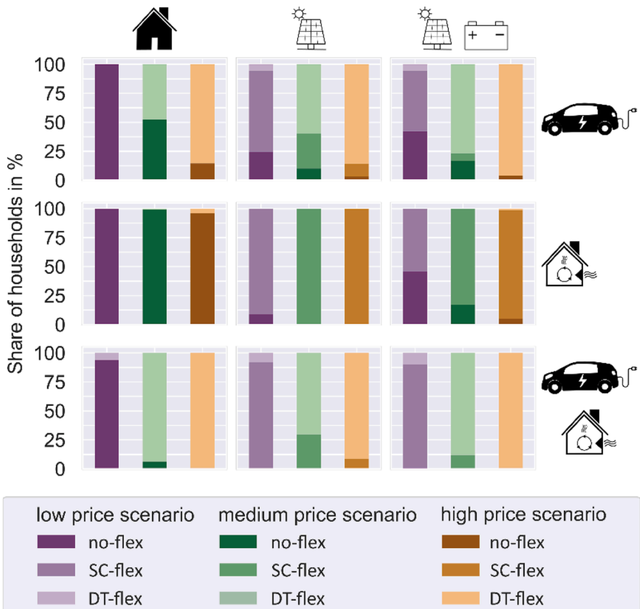


**Fig. 8.** Distribution of the most financially attractive option across all households for all electricity price scenarios and technology combinations.

households with an EV, a HP or both can be further increased by adding a PV system or a PV-BSS.

### *3.3.2. Threshold analysis: determining the maximum tolerable costs of HEMS and smart meter for incentivizing flexibility*

Our analysis highlights the importance of considering the investment costs in a HEMS and metering point operation costs when determining the financial attractiveness of using a HEMS, as well as dynamic tariffs. Therefore, we determine the maximum tolerable costs while still promoting the adoption of HEMS or dynamic tariffs. To do this, we assume that households will invest in a HEMS or a HEMS in combination with dynamic tariffs in the SC-flex and DT-flex case only if they can cover the costs of HEMS and metering point operation through savings in their annual unit rate costs compared to the no-flex case. We define the maximum tolerable costs of the HEMS and metering point operation as the annual unit rate cost savings.

Determining the maximum tolerable costs for all technology combinations and all three price scenarios shows a significant variation across households (refer to Fig. Annex 4), with less variance for households with a HP than for households with an EV. In reality, it is unlikely that all households will be incentivized to utilize their flexibility. Therefore, this analysis focuses on the 75th percentile of all households (refer to Table 8).

In the SC-flex case, households equipped with an EV and a PV system can tolerate maximum annual costs for the HEMS ranging from €171 in the low price scenario to €196 in the high price scenario. The addition of a BSS reduces these tolerable costs to between €126 and €145. For households equipped with a HP, a PV system or PV-BSS, the range of maximum tolerable costs for the HEMS is wider, ranging from €146 in the low price scenario (HP and PV-BSS) to €282 in the high price scenario (HP and PV system). Households that have both an EV and a HP can tolerate even higher costs for the HEMS.

In the DT-flex case, which additionally considers metering point operation costs, there is potential for higher maximum tolerable costs. For households with an EV and a PV system, the maximum tolerable costs range from €211 in the low price scenario to €413 in the high price scenario. For households with only an EV, the maximum tolerable costs range from €50 in the low price scenario to €316 in the high price scenario. For households with a HP, which tend to see lower cost savings in the DT-flex case, leading to correspondingly lower maximum tolerable costs, ranging from €84 in the low price scenario to €111 in the high price scenario. Introducing a PV system increases the maximum tolerable costs for HEMS and metering point operation to €186 in the low price scenario and €237 in the high price scenario. In the low and medium price scenarios, an additional BSS decreases the maximum tolerable costs.[15] However, in the high price scenario, the maximum tolerable costs increase slightly.

The analysis of the DT-flex and SC-flex cases shows clear patterns in the maximum tolerable costs for the considered technology combinations and electricity price scenarios:

- In the **DT-flex case**, households that solely own an EV have the lowest maximum tolerable costs in the low price scenario, at €50. In the medium and high price scenarios, households that solely own a HP have the lowest maximum tolerable costs, at €97 and €111, respectively.
- In the **SC-flex case**, households with an EV and a PV-BSS determine the lowest maximum tolerable costs in all price scenarios. The costs range from €126 in the low price scenario to €145 in the high price scenario.

**Table 8**
Maximum annual tolerable costs for the investment costs for HEMS or both, the investment costs for HEMS and metering point operation costs for smart meters for the SC-flex and DT-flex case, and all electricity price scenarios.

| | *SC-flex case* | | | *DT-flex case* | | |
|---|---|---|---|---|---|---|
| *Price scenario* | Low | Medium | High | Low | Medium | High |
| *EV* | – | – | – | €50 | €188 | €316 |
| *EV + PV* | €171 | €183 | €196 | €211 | €310 | €413 |
| *EV + PV-BSS* | €126 | €136 | €145 | €171 | €291 | €420 |
| *HP* | – | – | – | €84 | €97 | €111 |
| *HP + PV* | €200 | €241 | €282 | €186 | €209 | €237 |
| *HP + PV-BSS* | €146 | €183 | €220 | €144 | €197 | €255 |
| *EV + HP* | – | – | – | €153 | €330 | €501 |
| *EV + HP + PV* | €354 | €410 | €466 | €390 | €545 | €695 |
| *EV + HP + PV-BSS* | €281 | €331 | €383 | €324 € | €500 | €694 |

## 4. Discussion

We present a synthesis of our findings to address the research questions posed, while also acknowledging the limitations of our study.

### *4.1. Synthesis of findings*

Comparing the utilization of flexibility via HEMS in households under dynamic electricity tariffs with self-consumption in households equipped with a PV system, a difference can be observed in when peak loads occur at the grid connection point. In the SC-flex case, there is a peak in the morning hours for households with an EV, while the load is comparatively steady for households with a HP. The analysis of the DT-flex case shows a shift in households' load to the early morning hours and an increase in peak load when electricity prices are the lowest for households with an EV or a HP. The study finds that air/water HPs need a larger spread between high and low prices to respond effectively to dynamic electricity tariffs. Otherwise, households with only a HP experience a load shift mainly towards midday. The midday load shift is caused by the interaction between the ambient temperature-dependent COP and dynamic prices. Additionally, the results show that households with an EV or a HP in combination with a PV system or PV-BSS have an increase in self-consumption rates for both the DT-flex and the SC-flex

[15] The reason for this is that households with a BSS already experience lower overall electricity costs even without making use of flexibility. Hence, the additional cost savings gained through flexibility utilization in such households are relatively modest.

cases. Self-consumption rates in the DT-flex case are slightly lower and decrease with higher price scenarios.

Regarding the interaction of multiple flexible technologies and varying price spreads on the economic benefits of dynamic electricity tariffs, our analysis indicates that higher electricity prices and wider price spreads increase the financial incentives for households to use the flexibility of their HPs and EVs, both independently and in combination with PV systems and PV-BSSs. Cost savings can be achieved for both the DT-flex and SC-flex cases when using appropriate enabling technologies such as HEMS and smart meters. The highest benefits are observed in households with both an EV and a HP, emphasizing the importance of accounting for the interaction between both. In case a dynamic tariff is used, the largest benefits can be seen for households with an EV. Our findings align with those in Refs. [12,13]. However, Ref. [14] suggests that households with both an EV and a PV system could achieve higher cost savings by optimizing self-sufficiency rather than using a DA-RTP tariff. This contradicts our findings, but is likely due to the higher price spreads assumed in our calculations. According to our findings, households with a HP can achieve cost savings by using a dynamic tariff. These results are consistent with those found in Refs. [18–20]. However, our results indicate that the financially best choice for households with a HP is using a HEMS to increase self-consumption with a static tariff (SC-flex case). This highlights the importance of comparing the use of dynamic tariffs not only with the case of no flexibility use at all but also with the case of smart operation of flexible technologies for self-consumption.

Considering the associated costs of HEMS and smart meters and the question if possible cost savings from utilizing flexibility compensate for them, we analyzed the highest tolerable costs for both technologies that would still make the utilization of flexibility financially appealing for 75 % of the households considered. Households equipped with both an EV and a HP can tolerate the highest costs while benefiting the most from their flexibility utilization. Our results show that households with both an EV and a PV-BSS have the highest tolerable costs for the HEMS across all electricity price scenarios in the SC-flex case. For the DT-flex case, households with only an EV present the lowest tolerable costs in the low price scenario. However, in the medium and high price scenarios, this shifts towards households equipped with a HP.

### 4.2. Limitations of the study

To address the issue of data uncertainty in our modeling, we implemented strategies to ensure the reliability of our findings despite the limitations of our input data. Our model incorporates a comprehensive set of household load profiles to accurately reflect the heterogeneity of household behaviors and energy consumption. This approach aims to reduce the influence of the peculiarities of a single data set on our overall results. Lastly, the dataset we used in this paper has been used and validated by previous studies by various researchers [36,37].

To cover a wide range of potential future electricity market prices, our analysis examines three different price scenarios. These scenarios are based on recent trends observed in 2021 and 2022 to project higher price levels and larger price spreads, which are also anticipated with the growing share of renewable energies. Our scenarios aim to capture this, considering that actual electricity prices are subject to a multitude of factors, including the increase in renewable energies, the decommissioning of fossil fuel plants, and the electricity market design. While forecasting future electricity prices is beyond the scope of this paper, we can derive from our results that the future electricity mix with even higher shares of renewables and thus increased price spreads will make dynamic tariffs even more attractive.

Additionally, our analysis accounts for seasonal variations by using whole-year profiles to model energy consumption and generation. This ensures that fluctuations in household electricity demand and PV generation across different seasons are captured, which makes the study more comprehensive and provides a more accurate reflection of the year-round dynamics of household energy management under a dynamic pricing scheme.

However, our study acknowledges specific limitations, particularly regarding the representation of ambient temperature and PV generation profiles. The decision to model based on a single weather year introduces a simplification that may not fully encapsulate year-to-year variations in weather conditions, which could directly affect self-consumption levels and the operational efficiency of PV systems and PV-BSS. Expanding the analysis to include multiple weather scenarios would enhance the understanding of dynamic electricity tariffs' potential impacts.

Furthermore, although our model assumes perfect foresight in energy management decisions, we acknowledge the practical challenges of forecasting errors in real-world scenarios. To address this issue, we have included a rolling horizon scheme within the EVaTar-building model. This scheme attempts to approximate the impact of such forecasting errors, thereby providing a more nuanced and realistic assessment of the benefits and limitations of dynamic electricity tariffs and HEMS. Future iterations of our model could benefit from additionally integrating stochastic modeling techniques, as suggested by [35], to further refine our analysis by accounting for the probabilistic nature of many input variables. This would enhance the model's predictive accuracy and reliability.

The findings of our study demonstrate that the strategies analyzed can effectively be used for a variety of households, despite their heterogeneity. For EV charging, we considered heterogenous driving and availability profiles, but did not account for differences in individual household preferences or control affinity (as for example in [38]), which could influence the adoption of dynamic tariffs.

Our case study specifically focuses on air/water HPs. It is important to note that other types of HPs, such as brine/water, may offer different benefits due to their more stable COP, which may enhance their responsiveness to price signals. Our model assumes a constant indoor temperature, which simplifies real-world complexities. For example, households may adjust their thermostatic settings during high energy costs, which could further optimize energy flexibility.

Our study, which is centered on Germany, utilizes different price scenarios, and can therefore provide insights for other regions with comparable market dynamics and end-user costs. Our research contributes significantly to a better understanding of the value of flexibility in energy systems, aiding in the more effective integration of renewable energies and laying the groundwork for smart readiness. These aspects are crucial not just within the German context but also hold significant importance internationally, demonstrating the broader applicability of our study's insights. Our findings are particularly pertinent to regions that have already implemented dynamic tariffs, such as Norway, which also has a more advanced distribution of electric heating and EVs. For southern countries, where air conditioning plays a significant role in households' energy consumption, additional analyses including the flexibility of this technology could enrich the understanding of the effects on dynamic tariffs.

Within the study, we consider the additional costs for households incurred by the investment in a HEMS and metering point operation costs. In the context of developing new business models that pair dynamic electricity tariffs with HEMS, it is important to recognize the ancillary costs for suppliers. These include transactional expenses, data sharing, and the costs associated with forecasting weather, load, generation capacity, and pricing.

The upfront costs of EVs, HPs, or BSSs are not discussed in this study, as it assumes these technologies are acquired with expectations of static tariffs, and potential cost savings through dynamic tariffs are considered post-purchase. Including the investments would broaden the results but is outside the scope of this analysis.

Lastly, our analysis suggests broader implications for energy systems, indicating areas for future investigation, such as the potential of conflicting price signals with the introduction of dynamic grid charges and the retroactive effects of flexibility utilization on market dynamics. A holistic approach to modeling energy market responses is important due to the significant influence that factors can have on load shifting incentives and outcomes.

## 5. Summary and conclusion

Although dynamic electricity tariffs are already widely examined in the literature, we identified four important research gaps: (1) considering multiple flexible technologies and also the interaction between them, (2) explicitly comparing the benefits of dynamic tariffs with flexibility utilization to enhance self-consumption, (3) accounting for load variability and household heterogeneity and (4) adding the costs for intelligent metering and control infrastructure when evaluating dynamic tariffs. We addressed these gaps in the literature by analyzing the effects of higher electricity prices and larger price spreads on the financial attractiveness of the smart operation of electric vehicles and heat pumps.

Based on 316 measured household load profiles including various technologies such as electric vehicles, heat pumps, PV systems and battery storage systems, we used a MILP model to maximize the electricity cost savings for households.

Our findings show that dynamic electricity tariffs based on the day-ahead spot market price in Germany can offer significant economic benefits to a wide variety of households and therefore incentivize them to use the flexibility provided by electric vehicles and heat pumps. The key to realizing these benefits is to ensure that the financial gains from dynamic electricity tariffs and increased self-consumption outweigh the additional costs for buying and installing a home energy management system and metering point operation costs. Specifically, we found that the recent trend on the day-ahead spot market in Germany during the energy crisis 2021/2022, which saw the average electricity price increase by 15.2 €ct/kWh (+67 % of the average for the year 2019) and the average price spread increase by 8.9 €ct/kWh (+494 %), greatly enhances the attractiveness of dynamic tariffs, with the proportion of households achieving cost savings increasing from 3.9 % to 62.5 %.

Our findings suggest that dynamic tariffs can effectively enhance flexibility utilization and help to combat rising electricity costs for households. However, depending on the available technologies, these tariffs are not necessarily the best choice financially. Notably, for households with a heat pump, optimizing self-consumption, especially when combined with a photovoltaic (PV) system or a PV battery storage system, can lead to greater savings than dynamic tariffs. At the same time, however, flexibility from these households could be critical to alleviate grid congestion in winter due to the anticipated simultaneous heating demands and to facilitate wind energy integration. If this flexibility is to be utilized, price incentives must be sufficiently attractive, or the costs for home energy management systems and metering point operation need to be low enough to ensure households with a heat pump respond to dynamic pricing signals rather than only using their flexibility to maximize their own self-consumption.

From a market perspective, it can be advantageous for the providers of home energy management systems to offer their systems to households that have both electric vehicles and heat pumps, as this is where the most significant savings potential lies, although this also means additional challenges in terms of the interoperability of components.

The cost savings associated with a home energy management system and/or dynamic tariffs can make technologies such as heat pumps and electric vehicles financially more attractive and help promote a faster energy transition.[16] To further promote greater flexibility provision in residential electricity demand, efforts should focus on expanding rooftop PV systems, as the potential cost savings increase for households with electric vehicles and heat pumps when a PV rooftop system is added. At the same time, reducing the costs associated with smart meter operation and accelerating the smart meter rollout could further incentivize dynamic tariff adoption.

In conclusion, making use of the flexibility of electric vehicles, heat pumps and PV battery storage systems can mitigate rising electricity costs for a large number of households provided that business models and pricing schemes create sufficient incentives for all parties involved.

## CRediT authorship contribution statement

**Judith Stute:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Sabine Pelka:** Writing – review & editing. **Matthias Kühnbach:** Writing – review & editing, Conceptualization. **Marian Klobasa:** Writing – review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

The authors do not have permission to share data.

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## Annex

[16] If we assume an investment of €25,000, an interest rate of 2 % and a lifetime of 15 years for electric vehicles, the annual annuity is €1,375. In comparison yearly savings of €420 (so roughly 30 % of the annual annuity) were achieved in the high price scenario for a household with an electric vehicle and a PV battery storage system; If we make the same assumptions for the annual annuity of heat pumps, we can compare this to yearly savings of €255 (around 18 % of the annual annuity) for households with an additional PV battery storage system.

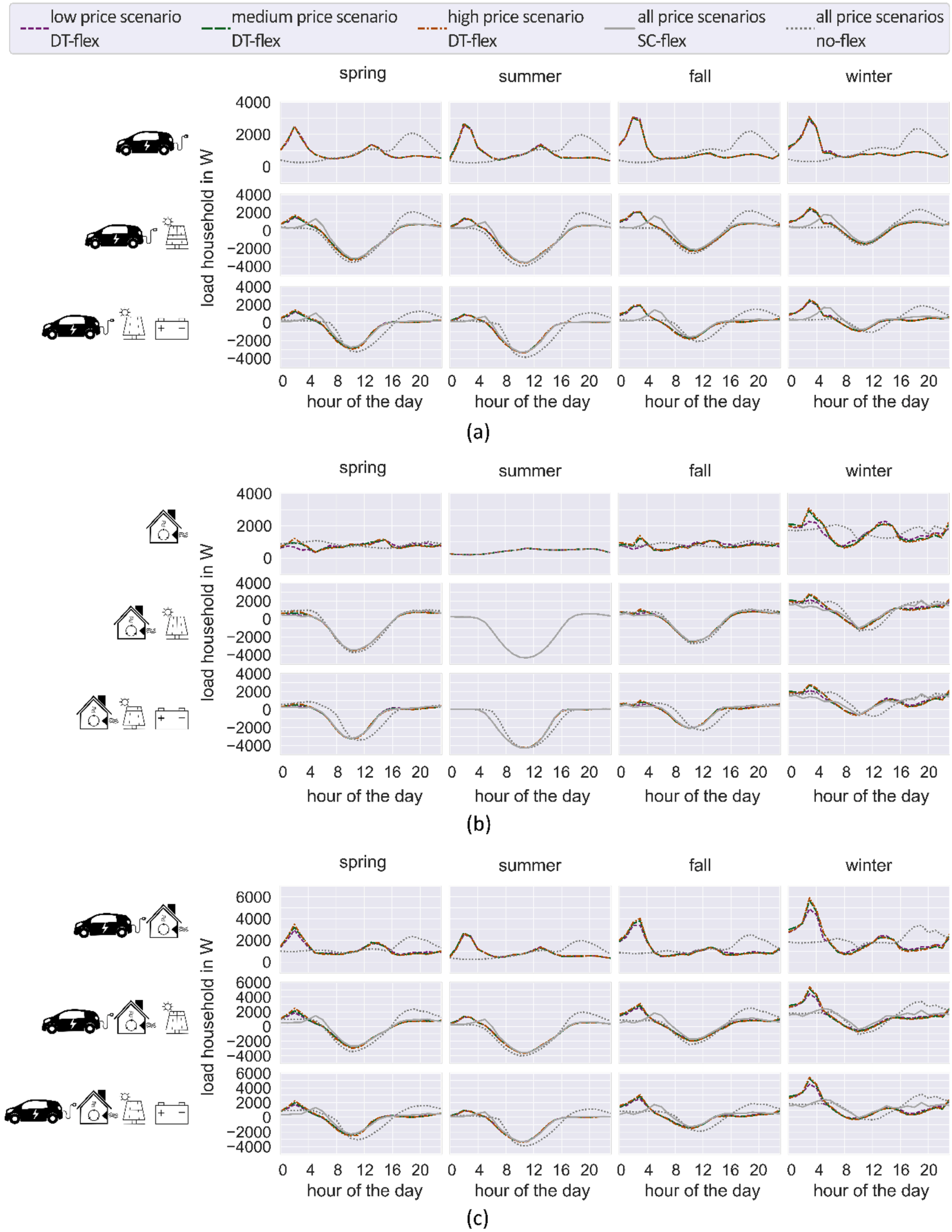


**Fig. Annex 1.** Average household load per season for each hour of the day including all households considered for the defined cases and scenarios.

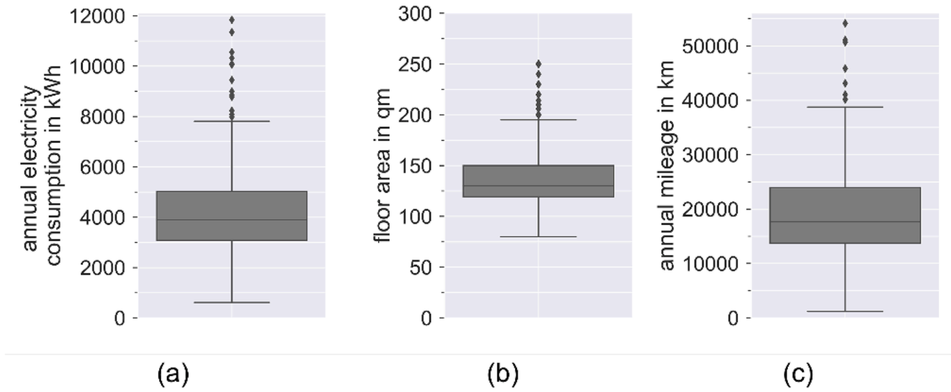


**Fig. Annex 2.** (a) Boxplot of annual electricity consumption for all households considered; (b) Boxplot of the heated floor area of all households considered; (c) Boxplot of the annual mileage of all EVs considered.

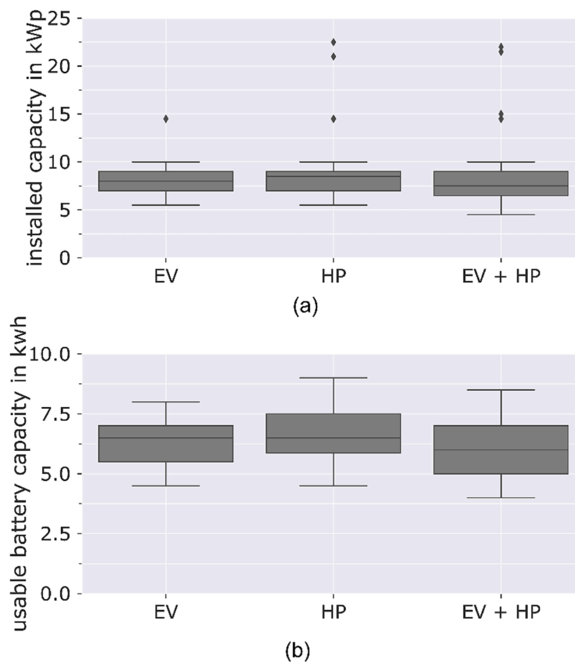


**Fig. Annex 3.** (a) Boxplot of the installed PV capacity for all households with an EV, a HP, or an EV and a HP; (b) Boxplot of the usable battery capacity for all households with an EV, a HP, or an EV and a HP.

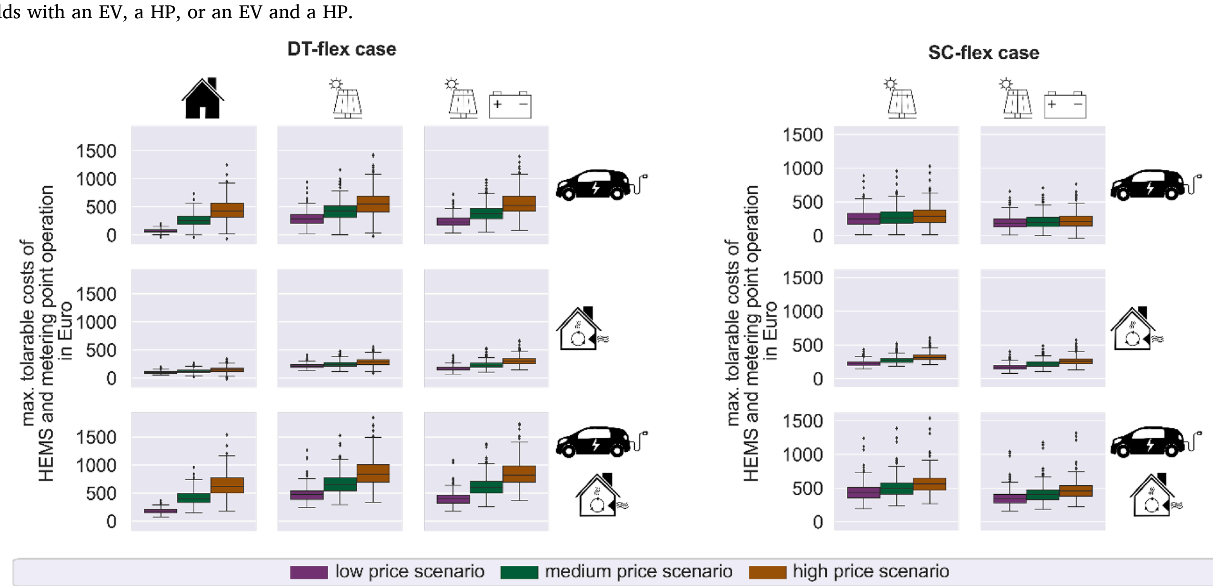


**Fig. Annex 4.** Max. tolerable costs of HEMS and metering point operation to make the utilization of flexibility financially attractive for households. Results are shown for the DT-flex (left) and the SC-flex (right) cases for all three price scenarios.

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