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Do dynamic electricity tariffs change the gains of residential PV-battery systems? A simulation-based evaluation using data from 448 households

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HIGHLIGHTS

- Battery energy storage systems (BESS) benefit from dynamic tariffs.
- Dynamic tariffs yield 12.7 % higher net gains than fixed tariffs on average.
- Perfect day-ahead forecasting increases profits by 6 % over naïve forecasting.
- Linear optimization with perfect data boosts profits by 14 % over rule-based methods.
- Findings guide homeowners, policymakers, and utilities on BESS and tariff adoption.

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ABSTRACT

Residential battery energy storage systems (BESS) and dynamic electricity tariffs are important building blocks for grid integration of renewable electricity. While various BESS operation strategies have been studied, a systematic comparison under dynamic tariffs (real-time pricing) is missing. Using rule-based and linear optimization approaches grounded on 5 years of data from 448 households, we estimate upper and lower bounds of net gains from using fixed and dynamic pricing. For a 10 kWh BESS, dynamic tariffs at a similar price level as fixed tariffs yield 12.7 % higher net gains, even under a price-agnostic self-consumption maximization strategy. We find that a perfect day-ahead forecast increases net profits by 6 % compared to naïve forecasts (e.g., previous day / week). Compared to a simple rule-based approach, operating BESS with linear optimization over a full-year of perfect information generates additional net profits of 14 %. With day-ahead forecasting, BESS above 15 kWh are best operated by maximizing self-consumption. Our findings offer practical guidance for homeowners considering investments and demonstrate benefits of switching tariffs. They also support policymakers in designing subsidies and regulations for private BESS and dynamic tariff adoption. For utility companies, the results help advance tariff schemes to redistribute market risks and realize grid flexibilities.

1. Introduction

In 2020, approximately 20 GWh of battery capacity had already been installed worldwide, and the available capacity is expected to grow to more than 150 GWh by 2026 (IEA, 2021). Hence, residential battery energy storage systems (BESS) are an essential building block of the energy transition. Many homeowners invest in the technology because it allows them to store self-produced electricity during sun hours, reduces the dependence on the electricity grid at continuously increasing price levels, and provides backup in the event of power outages. Moreover, residential BESS are supported by extensive subsidy programs in many countries (Commission, 2017; Mehdi and Moerenhout, 2023; Comello and Reichelstein, 2019).

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Nomenclature

Indices

T	Yearly maximum time horizon
t	Hourly time step
τ	Time step iterator

Parameters

η_c	Efficiency rating (charging)
η_d	Efficiency rating (discharging)
c_{feedin}	Feed-in tariff (constant)
$c_{\text{demand}}(t)$	Time-dependent demand tariff
C	Battery charging rate
p_{bat}^{max}	Maximum BESS charging or discharging power
$e_{\text{bat}}^{\text{min}}$	Minimum BESS energy level in kWh
$e_{\text{bat}}^{\text{max}}$	Maximum BESS energy level in kWh
SOC_{min}	Relative lower bound of BESS energy
SOC_{max}	Relative upper bound of BESS energy
cap_{bat}	Total gross BESS capacity in kWh

Variables

$p_{\text{load}}(t)$	Hourly electricity demand
$p_{\text{PV}}(t)$	Hourly PV production
$p_{\text{net}}(t)$	Hourly net electricity demand
$p_{\text{bat}}^{\text{ch}}(t)$	Hourly charging energy
$p_{\text{bat}}^{\text{dis}}(t)$	Hourly discharging energy
$p_{\text{grid}}^{\text{feedin}}(t)$	Hourly grid feed-in
$p_{\text{grid}}^{\text{demand}}(t)$	Hourly demand from the grid
$e_{\text{bat}}(t)$	Hourly BESS energy level

Maximization of self-consumption is thereby often promoted by legislators in countries with high shares of renewable electricity (Semmelmann et al., 2024). Many countries (e.g., several U.S. states and some European countries) have net metering programs in place that incentivize the use of locally produced electricity (Smith et al., 2021). In such schemes, grid feed-in is comparatively unattractive (Best et al., 2021) and BESS allow storing surplus photovoltaic (PV) production and discharging when the load exceeds PV generation before leaving the owner to grid supply. Yet, residential BESS might be of greater value to society when operated according to strategies benefiting the distribution grid—a topic that should be explored particularly in countries where the technology is heavily subsidized. A study in this journal just recently concluded that promoting self-consumption hardly creates welfare, in some cases even generating additional costs to be socialized among energy customers (Semmelmann et al., 2024).

A stronger market orientation of the charging and discharging behavior of BESS could compensate for the fluctuations in generation from wind and PV systems—both have strong influences on the electricity market price. When distribution grids lack storage capabilities, renewable production facilities often need to be curtailed. The International Energy Agency (IEA, 2023) reckons that curtailment of renewable electricity sources ranges between 1.5 % and 4.0 % of total green electricity production in the majority of large renewable energy markets. A dramatic increase in these numbers can be expected, considering the ongoing investment in PV installations and wind turbines. At a worldwide electricity generation by solar and wind of approximately 3,500 TWh in 2022 (Ritchie et al., 2024), the curtailment would account for 52.5 to 140 TWh for wind alone (EIA, 2023). Thus, climate-friendly electricity is lost and the owners of the curtailed plants may need to be compensated in many regulatory schemes (Bird et al., 2016; Joos and Staffell, 2018), leading to higher electricity prices, grid fees and government spending (BDEW, 2023b).

Governments and grid operators seek ways to reduce the need for curtailment, for example, by introducing dynamic pricing schemes as market mechanisms for flexibility. Electricity prices that vary over time are instruments of demand response and can help shift consumption to times when more electricity is available (Stanelyte et al., 2022). Those shifts are induced by price signals, offering lower prices in times of excess production and higher ones during peak consumption or low production periods. Several studies demonstrate that a considerable reallocation of peak loads to time frames with lower demand or off-peak periods is possible using such price schemes (Carroll et al., 2014; Cosmo et al., 2014; Guo and Weeks, 2022). Consequently, some countries require energy retailers to offer dynamic tariffs (e.g., Germany as of 01/2025 (EnWG, S41a)). Dynamic tariffs allow for a shift from a price-agnostic (maximizing self-consumption) to a rather grid-oriented operation, enabling an optimized infrastructure utilization and lower overall system costs (Burger, 2019).

However, the measures to reduce curtailment and shift loads appear to be implemented relatively independently of government incentives for investments in residential battery storage. This may make one or the other less effective. Equally, research to date has not examined the operation of residential BESS under dynamic tariffs in detail: While studies related to the benefits of dynamic tariffs neglect to focus on batteries (Stute et al. (2024), for example, only include heat pumps and electric vehicles in their recent analysis), studies that explore BESS under dynamic tariffs (e.g., Norouzi et al., 2025) do not focus on installations in single residential units but on microgrids or large-scale batteries. This may explain why optimizing self-consumption is the currently prevalent operation strategy for residential BESS, although it may not necessarily be optimal in dynamic tariff environments with a strong focus on electricity price information. Thus, the introduction of dynamic tariffs questions self-consumption optimization as the method of choice for a cost-optimal BESS operation *ceteris paribus*.

This study therefore explores three Research Questions (RQs). First, ***RQ1****: To what extent are the net gains of residential BESS (with different sizes and characteristics) affected by switching from a fixed to a dynamic tariff setting, using a price-agnostic operation?* We define the net gains as the difference between the annual electricity bill of a household in the *status quo* and the bill considering the simulation of BESS. The focus of our study lies thereby on the evaluation of PV-BESS systems in use, where we consider charging and discharging the battery with PV-generated electricity, but not the initial investments.

We then explore the change in the operation strategy by answering ***RQ2****: How do price-sensitive, compared to price-agnostic, operation strategies influence the net gains from BESS?* For optimal control of electricity flows between BESS, household load, PV, and the grid, knowledge of future electricity demand, production, and prices is essential. As this information is difficult to accurately predict, we consider two extremes, perfect forecasts (using actual measurements in an ex-post analysis) and naïve ones (e.g., considering values from the previous day or week) to explore the bandwidth of net gains. Consequently, we investigate ***RQ3****: What is the difference in net gains grounding price-sensitive BESS operation on a perfect forecast and a naïve one?*

To answer the RQs, we consider four scenarios to determine the net gains from BESS operation based on hourly load, PV production, and price data. We base those scenarios on empirical data from 448 German households for the years 2019–2023, using rule-based and linear optimization approaches to determine upper and lower bounds on net gains for the household sample, considering perfect and naïve forecasts as well as fixed and dynamic pricing schemes.

Before we present the method, results, and policy implications of our study, the next chapter provides an overview of dynamic electricity tariffs and summarizes research on BESS operation strategies and outlines the need for further research.

2. Background and scope of this work

The literature on residential BESS is rapidly evolving. In the field of energy policy, several studies compare public subsidy schemes for upfront investment support and evaluate their impact on the economic viability of storage systems (e.g., Gamonwet and Dhakal, 2023; Biancardi et al., 2025). Others explore the long-term diffusion of BESS under varying regulatory environments, often based on extrapolated household-level data (e.g., Fett et al., 2021).

Due to their emphasis on initial investment decisions, these studies typically rely on strong assumptions regarding battery operation, which warrant closer scrutiny. In particular, operational strategies are often either not modeled explicitly or are based on idealized control logic, such as perfect foresight or deterministic load-shifting. As a result, the actual performance and profitability of BESS under different tariff regimes remain insufficiently explored at the household level.

Parallel to this, a growing body of research examines the role of dynamic electricity tariffs schemes for the operation of distributed flexibility assets. For instance, Norouzi et al. (2025) investigate the optimization of PV-battery systems under multiple tariff structures within a residential microgrid. Similarly, Stute et al. (2024) analyze the potential of flexible electricity consumption from heat pumps and electric vehicles in response to dynamic pricing. While informative, these studies lack a systematic comparison of market-based dynamic vs. fixed retail tariffs for a considerable sample of residential BESS, nor do they assess the trade-offs across different control strategies.

Another critical aspect that remains underexplored is the role of forecasting quality. As shown by Benalcazar et al. (2024), the accuracy of demand and PV generation forecasts significantly affects the ability to optimize BESS operation. Yet, many studies neglect the forecast uncertainty or assume perfect knowledge of future prices and loads. This raises the question of how much economic value accurate forecasting actually adds—and how sensitive battery profitability is to the quality of predictions.

This paper contributes to these debates by systematically comparing the operation of household-scale BESS under fixed and dynamic electricity tariffs (RQ1), evaluating a range of control strategies under varying assumptions of information availability (RQ2), and quantifying the value of forecast accuracy for residential battery economics (RQ3). Before we present the results of a structured literature review and synthesize research gaps, we briefly introduce key concepts of dynamic electricity tariffs and BESS operational models.

2.1. Electricity tariffs

The literature distinguishes between four overarching tariff categories: *fixed tariffs*, *time of use (TOU) tariffs*, *real-time tariffs*, and volume-based pricing.

Under the *fixed tariff* regime, grid electricity demand is charged at fixed rates per kWh consumed. Several works consider only a stable rate (Aniello et al., 2021; Fioriti et al., 2022; Nazari-Heris and Asadi, 2023), while others consider a yearly price increase (Angenendt et al., 2018, 2019; Olaszi and Ladanyi, 2017; Dietrich and Weber, 2018).

TOU tariffs split the hours of the day into different phases with fixed prices for each. First, several studies consider two rates that differentiate between on- and off-peak times (Sani Hassan et al., 2017; Heine et al., 2019; Yi et al., 2022; De Hoog et al., 2018). A second group of studies adds a “shoulder step” with price levels in between (Ali et al., 2021; Di Santo et al., 2018; Gil Mena et al., 2023; Li, 2019; Lu et al., 2022; Su et al., 2023). Third, some authors differentiate between weekdays (e.g., three different prices per day) and Saturdays / Sundays (two prices) (Talent and Du, 2018; Mulleriyawage and Shen, 2020, 2021). A fourth group of studies uses additional pricing logic depending on the time of the year (Kazhamiaka et al., 2019; Qi et al., 2019).

Real-time pricing, according to Borenstein (2005), revolves around very frequent changes in electricity prices reflecting the underlying market dynamics of supply and demand. While Hemmati and Saboori (2017) and Mbungu et al. (2020) do not explicitly state the origin of the dynamic prices considered, Koskela et al. (2019) simulate their end-consumer electricity price based on hourly day-ahead spot market prices, to which they add a fictitious retailer margin and value-added tax to. Pena-Bello et al. (2017) determine their dynamic tariff based on wholesale market prices including network usage, community services and renewable energy incentives.

Sometimes, utilities offer *volume-based* prices together with one of the above tariff schemes. These can come as rebates for customers with very high demand (e.g., above 100,000 kWh) or as progressive price schemes where customers with high demand are charged a higher price (Jung et al., 2020; Najafi Ashtiani et al., 2020; Shivam et al., 2021).

2.2. BESS operating strategies

To get an understanding of operational strategies for combinations of BESS and PV systems, we have conducted a systematic literature review. We started with a recent review article (Zhang et al., 2024) and extended our view on the topic by querying the ScienceDirect and Association of Computing Machinery (ACM) Digital Library databases. We defined a search string per library (Fig. 1) and limited the results to publications released between 2018 and 2024 to focus on the most recent results. We further condensed the search results by filtering for the relevant subject areas *Energy*, *Engineering*, *Environmental Science*, *Economics, Econometrics and Finance*, and *Material Science*. With the results in both sources sorted by relevance, we selected the best suiting ones based on the title for the first 1,000 most relevant papers each, resulting in 94 publications from ScienceDirect and 19 from ACM Digital Library. In the last exclusion step, we scanned the abstracts of those papers. We only kept publications for a thorough analysis that have the operation of BESS as primary subject.

Ultimately, our sample of studies consists of 40 papers (where 13 came from Zhang et al. (2024), 24 from ScienceDirect and 3 from the ACM digital library), which we included in a detailed analysis. The studies show a high variety of operational strategies, e.g., the combination of (i) the electricity tariffs considered, (ii) the underlying set of objectives, (iii) the algorithmic approach to fulfill these objectives, and (iv) the forecast used. Furthermore, some consider a scenario differentiation and evaluate multiple cases (base-case, worst-case, best-case, and combinations).

2.2.1. Objectives

We group the underlying sets of objectives into five categories.

Electricity - household perspective. Aside from a maximization of self-consumption, this first category also includes papers focusing on self-sufficiency or the objective of avoiding PV curtailment (e.g., Mulleriyawage and Shen, 2020, 2021). Others maximize user comfort, i.e., avoiding inconveniences from delaying intended appliance operation or violations of ideal conditions (Shakeri et al., 2018).

Electricity - grid operator perspective. This category has a similar focus, although from a different viewpoint. A common objective is peak-shaving or a minimization of grid impact. Riesen et al. (2017) aim for a minimization of curtailment losses, while Yi et al. (2022) concentrate on BESS operation for a maximization of load flexibility.

BESS-specific. Here, the focus solely revolves around maximizing the respective system’s lifetime (Angenendt et al., 2018, 2019; Rezaeimozafar et al., 2024a).

Environmental. Minimizing CO_2 emissions is the most prominent objective in this category (Ali et al., 2021; Lu et al., 2022; Yi et al., 2022). Two other studies target an increase in energy efficiency (Lu et al., 2022; Shakeri et al., 2018).

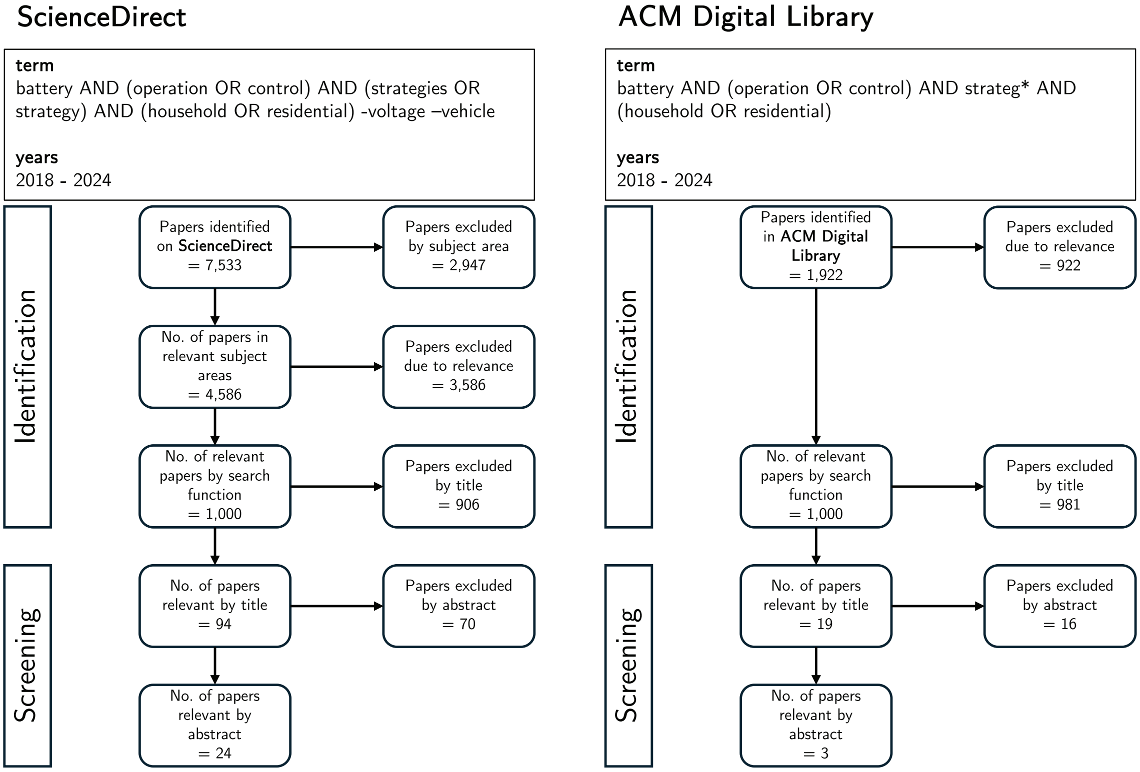

Fig. 1. Search and filtering process for relevant literature on residential BESS operation strategies.

Financial. This category contains a multitude of viewpoints. Some papers investigate the levelized cost of electricity resulting from the PV-BESS system (Angenendt et al., 2019; De Oliveira E Silva and Hendrick, 2017). Sani Hassan et al. (2017) aim at maximizing revenue through feed-in. Other investigations revolve around financial viability of the respective investment, determining net present value, payback time or rate of return (e.g., Talent and Du, 2018; Aniello et al., 2021; Fioriti et al., 2022). Authors who do not consider investment costs for their analyses mainly target a minimization of electricity costs (e.g., Ali et al., 2021; Di Santo et al., 2018; De Hoog et al., 2018; Kazhamiaka et al., 2019).

2.2.2. Algorithmic approaches

Algorithmic approaches used to reach the respective goals are diverse. For *Optimization*, most studies apply Mixed-Integer Linear Programming (e.g., Beck et al., 2016; Sani Hassan et al., 2017; Talent and Du, 2018; Jung et al., 2020) and Genetic Algorithms (e.g., Pena-Bello et al., 2017; Li, 2019). Others use an instance of the Multiple Knapsack Problem (Ali et al., 2021) or apply the JAYA algorithm (Gil Mena et al., 2023), which is a metaheuristic algorithm combining a particle swarm grounded approach with a genetic algorithm (da Silva et al., 2022). With Olaszi and Ladanyi (2017), Di Santo et al. (2018) and Rezaeimozafar et al. (2024b), only three publications make use of *Machine Learning* techniques for implementing BESS operation. The rest resort to *Rule-based* algorithms.

2.2.3. Forecasting used

Most studies rely on the application of the factual input data serving as a perfect forecast. The forecast horizon used (i.e., the number of future time steps considered per decision step) is often either full-day (e.g., Sani Hassan et al., 2017; Mbungu et al., 2020) or full-year (e.g., Najafi Ashtiani et al., 2020; Heine et al., 2019). Some authors, however, choose different approaches, e.g., using the estimated BESS life cycle (Fioriti et al., 2022) or a single time step following the decision step (Baraskar et al., 2024). The granularity of decision steps, i.e., the temporal resolution for which decisions are made usually is one hour or less.

2.3. Research needs and contributions of this study

In the scope of our study, we identify four areas that require further investigation. First, only few papers evaluate their proposed models with both, fixed and dynamic tariff settings. Pena-Bello et al. (2017) and Sani Hassan et al. (2017) do compare both settings with each other but allow for the BESS to be charged from the grid during off-peak times. A third study (Shivam et al., 2021) discusses fixed and dynamic tariff environments, but grounds their findings only on a single household profile. *Therefore, our RQ1 examines this aspect in detail.*

Second, the majority of studies draw conclusions based on a single entity (e.g., a single household profile). Just three publications (Fioriti et al., 2022; Li, 2019; Mulleriyawage and Shen, 2021) test their approaches on 100 or more household profiles. *We, thus, aim to provide a higher generalizability, taking 448 individual household profiles into account.*

Third, the use of real-world data—e.g., smart meter data, weather observations—for model building and evaluation is underrepresented. Many studies rely on other sources for gathering or generating the input data for model evaluation. Specialized software like the *LoadProfileGenerator* is used by Aniello et al. (2021) to *synthetically* generate data. Actual measurements from cases closely comparable with the one under study can serve as a *proxy*. Olaszi and Ladanyi (2017) use PV production data from a system located in Hungary to serve as input for a case in Munich. *Derived* data is calculated by assuming certain system characteristics (e.g., Gil Mena et al., 2023) and extending them with other influencing variables, like environmental conditions, if needed (e.g., Shivam et al., 2021). Of the 15 cases grounding their work on both, real-world measured load and PV production data, 14 develop their models on that particular historical data, assuming a perfect forecast (e.g., Hemmati and Saboori, 2017; Lu et al., 2022; Rezaeimozafar et al., 2024b). Only Riesen et al. (2017) additionally evaluate the model based on forecasting the load data using average values per 30-minute time step, thus applying a forecast approach with lower accuracy. *Our study, by contrast, uses data from 448 real household load and PV production profiles for our data-driven simulation. This allows us to obtain realistic estimations of the net gains of BESS operation in practice.*

Fourth, the majority of publications use optimization-based approaches to set up their BESS operation model optimizing for the underlying objective. A few publications resort to rule-based approaches (e.g., Muñoz-Rodríguez et al., 2021; Shakeri et al., 2018; Dong et al., 2018; Baraskar et al., 2024). Naturally, optimization-based models derive the best possible configurations with respect to the objective, but usually come at higher computational costs and complexity compared with rule-based approaches. This potentially renders the latter ones more applicable in realistic settings. *Therefore, we compare the performance of both, maximization of net gains using a self-developed price-sensitive rule-based vs. an optimization approach, aiming at deriving whether the additional resource need is justified by the results.*

3. Method and data

We use a data-based simulation approach to evaluate different operational strategies for residential BESS to answer our RQs. As an empirical base, we rely on (i) real electricity consumption and (ii) PV production data from residential households, as well as on (iii) electricity price data on an hourly basis. Besides that, we consider (iv) different sets of BESS parameters. We performed all analyses in the statistical programming environment GNU R with standard libraries. The source code can be shared upon request. Fig. 2 provides an overview of the general analysis setup of this study. Our approach takes PV production and demand data from households as is and simulates different BESS configurations.

3.1. Operation strategies

We assess four operation strategies: Each strategy consists of an *objective*, an *algorithmic approach* and a *forecast type* for input data. The *objective* is either maximization of self-consumption—only implicitly focusing on electricity cost reduction—or maximization of net gains (i.e., minimization of annual operational electricity costs)—operating the BESS according to market-based price information. As *algorithmic approaches*, we differentiate between rule-based and linear optimization. Finally, we use naïve and perfect *forecasts*. For the perfect forecast, we assume perfect knowledge of future developments and thus rely on the actual measurements we have. The naïve forecast in our analyses assumes that future development will closely follow the one measured in the past, therefore we take the best fitting past measurements determined by autocorrelation as inputs into our forecasting horizon (as we explain below). To ensure comparability among the different control strategies, the BESS is exclusively charged using surplus PV power, thereby preventing charging from the grid. Additionally, discharging into the grid is prohibited. These constraints align with current regulations and standards for residential PV-BESS utilization in Germany (Figgener et al., 2020; Semmelmann et al., 2024) and Italy (Petrovich et al., 2025).

We define four scenarios which form the basis for the later analysis. Scenario A (“*Status Quo*”) serves as base case, inheriting the BESS operation strategy of maximizing self-consumption. It neither requires forecasts of any residential smart meter data, nor electricity prices. Scenario B (“*Naïve forecast*”) serves as a lower bound within our rule-based price-sensitive operation strategy. In Scenario C (“*Perfect forecast*”), we instantiate the same objective and approach as in B but use the historical data serving as a perfect day-ahead forecast. This renders the upper bound of net gains achievable by our rule-based price-sensitive approach. We use a day-ahead window as a benchmark because, in practice, forecasting quality tends to decrease with larger forecasting windows. For forecasts beyond the day-ahead time frame, external factors like weather and market developments play a greater role making forecasts more difficult and potentially more costly. Finally, we introduce a scenario D (“*Theoretical maximum*”) where we use a perfect full-year forecast in combination with

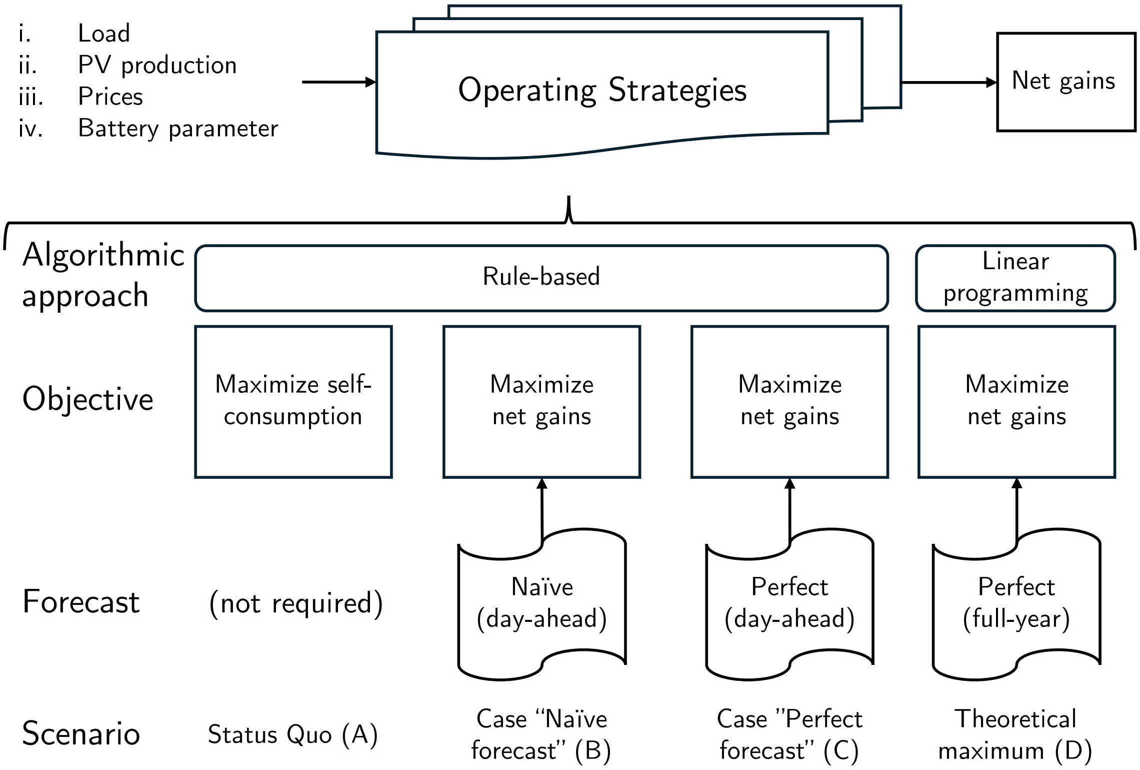

Fig. 2. Overview of the evaluation approach for residential BESS operation strategies.

Table 1
Scenario specifications.

Scenario	A	B	C	D
Objective				
max self-consumption	x			
max net gains		x	x	x
Algorithmic approach				
rule-based	x	x	x	
linear optimization				x
Forecast				
not required	x			
naïve		x		
perfect			x	x
Forecasting window				
day-ahead		x	x	
full-year				x

linear optimization to define the upper bound for maximizing the net gains.

Scenario D derives the theoretical maximum based on our input data set, such that it can give an indication of how well the other approaches perform. The rule-based scenarios B and C represent a more realistic setting for comparison with the base case scenario A. Table 1 provides a summary of the contents and inputs per analytical component, also visualized in Fig. 2.

3.1.1. Rule-based approaches

We implement two rule-based algorithmic approaches for BESS operation—the *status quo* maximization of self-consumption and a price-sensitive approach.

Maximization of self-consumption. The strategy of maximizing self-consumption solely relies on charging the BESS in case of PV production surplus and discharging it in case of excess load before resorting to grid supply. For this, only the current load, PV production, and BESS energy state are of interest for decision-making. Other factors like prices or forecasts are not considered. Due to the simplicity of this strategy, we implement a maximization of self-consumption only as a rule-based model (Scenario A). Such rule-based operation strategies are commonly used. A detailed description can be found for example in Bayer and Pruckner (2023).

Maximization of net gains. We implement an operational strategy for maximization of net gains by instantiating a heuristic, rule-based approach (scenarios B and C) while only allowing BESS charging with surplus PV power. The goal is pursued using a day-ahead forecasting window for net grid demand and electricity prices with an hourly resolution $\Delta t = 1\text{h}$. The procedure, which we describe in the following, applies to both forecasting methods.

The net load $p_{net}(t)$ serves as the basis for the rule-based implementation. It is determined by the household's demand $p_{load}(t)$ subtracting PV production $p_{PV}(t)$ at each hourly time step t over the time horizon of one year T, i.e.,

$$p_{net}(t) = p_{load}(t) - p_{PV}(t) \; \forall t \in T. \tag{1}$$

Negative values, thus, represent PV production surpluses ($p_{net} < 0$), while positive ones indicate excessive loads ($p_{net} > 0$). Furthermore, we consider the next 24 hours as the basis for the individual decision per hourly time step t, serving as a day-ahead forecast.

In case of the PV production surpassing the load ($p_{net} < 0$), the first check is whether a grid feed-in is attractive, considering the day-ahead forecast. For this, the feed-in tariff (FiT) is the corresponding decision criterion. Should the hourly electricity prices represented by $c_{demand}(t)$ in the day-ahead time frame all lie below the FiT, which is denoted by c_{feedin}, the self-produced PV surplus is directly fed into the grid. This decision criterion considers efficiency losses from both, charging and discharging, represented by η_c and η_d, respectively, and is formalized as follows:

$$\forall \tau \in \{t+1, \dots, t+24\} : c_{demand}(\tau) < \frac{c_{feedin}}{\eta_c \eta_d}. \tag{2}$$

If this decision criterion is true, the excess production is directly fed into the grid. Should at least one hourly price in the next 24-hours lie above that value, the second check is performed. If the current BESS energy state $e_{bat}(t)$ is equal to the upper limit of the BESS energy level e_{bat}^{max}, the BESS is full and thus the PV production is fed into the grid. If the sum of the current BESS energy state and surplus of PV electricity considering the charging coefficient η_c at the respective step is smaller than or equal to the upper BESS energy limit, i.e.,

$$e_{bat}(t) + |p_{net}(t)| \cdot \eta_c \cdot \Delta t \le e_{bat}^{max}, \tag{3}$$

the BESS is charged. This leads to the BESS energy state at time step $t+1$ to be calculated as

$$e_{bat}(t+1) = e_{bat}(t) + |p_{net}(t)| \cdot \eta_c \cdot \Delta t \tag{4}$$

If the upper limit would be surpassed, i.e.,

$$e_{bat}(t) + |p_{net}(t)| \cdot \eta_c \cdot \Delta t > e_{bat}^{max}, \tag{5}$$

only the proportion of PV surplus up to that limit is stored (considering efficiency losses), the rest is fed into the grid, i.e.,

$$p_{bat}^{ch}(t) = \frac{e_{bat}^{max} - e_{bat}(t)}{\Delta t} \tag{6}$$

$$p_{grid}^{feedin}(t) = -p_{net}(t) - \frac{e_{bat}^{max} - e_{bat}(t)}{\eta_c \cdot \Delta t}. \tag{7}$$

Should the load be larger than the corresponding PV production at a given point in time, i.e., $p_{net}(t) > 0$, the model first checks whether the BESS energy state is equal to the lower limit of BESS energy level, hence

$$e_{bat}(t) = e_{bat}^{min}. \tag{8}$$

If so, the excess load has to be fulfilled by grid-supply completely, and thus

$$p_{grid}^{demand}(t) = p_{net}(t). \tag{9}$$

Next, the routine checks whether the BESS contains usable energy, i.e., $e_{bat}(t) - e_{bat}^{min} > 0$ and if the grid electricity price is the highest considering the day-ahead prediction, hence

$$c_{demand}(t) = \max_{t \le \tau \le t+24} c_{demand}(\tau) \tag{10}$$

In this case, the discharging power of the BESS is set to exactly match the net load $p_{net}(t)$, accounting for the discharging efficiency η_d. However, the required energy during this step may exceed the usable energy available in the BESS, i.e., $p_{net}(t) \cdot \frac{1}{\eta_d} \cdot \Delta t > e_{bat}(t) - e_{bat}^{min}$. In such cases, the discharging power must be limited to the maximum deliverable amount, which is $\frac{1}{\Delta t}(e_{bat}(t) - e_{bat}^{min})$. This calculation can be summarized in the following formula:

$$p_{bat}^{dis}(t) = \min \left\{ \frac{p_{net}(t)}{\eta_d}, \frac{e_{bat}(t) - e_{bat}^{min}}{\Delta t} \right\} \tag{11}$$

The last check is to ensure that there will be no BESS overflow (i.e., PV production surplus cannot be stored due to full BESS) within the day-ahead time frame, if the electricity price at the current time step is not the highest one considering the day-ahead forecast, i.e.,

$$c_{demand}(t) \neq \max_{t \le \tau \le t+24} c_{demand}(\tau), \tag{12}$$

If no overflow is predicted, the load demand is just satisfied from the grid, hence

$$p_{grid}^{demand}(t) = p_{net}(t). \tag{13}$$

In case of an expected PV production that exceeds the available BESS loading capacity, the BESS will be discharged as much as possible in order to be able to take up the next predicted surpluses again, because direct feed-in would yield less revenue. According to the operational strategy, the BESS neither draws energy from nor feeds energy into the grid, as evident from Eqs. (4) and (11). The BESS can only be charged with surplus PV power and discharged if $p_{net}(t) > 0$.

Another aspect is that for some time steps t the requested BESS charging or discharging power, i.e., $p_{net}(t)$, may exceed the maximum power of the BESS which is defined relative to the actual BESS capacity e_{bat}^{max} by

$$p_{bat}^{max} = C \cdot e_{bat}^{max} \cdot \frac{1}{\Delta t} \tag{14}$$

with C denoting the C-Rate of the BESS. In this situation, we set $p_{net}(t) = p_{bat}^{max}$ during the calculation of the Eqs. (3), (4), (6) and (11).

3.1.2. Optimization approach

To evaluate the theoretical upper boundary for the achievable financial benefit, we use a linear optimization based on the realized demand and PV generation data for a complete year (Scenario D). The main optimization variables are the charging $p_{bat}^{ch}(t)$ and the discharging power $p_{bat}^{dis}(t)$ of the BESS per time step t over the time horizon of one year T with an hourly resolution $\Delta t = 1\text{h}$. To capture the grid interactions, we introduce a variable for grid supply to the household $p_{grid}^{demand}(t)$ and feed-in of surplus PV generation to the grid $p_{grid}^{feedin}(t)$ for every time step $t \in T$. Additionally, we introduce an optimization variable for the state of energy $e_{bat}(t)$ of the BESS at time step $t \in T$. The target of the optimization is the minimization of the annual electricity costs given by

$$\min \sum_{t \in T} \left(c_{demand}(t) \cdot p_{grid}^{demand}(t) - c_{feedin} \cdot p_{grid}^{feedin}(t) \right) \cdot \Delta t. \tag{15}$$

We derive the net gains by deducting the resulting annual electricity costs from the baseline case, i.e., without consideration of additional storage capacity. All introduced variables are constrained by the lower bound of zero. Moreover, the BESS energy state is limited by the minimum and maximum capacity, i.e., $e_{bat}^{min} \leq e_{bat}(t) \leq e_{bat}^{max}$. The power of the BESS is limited according to the maximum capacity as given by the C-rate, i.e., $0 \leq p_{bat}^{ch} \leq p_{bat}^{max}$ and $0 \leq p_{bat}^{dis} \leq p_{bat}^{max}$ with p_{bat}^{max} defined in Eq. (14). This constraint reflects the physical limitations of the BESS hardware, where the maximum charging and discharging power is proportional to the storage capacity via the C-rate.

The first constraint defines the BESS balance equation at every time step, i.e., $\forall t \in T$:

$$e_{bat}(t+1) = e_{bat}(t) + \eta_c \cdot p_{bat}^{ch} \cdot \Delta t - \frac{1}{\eta_d} \cdot p_{bat}^{dis} \cdot \Delta t \tag{16}$$

The formulation of Eq. (16) follows related studies (Beck et al., 2016; Olivieri and McConky, 2020). In a second constraint, we define the power balance equation at the building level. As BESS charging from the grid should not be possible, we introduce two separate balance equations. This modeling choice avoids the need for binary decision variables that would otherwise be required to enforce mutually exclusive charging and discharging behavior. By doing so, we maintain a linear formulation, which ensures computational efficiency during the optimization. The first equation is required for the case of a demand, i.e., $\forall t \in T$:

$$p_{bat}^{dis}(t) + p_{grid}^{demand}(t) = p_{net}^{+}(t) \tag{17}$$

with $p_{net}^{+}(t) := \max(0, p_{net}(t))$ denoting the positive values of the net-load. The second equation is required for the case of a feed-in, i.e., $\forall t \in T$:

$$p_{bat}^{ch}(t) + p_{grid}^{feedin}(t) = p_{net}^{-}(t) \tag{18}$$

with $p_{net}^{-}(t) := -\min(0, p_{net}(t))$ denoting the absolute negative values of the net-load. Moreover, the initial state of energy of the BESS is set to its minimum capacity, i.e., $e_{bat}(0) = e_{bat}^{min}$ to stay in line with the two rule-based approaches.

In the optimal solution, simultaneous BESS charging and discharging will not occur if either the charging or discharging efficiency is less than 100 %, and the feed-in tariffs are positive. Thus, we exclude binary variables that would enforce mutually exclusive charging and discharging behavior—following the same rationale applied in the separation of the power balance in Eqs. (17) and (18). Moreover, the linearity of this optimization problem ensures that solvers can always find and verify that the solution found is the global optimal solution. This is an advantage, as providing such a guarantee is not always possible for general non-linear optimization tasks, which might only find local optima (Bertsimas and Tsitsiklis, 1997).

3.2. Forecasting approaches

For the price-sensitive rule-based method to operate the BESS charging and discharging behavior at each individual hourly decision step, we use a day-ahead forecast (i.e., 24 hourly values following the decision step). Forecasting electricity demand for longer periods ahead could potentially lead to higher forecasting errors (El-Baz et al., 2018; Giacomazzi et al., 2023). This, in turn, could lead to disadvantageous operation of the BESS (Hanna et al., 2014). For evaluation of the rule-based model aiming at a maximization of net gains, we benchmark the following two forecasting approaches against each other.

Perfect forecast. As one of our goals is to determine the best possible economic outcome of operating BESS and since we have load as well as PV production data available for the years 2019 to 2023, we use the actual data as a perfect forecast. This leads to the optimum that is realizable on a day-ahead basis.

Naïve forecast. We use the data just before the decision step and empirically determine a meaningful lag by performing separate autocorrelation analyses for the input data, in line with Angenendt et al. (2018). In Appendix B, we show exemplary autocorrelation plots for both, the net-load and EPEX prices. For net-load $p_{net}(t)$, the prior day shows the highest autocorrelation. For $c_{demand}(t)$ it is the same time step in the week before. This gives us a simple-to-implement approach, at the cost of comparably poorer results.

3.3. Data and model parameters

Our analyses span five years and rely on real-world data from 448 unique households in southern Germany, containing load and PV production time series with an hourly resolution. Furthermore, we consider residential electricity tariffs, which we take from average market values in case of the fixed tariff and the European Power Exchange (EPEX) spot market in case of dynamic pricing. The EPEX is the German electric power exchange for short-term energy trading. For the dynamic tariff, we apply a calculation scheme to harmonize the dynamic tariff based on EPEX spot market prices to the price level of the fixed tariff. Lastly, from the publications identified in the literature analysis (Section 2), we derive the relevant BESS-specific characteristics to use as parameters for our modeling approaches.

3.3.1. Load and PV production data

We obtained both, the load and PV production data, from a small Distribution System Operator (DSO) in southern Germany. The DSO granted us access to hourly load data from 10,099 and PV production data from 2,091 unique smart meters. We have data for the years 2019 to 2023 as basis for the analyses in this work. From this, 2019 is the last complete year before the Covid-19 pandemic and Russia's attack on Ukraine. 2023 serves as the first near-normal year after several crises to investigate the aftereffects.

We prepare the yearly data per metering ID as follows: First, we removed measurements in the dataset that the DSO labeled as "*dummy*",

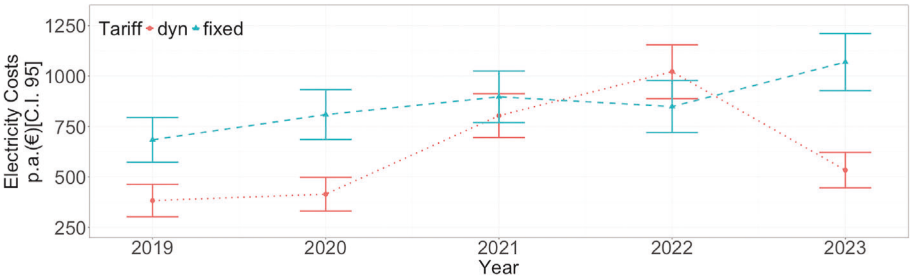

Fig. 3. Annual operational costs in € *per annum* (p.a.) for dynamic and fixed prices without BESS considering *status quo* price levels of a selected electricity retailer as a point estimate with 95 % confidence interval (C.I.).

"*temporary*," and "*defective*" (e.g., from data transmission or measurement errors). This way, the metering IDs for measuring load decrease by 1,624, and the ones measuring PV production by 1,004, respectively. Second, metering IDs with electricity demand values of under 100 kWh per year are excluded (895 cases). Finally, we consider singular measurements of over 1,000 kWh outliers for being unusually high and removed them consequently—for load and PV production, simultaneously. However, this only concerns singular measurements and not complete time series for a specific metering ID. We eventually fill blank measurements resulting from prior checks and filters by also applying linear interpolation for the load measurements (0.67 % of total observations) and replaced the missing PV production values with 0 (0.88 % of total observations), to avoid overestimating the net gain, when production is zero but demand was interpolated. After the complete cleaning and filtering procedure, we have 9,001 unique load and 1,368 PV production meters at hand. Some buildings might have multiple meters installed, for example, for an individually metered PV installation, a separate heat pump, or because there are multiple apartment units in a building. Thus, we finally aggregate the time series of the individual meters at the level of each building, as identified by the unique postal address considering one building as one household, regardless of the actual number of apartments—following earlier studies (Bayer et al., 2024; Bayer and Pruckner, 2024). We ensured that for all households, we have PV production data. As we are only interested in private actors, we filter the unique addresses for PV systems listed as privately owned in the German "Marktstammdatenregister"[1]—a central online repository for energy-economic data. This leaves us with 448 unique cases as our sample, which we consider households in the following.

Regarding the population of data that we were provided with by the DSO, we do not find a statistical difference between the final sample mean consumption (M = 5,127 kWh, SD = 5,310 kWh) and the statistics of all customers (M = 5,030 kWh, SD = 5,638 kWh, t = -.3993, p = .6898). Regarding the general German population of private consumers,[2] however, the mean electricity consumption in 2021 is M = 3,383 kWh, which is significantly lower than in our sample. This can be explained by a higher share of larger homes and houses in the rural origin of our sample data and due to our selection of customers with PV installations.

3.3.2. Electricity prices

We consider the fixed electricity prices published by the German Association of Energy and Water Industries (BDEW, 2023a). These numbers represent mean electricity prices for residential consumers and already include a proportionate value for any non-variable price components.

The FiT is another variable to consider. It is the price paid to PV system owners for feeding electricity into the grid. We oriented the FiT to the official one granted through German legislation (EEG, 2025).[3] That way, we consider 0.0811 €/kWh as the FiT for our models. We extract the EPEX spot prices in hourly steps using the free REST interface provided by the electricity retailer aWATTar.[4]

Other than for the fixed tariffs, there is no market average for end-customer prices in the dynamic tariff environment. Therefore, we derive the hourly charges by applying the consumer price calculation scheme used by a typical electricity retailer (aWATTar, see Footnote 4). Their calculation scheme consists of a 3 % surcharge on the EPEX price plus 0.1609 €/kWh for taxes and other fees. When taking a first look at the entire time frame, we noticed substantially lower price levels for the dynamic tariff in the years 2019, 2020 and 2023. Considering the complete time frame under investigation, the average annual bill for our sample ranges from 656.0 € for the dynamic tariff and 876.60 € for the fixed tariff (Fig. 3). Thus, on average, our sample households would have saved over 220 € simply by switching tariff environments. We can explain this effect by the practice of utility companies shifting their market risk to the consumer with dynamic tariffs and offering a respective risk premium (Numminen et al., 2022; Dutta and Mitra, 2017). Another (rather speculative) explanation for the low dynamic rates is that retailers are currently pursuing an aggressive pricing policy. In 2021, the annual bills approached the fixed tariff ones, even surpassing them in 2022. This effect is attributable to diverse price shocks starting in 2021, becoming even more severe after Russia launched its attack on Ukraine. Although a general upward trend is visible in the fixed tariff environment, it is considerably more moderate than the increase in annual bills in the dynamic tariff setting from 2020 into 2021 and 2022. The general reason for this seems to be the dynamic tariff's linkage to the German-wide market prices for electricity.

Given the focus of our study on the effects of dynamic tariffs on net gains of BESS, the baseline differences between the dynamic and fixed tariff environments would be a strong external confound. To determine the potential net gains in the respective BESS operation strategies, we scale the EPEX prices to the fixed tariff level per year by $f_{EPEX}(T) = \frac{c_{fix}(T)}{c_{demand}(t)}$ and multiply the hourly EPEX spot prices with it. Table 2 provides an overview of the fixed prices we consider and statistics for the EPEX spot, as well as the harmonized dynamic prices.

After harmonizing the two tariff environments with respect to the overall price level, we arrive at a much more homogeneous picture. As

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[1] https://www.marktstammdatenregister.de/MaStR, last accessed Oct 25, 2024.

[2] Using data published by the German Federal Statistical Office accessible at https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Umwelt/UGR/private-haushalte/Tabellen/stromverbrauch-haushalte.html; last accessed on Sept 30, 2024.

[3] We take the tariff parameters according to German law (EEG, 2025) for partially self-consuming PV systems that are connected to the grid as a constant for the whole time frame investigated.

[4] aWATTar, also traded as tado in Germany and Austria, is an electricity provider offering dynamic tariffs based on EPEX spot market prices; see https://energy.tado.com/tariffs, last accessed November 22, 2024.

Table 2
Overview of prices per kWh in € ct. for different price environments.

Measure	2019	2020	2021	2022	2023
Fixed prices	30.46	31.81	32.16	37.91	45.73
EPEX Spot prices					
Mean	3.77	3.05	9.68	23.54	9.52
Standard deviation	1.55	1.75	7.37	14.28	4.76
Minimum	−9.00	−8.39	−6.90	−1.90	−50.00
Maximum	12.15	20.00	62.00	87.10	52.43
Dynamic tariff (harmonized)					
(Harmonization factor)	(8.09)	(10.44)	(3.32)	(1.61)	(4.80)
Mean	30.46	31.81	32.16	37.91	45.73
Standard deviation	12.54	18.27	24.47	22.99	22.86
Minimum	−72.79	−87.63	−22.91	−3.07	−240.24
Maximum	98.22	208.83	205.88	140.24	251.90

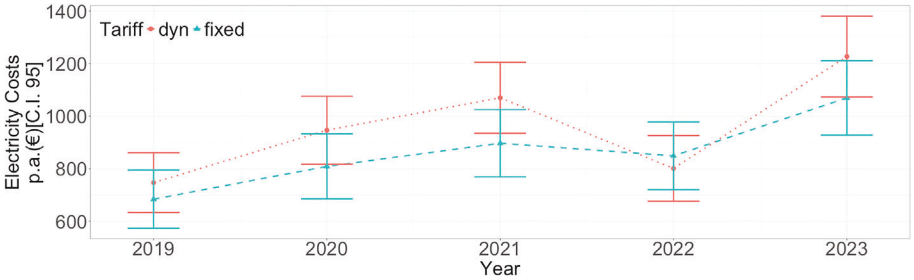

Fig. 4. Annual operational costs for dynamic and fixed prices without BESS, with harmonized prices.

Fig. 4 suggests, the annual operational electricity costs between the two tariffs without modeling additional BESS capacity still differ for our sample. However, the averages now converge throughout the investigated time frame. The differences are caused by usual consumption patterns leading to electricity use in high-price time frames in the harmonized dynamic tariff environment.

3.3.3. BESS-specific parameters

To find suitable values for the BESS capacity, SOC_{min} and SOC_{max}, BESS efficiency and C-rate—both for charging and discharging—as well as losses from self-discharge, we use results from our literature review. Unfortunately, most publications do not provide exact values for each of these characteristics. Only three papers cover all mentioned parameters (Beck et al., 2016; Talent and Du, 2018; Jung et al., 2020). Similarly to Beck et al. (2016), we neglect self-discharge losses due to their insignificant influence on the system. Moreover, we set the minimum State of Charge (SOC) to 20 % of the total capacity cap_{bat}, following Jung et al. (2020). To get a usable capacity of 80 % following Beck et al. (2016), we set the maximum SOC to a value of 100 %. We further assume a starting SOC of 20 % per year, not considering potential remaining BESS capacity at the end of a prior year, as residential BESS tend to have an energy state near the lower bound between December and February in Germany.

To identify potentially influential factors towards net gains in the remaining parameters, we iterate over various values. Other authors model the BESS capacity (here: cap_{bat}) ranging from 1 (Pena-Bello et al., 2017) to 24 kWh (Angenendt et al., 2019) as realistic capacity sizes for residential BESS, and extreme values of 0.01 (Muñoz-Rodríguez et al., 2021) and 300 kWh (Hemmati and Saboori, 2017). To account for the large variation of different capacity sizes used in the reviewed papers, we calculate the mean of all stated capacities (i.e., 22.30 kWh) as orientation. From there, we conducted a sensitivity analysis in which we set the inputs for our models ranging from 5 to 30 kWh with an increment of 5 kWh as this magnitude seems reasonable for use in a residential context. The respective bounds for the BESS energy level can thus be calculated as $e_{bat}^{min} = cap_{bat} \cdot SOC_{min}$ and $e_{bat}^{max} = cap_{bat} \cdot SOC_{max}$, respectively.

Another parameter is the C-rate, which describes how quickly a BESS can be charged and discharged (see Eq. (14)). Although C-rates in the literature range widely from 0.2 (Zhang and Tang, 2019) to 5 (Beck et al., 2016), we fixed the C-rate to a representative value of $C = 1$, which corresponds to a full charge or discharge within one hour, a commonly used value for existing BESS in Germany according to Figgener et al. (2020). This decision was based on preliminary tests that showed no substantial impact of varying C-rates on the aggregated results for our sample. Fixing this parameter allowed us to reduce complexity and focus on more influential factors in the analysis. Moreover, C-rates for lithium-ion batteries are typically limited to values below $C = 2$ to ensure thermal safety and minimize electrode degradation (Doppelbauer, 2020).

Lastly, efficiency assumptions for both, η_c and η_d, also vary significantly and range between 80 % (Shivam et al., 2021) and 98 % (Aniello et al., 2021; Dong et al., 2018; Koskela et al., 2019). We consider three different steps with 85 %, 90 %, and 95 % for η_c and η_d. For simplification purposes, we assume the same value for charging and discharging efficiencies resulting in round trip efficiency values of 72.25 %, 81.00 %, and 90.25 %.

4. Results and discussion

We start our analyses with the evaluation of the effects of BESS usage in fixed and dynamic tariff environments, before we investigate how different BESS characteristics drive the net gains in both tariffs. The subsequent analyses further explore the dynamic tariff environment and start with a comparison of the *status quo* maximization of self-consumption (A) with a price-sensitive BESS operation based on a perfect day-ahead forecast (C) in Section 4.2. After a comparison of the results from price-sensitive operation based on a perfect (C) and a naïve forecast (B) in Section 4.3 to determine the general value of forecast accuracy in the context of realistic settings, we conclude this part with a

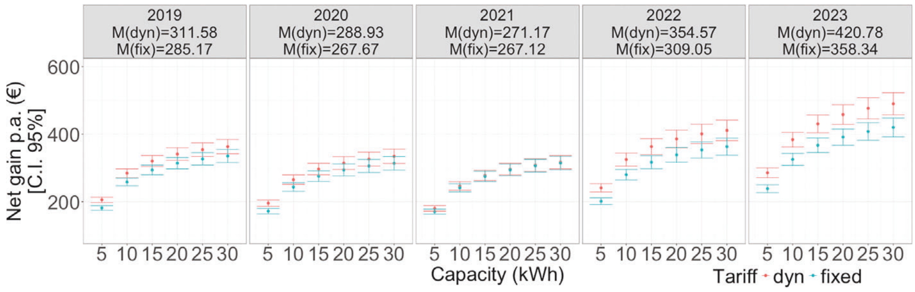

Fig. 5. Net gains from BESS usage (harmonized prices) for different battery capacities.

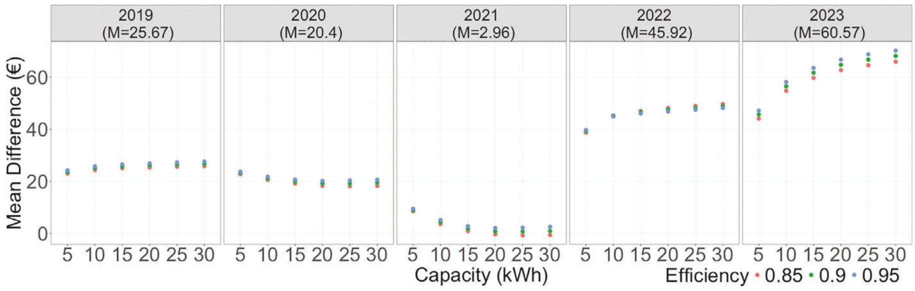

Fig. 6. Differences in net gains between harmonized dynamic and fixed tariff.

benchmarking of our rule-based (C) and linear optimization approaches (D) in Section 4.4 to estimate the theoretical maximum in case of perfect foresight for the input variables.

4.1. Effect of BESS usage

Having controlled for the annual price levels between fixed and dynamic tariffs, the rule-based approach with the aim of maximizing self-consumption (A) leads to average net gains ranging from 170.66 € for the fixed and 180.13 € for the dynamic tariff regime—both for the smallest BESS size of 5 kWh and the year 2021—to 419.89 € and 490.11 € respectively—both for the largest capacity of 30 kWh and the year 2023.[5] Fig. 5 compares the harmonized dynamic prices with the fixed ones, considering different battery capacities (charging and discharging efficiency of 95 % each). Fig. 6 shows a sensitivity analysis comparing different battery efficiencies.

The results suggest that the differences between tariffs are rather driven by BESS capacity than efficiency, although the latter gains importance with increasing capacity. These findings answer RQ1: *With respect to a BESS with 10 kWh capacity, the achieved net gains are* 251.79 € *for the fixed and* 283.88 € *for the dynamic tariff on average and thus 12.7 %*[6] higher with dynamic pricing compared with the fixed tariff setting.

4.2. Self-consumption vs. net gains (day-ahead perfect forecast): a heterogeneous picture

For operating the BESS with the aim of a maximization of self-consumption (scenario A) and a maximization of net gains based on a perfect day-ahead forecast (scenario C) we observe differences ranging from 9.76 € in favor of C for the 15 kWh BESS in 2020 to 12.64 € in favor of A for 30 kWh in 2023. According to our definition of net gains, all figures reported here are *per annum* (p.a.). The heterogeneous effects can be explained by different BESS capacities:

Small BESS. Fig. 7 reveals that a price-sensitive operation (scenario C) seems to be superior for BESS sizes below 20 kWh and especially for a 10 and 15 kWh BESS. Only BESS with a capacity between 5 and 15 kWh consistently produce better results under price-sensitive operation for the investigated sample over the entire time frame analyzed. Focusing on a 10 kWh BESS case, scenario C achieves 3.2 % higher net gains on average compared with scenario A[6]. The 5 kWh BESS shows negligible differences between price-agnostic and price-sensitive operation. Lower capacities offer hardly any flexibility to clearly distinguish different modes of operation.

Large BESS. A price-sensitive operation of the largest BESS sizes does not seem to be a reasonable option, except for 2020 and 2021 (which are years of high turbulence in energy markets), because the advantage of this strategy is more or less lost for capacities beyond 15 kWh due to the day-ahead forecasting window. As larger batteries can store larger amounts of electricity for longer durations, the operation strategy would favor realization of peak prices over consuming larger portions of stored electricity during longer periods with only medium-high prices. Hence, the point at which discharging makes sense cannot simply be determined. This gives a first indication of the *day-ahead forecast potentially lacking the ability to leverage the full capabilities of the BESS*. Aiming for maximization of self-consumption, we achieve higher net gains for BESS beyond 15 kWh.

Appendix A compares the SOC of BESS in the price-agnostic vs. price-sensitive operating strategy in a time frame with medium and high PV production. From this analysis, we see that with constantly high BESS energy state in times of excessive solar irradiation, scenario C resembles A. Therefore, the potential for scenario C to differentiate itself from A is rather evident in fall or winter. It is important to note that the magnitude of differences in favor of operation when aiming for maximization of net gains might not be sufficient to justify implementation of novel algorithmic approaches. This is because investments in additional hardware and forecasting solutions might be necessary.

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[5] The calculation base for these numbers was the respective annual electricity costs as basis for the calculation of net gains per tariff setting, which we obtained by multiplying the load satisfied from the grid with the individual price per kWh in the respective year in the fixed setting and with the corresponding price for that particular hour in the dynamic setting. In both cases, potential feed-ins were then multiplied with the fixed FiT and subtracted from the costs caused by grid load.

[6] Derived as the mean across all investigated years and efficiency ratings.

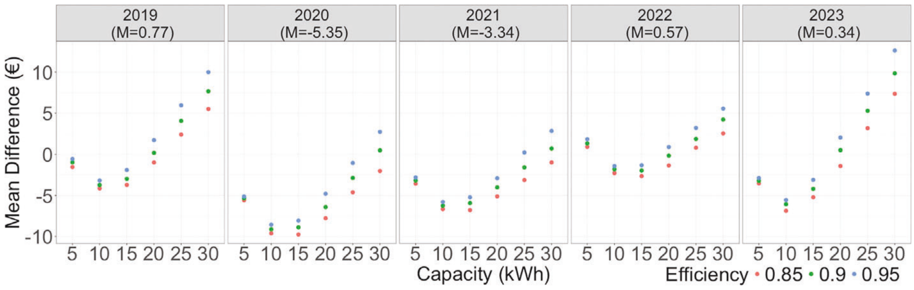

Fig. 7. Differences in net gains between objectives (A vs. C) for dynamic pricing.

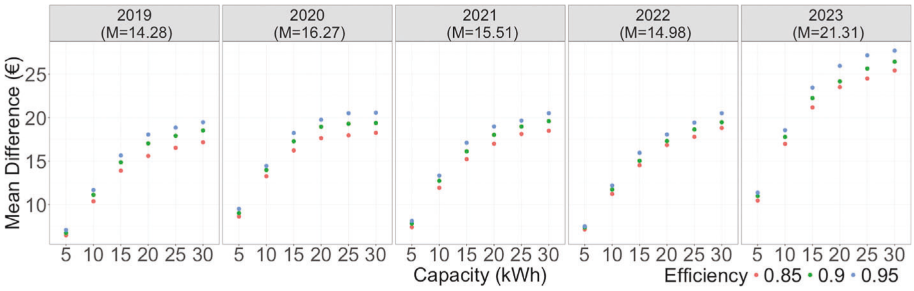

Fig. 8. Differences in net gains between perfect (C) and naïve (B) forecast.

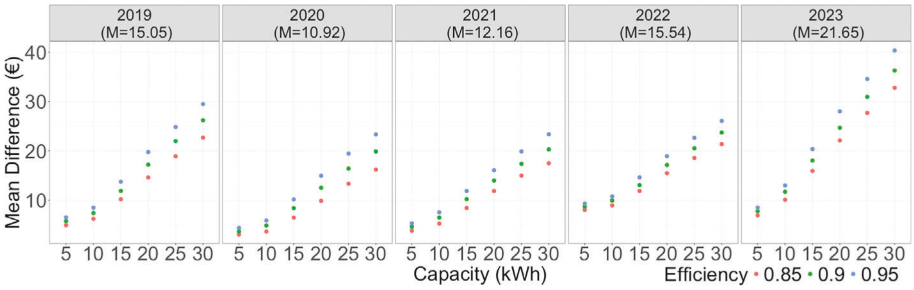

Fig. 9. Differences in net gains comparing maximization of self-consumption (A) with the price-sensitive approach based on a naïve (B) forecast.

4.3. Maximizing net gains: influence of forecast accuracy

Operating the BESS with the objective of maximizing net gains, we further differentiate between using a perfect day-ahead forecast based on the historically measured data (scenario C) and projecting past values into the future, thus, constructing a naïve forecast (scenario B) in this way. The following analysis thus answers our RQ3. Fig. 8 reveals the mean differences between these strategies. The superiority of the perfect forecast (scenario C) leads to a mean difference spanning from 6.46 € for the 5 kWh BESS in 2019 to 27.71 € for 30 kWh in 2023. For our reference BESS with 10 kWh the perfect forecast (scenario C) leads to 6 % higher net gains on average.[6]

The low differences result from the fact that the naïve forecast comes close to the results achieved based on the perfect forecast data, especially for smaller BESS capacities, with the same reasoning as in the comparison before. Earlier studies (Angenendt et al., 2018; Riesen et al., 2017) similarly conclude that naïve forecasts lead to comparable results as perfect ones. We visualize this in Appendix C.

The flattening of the curve in larger BESS cases—probably due to similar effects that lead to reasoning in Section 4.2—also suggests that focusing on *improvements in forecast accuracy might only be beneficial in cases with large BESS*. The full potential of larger BESS with respect to forecast accuracy becomes clearer when considering the results presented in the next Section 4.4 as well.

Overall, similar to the prior results, the magnitude of differences in net gains between the two forecasting approaches is comparably small. To complete the picture, we extend the view by comparing the *status quo* maximization of self-consumption strategy (scenario A) and the price-sensitive one based on a naïve forecast (scenario B) as visualized in Fig. 9. This reveals a superiority of the maximization of self-consumption approach, producing higher net gains ranging from 3.05 € for the 5 kWh BESS in 2020 to 40.36 € for 30 kWh in 2023. In the availability of only naïve forecasts comparable to the ones we introduce here, aiming for a maximization of self-consumption would be the better option with respect to achieving higher net gains.

4.4. Good forecasts make the difference: rule-based vs. optimization approach

For benchmarking the perfect day-ahead forecast applied before with the theoretical maximum assuming a full-years knowledge, we compare our rule-based algorithm (scenario C) with a linear optimization approach (scenario D). The results provide an indication of whether it might be financially worthwhile to concentrate on improvements in forecasting with respect to its applicability in practice.

The results visualized in Fig. 10 show clear differences between the two strategies. The optimization (scenario D) consistently leverages higher net gains compared with the rule-based day-ahead forecast

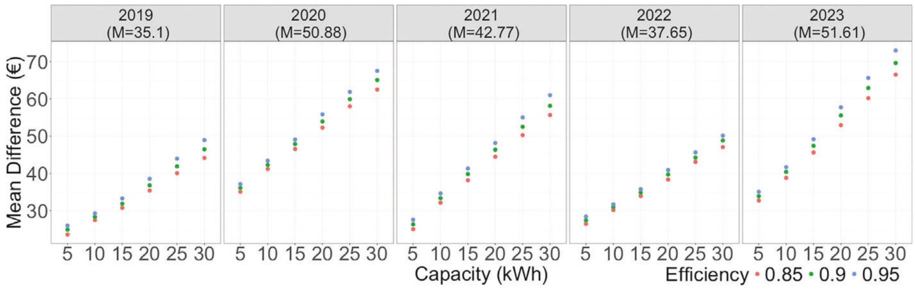

Fig. 10. Differences in net gains between rule-based (C) and optimization (D) approach.

approach (scenario C). Differences in favor of the optimization routine range from 23.60 € for the 5 kWh BESS in 2019 to 73.01 € for 30 kWh in 2023 (Fig. 10). This aligns with the investigations visualized in Section 4.3. However, contrary to the findings there, a clear linear trend is visible here regarding the superior performance of scenario D with respect to an increase in BESS capacity. Overall, for a 10 kWh BESS using the optimization approach with full-year perfect forecast results in 14 % higher net gains compared with the rule-based approach with day-ahead forecast.[6] Thus, assuming the theoretically optimal conditions, *larger BESS correspond with equivalently superior performances of the optimization algorithm when compared with the rule-based approach*.

By using a full-year perfect forecast, the optimization is able to determine the optimal consumption points for each and every single BESS operation step. The performance of this approach naturally increases with larger BESS sizes. Furthermore, considering the full-year data, scenario D would not encounter the problems described in Section 4.2.

The linear optimization approach only inherits a better performance of approximately 44 € on average. Simultaneously, optimization approaches are naturally more hardware intensive and complex, making them less applicable in natural settings and less user-friendly to laypersons. Also, the assumption of a full-year perfect forecast for both—net-demand and EPEX spot prices—is far from realistic. Especially the flexibility of BESS poses a challenge with respect to optimization approaches (Schrage et al., 2023). This perspective, however, gives an indication of the extent of further improvements in forecasting enabling an increase in the net gains from a financially more effective operation of the BESS.

5. Conclusion and policy implications

Our analysis suggests five conclusions, which have tangible implications for energy policy (see Table 3 for an overview). First, dynamic electricity tariffs, based on EPEX spot market prices—at a similar level as fixed tariffs—currently hold cost saving potential for residential BESS owners. This is in line with findings by Comello and Reichelstein (2019), who demonstrate economic viability of residential “behind-the-meter storage” in the case of a substantial difference between electricity retail rates and feed-in tariffs.

Our second finding is that for residential owners of PV systems with BESS, even after adjusting for price levels, the currently dominant price-agnostic operation strategy of maximizing self-consumption is still the financially best option among the considered rule-based strategies. This is because the grid demand is relatively in line with the price development, meaning that the electricity stored in the BESS is usually already used during times with higher prices and excess demand typically occurs during lower-price times. Third, particularly BESS with a capacity of up to 15 kWh seem to leverage potential by deviating from the currently prevalent self-consumption maximization. For larger BESS, retaining the *status quo* maximization of self-consumption goal still generates larger financial gains, given the forecasting horizon limited to day-ahead in our work.

Fourth, the value of *price-sensitive strategies can only be leveraged with sufficient forecasts*, and even then the gains are relatively low: With a day-ahead forecast horizon, the rule-based approach aiming to maximize net gains turned out to be only more effective than maximization of self-consumption in certain cases—even in the availability of a perfect forecast. Grounding a price-sensitive operation of the BESS on a naïve forecast does not perform better than simply resorting to a maximization of self-consumption in any of the investigated BESS specifications.

Fifth, by using a linear optimization approach, we derive the theoretical maximum net gains for the sample data investigated. However, the overall potential monetary effect is rather negligible, considering the effort it takes to obtain a sufficiently good forecast in practice.

5.1. Implications for energy policy

These results are relevant for policymakers. In our approach to adjusting price-levels between dynamic and fixed tariffs (see section 3.3.2), we discovered a considerable saving potential from simply switching to a dynamic tariff in currently offered tariffs. This insight highlights the potential for reducing electricity bills of households without the need for large federal spending and contributes to the controversial debate on high end consumer electricity prices, e.g., in Germany, Denmark, and Ireland (Eurostat, 2025) over the past years. Legislators could develop *tailored information campaigns conveying the advantages of market-based electricity tariffs to consumers*—perhaps enriched by suggestions on how to benefit the most from changing prices by adjusting the consumption behavior.

Second, our results indicate decreasing marginal net gains with increasing BESS capacity. This provides an impetus for policymakers to (re-)evaluate *subsidy programs* or create new ones tailored to potentially overarching goals to achieve *increases in private investments in BESS*.

To illustrate the marginal net gains for a decision maker (e.g., a homeowner), we provide a numerical example in the following: Table 4 shows a median split of the simulated net gains for a 10 kWh BESS with the assumption of 95 % efficiency. The values are taken from the optimization approach and thus represent theoretical optima. Assuming annual savings of around 300 € (the maximum gains of the *below median* group of our sample households), investments in a 10 kWh BESS, which costs roughly 4,000 € at cost of capital of 6 %, would not be a fruitful venture for residential actors from a financial point of view, when we exclude the risk premium from dynamic prices (through our harmonization of price levels). Given the investment costs for the storage alone (i.e., without installation costs or additional parts), the storage would show a positive net present value after 28 years—well past the end of its estimated lifetime of up to 10 years (Angenendt et al., 2018). Since BESS are discussed as a means to mitigate costs from grid upgrades and curtailment compensation, additional evaluations should be performed to find ways to retain or even boost the long-term interest in private investments in BESS.

This analysis suggests further important aspects with respect to the potential financial viability of an investment in a residential BESS: The *below median* group has an average annual load of roughly 3,218 kWh,

Table 3
Overview of key findings, policy and research implications.

Key Finding	Policy	Utilities	Research
1. Net gains for BESS owners from dynamic tariffs are higher than that of fixed tariffs (considering equal price levels)	Facilitate market penetration of dynamic tariffs (as relief to consumers).	1) Raising awareness among consumers to leverage potential for financial relief. 2) Market risk can be shifted to customers. 3) Update calculation base of customer prices	1) Identification of households with higher benefits from dynamic tariffs. 2) Investigation of differences in pricing on the supplier side.
2. Even with a price-agnostic strategy (maximization of self-consumption), average consumption of the sample reflects market price trends.	–	If the load pattern should be altered, additional incentives are needed.	Investigation of future scenarios in pricing behavior at the electricity market to find necessities in changing operation strategies.
3. Up to 15 kWh of BESS capacity show linearly increasing net gains. The marginal gains decrease with larger BESS, thus questioning their financial viability.	Should the strategy be to create more decentralized storage capacity in the grid, financial incentives must be created targeting larger BESS.	Develop and implement new business models to let owners of bigger BESS benefit from their investment (i.e., due to allowing the BESS to be used in grid relief measures)	–
4. In the absence of good forecasts, price-agnostic operation (maximizing self-consumption) seems to be in many cases the financially most attractive strategy. Even with perfect day-ahead forecasts, only BESS up to 15 kWh capacity show increased net gains. This might not be sufficient to justify the additional costs.	1) It cannot be assumed that BESS will be operated in a grid-friendly way. Thus, reasons for BESS subsidies need to be revised. 2) Expand regulatory options for dynamic tariffs, e.g., enable flexible grid fees to incentivize grid-friendly operation.	Implement dynamic tariffs that leverage available BESS capacity for curtailment prevention using price signals.	1) Evaluate welfare potential of different BESS operation strategies, e.g., with a focus on grid relief. 2) Transferring forecasts into practice.
5. The full potential of price-sensitive BESS operation can be achieved with linear optimization when a full-year of perfect forecasts is available. However, the financial effects are rather low compared to the *status quo* maximization of self-consumption.	Fostering a decentralized smart grid requires better forecasts that are accessible to end-customers.	New business models to monetize good forecasts	Improving forecasts to lower errors and evaluate their respective saving potential.

Table 4
Statistics for a median split of the net gains of a 10 kWh, 95 % efficiency BESS case (Scenario D).

	below median	above median
no. of households	225	223
minimum gains (€)	0.14	318.88
maximum gains (€)	318.40	933.96
average gains (€)	179.82	474.49
minimum load (kWh)	274.99	1,491.05
maximum load (kWh)	24,254.35	26,606.49
average load (kWh)	3,218.43	6,234.75
minimum production (kWh)	0.52	363.62
maximum production (kWh)	23,208.79	34,192.04
average production (kWh)	3,878.64	8,531.65

which resembles the German population average of 3,383 kWh (see Section 3.3.1). With average gains of 179.82 €, this group stands on a more disadvantageous basis with respect to the net present value calculation, making the BESS investment even less financially viable without any subsidies. Taking the overall lower price level of dynamic tariffs into consideration—as shown in Section 3.3.2—this might be even more pronounced. Without subsidy programs, the investment in residential BESS storage might thus be a viable option only for true believers. *Tax-funded subsidy schemes may only be reasonable and justifiable if an additional home battery (supplementary BESS) provides further benefits*, e.g., by relieving the grid, thus mitigating the need for investments in other domains like upgrades in the grid infrastructure. Together with the findings by Semmelmann et al. (2024), investments in subsidy programs would then again potentially require alternative operation strategies to increase welfare for the overall system as justification, since it can hardly be found in the current self-consumption promoting regime.

Third, at the same time we suggest subsidy programs to be revised, because we cannot safely assume that BESS operation happens in a grid-friendly way. *Policymakers could, for example, complement subsidies with the mandate that BESS are operated using a market-based or grid-based operating strategy*, as we have explored in this paper. Simultaneously, it can be beneficial to evaluate how dynamic tariffs can be tailored more closely to grid-friendliness, e.g., by enabling flexible grid fees.

Lastly, we show that the financial benefits from price-sensitive BESS operation heavily rely on good forecasting quality. Corresponding legislation *making forecasts available to the broad public* could be a way to facilitate appropriate BESS operation.

5.2. Implications for utility companies

With respect to utilities, we find that first, they could benefit from fostering customer acceptance of dynamic tariffs and increasing awareness of financial potential because this would allow them to shift market risk to consumers (Numminen et al., 2022; Dutta and Mitra, 2017). The currently offered tariffs in Germany lead to lower overall expenses for consumers in normal years (in crisis years, consumers with fixed tariffs were better off).

Second, given the overall good fit of the status-quo maximization of self-consumption, utilities might need to offer additional incentives should they want customers to adjust their consumption behavior. This also goes hand in hand with our third to fifth findings. By creating and promoting new business models, customers might leverage additional revenue, thus utilities can incentivize BESS investments and new ways to operate them. Making available the residential BESS as a controllable asset for the DSO to some extent—e.g., via integration as a digital twin into grid management software (Brosinsky et al., 2024)—might create new benefits for both, consumers and DSOs. This could also include the provision or monetization of accurate forecasts, ways to benefit from excess renewably produced electricity in the grid or retention of stored electricity for times of low shares of renewables in the overall grid electricity.

5.3. Limitations and future work

Our work comes with some limitations that serve as avenues for future research.

First, our analysis pursues an aggregated view, investigating mean effects of a sample of households in different scenarios. Future work should explore characteristics of households that influence the optimal operation of BESS under dynamic tariffs, including tariff choices of households. This could lead to an indication of prerequisites under which what scenario and forecasting approach would work best. Another aspect that we kept constant across our analysis was the C-rate because it did not turn out to be an influential factor herein regarding the overall results for our sample. However, there might be cases (i.e., households with sufficiently large PV systems or small BESS) where this would pose a considerable potential to substantially decrease the estimated gains through BESS usage.

Second, our investigations consider BESS charging from PV production surpluses only but no grid charging, e.g., in times of low or even negative prices. Discharging the BESS to feed the stored electricity into the grid during periods of peak prices could generate additional gains but entails additional risks. Future works could build upon previous studies (Jung et al., 2020; Komorowska et al., 2022) together with our approach to explore the monetary benefits of grid charging.

Third, our analyses are grounded on a *status quo* view, neglecting several potential changes in market pricing based on a broader alteration of consumption behaviors. In that, we consider an exemplary calculation scheme for end-consumer prices in the dynamic tariff regime. Future work should evaluate variations in market pricing and respective re-evaluations of our tariff comparisons and operation strategies. Similarly, it would be interesting to explore how an increasing share of BESS that operate price-oriented would alter grid demand.

Fourth, in line with the focus of Semmelmann et al. (2024), influences of BESS operation beyond the individual households with a focus on overall welfare are a good way to provide additional perspectives. Should future works be able to identify welfare increasing potential; this might serve as the basis for policymakers to re-evaluate subsidies yet again and tailor their spending more closely to their goals.

Fifth, our aim in constructing a rule-based approach for BESS application was to provide a higher applicability in realistic settings, in contrast to the extensive hardware and time demands of the benchmarked linear optimization approach. For this, we concentrated only on forecasting on a day-ahead basis, due to the increasing complexity in forecasting electricity consumption (Giacomazzi et al., 2023). The best-case view based on global optima applying a linear optimization approach showed the potential that might be leveraged by implementing larger forecast time horizons and using accurate forecasting. Another aspect that can be considered here is the computational complexity of the forecasting as well as optimization approaches, which may negatively influence the net gains when considering a system's perspective.

Sixth, given our focus on net benefits, we neglected certain factors in the economic analysis. One is the initial BESS investment costs and hardware replacement costs, given that these are subject to continuous price changes. Therefore, we also did not evaluate how different operation strategies influence battery degradation and did not track the charging cycles.

Seventh, we designed our setup consisting of comparisons between two types of algorithmic approaches (rule-based vs. optimization), two different aims (price-agnostic vs. price-sensitive), and two forecasting benchmarks (naïve vs. perfect). This was done to derive a certain span of potential results and determine whether it would be reasonable to invest even more time in applying hardware-intensive and time-consuming machine learning approaches or even developing tailored ones. The results of our study show that the current price environment offers hardly any incentive. Furthermore, given the broad scope of our work, we chose to leave application of machine learning approaches to future work. An example here would be the forecasting of electricity prices considering neighboring energy markets (e.g., Ziel et al., 2015) or the use of time-series decomposition techniques (e.g., Ghimire et al., 2025)

Finally, our market-driven analysis could be used in future research to investigate the acceptance and adaptation of dynamic tariffs by different stakeholder groups, considering the existence of BESS.

CRediT authorship contribution statement

Christian Lorenz: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Data curation, Conceptualization. **Daniel R. Bayer:** Writing – review & editing, Writing – original draft, Methodology, Data curation. **Marco Pruckner:** Writing – review & editing, Validation. **Thorsten Staake:** Writing – review & editing, Validation, Supervision, Conceptualization. **Konstantin Hopf:** Writing – review & editing, Writing – original draft, Validation, Supervision, Conceptualization.

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.

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Appendix A. SOC comparison

The following figures (Figs. A.11–A.14) represent the BESS SOC for an exemplary household and different BESS characteristics. We compare the rule-based price-agnostic (maximization of self-consumption) with the rule-based price-sensitive approach used in our analyses throughout a time frame with moderate and one with high PV production.

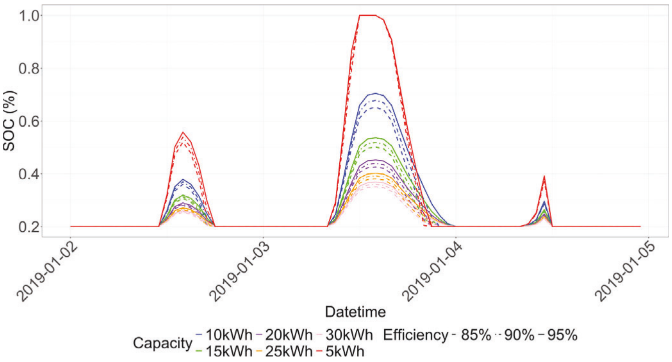

Fig. A.11. SOC with price-agnostic operation during moderate PV production.

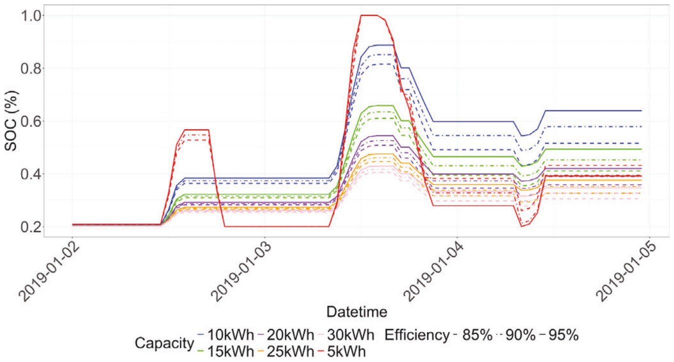

Fig. A.12. SOC with price-sensitive operation during moderate PV production.

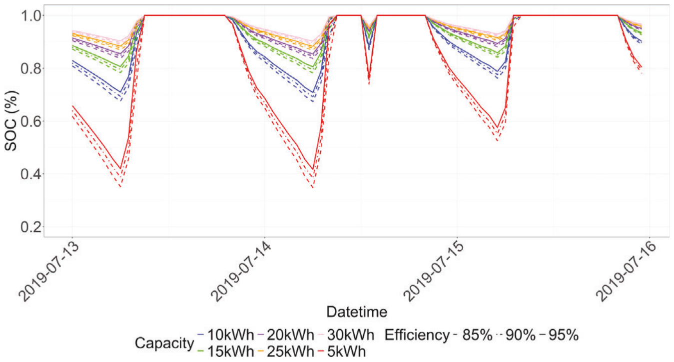

Fig. A.13. SOC with price-agnostic operation during high PV production.

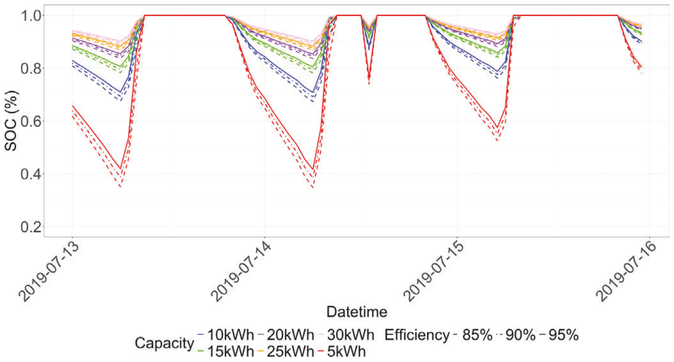

Fig. A.14. SOC with price-sensitive operation during moderate PV production.

Appendix B. Autocorrelation for naïve forecast

The following figures (Figs. B.15 and B.16) shows exemplary autocorrelation plots for both—the EPEX spot prices and electricity net-demand—which were used to visually determine the lag for the corresponding values to use as a naïve forecast in our analyses.

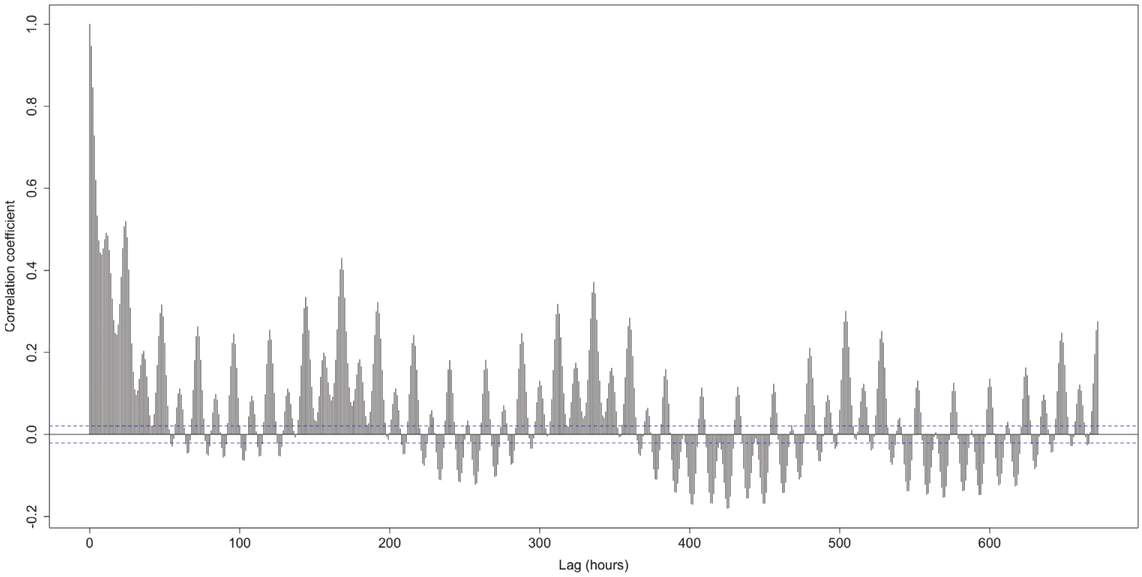

Fig. B.15. Autocorrelation for EPEX spot prices.

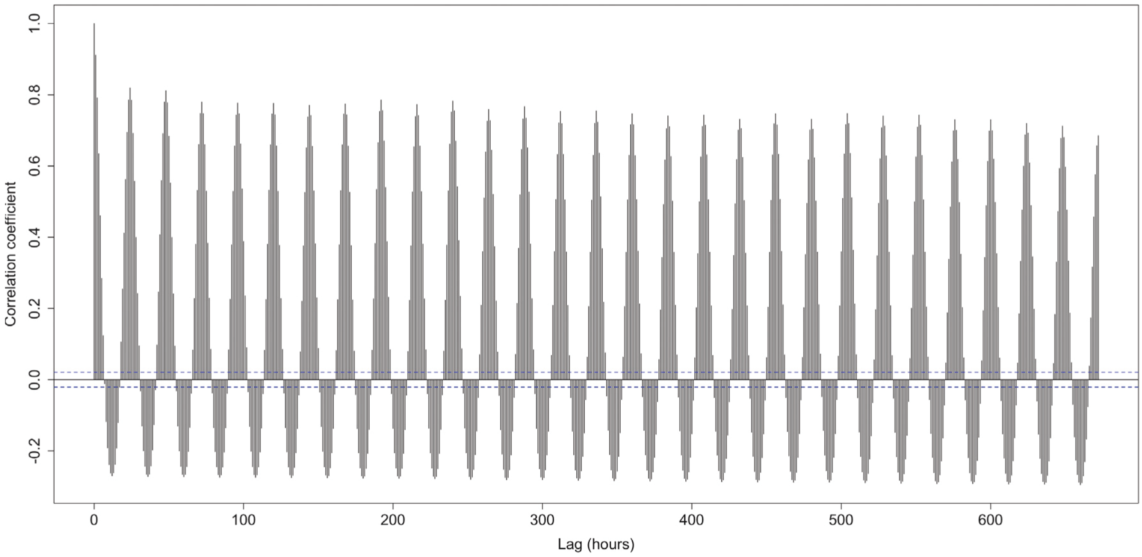

Fig. B.16. Autocorrelation for net-demand.

Appendix C. Forecast comparison

The figures shown below (Figs. C.17 and C.18) make visible how the naïve forecast derived by using past values with high autocorrelation relates to the actual values of the corresponding data (used as perfect forecast in our analyses).

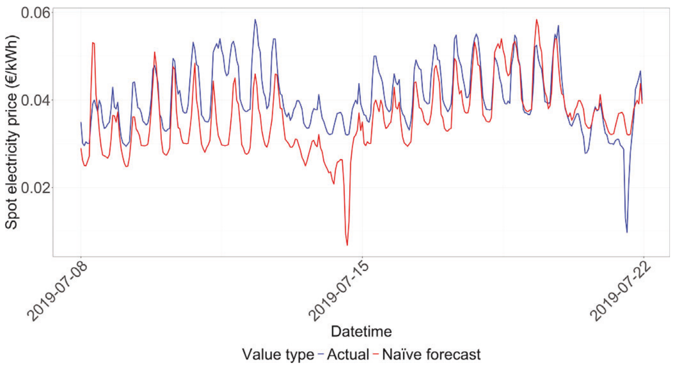

Fig. C.17. Forecast comparison for EPEX spot prices.

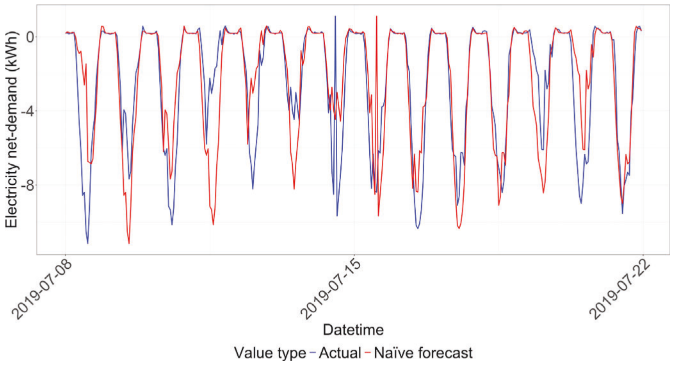

Fig. C.18. Forecast comparison for net-demand.

Data availability

The authors do not have permission to share data.

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