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Business cases of aggregated flexibilities in multiple electricity markets in a European market design

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ABSTRACT

Distributed flexible energy consumption, production and storage technologies are an option to increase the flexibility of electricity systems and foster the integration of variable renewable energy sources. Aggregation business models, providing residential customers access to different electricity markets, can activate and utilize this untapped flexibility potential. However, economic feasibility for both aggregator and customers is a pre-requisite for the adoption of these business models. In a European electricity market design with sequential markets, participation on multiple markets is supposed to further increase the economic benefits of aggregated demand response. In this work, a modular and extensible operational optimization and simulation framework based on mixed interger linear programming is developed to investigate different business models for aggregation of residential flexibility options on multiple markets. Simulation results of a specific case study show that considering day-ahead, balancing and intraday markets with adequate risk management in the optimization can significantly improve economic benefits compared to single-market optimization. Battery storages contribute most to these benefits. Business models on multiple markets are complex in terms of business model design and optimization, but they are economical for both aggregator and customers. Moreover they provide additional flexibility options to electricity systems. Thus, barriers for their implementation should be mitigated.

1. Introduction

Increased flexibility is a crucial requirement for the ongoing integration of variable Renewable Energy Sources (RES) and the transition to a sustainable renewable energy system [1]. Aggregation of distributed flexible demand and production and provision of access to wholesale electricity and balancing markets is one of many promising options to increase the flexibility of electricity systems [2].

However, the multitude of different flexible end user components and portfolios, different characteristics for different electricity markets and the complexity of corresponding business model design makes the aggregation and coordinated control of distributed flexible technologies a challenging task [3]. Technical constraints of individual components as well as customers' comfort limits have to be respected. Furthermore, interfering in the operation of end user components might yield undesired effects on total energy efficiency, technical lifetime or grid costs.

In this work a modular optimization framework is presented that allows to optimize a portfolio of flexible electricity consumption, production and storage technologies on the day-ahead spot market and a balancing market. It is embedded in a simulation framework to simulate stochastic balancing market activations and corresponding reactions of the aggregator on the intraday market. The underlying sequence of electricity markets (day-ahead, intraday and balancing markets) reflects the electricity market design in many regions in Europe [4].

The framework is applied to a specific case study considering an aggregator of residential customers optimizing their flexible components on the day-ahead spot market, a balancing market and the intraday market. Different scenarios and portfolio configurations are analyzed to identify crucial impact factors for the economic feasibility of aggregator business models and to answer the following research questions:

- What economic benefits can be achieved with aggregated residential flexible components on various markets?
- What is the contribution of different technology types (battery, electric vehicle, heat pump, electric boiler, photovoltaic (PV) system) to these benefits?
- How does market-driven flexibility optimization impact the share of PV self-consumption of prosumers?
- What is the optimal level of aggregation for the optimization of multiple components?

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Nomenclature

Abbreviations

aFRR	automatic Frequency Restoration Reserve
CVaR	Conditional Value at Risk
DER	Distributed Energy Resources
ENTSO-E	European Network of Transmission System Operators for Electricity
ISO	Independent System Operator
LCOE	Levelized cost of energy
mFRR	manual Frequency Restoration Reserve
PV	photovoltaic
RES	Renewable Energy Sources
RR	Replacement Reserves
TSO	Transmission System Operator
VaR	Value at Risk

Sets

$\mathscr{B}^\delta$	Indices for possible price bids for each balancing market direction
$\mathscr{D}$	Balancing market directions ($\mathscr{D} = \{-,+\}$)
$\mathscr{P}^\delta$	Indices for balancing products considered for each direction in the optimization
$\mathscr{T}_{\text{opt}}$	Considered time steps for the optimization
$\mathscr{T}_{\text{sim}}$	Considered time steps for the simulation
$\mathscr{T}_i^\delta$	Time steps of the ith balancing product

Parameters

Δt	Step length in hours
τ^{bal}	Reduced grid tariff for negative balancing in EUR/MWh
τ^{reg}	Regular grid tariff in EUR/MWh
$p^\delta_{\text{act},i,j}$	Balancing activation price bid for balancing bid j of product i
$p_{\text{da},t}$	Day-ahead market price at time t
$p^\delta_{\text{res},i,j}$	Balancing reserve price for balancing bid j of product i
$P^\delta_{i,j}$	Activation probability for balancing bid j of product i
$P^\delta_{t,j}$	Activation probability of price bid j at time t
$r^\delta_{\text{min},i,j}$	Minimum bid size for bid j of product i
V_{bal}	Balancing market volume

Model expressions and variables

χ_t^{in}	Charging schedule of a component at time t
χ_t^{out}	Discharging schedule of a component at time t
soc_t	State-of-charge of a component at time t
π	Total expected profit
π_{bal}	Expected balancing market profit
π_{da}	Day-ahead market profit
$b^\delta_{\text{bid},i,j}$	Binary variable indicating whether a bid is placed for bid j of product i
c^{tot}	Total cost
c_{op}	Operational cost of a component
c_{tar}	Expected grid tariff costs
$r^\delta_{\text{bid},i,j}$	Balancing market bid size of bid j for the ith product
$r^\delta_{\text{tot},t,j}$	Total balancing market reserve for bid j at time t
$r^\delta_{t,j}$	Balancing market reserves of a component for price bid j
s_t^{in}	Input schedule of a component at time t
s_t^{out}	Output schedule of a component at time t
s_t^{tot}	Total day-ahead market schedule at time t
$s^{\text{buy}}_{\text{da},t}$	Day-ahead market buying schedule of a component
$s^{\text{sell}}_{\text{da},t}$	Day-ahead market selling schedule of a component

The paper is organized as follows: Section 2 provides an overview of work related to electricity aggregators, the regulatory framework and portfolio optimization on multiple markets and explains the contributions of this work beyond the state of the art. Section 3 describes the mathematical approach of the optimization and simulation framework. The empirical scaling for the investigated case study is described in Section 4. Section 5 presents the quantitative results. A discussion of business model design, barriers and challenges is provided in Section 6. Section 7 concludes the paper.

2. State of the Art

A comprehensive review of the theoretical value of aggregation is given by Burger et al. [5]. Lu et al. [3] provide an overview of the fundamentals and business model of demand response aggregation on electricity markets. Carreiro et al. [6] present a literature survey of energy management systems aggregation. Besides related review papers, the following subsections discuss important references in the different categories relevant for the analysis in this work.

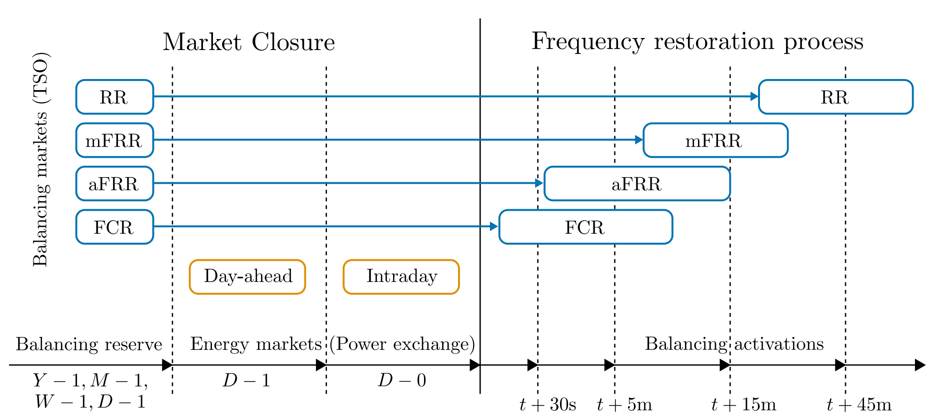

Fig. 1. European sequential electricity markets. The left side shows the market closure times for balancing reserve procurement and energy markets. The right side illustrates the balancing market activation schedule in the frequency restoration process. (Own illustration based on Poplavskaya [8] and ENTSO-E [9]).

2.1. Electricity markets

This work considers the European electricity market design. In the U.S., market participants place complex bids including operational constraints and start-up cost. The Independent System Operator (ISO) usually co-optimizes energy and balancing reserves in a centralized unit commitment model. In contrast, in Europe energy and balancing procurement are organized in sequential markets with simpler bids and separate clearing mechanisms. The market participants are responsible for unit commitment. Botterud and Auer [4] provide a comprehensive comparison of European and U.S. electricity market design.

Fig. 1 schematically illustrates the market closure times of the European sequential electricity markets. Short-term energy-only markets are auctioned either day-ahead or intraday and are operated by power exchanges. The balancing markets are operated by the Transmission System Operator (TSO). They are typically divided into four markets for Frequency Containment Reserve (FCR), automatic Frequency Restoration Reserve (aFRR), manual Frequency Restoration Reserve (mFRR) and Replacement Reserves (RR) respectively. Hirth and Ziegenhagen [7] provide a comprehensive description of the European balancing markets and three links to the integration of variable RES.

Dallinger et al. [10] investigate the impact of balancing market design on European balancing markets. They find that shorter balancing products promote market access for distributed energy resources and RES. Furthermore, they show that distributed energy resources can significantly reduce balancing procurement cost, CO_2 emissions and spillage of RES. Roos and Bolkesjø [11] analyze the effects of using demand response for balancing capacity procurement. They present similar findings of significant reduction of cost and RES curtailment.

2.2. Regulatory framework and barriers

According to Carreiro et al. [6] the practical implementation of business models for electricity aggregation still faces challenges. They highlight the importance of adequate regulatory frameworks. Barbero et al. [12] investigate barriers for aggregation of electricity demand in Belgium, Finland, France and UK and find that results are strongly country-dependent. They categorize balancing market access barriers into regulatory, technical and economic barriers. Incomplete regulations defining the roles of market participants and a high number of required contracts can be regulatory barriers. Technical barriers include high minimum bid sizes, symmetric products and long product resolution. Economic barriers range from insufficient incentives from market signals or high cost for smart meters and ICT infrastructure to high penalization costs and subsidies of peak power plants.

Poplavskaya and de Vries [13] conduct a similar analysis for the balancing markets in Austria, Germany and The Netherlands. They consider minimum bid sizes ranging from MWto MW5 fairly restrictive for aggregation of Distributed Energy Resources (DER). They recommend pool-based prequalification, increasing the bidding frequency and higher product resolution. They acknowledge that recent regulation [14] addresses all key design variables except for product resolution. However, the Network Codes on Electricity Balancing [15] of the European Network of Transmission System Operators for Electricity (ENTSO-E) provide for a product validity period of 15 min.

Nysten and Wimmer [16] discuss the barriers for several aggregator business models related to the regulatory framework and data availability. They elaborate on the dynamic interdependency between national and EU regulations, focusing on the "Clean Energy for all European" package [17].

2.3. Portfolio optimization in multiple markets

For the adoption of business models for aggregation their economic feasibility is a necessary requirement. Several contributions aim to evaluate the techno-economic potential of business models for an energy aggregator operating in multiple markets. For this purpose the dispatch of the aggregator's portfolio of end user flexibilities on several markets is optimized respecting technical constraints and customer preferences. The result is compared to a baseline case without pooling and market access.

Most existing literature presents scenario-based multi-stage stochastic optimization models [18] to calculate the market schedule of an aggregator. For example, Ottesen et al. [19] use a two-stage model with different price scenarios to quantify the potential benefits of an aggregator of prosumers with shiftable electric heat demand and curtailable loads on the day-ahead and balancing market. However, the balancing market is not modeled explicitly but represented via imbalance penalties. Ottesen et al. [20] extend this approach to a three-stage model considering an options market, a spot market and a short-term flexibility market. In this analysis the options market corresponds to balancing procurement and the flexibility market to balancing activation of the mFRR market. For each of the three market segments different price scenarios are considered. In contrast, Iria et al. [21] introduce uncertainty of prosumers' load and generation profiles in a two-stage stochastic model. They consider an aggregator of prosumers operating on the aFRR market. Rashidizadeh-Kermani et al. [22] introduce a bi-level stochastic optimization model with the upper level optimizing an aggregator's profit and the lower corresponding to the customers' behavior based on a cost function. Şengör [23] present an optimization model for an aggregator of electric vehicle parking lots. They tackle uncertainty by considering multiple scenarios for both, electric vehicle customer behavior and market prices for Finland, Turkey and the U.S.

None of the above contributions consider the inherent uncertainty of balancing market activations. Most of flexible end user technologies, like batteries, electric vehicles or electric heating, show properties of an energy storage and are characterized by a state-of-charge. Unexpected balancing activations yield unexpected state-of-charge levels. This might force the technology to deviate from schedule and cause imbalances or penalties for not supplied balancing reserve. Iria and Soares [24] evaluate this in a model predictive control approach. In a deterministic optimization model day-ahead market bids and balancing reserves are scheduled. The controller adjusts the operating point of flexible technologies to the signal provided by balancing market activations.

All contributions find significant potential benefits especially on balancing markets for the aggregation of flexible end users. However, they do not consider the complete electricity bill, including grid tariffs, fees and surcharges, in the optimization of end user flexibilities. This can yield suboptimal results. The impact of grid tariffs on coordinated demand response is analyzed by [25]. However, they only consider the day-ahead market.

2.4. Novelty and contribution to the progress beyond the state of the art

On a methodoligical level the contribution of this work is a mathematical framework to optimize and simulate the operation of a portfolio of flexible technologies on multiple short-term markets in a European electricity market design, including balancing, day-ahead and intraday markets. This allows to evaluate a wide range of business models in the context of energy aggregation. The novelty of this framework is twofold:

- It is designed with a focus on modularity and extensibility.

  A specific use case including the day-ahead, intraday and aFRR balancing market is presented in detail. However, in general, any combination of day-ahead, intraday and multiple balancing markets, characterized by reserves and uncertain activations, with arbitrary, potentially different, product lengths can be considered.

  Furthermore, the framework is not limited to specific technologies but formulated in terms of *a generic component interface*. Potential representations of batteries, electric vehicle charging stations, heat pumps, electric hot water boilers and PV systems in the generic

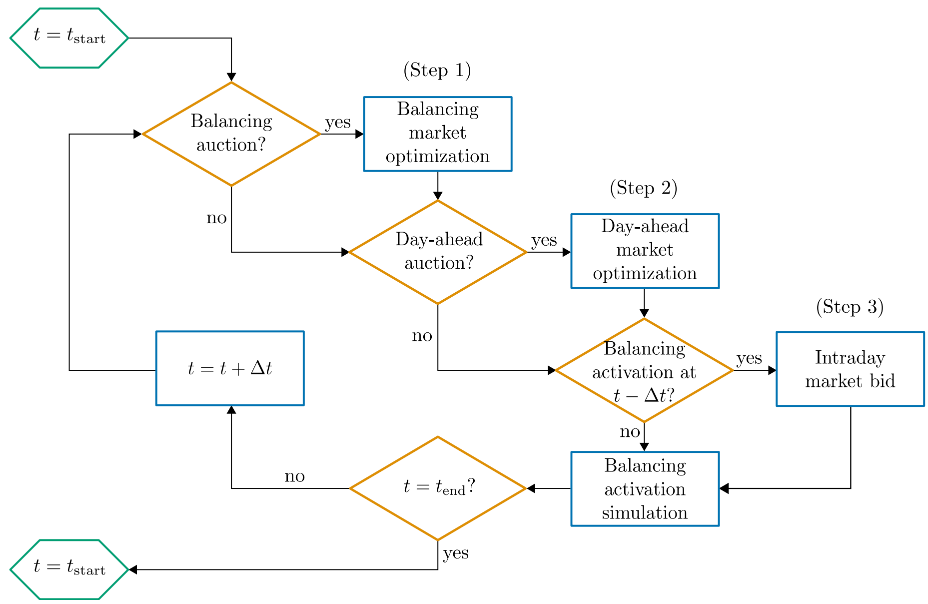

Fig. 2. Simulation Framework Flowchart.

interface are presented, but new technologies can easily be added for further analyses.

Finally, different portfolios of technologies can be flexibly composed and the components can be optimized individually, clustered to households or altogether.

- The framework provides a high level of detail in terms of operational simulation.

Most contributions to literature related to participation on balancing markets focus on the optimization of market schedules only using stochastic optimization or similar scenario-based approaches. However, they disregard the impact of unexpected balancing activations on the state-of-charge of flexible components and potential effects on energy efficiency and total cost reduction. In contrast, the presented framework couples day-ahead optimization of market schedules with quarter-hourly simulation of balancing activations and corresponding reactions to unexpected activations on the intraday market. The option to balance state-of-charge deviations on the intraday market is already considered in the day-ahead optimization, ensuring technically feasible operation of the components and allowing to offer significantly more flexible reserves to balancing markets.

Furthermore, the framework does not only consider market interactions in the optimization, but includes a detailed representation of grid tariffs, fees and surcharges, even considering tariff reductions for balancing market participation. This allows to consider the complete end user electricity bill and ensure actual cost reduction.

On an energy-economic and systemic level this work provides the following contributions by applying the presented methodological framework to different configurations of a case study and discussing the quantitative results:

- The economic potential of business models for the aggregation of flexible residential technologies is quantified considering the full end user electricity bill.
- The contributions of different components to the total cost reduction achieved on different markets are evaluated and the advantages and disadvantages of various flexibility options for different markets are disussed.
- The impact of unexpected balancing activations on the profitability of these business models is analyzed and different strategies to mitigate the risk of unexpected cost increase are investigated.
- The advantages and disadvantages of different aggregation levels in the formulation and solution of the optimization problems themselves are quantified and discussed.

3. Methods

This section provides a mathematical formulation of the framework used to simulate the operation of different flexible technology portfolios on multiple electricity markets. The framework is implemented in the Julia [26] programming language using the JuMP [27] package to model optimization problems. The models are solved using the Gurobi solver [28]. Section 3.1 describes the general structure of the simulation set-up. The basic formulation of the optimization problem in multiple markets is provided in Section 3.2. Details about the implementation of different flexible technologies are given in Appendix A.

3.1. Simulation framework

The framework simulates the actual day-to-day operation of a technology portfolio in multiple markets close to real-life conditions in many regional European electricity market designs. Here, a day-ahead energy-only market with uniform pricing and a daily auctioned balancing market with four-hourly products and pay-as-bid pricing are considered. In the day-ahead market, the components can buy or sell electricity for the following day until market closure time. Furthermore, balancing reserve, both negative and positive, can be offered day-ahead for six four-hourly products until balancing market closure time. The components get remunerated for the reserve with the offered balancing reserve price and for actual activations with the bidden balancing activation price. Most components require control over their state-of-charge. To compensate stochastic activations from the balancing market in these cases, the intraday market is used. It is characterized by a time series of prices and a lead time, describing minimum duration between the last potential trade and the actual delivery.

The general structure of the simulation framework is illustrated in Fig. 2. It can run for an arbitrary set of time steps $\mathscr{T}_{\text{sim}}$ with a step length Δt. The simulation iterates through all time steps $t \in \mathscr{T}_{\text{sim}}$.

If t is the market closure time of a balancing market, first an optimization model is built and solved providing the optimal balancing reserve bids of the portfolio for all auctioned market products (Step 1). Typically these are the six four-hour products of the following day, but in general other market structures, e.g. with weekly peak and off-peak products, can be considered, too. In the balancing market optimization both the balancing and the day-ahead market are considered, because the day-ahead prices provide the opportunity cost for offering balancing reserves. Furthermore, in this framework it is assumed that the day-ahead schedule provides the baseline for deviations caused by balancing market activations. The simulations of the use case presented in this work use an overlapping rolling horizon of two days. Each day the optimal day-ahead and balancing market schedules for the 192 quarter-hourly time steps of the next two days are determined. However, only the results for the following day are fixed. The values for the second day overwritten by the optimization results of the next day. A description of the optimization model is provided in Section 3.2.

If t is the market closure time of the day-ahead market, next a further optimization model may be formulated and solved updating the day-ahead schedule and respecting the already accepted balancing reserves (Step 2). This step is only required if the information about day-ahead market prices or load and production forecasts has improved since the balancing market optimization. Otherwise it yields the same results.

If there have been balancing market activations at time step $t-1$ and they have to be compensated, an intraday market bid can be placed at time step t respecting the lead time (Step 3). Finally, at each time step $t \in \mathscr{T}$ balancing market activations are simulated (Step 4). For this either historical values of positive and negative activations are used or random numbers with the appropriate expectation are generated.

3.2. Optimization on multiple markets

This section presents the general structure for the optimization model considering multiple markets that is solved in Step 1 in Fig. 2. To allow the consideration of manifold energy technology portfolios, several model expressions are initialized that can be added to for each considered device. Model expressions mean linear combinations of model variables of the form

$$a_0 + \sum_{i=1}^{n} a_i \cdot x_i, \tag{1}$$

where a_i for $i = 0, \ldots, n$ are constants and x_i for $i = 1, \ldots, n$ are model variables.

3.2.1. Market representation

Balancing markets are represented in the framework as a set of positive and negative balancing products, where each product is characterized by its active time steps, the market closure time of its auction, a set of price bids and a minimum bid size.

The price bids are described by a balancing activation price, a balancing reserve price and an activation probability. During the simulation, activations are generated randomly based on the activation probability. Market participants are remunerated with the balancing reserve price if a bid is accepted and with the balancing activation price for actual activations. Both prices are provided in EUR/MWh[1]. Balancing products can be described by all historical price bids, representing the total merit-order curve, or by a selection of several price bids. In the optimization model the portfolio can decide how much to reserve for each available bid.

Both the day-ahead and the intraday market are represented by a time series of prices in EUR/MWh. For the day-ahead market an auction closure time is provided in addition. The intraday market is characterized by a minimum lead time.

The framework is formulated generally in terms of time resolution. For the simulations in this work hourly day-ahead market prices and quarter-hourly intraday market prices are assumed. Balancing market activations are simulated with a quarter-hourly resolution. In the simulations it is assumed that the balancing market closure time is before the day-ahead market auction.

3.2.2. Initialization of model expressions

At each balancing market closure time t in the simulation illustrated in Fig. 2 an optimization model is built, considering all balancing products that are auctioned at time t. First, all time steps $\mathscr{T}_{\text{opt}} \subseteq \mathscr{T}_{\text{sim}}$ of the considered products are identified. These are typically all time steps of the next day or week. In the following $\delta \in \mathscr{D} = \{-, +\}$ is written for the balancing market direction. Let $\mathscr{B}^{\delta}$ denote the set of indices for possible price bids for balancing market products in each direction. Next, model expressions for the positive and negative reserve for each price bid at each time step $r^{\delta}_{\text{tot},t,j}$, expressions for the day-ahead market schedule of the portfolio at every time step s_t and an expression for operational cost c are initialized.

$$r^{\delta}_{\text{tot},t,j} = 0 \quad j \in \mathscr{B}^{\delta}, \delta \in \mathscr{D}, t \in \mathscr{T}_{\text{opt}} \tag{2}$$

$$s_t = 0 \quad t \in \mathscr{T}_{\text{opt}} \tag{3}$$

$$c = 0 \tag{4}$$

For the day-ahead schedule the convention is used that positive values correspond to sales while negative ones represent purchases. Variables or expressions for different components can be added to these expressions subsequently. Section 3.3 and Appendix A describe in detail how this can be done for various technologies and which constraints have to be added to the optimization model.

3.2.3. Model finalization

When all individual component expressions are added to the model expression, the balancing reserves in the model are the sum of all technology reserves and the model day-ahead schedule is the sum of all individual schedules. Next, some constraints regarding the bid size for each bid are added to the model, the objective function is formulated and a solver is started.

Let $\mathscr{P}^{\delta}$ denote the indices of considered products for each direction in the optimization problem. Furthermore, let $\mathscr{T}^{\delta}_{i}$ for $i \in \mathscr{P}^{\delta}$ be the time steps corresponding to the ith balancing product. The decision variable for the size of bid j for the ith product in each direction is written as $r^{\delta}_{\text{bid},i,j}$. The following constraints ensure that the sum of all component bid sizes is the same for every bid at each relevant time step.

$$r^{\delta}_{\text{tot},t,j} = r^{\delta}_{\text{bid},i,j} \quad t \in \mathscr{T}^{\delta}_{i}, i \in \mathscr{P}^{\delta}, j \in \mathscr{B}^{\delta}, \delta \in \mathscr{D} \tag{5}$$

To consider minimum bid sizes for balancing markets binary variables $b^{\delta}_{\text{bid},i,j}$ are introduced for each bid of all products. With the total balancing market volume V_{bal} and minimum bid sizes $r^{\delta}_{\min,i,j}$ they can be respected in Eqs. (6)–(8).

$$b^{\delta}_{\text{bid},i,j} \in \{0, 1\} \quad i \in \mathscr{P}^{\delta}, j \in \mathscr{B}^{\delta}, \delta \in \mathscr{D} \tag{6}$$

$$r^{\delta}_{\text{bid},i,j} \leqslant V_{\text{bal}} \cdot b^{\delta}_{\text{bid},i,j} \quad i \in \mathscr{P}^{\delta}, j \in \mathscr{B}^{\delta}, \delta \in \mathscr{D} \tag{7}$$

$$r^{\delta}_{\text{bid},i,j} \geqslant r^{\delta}_{\min,i,j} \cdot b^{\delta}_{\text{bid},i,j} \quad i \in \mathscr{P}^{\delta}, j \in \mathscr{B}^{\delta}, \delta \in \mathscr{D} \tag{8}$$

Let $P^{\delta}_{i,j}$ denote the activation probability for bid j of product i. The balancing activation and reserve prices of the respective products are written as $p^{\delta}_{\text{act},i,j}$ and $p^{\delta}_{\text{res},i,j}$. Then the expected profit on the balancing market is given by Eq. (9).

[1] Balancing reserve prices are often provided in EUR/MW. They can be easily transformed to EUR/MWh by dividing by the product's duration in hours.

Table 1
Functions describing the generic component interface. The functions take a component C, a time step t or a vector of time steps $\vec{t}$, and the duration of a time step in hours Δt as input argument. The table shows the second argument $f(\tilde{t}) \cong f(C, \tilde{t}, \Delta t)$ only. The default return values of the functions are listed in column D.

Function	D	Unit	Description
$s^{in}_{max}(t)$	0	MW	Maximum consumption power
$s^{in}_{min}(t)$	0	MW	Minimum consumption power
$s^{out}_{max}(t)$	0	MW	Maximum production power
$s^{out}_{min}(t)$	0	MW	Minimum production power
$\eta^{in}(t)$	1		Charging efficiency
$\eta^{out}(t)$	1		Discharging efficiency
$\phi(t)$	1	$\frac{\text{MWh}}{\text{Unit}}$	Conversion factor between MWh of electric energy and the energy unit in the storage
$\alpha(t)$	1	Bool*	Availability**
$\text{soc}_{max}(t)$	0	Unit	Maximum state-of-charge
$\text{soc}_{min}(t)$	0	Unit	Minimum state-of-charge
$\text{soc}_{base}(t)$	0	Unit	Base state-of-charge
$\text{soc}_{start}(\vec{t})$	0	Unit	Starting state-of-charge before the time steps in $\vec{t}$
$\text{soc}_{stop}(\vec{t})$	0	Unit	Minimum state-of-charge at the end of $\vec{t}$
$q_{ext}(t)$	0	Unit	External storage input or output
$\lambda_{const}(t)$	0	$\frac{\text{Unit}}{\text{h}}$	Constant storage loss factor
$\lambda_{lin}(t)$	0	$\frac{1}{\text{h}}$	Linear storage loss factor
$c^{in}(t)$	0	$\frac{\text{EUR}}{\text{MWh}}$	Cost associated with consumption excluding market cost and tariffs
$c^{out}(t)$	0	$\frac{\text{EUR}}{\text{MWh}}$	Cost associated with production excluding market cost and tariffs
$c^{in}_{charge}(t)$	0	$\frac{\text{EUR}}{\text{Unit}}$	Cost associated with charging
$c^{out}_{charge}(t)$	0	$\frac{\text{EUR}}{\text{Unit}}$	Cost associated with discharging

* A Boolean value can either be true or false.
** Electric vehicles, for example, are not connected during all time steps.

$$\pi_{bal} = \Delta t \cdot \sum_{\substack{\delta \in \mathcal{D}, i \in \mathcal{P}^{\delta} \\ j \in \mathcal{B}^{\delta}, t \in \mathcal{T}^{\delta}_{i}}} \left(P^{\delta}_{i,j} \cdot p^{\delta}_{act,i,j} + p^{\delta}_{res,i,j} \right) \cdot r^{\delta}_{bid,i,j} \tag{9}$$

With the day-ahead market prices at time t written as $p_{da,t}$ the spot market profit is given in Eq. (10).

$$\pi_{da} = \Delta t \cdot \sum_{t \in \mathcal{T}_{opt}} p_{da,t} \cdot s^{tot}_{t} \tag{10}$$

The cost expression c^{tot} is already populated with potential additional cost of different components. The objective function of the model is given by the total expected profit π which is defined in Eq. (11).

$$\pi = \pi_{bal} + \pi_{da} - c^{tot} \tag{11}$$

Finally, the model is solved maximizing π and the resulting schedules of individual components are stored.

3.3. Generic storage interface

In this work different types of flexible components are considered: batteries, electric vehicles, heat pumps, electric domestic hot water boilers and PV systems. They differ significantly in terms of functionalities as well as from a technical and service delivery perspective. However, they share many characteristics in terms of market operation and representation in the optimization and simulation framework. All components can (at least theoretically) provide negative and positive balancing reserves and purchase electricity from the day-ahead market. Technically they are characterized by efficiencies, maximum and minimum operating points and temporal availability. Furthermore, in general, most components can consume electric energy, convert it into another energy carrier (like thermal energy) and store it subject to losses over time.

Hence, a functional generic component interface is introduced, capable of describing the key characteristics of all considered components. The 20 functions defining the interface are listed in Table 1. They take a component C, a time step t or a vector of times steps $\vec{t}$, and the length of a model time step Δt as input. Table 1 shows the default return values of fallback methods defined for generic components. They describe a component without any flexibility. For specific sub-types of generic components new methods can be defined overwriting these default values and adding flexibility.

Fig. 3 illustrates the key elements of the functional interface. Any component can consume and produce electricity subject to input and output power limits and efficiencies. The consumed electric energy is converted into another energy carrier described by the state-of-charge unit of the storage, like MWh for batteries or °C for electric boilers. The state-of-charge is constrained by lower and upper bounds and exposed to constant and linear losses as well es fixed external input or output. Linear losses depend on the difference between the current state-of-charge and a base state-of-charge. Input, output, charging and discharging can be associated with corresponding cost.

The following paragraphs describe, how different components can be considered in the model by adding variables for individual schedules and cost to the global model expressions in Eqs. (2) to Eq. (4) and introducing new constraints, only relying on the generic component interface. The colored elements in Fig. 3 represent the variables that are

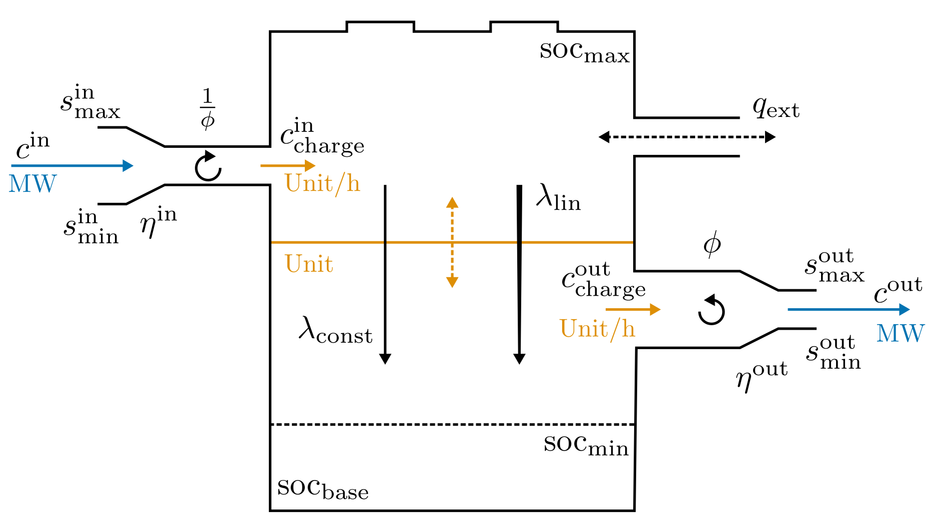

Fig. 3. Generic component interface.

added to the optimization problem for each time step and for each considered component. In the simulation framework every component stores a schedule for its state-of-charge, its negative and positive balancing market reserves and its day-ahead and intraday market schedules for each $t \in \mathscr{T}_{\mathrm{sim}}$. Hence, values from previous optimization runs can be accessed during model set-up.

3.3.1. Technical constraints

Let s_t^{in} and s_t^{out} denote the input and output schedule of a component at time t. The schedules for charging and discharging are given by χ_t^{in} and χ_t^{out}. The state-of-charge at time t is written as soc_t. Eq. (12) to Eq. (14) ensure the power and storage limits of a component. The efficiencies and the conversion between MWh and the corresponding Unit are included in Eq. (15) to Eq. (16).

$$s_{\min}^{\mathrm{in}}(t) \leqslant s_t^{\mathrm{in}} \leqslant s_{\max}^{\mathrm{in}}(t) \quad t \in \mathscr{T}_{\mathrm{opt}} \tag{12}$$

$$s_{\min}^{\mathrm{out}}(t) \leqslant s_t^{\mathrm{out}} \leqslant s_{\max}^{\mathrm{out}}(t) \quad t \in \mathscr{T}_{\mathrm{opt}} \tag{13}$$

$$\mathrm{soc}_{\min}(t) \leqslant \mathrm{soc}_t \leqslant \mathrm{soc}_{\max}(t) \quad t \in \mathscr{T}_{\mathrm{opt}} \tag{14}$$

$$\phi(t) \cdot \chi_t^{\mathrm{in}} = \eta^{\mathrm{in}}(t) \cdot s_t^{\mathrm{in}} \quad t \in \mathscr{T}_{\mathrm{opt}} \tag{15}$$

$$s_t^{\mathrm{out}} = \eta^{\mathrm{out}}(t) \cdot \phi(t) \cdot \chi_t^{\mathrm{out}} \quad t \in \mathscr{T}_{\mathrm{opt}} \tag{16}$$

Eq. (17) to Eq. (18) set the start and end values of the state-of-charge. Here t_1 and t_n denote the first and the last considered time step. The values for the state-of-charge stored in the simulation schedules from previous optimizations are written as $\mathrm{soc}_t^{\mathrm{sim}}$.

$$\mathrm{soc}_{t_1 - \Delta t} = \begin{cases} \mathrm{soc}_{t_1 - \Delta t}^{\mathrm{sim}} & t_1 - \Delta t \in \mathscr{T}_{\mathrm{sim}} \\ \mathrm{soc}_{\mathrm{start}}(\mathscr{T}_{\mathrm{opt}}) & t_1 - \Delta t \notin \mathscr{T}_{\mathrm{sim}} \end{cases} \tag{17}$$

$$\mathrm{soc}_{t_n} = \mathrm{soc}_{\mathrm{stop}}(\mathscr{T}_{\mathrm{opt}}) \tag{18}$$

Eq. (19) connects the state-of-charge to its value in the last time step and storage input, output and losses. Note that the external storage input $q_{\mathrm{ext}}(t)$ can also have negative values.

$$\mathrm{soc}_t = \mathrm{soc}_{t-\Delta t} + q_{\mathrm{ext}}(t) + \Delta t \cdot \left(\chi_t^{\mathrm{in}} - \chi_t^{\mathrm{out}} - \lambda_{\mathrm{const}}(t) - \lambda_{\mathrm{lin}}(t) \cdot \left(\mathrm{soc}_{t-\Delta t} - \mathrm{soc}_{\mathrm{base}, t-\Delta t} \right) \right) \quad t \in \mathscr{T}_{\mathrm{opt}} \tag{19}$$

3.3.2. Market constraints

The variables for balancing market reserves of a component are written as $r_{t,j}^{\delta}$ for each possible price bid j, direction δ and time step t. The corresponding activation probabilities are given by $P_{t,j}^{\delta}$. The variables for selling and buying on the day-ahead spot market are denoted by $s_{\mathrm{da},t}^{\mathrm{buy}}$ and $s_{\mathrm{da},t}^{\mathrm{sell}}$. Eq. (20) ensures the balance between technical and market variables.

$$s_t^{\mathrm{out}} - s_t^{\mathrm{in}} = \sum_{j \in \mathscr{B}^+} P_{t,j}^+ \cdot r_{t,j}^+ - \sum_{j \in \mathscr{B}^-} P_{t,j}^- \cdot r_{t,j}^- + s_{\mathrm{da},t}^{\mathrm{sell}} - s_{\mathrm{da},t}^{\mathrm{buy}} \quad t \in \mathscr{T}_{\mathrm{opt}} \tag{20}$$

The daily optimization requires a starting value for the state-of-charge in. efeq:socstart. It corresponds to the final state-of-charge value from the previous schedule. However, market closure time is typically several hours before midnight. Balancing market activations can still occur after schedule planning affecting the actual state-of-charge of the storage. To overcome this issue an intraday market is considered in the simulation framework. It allows to react on unexpected activations with a small delay, the intraday market lead time. Components can act on the intraday market to balance reserve activations only if the operating point limits, the current day-ahead market schedules and balancing reserves allow additional trades. Hence, balancing market reserves also require intraday market reserves.

Model expressions describing the reserves for buying and selling on the intraday market $r_{\mathrm{id},t}^{\mathrm{buy}}$ and $r_{\mathrm{id},t}^{\mathrm{sell}}$ are introduced. Expected balancing market activations are already respected in Eq. (20). The required reserves in both directions considering the expected schedule are written as $r_{\mathrm{exp},t}^{\delta}$ and given in Eq. (21). For time steps $t \notin \mathscr{T}_{\mathrm{opt}}$ the stored results from previous optimizations $r_{t,j}^{\mathrm{sim},\delta}$ are chosen for $r_{t,j}^{\delta}$ and for $t \notin \mathscr{T}_{\mathrm{sim}}$ they are set to zero.

$$r_{\mathrm{exp},t}^- = \sum_{j \in \mathscr{B}^-} (1 - P_{t,j}^-) \cdot r_{t,j}^- + \sum_{j \in \mathscr{B}^+} P_{t,j}^+ \cdot r_{t,j}^+ \quad t \in \mathscr{T}_{\mathrm{sim}} \tag{21}$$

$$r_{\mathrm{exp},t}^+ = \sum_{j \in \mathscr{B}^+} (1 - P_{t,j}^+) \cdot r_{t,j}^+ + \sum_{j \in \mathscr{B}^-} P_{t,j}^- \cdot r_{t,j}^- \quad t \in \mathscr{T}_{\mathrm{sim}} \tag{22}$$

Furthermore, the storage loss factor of n linear losses until time step t is denoted by Λ_t^n and defined in Eq. (23). It can be interpreted as the share of energy fed into the storage at time $t - n \cdot \Delta t$ that is left at time t.

$$\Lambda_t^n = \prod_{i=0}^{n-1} (1 - \Delta t \cdot \lambda_{\mathrm{lin}}(t - i \cdot \Delta t)) \tag{23}$$

With the intraday market lead time written as n_{id}, the factors κ_t^{buy} and κ_t^{sell} to calculate intraday reserves at time t from balancing deviations at time $t - n_{\mathrm{id}} \cdot \Delta t$ are given in Eq. (24). They are used to calculate the intraday market reserves in Eq. (26), for $t \in \{t_1 - n_{\mathrm{id}} \cdot \Delta t, t_1 - (n_{\mathrm{id}} - 1) \cdot \Delta t, \ldots, t_n\}$.

$$\kappa_t^{\mathrm{buy}} = \frac{\eta_{\mathrm{in}}(t) \cdot \phi(t) \cdot \Lambda_t^{n_{\mathrm{id}}}}{\eta_{\mathrm{out}}(t - n_{\mathrm{id}} \cdot \Delta t) \cdot \phi(t - n_{\mathrm{id}} \cdot \Delta t)} \tag{24}$$

$$\kappa_t^{\mathrm{sell}} = \frac{\eta_{\mathrm{in}}(t - n_{\mathrm{in}} \cdot \Delta t) \cdot \phi(t) \cdot \Lambda_t^{n_{\mathrm{id}}}}{\eta_{\mathrm{out}}(t) \cdot \phi(t - n_{\mathrm{id}} \cdot \Delta t)} \tag{25}$$

$$r_{\mathrm{id},t}^{\mathrm{buy}} = \kappa_t^{\mathrm{buy}} \cdot r_{\mathrm{exp},t-n_{\mathrm{id}} \cdot \Delta t}^+ \tag{26}$$

$$r_{\mathrm{id},t}^{\mathrm{sell}} = \kappa_t^{\mathrm{sell}} \cdot r_{\mathrm{exp},t-n_{\mathrm{id}} \cdot \Delta t}^- \tag{27}$$

Eq. (28) to Eq. (29) ensure that unexpected balancing market activations and intraday reactions respect the technical power limits of the component.

$$s_{\mathrm{da},t}^{\mathrm{sell}} - s_{\mathrm{da},t}^{\mathrm{buy}} + r_{\mathrm{id},t}^{\mathrm{sell}} + \sum_{j \in \mathscr{B}^+} r_{t,j}^+ \leqslant \alpha(t) \cdot s_{\max}^{\mathrm{out}}(t) \quad t \in \mathscr{T}_{\mathrm{opt}} \tag{28}$$

$$s_{\mathrm{da},t}^{\mathrm{buy}} - s_{\mathrm{da},t}^{\mathrm{sell}} + r_{\mathrm{id},t}^{\mathrm{buy}} + \sum_{j \in \mathscr{B}^-} r_{t,j}^- \leqslant \alpha(t) \cdot s_{\max}^{\mathrm{in}}(t) \quad t \in \mathscr{T}_{\mathrm{opt}} \tag{29}$$

Reserve activations can be balanced after n_{id} steps using the intraday market. For the time steps in between energy has to be reserved in the storage to respect the state-of-charge limits even in case of balancing market activations. Let $\eta_t^{\min}$ and $\eta_t^{\max}$ denote the minimum and maximum of charging and discharging efficiency of a component at time t.

$$\eta_t^{\min} = \min\{\eta_{\mathrm{in}}(t), \eta_{\mathrm{out}}(t)\} \tag{30}$$

$$\eta_t^{\max} = \max\{\eta_{\text{in}}(t), \eta_{\text{out}}(t)\} \tag{31}$$

The negative and positive storage reserves are written as $r^{\delta}_{\text{soc},t}$. They consist of the total charged or discharged energy from all possible unexpected balancing market activations and intraday market trades in the last n_{id} time steps. They are provided in Eq. (32) and (33) for $t \in \mathcal{T}^{\text{soc}}_{\text{opt}} = \{t_1, t_1 + \Delta t, \ldots, t_n + n_{\text{id}} \cdot \Delta t\}$. The reserves $r^{\delta}_{\exp,t}$ are set to zero for $t > t_n$.

$$r^{+}_{\text{soc},t} = \Delta t \cdot \sum_{i=1}^{n_{\text{id}}} \frac{\Lambda^{i}_{t} \cdot \left(r^{\text{sell}}_{\text{id},t-i\cdot\Delta t} + r^{+}_{\exp,t-i\cdot\Delta t}\right)}{\eta^{\min}_{t-i\cdot\Delta t} \cdot \phi(t - i\cdot\Delta t)} \tag{32}$$

$$r^{-}_{\text{soc},t} = \Delta t \cdot \sum_{i=1}^{n_{\text{id}}} \frac{\Lambda^{i}_{t} \cdot \eta^{\max}_{t-i\cdot\Delta t} \cdot \left(r^{\text{buy}}_{\text{id},t-i\cdot\Delta t} + r^{-}_{\exp,t-i\cdot\Delta t}\right)}{\phi(t - i\cdot\Delta t)} \tag{33}$$

With that the state-of-charge reserve is ensured with Eq. (34).

$$\text{soc}_t \geqslant \text{soc}_{\min}(t) + r^{+}_{\text{soc},t} \quad t \in \mathcal{T}^{\text{soc}}_{\text{opt}} \tag{34}$$

$$\text{soc}_t \leqslant \text{soc}_{\max}(t) - r^{-}_{\text{soc},t} \quad t \in \mathcal{T}^{\text{soc}}_{\text{opt}} \tag{35}$$

Finally the market schedules for each component $r^{\delta}_{t,j}$ and $s^{\text{sell}}_{\text{da},t} - s^{\text{buy}}_{\text{da},t}$ are added to the global model expressions $r^{\delta}_{\text{tot},t,j}$ and s_t in Eq. (2).

3.3.3. Component-specific cost

The market related cost and revenues of all components are already considered with π_{bal} and π_{da} in the global objective function. Considering the expected balancing activations only in the objective function disregards the potential additional cost associated with unexpected balancing activations. For example, for a component with an idle expected schedule, balancing activations might cause extra cost for the grid tariff, fees and surcharges as well as component wear costs.

To make the optimization more robust with respect to these stochastic cost components, model expressions for the expected upward and downward deviation $\Delta a^{\delta,\uparrow}_{t,j}$ and $\Delta a^{\delta,\downarrow}_{t,j}$ from expected balancing activations are introduced. In Eq. (36) they are defined using the variance $p\cdot(1-p)$ of a $B(1,p)$ binomially distributed random variable.

$$\Delta a^{\delta,\uparrow}_{t,j} = \Delta a^{\delta,\downarrow}_{t,j} = P^{\delta}_{t,j} \cdot \left(1 - P^{\delta}_{t,j}\right) \cdot r^{\delta}_{t,j} \quad j \in \mathcal{B}^{\delta}, \delta \in \mathcal{D} \tag{36}$$

The deviations from schedule cause upward and downward intraday market trades $\Delta \text{id}^{\uparrow}_t$ and $\Delta \text{id}^{\downarrow}_t$ given in Eq. (37).

$$\Delta \text{id}^{\uparrow}_t = \kappa^{\text{sell}}_t \cdot \sum_{\delta \in \mathcal{D}} \sum_{j \in \mathcal{B}^{\delta}} \Delta a^{\delta,\downarrow}_{t-n_{\text{id}}\cdot\Delta t,j} \tag{37}$$

$$\Delta \text{id}^{\downarrow}_t = \kappa^{\text{buy}}_t \cdot \sum_{\delta \in \mathcal{D}} \sum_{j \in \mathcal{B}^{\delta}} \Delta a^{\delta,\uparrow}_{t-n_{\text{id}}\cdot\Delta t,j} \tag{38}$$

Now the expected deviations from input, output, charge and discharge $\Delta s^{\text{in}}_t, \Delta s^{\text{out}}_t, \Delta \chi^{\text{in}}_t$ and $\Delta \chi^{\text{out}}_t$ can be calculated with Eqs. (39) to Eq. (42).

$$\Delta s^{\text{in}}_t = \Delta \text{id}^{\downarrow}_t + \sum_{\delta \in \mathcal{D}} \sum_{j \in \mathcal{B}^{\delta}} \Delta a^{\delta,\downarrow}_t \tag{39}$$

$$\Delta s^{\text{out}}_t = \Delta \text{id}^{\uparrow}_t + \sum_{\delta \in \mathcal{D}} \sum_{j \in \mathcal{B}^{\delta}} \Delta a^{\delta,\uparrow}_t \tag{40}$$

Table 2
Considered grid tariff, fees and surcharges. In general they consist of an annual fixed component and a volumetric component in EUR/MWh. For balancing activations a reduced volumetric component is charged.

	Fixed EUR/a	Regular $\frac{\text{EUR}}{\text{MWh}}$	Reduced $\frac{\text{EUR}}{\text{MWh}}$
Grid tariff [29]			
System usage charge	30.00	36.9	0.85
System loss charge		3.36	3.36
Metering fee	28.80		
Green electricity subsidy [31]			
System usage charge	4.90	6.90	6.90
System loss charge		0.46	0.46
Green electricity flat rate [32]	28.38		
CHP flat rate [33]	1.25		
Electricity tax [34]		15.00	15.00
Usage tax [35]	1.80	2.42	0.25
Total	95.13	65.04	26.82

$$\Delta \chi^{\text{in}}_t = \Delta t \cdot \frac{\eta^{\min}_t}{\phi(t)} \cdot \Delta s^{\text{in}}_t \tag{41}$$

$$\Delta \chi^{\text{out}}_t = \Delta t \cdot \frac{1}{\eta^{\max}_t \cdot \phi(t)} \cdot \Delta s^{\text{out}}_t \tag{42}$$

The expected cost associated with the operation of a component c_{op} given in Eq. (43) are added to the global model cost expression c^{tot} in Eq. (4).

$$c_{\text{op}} = \sum_{t \in \mathcal{T}_{\text{opt}}} \left(c^{\text{in}}(t) \cdot \left(s^{\text{in}}_t + \Delta s^{\text{in}}_t\right) + c^{\text{out}}(t) \cdot \left(s^{\text{out}}_t + \Delta s^{\text{out}}_t\right) + c^{\text{in}}_{\text{charge}}(t) \cdot \left(\chi^{\text{in}}_t + \Delta \chi^{\text{in}}_t\right) + c^{\text{out}}_{\text{charge}}(t) \cdot \left(\chi^{\text{out}}_t + \Delta \chi^{\text{out}}_t\right)\right) \tag{43}$$

Cost for the grid tariff, fees and surcharges also have to be added for each component individually, because different components may be located in different areas or connected at different voltage levels and can in general be charged different tariffs. Furthermore, in general, grid charges can be different for electricity purchased on the day-ahead market and consumption caused by negative balancing market activations. In Austria, for example, negative reserve activations are charged a reduced grid tariff [29]. Tariffs, however, only have to be paid for net consumption.

Let τ^{reg} and τ^{bal} denote the charges for regular consumption from the day-ahead and intraday market and the reduced charges for negative balancing in EUR/MWh. Variables for the expected net consumption q_t excluding negative balancing activations are introduced and constrained by Eq. (44).

$$q_t \geqslant 0 \quad t \in \mathcal{T}_{\text{opt}} \tag{44}$$

$$q_t \geqslant s^{\text{buy}}_{\text{da},t} - s^{\text{sell}}_{\text{da},t} + \Delta \text{id}^{\downarrow}_t + \sum_{j \in \mathcal{B}^{+}} \left(\Delta a^{+,\downarrow}_{t,j} - P^{+}_{t,j} \cdot r^{+}_{t,j}\right) \quad t \in \mathcal{T}_{\text{opt}} \tag{45}$$

With the expected negative balancing market activations written as $q^{\text{bal}}_t = \sum_{j \in \mathcal{B}^{-}} \left(P^{-}_{t,j} \cdot r^{-}_{t,j} + \Delta a^{-,\downarrow}_{t,j}\right)$, the grid tariff, fees and surcharges cost c_{tar} for the component is given by Eq. (46) and added to c^{tot}.

$$c_{\text{tar}} = \Delta t \cdot \sum_{t \in \mathcal{T}_{\text{opt}}} \left(\tau^{\text{reg}} \cdot q_t + \tau^{\text{bal}} \cdot q^{\text{bal}}_t\right) \tag{46}$$

If multiple components share a grid connection point the aggregated schedules for day-ahead market operation and balancing market

Table 3
Summary of dynamic household parameters.

Parameter	Unit	Period 1	Period 2
Inflexible electricity consumption	kWh	4970	3346
Hot water load	kWh	1857	892
PV production	kWh	6417	3961
Elcetric vehicle consumption	kWh	2989	2111

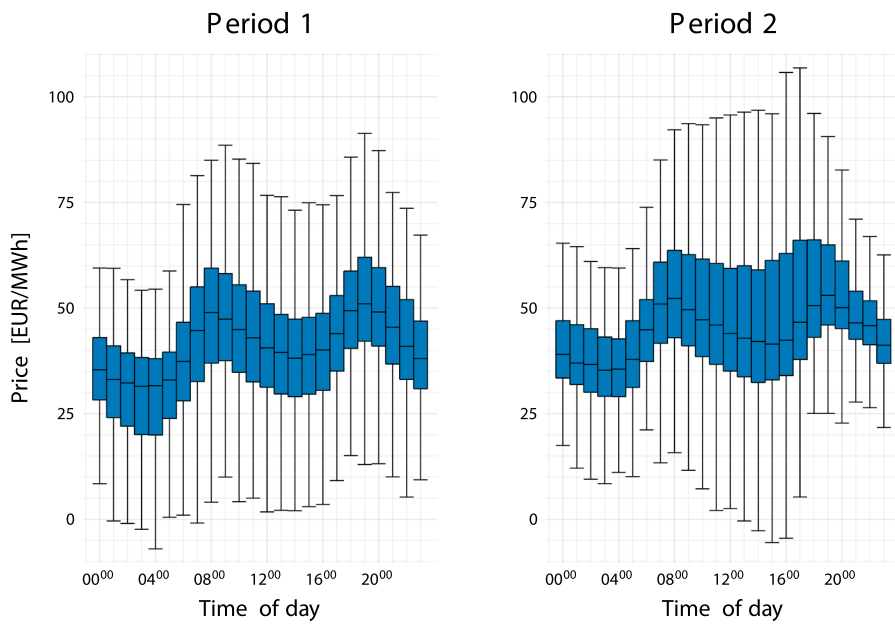

Fig. 4. Day-ahead market prices in the two periods (Source: EPEX SPOT [37]).

reserves are used for the calculation of cost for grid tariff, fees and surcharges.

Details about the implementation of different components in the generic component interface are provided in Appendix A.

4. Model setup and empirical scaling

The optimal dispatch of an Austrian household with five flexible components is calculated during two time periods. *Period 1* covers a whole year from October 1, 2017 to September 30, 2018. *Period 2* covers eight months from November 1, 2018 to June 30, 2019. These two periods are separated by the market splitting of the German and the Austrian electricity price zone in October 2018 [30].

4.1. Household

A household with a battery, a charging station for an electric vehicle, a heat pump, an electric boiler and a PV system is analyzed. The static parameters for the battery, the charging station, the heat pump and the electric boiler are Tables A.1 to Eq. (A.4). For the PV system a nominal capacity of kW5 is assumed. The considered grid tariff, fees and surcharges are listed in Table. 2.

For each period a PV production profile, an inflexible electricity load profile and a domestic hot water load profile are generated using the `LoadProfileGenerator` developed by Pflugradt and Muntwyler [36]. The software also provides corresponding outdoor temperature profiles. Charging cycles for the electric vehicle are generated randomly based on usage probabilities and normally distributed random variables for departure and arrival times and the distance driven, considering working days and weekends. A summary of dynamic model parameters for the two periods is listed in Table 3.

4.2. Markets

For the day-ahead and intraday market historic price data from the European Power Exchange EPEX SPOT SE [37] is used. Fig. 4 shows a boxplot with the daily day-ahead market prices in the two considered periods.

In the model each four-hour balancing market product is characterized by two price bids: a bid with low balancing activation price p_{en}^{δ} and high activation probability P_{act}^{δ} and a bid with inverse characteristics. Furthermore each bid provides a balancing reserve price p_{res}^{δ} that is paid regardless of balancing activations. The prices and corresponding activation probabilities are provided by Flex+ [2] research project partner TIWAG[3].

With the expected day-ahead price during a product period p_{da} as opportunity price, the expected profit π^{δ} can be calculated with Eq. (47) for negative and Eq. (48) for positive balancing products.

$$\pi^{-} = p_{\text{pow}}^{-} + P_{\text{act}}^{-} \cdot (p_{\text{da}} - p_{\text{en}}^{-}) \quad (47)$$

$$\pi^{+} = p_{\text{pow}}^{+} + P_{\text{act}}^{+} \cdot (p_{\text{en}}^{+} - p_{\text{da}}) \quad (48)$$

Fig. 5 shows the expected profit of daily balancing market products in the two considered time periods.

Balancing market activations are simulated randomly based on the provided activation probabilities. For a probability p a random variable from the Beta$\left(\frac{1}{100}, \frac{1}{100} \cdot \frac{(1-p)}{p}\right)$ distribution [38] is generated. The chosen distributions has an expected value of p and a bimodal probability density function with modes 0 and 1. Fig. 6 shows the cumulative density function of Beta$\left(\frac{1}{100}, \frac{1}{100} \cdot \frac{(1-p)}{p}\right)$ for selected values of p.

[2] https://www.flexplus.at/ (Accessed on 8/6/2020.)
[3] https://www.tiwag.at/en/ (Accessed on 8/6/2020.)

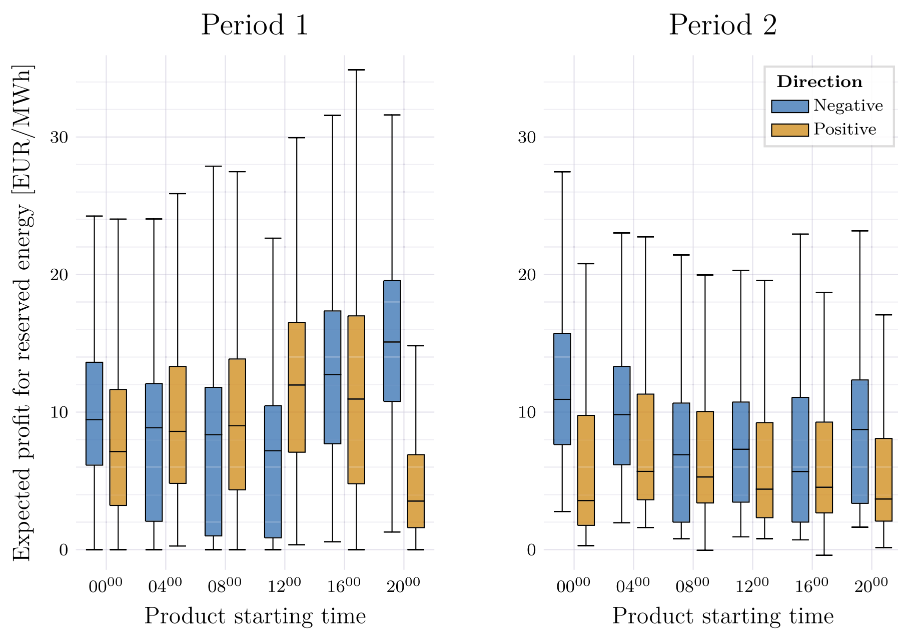

Fig. 5. Expected profits from balancing market products in the two periods.

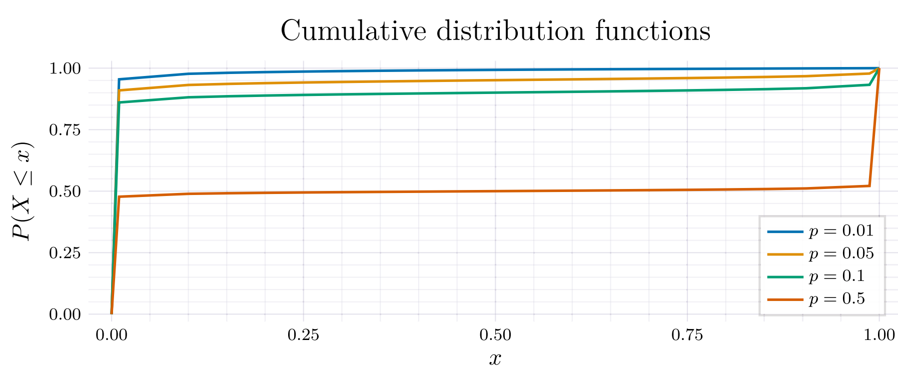

Fig. 6. Cumulative density functions of $\mathrm{Beta}\left(\frac{1}{100}, \frac{1}{100}\cdot\frac{1-p}{p}\right)$ for selected values of p.

Table 4
Considered optimization strategies.

Strategy	Description
Baseline	The technology schedules are optimized considering constant electricity prices and disregarding balancing markets.
Day-Ahead	The flexible components are used to minimize electricity procurement cost with day-ahead market prices.
Balancing	The technology portfolio has access to the day-ahead market, the aFRR balancing market and the intraday market.

4.3. Optimization strategies

To analyze the effects of market integration for households with flexible components, first, a simulation with the *Baseline* optimization strategy is run considering constant electricity prices and disregarding balancing markets. Next, this is compared to the *Day-Ahead* optimization strategy which uses the components' flexibility only to minimize the electricity procurement cost with day-ahead market prices. Finally, the *Balancing* optimization strategy provides access to the day-ahead market, the aFRR balancing market and the intraday market for balancing unexpected activations. It is assumed that market access is provided by an aggregator. Hence, minimum bid sizes are neglected in the simulations. The different optimization strategies are listed in Table 4.

5. Results

This section provides numerical results of different simulation runs using the mathematical framwork in Section 3 to answer various research questions. Section 5.1 provides the potential total benefits for the optimization strategies presented in Section 4.3. In Section 5.2 the impact of the battery's Levelized Cost Of Energy (LCOE) on its operation and the PV self-consumption is investigated. Section 5.3 investigates the effects of cost related to unexpected balancing activations and different strategies to deal with these uncertainties. The individual contributions of different components to the total cost reduction are identified in Section 5.4 and Section 5.5 compares different aggregation levels in the optimization of a pool of households.

5.1. Potential benefits of aggregation and multiple market participation

Fig. 7 shows the cost components of the household under investigation for different optimization strategies in the two considered

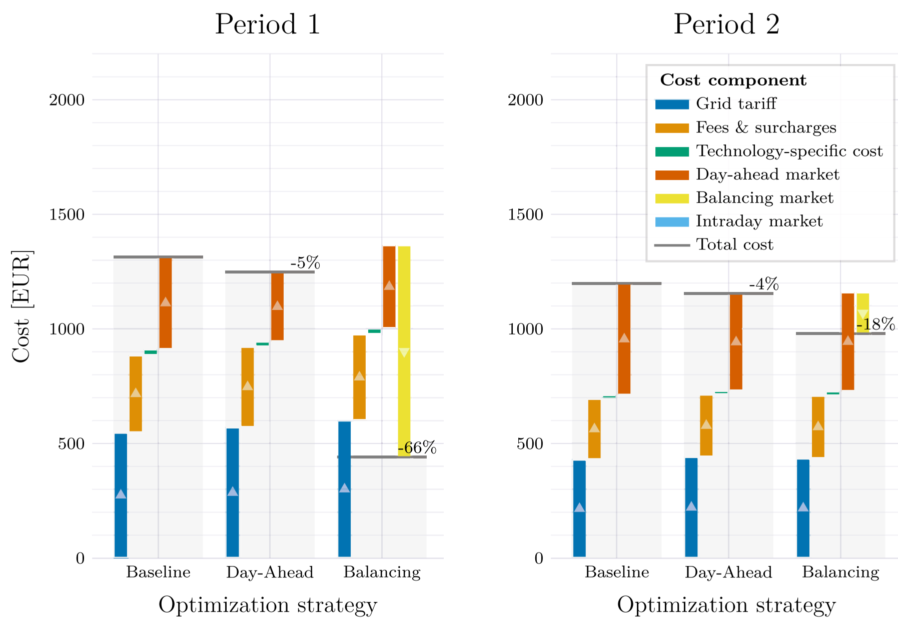

Fig. 7. Total household electricity procurement cost for the optimization strategies described in Table 4 in .the two periods.

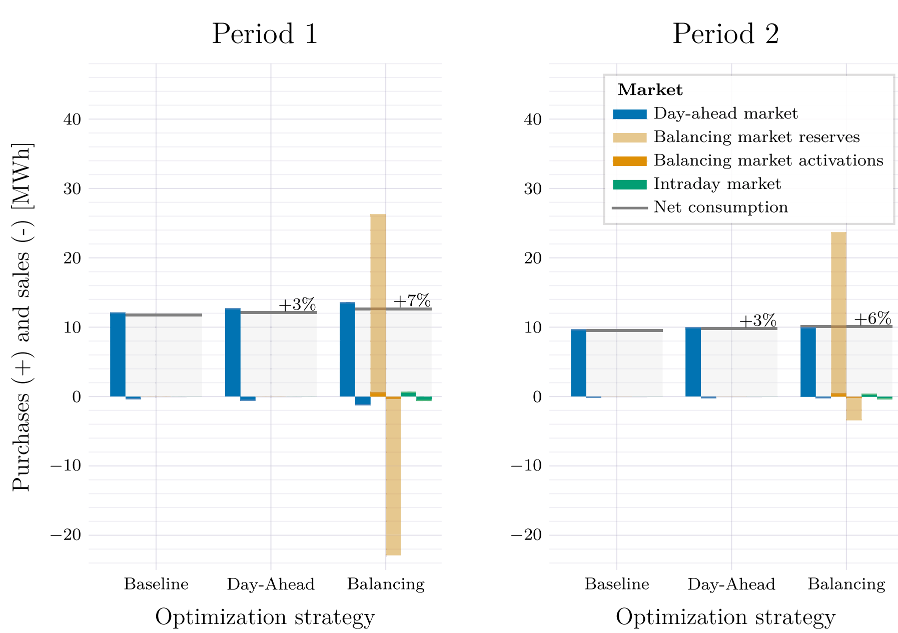

Fig. 8. Quantities traded on different energy markets and net consumption for the optimization strategies described in Table 4 in .the two periods.

periods. The total cost consist of the grid tariff, fees and surcharges, technology-specific cost and cost from operating on the considered markets. In this setup technology-specific cost correspond to the LCOE of the battery.

The *Day-Ahead* optimization strategy increases cost for grid tariff, fees and surcharges in both periods. However, the cost reduction from day-ahead market operation yields a total cost reduction of 5% and 4%.

Similarly, the *Balancing* optimization strategy yields a cost increase for grid tariff, fees and surcharges. In *Period 1*, furthermore, the cost on the day-ahead market increases. Nevertheless, the profits on the balancing markets provide significant total cost reductions of 66% in *Period 1* and 18% in *Period 2* compared to the *Baseline* strategy. Comparing the two considered periods indicates a significant reduction of the economic potential on balancing markets for residential flexibilities after the electricity market split between Germany and Austria.

Fig. 8 shows the quantities traded on different markets for different optimization strategies in the two periods. The *Baseline* optimization strategy does not consider market signals. Hence, the only way to reduce cost is to minimize electricity consumption. Thus, it provides the most energy efficient operation. In the *Day-Ahead* optimization strategy both purchases and sales on the day-ahead market are increased. This results in a net consumption increase of 3% in both periods. Using the flexibility of components for balancing reserves in the *Balancing* optimization strategy further decreases technical efficiency. This yields a net consumption increase of 7% in *Period 1* and 6% in *Period 2*.

These results suggest that there is significantly more economic

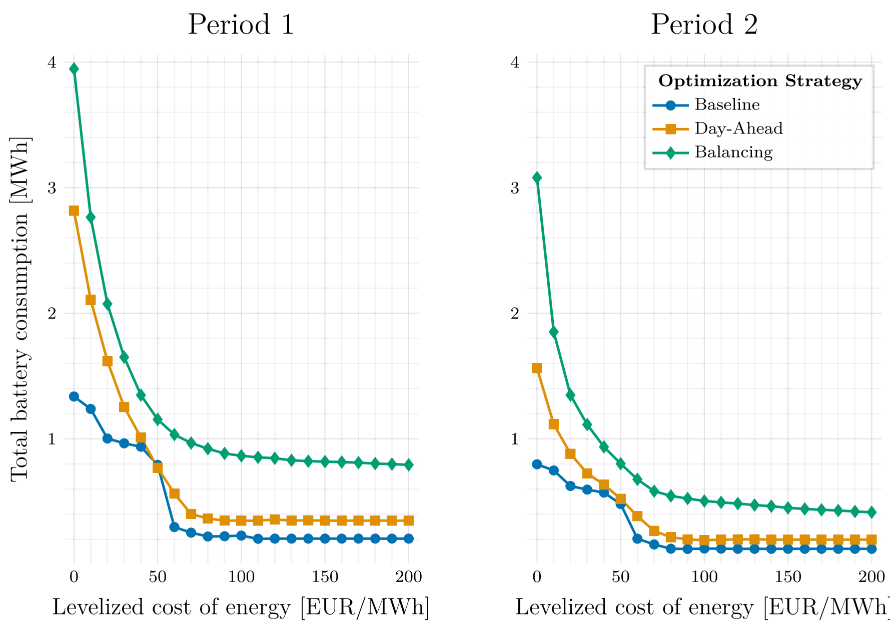

Fig. 9. Battery consumption for different battery LCOE in the two periods.

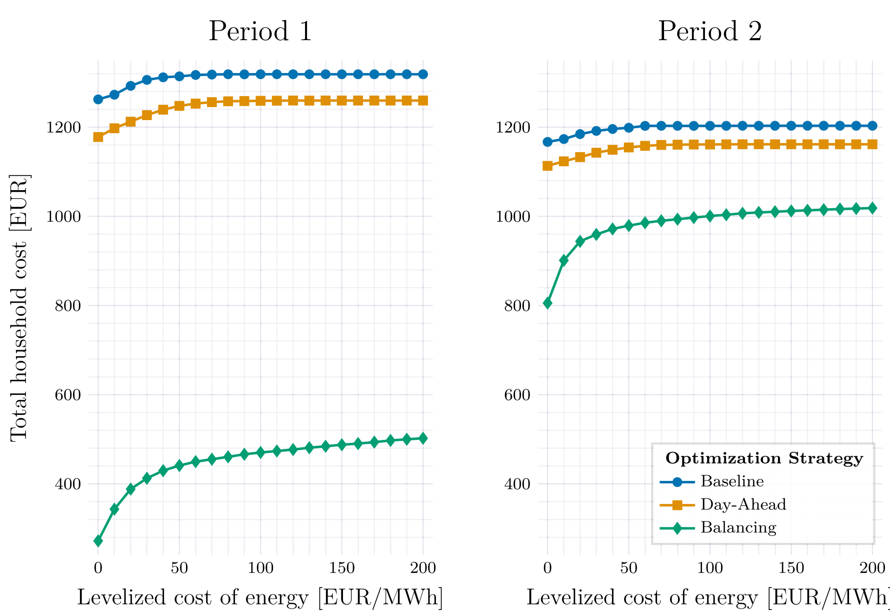

Fig. 10. Battery consumption for different battery LCOE in the two periods.

potential for flexible technologies on the balancing market than on the day-ahead market under the assumed price conditions. Market participation has a negative impact on the energy efficiency of considered components compared to the *Baseline* strategy. However, it is important to note that the *Baseline* strategy represents a technically optimal operation under perfect foresight. Real-life operation might be based on simpler heuristics yielding higher total consumption. In that case, introducing market-based optimization and control of flexible technologies might result in lower consumption increase. Furthermore, even with the increase in consumption and the corresponding increase in cost for grid tariff, fees and surcharges a significant total cost reduction was achieved with the *Balancing* strategy. Section 6.1 provides a discussion of potential approaches to divide the total benefits among the aggregator and end users.

5.2. *Battery cycle cost and photovoltaic self-consumption*

Batteries have a limited number of charging cycles. To avoid too much increase in battery usage and a related reduction of battery lifetime, battery operation has to be associated with cost in the objective function of the optimization models. The LCOE of a battery can be used for this purpose as it describes the price at which electricity should be sold to cover all cost components of the battery [39].

The impact of the LCOE on the operation of the battery is analyzed by simulating the *Baseline*, *Day-Ahead* and *Balancing* optimization strategy for the values $c_{op}^{Bat} = 0, 10, \ldots, 200$ EUR/MWh.

Fig. 9 shows the total battery consumption versus battery operation cost for different optimization strategies in the two periods. Battery

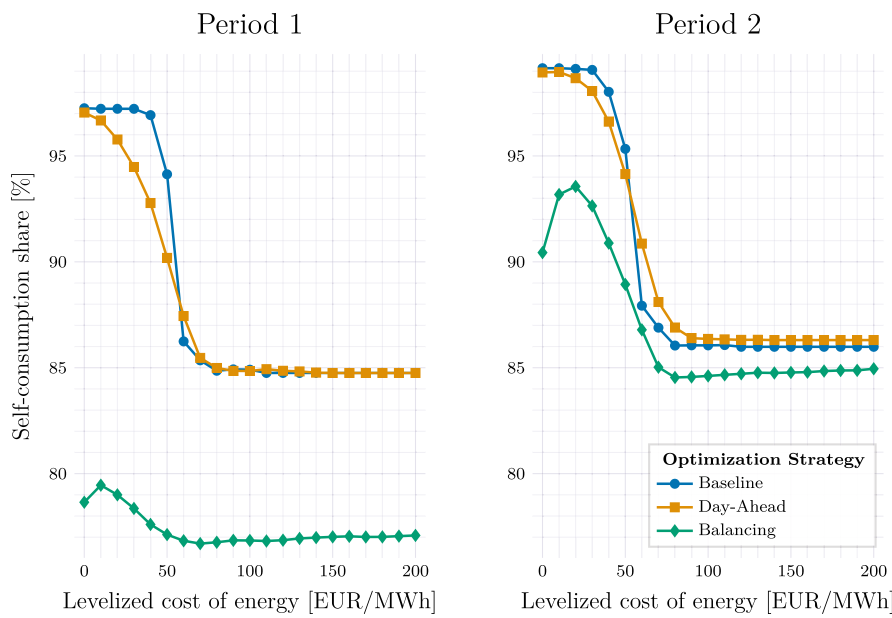

Fig. 11. PV self-consumption for different battery LCOE in the two periods.

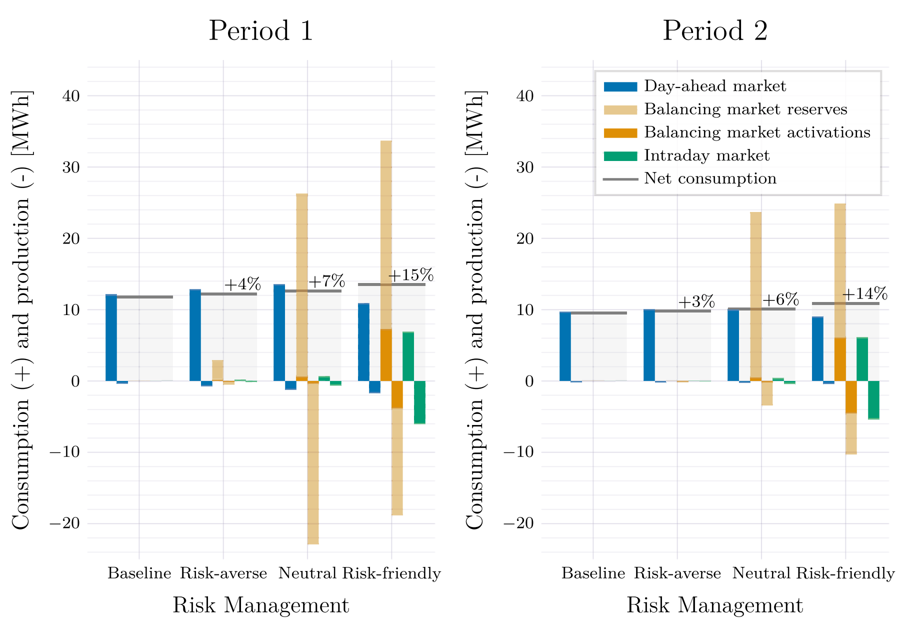

Fig. 12. Quantities traded on different markets and net consumption for different risk management approaches in the two periods.

usage declines with increasing LCOE. The decrease in usage is more uniform for the *Day-Ahead* and the *Balancing* optimization strategy. Both show more battery usage than the *Baseline* optimization strategy.

Due to the low activation probabilities, the revenue of actual battery consumption and production is very high in the *Balancing* optimization strategy. Hence, the battery is used significantly more compared to the other optimization strategies, even for higher LCOE. Fig. 10 shows the total household cost with the three optimization strategies for different values of battery LCOE. Even for LCOE of 200 EUR/MWh the *Balancing* optimization strategy yields significantly lower total cost than *Baseline* and *Day-ahead* with zero battery usage cost. Hence, balancing market participation can provide an additional stream of revenue for flexible components with high operational cost and improve the economic efficiency of an investment.

For the *Baseline* optimization strategy a significant change in battery usage can be noticed at 60 EUR/MWh. 50 EUR/MWh seems to be the highest LCOE where battery operation for increasing self-consumption is still economically efficient. This can also be observed in Fig. 11 showing the household's self-consumption share of PV production for different LCOE in all optimization strategies and periods. Up to LCOE of 50 EUR/MWh the *Baseline* optimization strategy provides the highest self-consumption share. For higher values the *Day-Ahead* optimization strategy shows slightly higher shares, triggered by market signals. The *Balancing* optimization strategy provides the lowest shares of PV self-consumption, because for many balancing market bids the economic benefits in EUR/MWh of expected battery usage is higher than the benefit of saving cost for grid tariff, fees and surcharges. In all other simulations LCOE of 50 EUR/MWh are assumed to incentivize

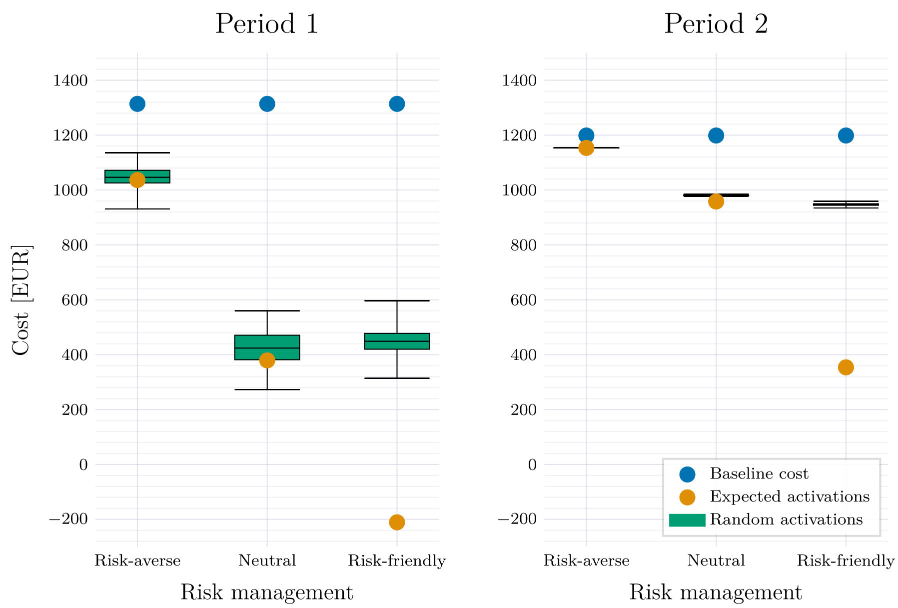

Fig. 13. Total household cost for different risk management approaches with expected and random activations in the two periods.

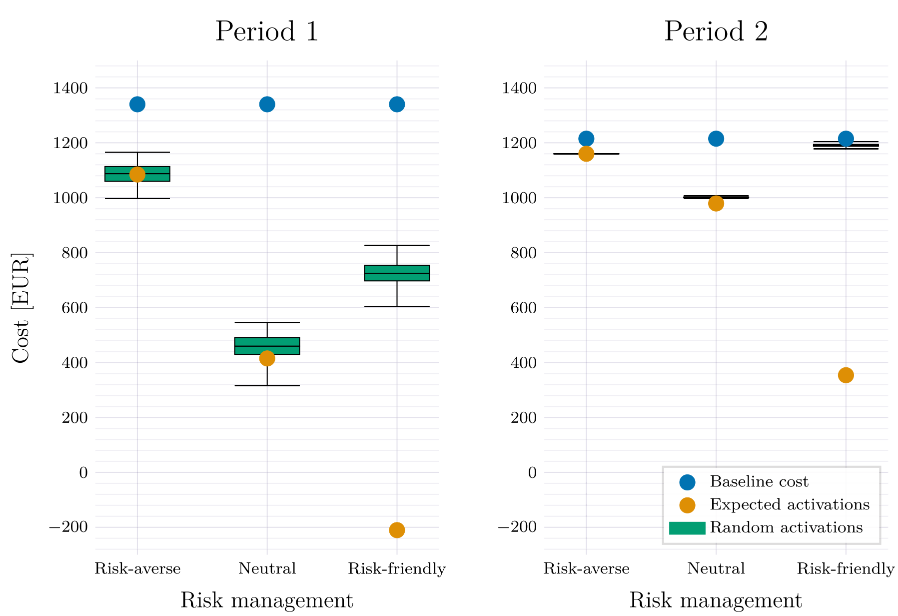

Fig. 14. Total household cost for different risk management approaches with expected and random activations with battery LCOE of 100 EUR/MWh in the two periods.

maximizing self-consumption in the *Baseline* optimization strategy.

5.3. Impact of activations and risk management

The risk of extra cost caused by unexpected balancing activations is weighted with the variance of a binomially distributed random variable defined in Eq. (36) in the objective function of the daily optimization models. In the following this is labelled the *neutral* approach.

Alternatively, in a more *risk-averse* approach Eq. (36) could be replaced by Eqs. (49) to Eq. (52).

$$\Delta a_{t,j}^{-,\uparrow} = P_{t,j}^{-} \cdot r_{t,j}^{-} \quad j \in \mathscr{B}^{-} \tag{49}$$

$$\Delta a_{t,j}^{-,\downarrow} = \left(1 - P_{t,j}^{-}\right) \cdot r_{t,j}^{-} \quad j \in \mathscr{B}^{-} \tag{50}$$

$$\Delta a_{t,j}^{+,\uparrow} = \left(1 - P_{t,j}^{+}\right) \cdot r_{t,j}^{+} \quad j \in \mathscr{B}^{+} \tag{51}$$

$$\Delta a_{t,j}^{+,\downarrow} = P_{t,j}^{+} \cdot r_{t,j}^{+} \quad j \in \mathscr{B}^{+} \tag{52}$$

Here the maximum deviations from expected activations are considered in the component-specific cost in the objective function.

Finally, a more *risk-friendly* approach is to optimize the expected cost only, disregarding any cost from potential deviations from balancing activations. This can be achieved by replacing Eq. (36) with Eq. (53).

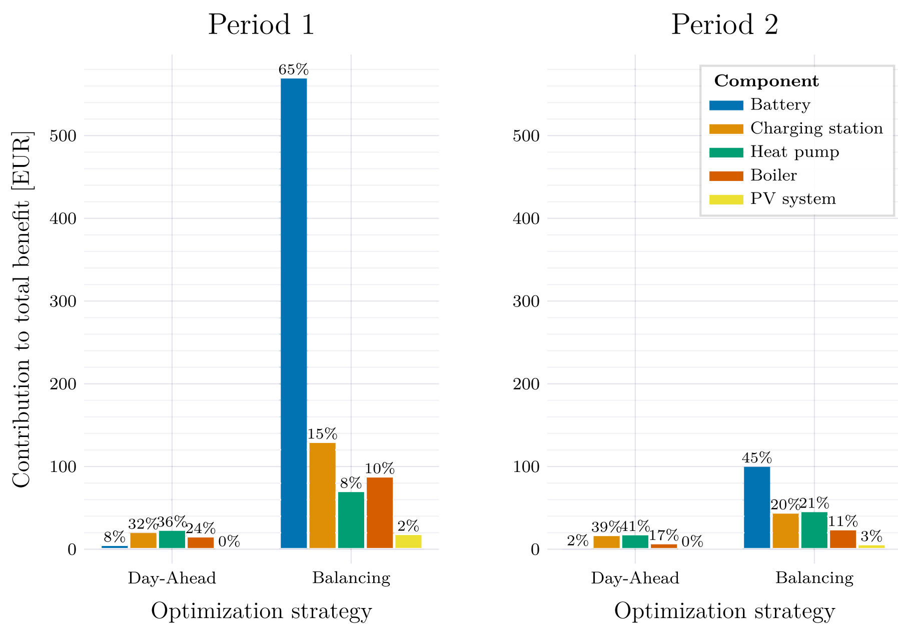

Fig. 15. Contribution of individual components to the total benefit with different optimization strategies described in Table 4 for .the two periods.

$$\Delta a_{t,j}^{\delta,\uparrow} = \Delta a_{t,j}^{\delta,\downarrow} = 0 \quad j \in \mathscr{B}^{\delta}, \delta \in \mathscr{D} \tag{53}$$

Fig. 12 shows the impact of the chosen risk management approach on the quantities traded on different markets and the total net consumption of the household. The *risk-averse* approach adds a higher penalty for unexpected deviations to the objective function and, hence, increases the cost associated with balancing market products. Thus, it provides the lowest amount of balancing market reserves and results in the lowest net consumption increase. The *risk-friendly* approach does not consider additional cost for deviations at all and, hence, provides the most balancing reserves. Furthermore, it selects significantly more balancing products with higher activation probabilities, resulting in more balancing activations and intraday market trades. This also yields the highest net consumption increase of 15% and 14%, respectively.

To analyze the impact of random activations on the total household cost in the different risk management approaches, 100 scenarios for random activations are generated and simulated. Fig. 13 shows the total household cost for expected and random activations. The *risk-averse* approach yields the least cost reduction. With expected activations the highest benefit is achieved using the *risk-friendly* approach. However, with random activations this results in significantly higher cost compared to expected activations. The *neutral* risk management approach provides significantly less deviations from the cost with expected activations. For random activations the cost reduction with the *risk-friendly* approach is about the same as with the *neutral* approach.

However, the results look different for higher operational cost. Fig. 14 shows the respective results for the same household with battery

Table 5
Levels of aggregation in the market operation optimization of multiple households.

Level	Description
Single	Each component is optimized individually without considering other households, components or non-flexible loads.
Technical	All components of the same type are aggregated to component specific pools and optimized without considering other component types or non-flexible loads.
Local	All components of a household are aggregated locally and optimized without considering other households.
Central	All components are aggregated and optimized centrally.

LCOE of 100 EUR/MWh. Here the cost with random activations are significantly higher with the *risk-friendly* approach. In *Period 2* they even exceed the cost of the *risk-averse* approach.

The *risk-averse* approach seems to be too conservative. The *risk-friendly* approach is too unpredictable with higher operational cost and can even result in a cost increase. Hence, for all other simulations the *neutral* approach is chosen. Note that there are alternatives to the presented risk managment approaches based on the Value at Risk (VaR) or the Conditional Value at Risk (CVaR), which might yield better results. Their investigation goes beyond the scope of this work and is left to future research.

5.4. Individual contributions of flexible components

In Section 5.1 the potential total benefits of all flexibile components are presented. To determine the contribution of individual technologies to the achieved total cost reduction, different household *flexibility configurations* are considered and simulated. A household *flexibility configuration* specifies for each component if its baseline operation is added to the household's non-flexible load or if its flexibility is used for market optimization. To identify the contribution of each flexible component to the benefits achieved on different markets, the *Day-Ahead* and the *Balancing* optimization strategy are simulated for all 32 possible flexibility configurations. Subsequently, the resulting cost benefits compared to the *Baseline* optimization strategy are used to calculate the *Shapley value* [40] for each component. The *Shapley value* describes the average contribution of a component to the total utility. A comprehensive description of this approach is provided in [41].

Fig. 15 shows the contribution of each component to the total benefit achieved compared to the *Baseline* optimization strategy. In the *Balancing* optimization strategy the battery clearly provides the most significant relative contribution with 65% in *Period 1* and 45% in *Period 2*. The battery is the only component qualified to offer power in both directions, consumption and feed-in. Furthermore, it is always available. Hence, it can provide the most balancing reserve.

In contrast, the electric vehicle is not permanently connected to the charging station. Furthermore, vehicle-to-grid operation was not considered. Hence, it can offer less flexibility than the battery resulting in a relative contribution of 15% in *Period 1* and 20% in *Period 2*.

Table 6
Flexible component configurations of pooled households.

Household	1	2	3	4	5	6	7	8	9	10
Battery	✓	✓	✓	✓	✓					
Electric car	✓	✓				✓	✓	✓		
Heat pump	✓		✓			✓			✓	✓
Boiler	✓	✓	✓	✓		✓	✓		✓	
PV system	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

The heat pump's and the boiler's flexibility potential is limited by the demand for space heating and domestic hot water, which is determined by the user-defined temperature limits and the surrounding temperature. Both power-to–heat technologies can only consume electricity. This constrains their availability for flexibility provision. In *Period 1* the heat pump adds 8% to the total cost reduction. In *Period 2* the relative contribution of the heat pump is increased to 21% because the months July to October are not covered, where heat pumps usually operate less due to lack of heat demand. The electric boiler contributes 10% in *Period 1* and 11% in *Period 2*.

The only flexibility option for PV systems is curtailment. This option is used on the balancing market resulting in a relative contribution of 2%

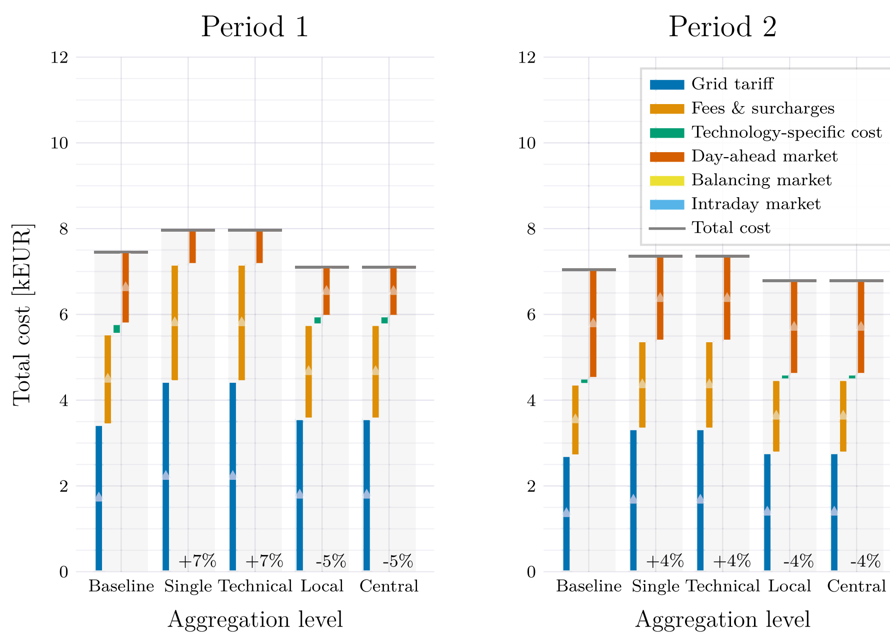

Fig. 16. Total cost of all ten households with the *Day-Ahead* optimization strategy for different levels of aggregation in the two periods.

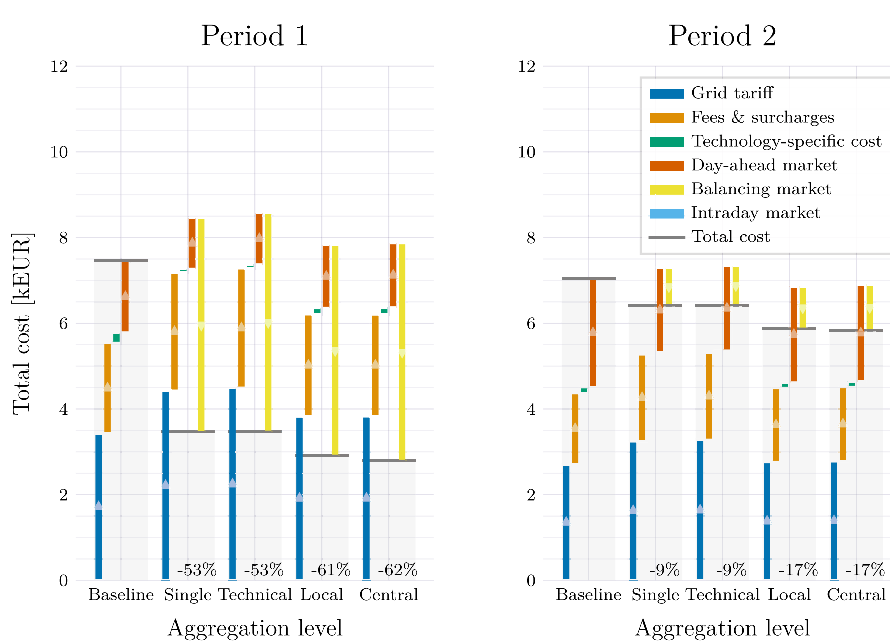

Fig. 17. Total cost of all ten households with the *Balancing* optimization strategy for different levels of aggregation in the two periods.

in *Period 1* and 3% in *Period 2*.

For the *Day-Ahead* optimization strategy the heat pump provides the highest relative contribution with 36% in *Period 1* and 41% in *Period 2*. Similar results can be observed for the charging station with 32% and 49%, respectively. With 24% and 17% even the electric hot water boiler contributes more to cost reduction than the battery with 8% and 2%, respectively. This can be explained with the high LCOE of the battery, which would require more economic incentives than the day-ahead market price spreads for flexibility activations. The PV system is not curtailed at all with the *Day-Ahead* optimization strategy. Hence, it does not contribute any flexibility to the total achieved benefits.

5.5. The value and different levels of aggregation

In this work minimum bid sizes for balancing market products are neglected, because it is assumed that the balancing bids are collected by an aggregator and incorporated as part of the bids of a balancing service provider. Hence, optimization could happen also locally and for each individual component. In an alternative approach an aggregator could collect all forecasts and technical data for each component of multiple households and manage the dispatch of end-user flexibilities centrally. To identify the value of aggregation, in the following the operation of ten households is optimized for different levels of aggregation listed in Table 5. Table 6 provides the flexible component configurations for each household.

Fig. 16 shows the total cost of all ten households for different levels of aggregation with the *Day-Ahead* optimization strategy. In the *Single* and *Technical* aggregation the components are optimized without any information on the actual residual load of the households. Hence, the flexible components cannot be used to maximize self-consumption of the households. This results in a total cost increase of 4 - 7% compared to the *Baseline* optimization strategy, which is simulated at a *Local* aggregation level but without market access. With the *Local* and *Central* aggregation level all household components and loads can be considered in the optimization, resulting in a lower cost increase for the grid tariff, fees and surcharges and a total cost reduction of 4 - 5%. Considering multiple households simultaneously in the optimization does not provide any further benefit.

The total pool cost with the *Balancing* optimization strategy in Fig. 17 show similar results. Technology-specific aggregation results in higher cost for the grid tariff, fees and surcharges. However, here the profits from the balancing markets significantly exceed the cost increase in charges. Aggregating on a household level increases the relative cost reduction by 8 percentage points compared to technology-specific aggregation in both periods. In *Period 1* the *Central* optimization provides a slightly higher benefit over the *Local* aggregation. This is caused by at least one balancing market product, for which at least one households can not provide sufficient reserve individually.[4] In *Period 2* no further benefit of the *Central* aggregation over the *Local* aggregation can be observed.

Considering the complexity of solving a optimization problem for hundreds or thousands of customers centrally the *Local* aggregation, corresponding to de-centralized optimization at a household level, seems like a more pragmatic approach. For scalable practical implementations data-driven machine learning models might pose a sensible alternative to linear programming.

[4] Consider in a simplified example two electric vehicles. One is connected until 19:00, the other starting from 17:00. Individually, neither can provide reserve for the balancing products between 16:00 and 20:00. However, in a global optimization the required reserve can be achieved by both vehicles together.

Table 7
Summary of rates in different tariff setups for the two periods. All rates are provided in EUR/MWh.

	Dynamic rate*	Constant rate	Flexibility rate**
Period 1			
Simple		55.74	−8.76
Transparent	$p_{da,t}$ (35.74)	20.00	8.76
Period 2			
Simple		71.21	−3.98
Transparent	$p_{da,t}$ (51.21)	20.00	3.98

* $p_{da,t}$ is the hourly day-ahead electricity market price. The mean value weighted with the customers' total residual load profile is provided in brackets.
** The flexibility rate is charged per MWh of balancing reserve provided by the households. Negative values correspond to payments from the aggregator to the customers.

6. Discussion

Section 6.1 proposes possible business model and tariff design options based on the quantitative results in Section 5.5. Section 6.2 discusses the value of intraday market access in the presented optimzation and simulation framework. In Section 6.3 the major barriers for business models related to the aggregation of residential flexible components are explained.

6.1. Business model considerations

For simplicity it is now assumed that a single aggregator is supplying the end users with electricity and offering market optimization for flexible components.[5] In general, end users do not pay the hourly electricity market prices. Instead they are offered a supply tariff. This can be a constant or dynamic rate in EUR/MWh, a flat rate or a combination thereof. The simulation models, however, optimize the aggregator's operation on multiple markets, additionally considering customer grid tariffs, fees and surcharges. There are various ways to incentivize customers to provide their component's flexibilities for this purpose. The aggregator can provide a flexibility remuneration to the end users. This can be in the form of an annual or monthly flat rate or paid per flexibility activations or per balancing reserves in EUR/MWh. Another approach is to forward the benefits from flexibility optimization on different markets to the end users in a transparent manner. In that case the end users can pay a fee for the service of market access, either flat or based on flexibility activations or balancing reserves, respectively.

To illustrate the differences, consider the following tariff configurations. In the *Simple* tariff setup the households are charged a constant energy tariff chosen as the weighted average day-ahead market price plus 20 EUR/MWh. The aggregator can use the flexibility of household components and remunerates the customers with a flexibility rate in EUR/MWh charged per MWh of balancing reserve provided. Here the flexibility rate is chosen as half of the total benefit achieved in EUR divided by the total balancing reserves in MWh.

Alternatively, in the *Transparent* configuration customers are charged the actual hourly day-ahead price plus 20 EUR/MWh. The benefits from balancing market operation are directly forwarded to the households, who pay the flexibility rate in EUR/MWh for balancing reserve to the aggregator for providing the market access. Table 7 shows

[5] Business models that provide market access to end user flexibilities require a supplier, a balancing responsible party, a market participant operating on balancing markets and an aggregator responsible for the optimization and communication of household components. In theory there can even be multiple aggregation. For example technology manufacturers can already equip flexible components with the necessary technologies for data exchange and remote control and offer market optimization as a service to their customers. Conversely, one market participant can take up multiple of the required roles.

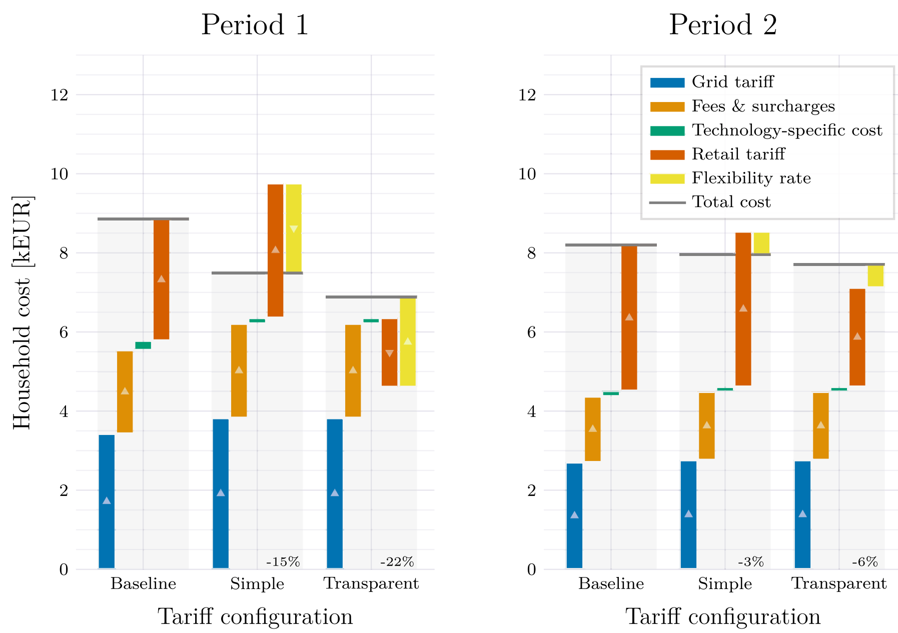

Fig. 18. Total household cost for different tariff configurations.

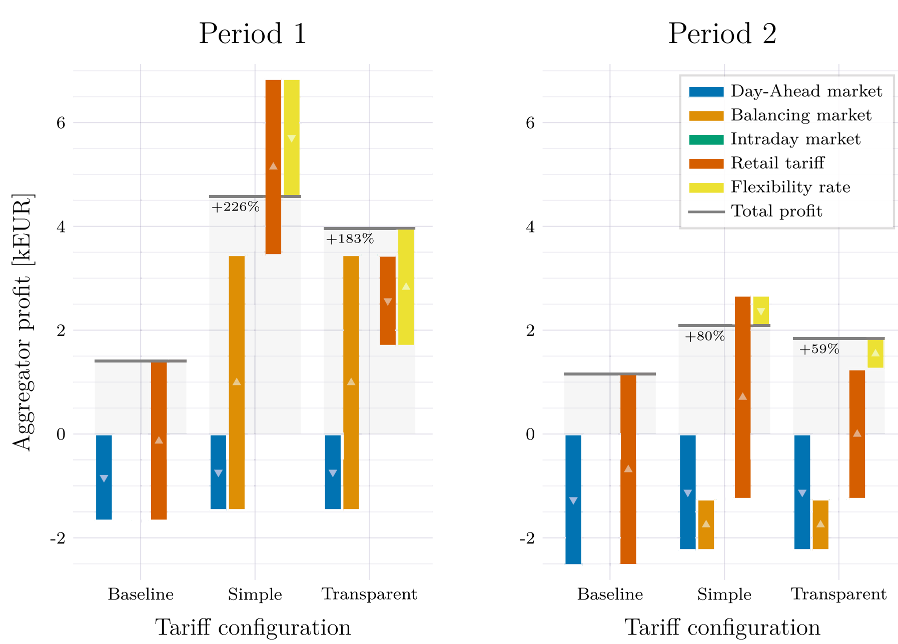

Fig. 19. Aggregator profit for different tariff configurations.

the values of the supply tariffs and flexibility rates for the *Simple* and *Transparent* setup in both periods. Both tariff configurations yield the same cost with the *Baseline* optimization strategy.

Fig. 18 shows the total cost of all ten households for different tariff setups. With the *Balancing* optimization strategy cost for the grid tariff, fees and surcharges increase. In the *Simple* tariff configuration supply tariff cost increase, too. However, due to the flexibility rate a total cost reduction of 15% in *Period 1* and 3% in *Period 2* is achieved. With a *Transparent* setup the energy supply component of the end user bill decreases significantly. In *Period 1* it is even negative. The additional cost for the flexibility rate paid to the aggregator yields a total cost reduction of 22% in *Period 1* and 6% in *Period 2*.

Fig. 19 shows the aggregator profit for different tariff setups. The aggregator can achieve substantial benefits on the day-ahead and balancing markets with the balancing optimization strategy. Note that additional cost for market access, ICT infrastructure and software and data management are not considered here. With the *Simple* tariff configuration the revenues from electricity supply increase, too. Considering the additional cost from the flexibility rate paid to the customers still yields a significant profit increase of 226% in *Period 1* and 80% in *Period 2*. In the *Transparent* tariff setup the benefits from flexible market operation are passed on to the end users in the supply tariff. However, with the extra revenue from the flexibility rate profit increases by 183% in *Period 1* and 59% in *Period 2*.

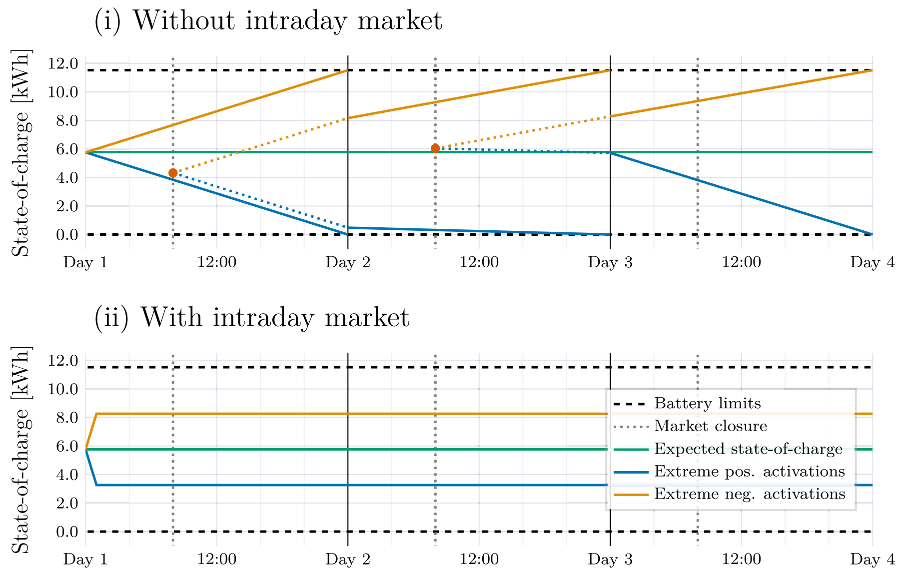

Fig. 20. State-of-charge limits of the battery without (i) and with (ii) access to the intraday market.

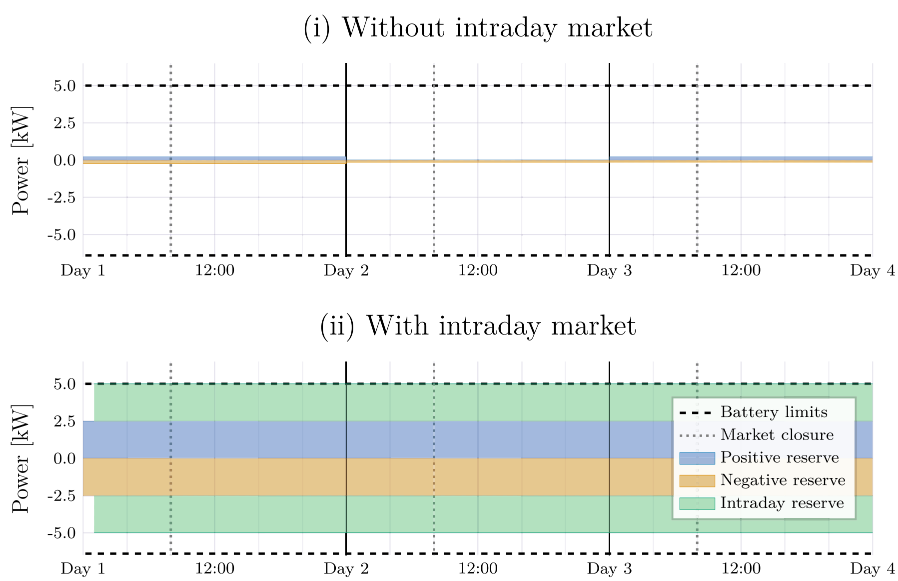

Fig. 21. Maximum balancing market bid sizes of the battery without (i) and with (ii) access to the intraday market.

Both tariff setups result in win–win situations among the aggregator and the customers. However, they do not ensure by construction economic benefits for individual ened users. Designing tariffs that ensure win–win situations among the aggregator and each individual customer is a difficult task and subject to future research. Nevertheless, economic benefits might not be the only incentive driving the decisions of end users. Contributing to the electricity system's flexibility and, consequently, to the integration of variable RES and the reduction of greenhouse gas emissions can also motivate customers to participate in business models related to the aggregation of residential flexibilities.

6.2. Intraday market access

Most contributions to literature presented in Section 2.3 use a scenario-based multi-stage stochastic modeling approach to evaluate business models of aggregators operating on balancing markets. However, they do not consider unexpected activations, their impact on components' state-of-charge levels or the intraday market as an option to balance unexpected state-of-charge deviations. This section explains the benefits of the approach chosen in this work using a simplified example.

Consider the household's battery bidding on the balancing market. For simplicity assume that it has no conversion losses and it bids the same size b^- and b^+ for all six four-hour products of a day and that both negative and positive products have the same activation probability.

If no access to the intraday market is available the battery has to meet all activations with the state-of-charge at the beginning of the day. In the extreme case of 100% positive activations and zero negative activations $24{\cdot}b^+$ MWh would be discharged from the battery. Conversely, for negative activations only, $24{\cdot}b^-$ MWh would be fed into the storage. With a state-of-charge of 50% at the beginning of the day and no other planned operation for the battery, at most $b^- = b^+ = \frac{C^{\mathrm{Bat}}}{48}$ MW can be offered for balancing. The corresponding state-of-charge limits are illustrated in subplot (i) of Fig. 20 for day 1. Assume now that the battery is already providing balancing reserve during the day when the bids for the next day are placed. In that case at market closure time the state-of-charge at the end of the day is known within some range only. This uncertainty further reduces the maximum balancing market bid sizes for the next day. Subplot (i) of Fig. 20 illustrates the state-of charge limits in this scenario for days 2 and 3. The corresponding maximum balancing market bid sizes are shown in subplot (i) of Fig. 21.

If intraday market access is available the battery can react on activations and balance deviations from the planned state-of-charge immediately subject to the intraday market lead time. With a lead time of one hour this means that at each time step, state-of-charge reserves for the activations of the following hour only have to be considered. However, additional power has to be reserved for potential intraday market activations. Hence, the maximum bid size is given by $\frac{\min\{P_{\text{in}}^{\text{Bat}},P_{\text{in}}^{\text{Bat}}\}}{2}$ where $P_{\text{in}}^{\text{Bat}}$ and $P_{\text{out}}^{\text{Bat}}$ are charging and discharging power limits of the battery. Thus, in that case the limiting factor is not the battery's capacity but its power. Furthermore, a fixed state-of-charge can be assumed at the end of the day every day since all unexpected activations are balanced within one hour. The state-of-charge limits with intraday market access are illustrated in subplot (ii) of Fig. 20. Fig. 21 shows that significantly more balancing market reserves can be offered if access to the intraday market is available. A detailed description of reserves for the intraday market with this strategy is provided in Section 3.3.2.

The approach chosen in this work uses the first possible intraday product to balance unexpected reserve market activations. The economic results might be slightly improved by performing a rolling optimization for the intraday market as well. Furthermore, periodic intraday optimization can be used to react on forecast errors, which are not considered here.

6.3. Barriers and challenges

Minimum bid sizes can constitute a major barrier for aggregators of flexible end user components [13].

In this work cooperation with a balancing market participant controlling large-scale power plants is assumed to overcome this barrier. Without this assumption a large number of households is required for a single balancing market bid. With local aggregation in the optimization, individual households might find optimal schedules that can not be placed as market bids because in total the minimum bid size can not be achieved. For global aggregation the optimization models might become to complex to solve in reasonable time.

Regardless of the level of aggregation in the optimization a large amount of communication and data transfer is required. In the simulation models it is implicitly assumed that individual small-scale household components provide operation schedules and that the evidence of balancing energy provision is determined by the deviation from these schedules. This approach requires continuous measurement and extensive data exchange with the system operator, which is a challenge for real-life implementation. Furthermore, costumers might raise privacy concerns taking into account the required data communication for these business models.

The simulations in this work assumed perfect foresight for load, generation, temperature or market prices. Hence, a real-life implementation of the proposed optimization strategy will yield less optimal results. Especially on a single household level forecasting of non-flexible loads is a difficult task. A rolling intraday market operation might be a suitable tool to deal with day-ahead load forecast errors. This work only considers the uncertainties in terms of balancing activations. Analyzing the impact of forecast errors and developing methods to handle these uncertainties in the presented framework are left to future research.

For metered households the grid tariff often includes a peak component that is charged for the maximum load within a month or year, respectively. Due to the short optimization period of 24 to 48 h in the rolling optimization approach this cannot be included exactly into the model's objective function. Not considering it at all might yield increased household cost. Considering the full peak component or part of it in each daily optimization might result in using too much flexibility to restrict the maximum load. There might be higher peaks on different days and unnecessary peak load reduction reduces flexibility for market optimization. Developing and analyzing different strategies to include a peak component of the grid tariff into daily optimization is a task for future research.

7. Conclusions

A modular mathematical framework to model the operation of energy aggregators on day-ahead, balancing and intraday markets is presented. It has proven to be effective to tackle a variety of research questions related to the flexibility provision of end users.

Based on the quantitative analysis of a specific case study the following generalized conclusions in the context of aggregators operating on multiple electricity markets can be drawn:

- Under the considered price conditions, balancing market participation provides significantly higher economic potential than optimizing with respect to day-ahead market prices only.
- The cost reduction achieved on balancing markets allow business model and tariff designs resulting in win–win situations among the aggregator and the end users.
- Balancing market participation results in a reduction of PV self-consumption share. However, battery operation on balancing markets is economically feasible for higher LCOE than battery usage for self-consumption.
- Both neglecting the risk of additional cost through unexpected balancing activations and assuming the worst case scenario in the objective function yields suboptimal results. Hence, the introduction of a more elaborate risk measure to the optimization models is recommended.
- Batteries can provide the highest contribution to balancing market operation and achieved benefits due to their permanent availability and symmetry in consumption and production. However, on the day-ahead market the heat pump, the electric vehicle and the electric boiler achieve higher contributions because of the batteries' high LCOE.
- Optimizing components individually or aggregated to a technology-specific pool yields suboptimal results. Considering the computational complexity for large pool sizes, a local optimization on a household level through an energy management system is recommended.
- Considering the intraday market to react on balancing market activations allows to offer significantly more balancing markets reserves.

Future work may investigate further risk management approaches to handle the uncertainties of balancing activations. Furthermore, it is planned to include methods to handle forecast errors in the presented framework. Another direction of future research might investigate tariff design for aggregator business models and its implications on individual customers in greater detail. Finally, the development and analysis of different approaches to handle peak tariff components in daily optimization is left to future work.

CRediT authorship contribution statement

Daniel Schwabeneder: Methodology, Software, Formal analysis, Investigation, Validation, Visualization, Writing - original draft. **Carlo Corinaldesi:** Methodology, Data curation, Writing - review & editing. **Georg Lettner:** Conceptualization, Funding acquisition, Resources, Writing - review & editing. **Hans Auer:** Supervision, Conceptualization, 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.

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Appendix A. Implementation of different components

This section provides a brief overview on how different components are implemented in the generic component interface.

A.1. Batteries

Batteries provide the highest flexibility. They are the only component type allowing power output and being available all the time. Table A.1 lists the parameters characterizing a battery. The methods defined for a battery B in the generic component interface are given in Eqs. (A.1) to (A.9) in terms of these parameters.

$$s^{\text{in}}_{\max}(B,t,\Delta t) = P^B_{\text{in}} \tag{A.1}$$

$$s^{\text{in}}_{\text{out}}(B,t,\Delta t) = P^B_{\text{out}} \tag{A.2}$$

$$\text{soc}_{\max}(B,t,\Delta t) = C^B \tag{A.3}$$

$$\eta^{\text{in}}(B,t,\Delta t) = \eta^B_{\text{in}} \tag{A.4}$$

$$\eta^{\text{out}}(B,t,\Delta t) = \eta^B_{\text{out}} \tag{A.5}$$

$$\lambda_{\text{lin}}(B,t,\Delta t) = \lambda^B \tag{A.6}$$

$$c^{\text{out}}(B,t,\Delta t) = c^B_{\text{cycle}} \tag{A.7}$$

Table A.1
Parameters describing batteries.

Parameter	Default	Unit	Description
$P^{\text{Bat}}_{\text{in}}$	0.0064	MW	Nominal input power
$P^{\text{Bat}}_{\text{out}}$	0.005	MW	Nominal output power
C^{Bat}	0.01152	MWh	Storage capacity
$\eta^{\text{Bat}}_{\text{in}}$	0.944		Charging efficiency
$\eta^{\text{Bat}}_{\text{out}}$	0.922		Discharging efficiency
λ^{Bat}	0.01	1/h	Standby loss
$c^{\text{Bat}}_{\text{op}}$	50	EUR/MWh	Levelized cost of energy

Table A.2
Parameters describing charging cycles of charging stations.

Parameter	Default	Unit	Description
$t^{\text{Cycle}}_{\text{on}}$			Time of connection to the charging station
$t^{\text{Cycle}}_{\text{off}}$			Time of connection to the charging station
$\text{soc}^{\text{Cycle}}_{\text{on}}$		MWh	State-of-charge at connection time
$\text{soc}^{\text{Cycle}}_{\text{off}}$		MWh	State-of-charge at disconnection time
$P^{\text{Cycle}}_{\text{in}}$	0.011	MW	Nominal input power
$P^{\text{Cycle}}_{\text{out}}$	0	MW	Nominal output power
C^{Cycle}	0.04	MWh	Storage capacity
$\eta^{\text{Cycle}}_{\text{in}}$	0.953		Charging efficiency
$\eta^{\text{Cycle}}_{\text{out}}$	0.953		Discharging efficiency
λ^{Cycle}	0.01	1/h	Standby loss
$c^{\text{Cycle}}_{\text{cycle}}$	0	EUR	Life cycle cost of one charging cycle

Table A.3
Parameters describing heat pumps.

Parameter	Default	Unit	Description
$\overrightarrow{T}^{HP}_{out}$		°C	Vector of outdoor temperatures
P^{HP}_{in}	0.00278	MW	Nominal input power
A^{HP}	100	m^2	Living area
T^{HP}_{min}	20	°C	Minimum indoor temperature
T^{HP}_{max}	25	°C	Maximum indoor temperature
η^{HP}_{in}	1		Charging efficiency
cop^{HP}_{lin}	0.05	$\frac{MWh_{th}}{MWh_{el}{}^{\circ}C}$	Outdoor temperature dependent part of coefficient of performance
$\mathrm{cop}^{HP}_{const}$	3.5	$\frac{MWh_{th}}{MWh_{el}}$	Constant part of coefficient of performance
ϕ^{HP}	0.00444	$\frac{MWh}{^{\circ}C}$	Conversion factor between thermal energy and room temperature change
λ^{HP}_{lin}	0.00176	1/h	Linear building temperature losses
λ^{HP}_{const}	−0.0178	°C/h	Constant building temperature losses

$$\mathrm{soc}_{start}\left(B, \overrightarrow{t}, \Delta t\right) = \frac{C^B}{2} \tag{A.8}$$

$$\mathrm{soc}_{stop}\left(B, \overrightarrow{t}, \Delta t\right) = \frac{C^B}{2} \tag{A.9}$$

A.2. Electric vehicles

Electric vehicles are included via charging stations. A charging station is characterized by a set of charging cycles, describing when an electric vehicle is connect, when it will be disconnected, the state-of-charge at connection time and the required state-of-charge at disconnection time. Furthermore, all parameters describing a battery can be specified. Table A.2 lists all parameters characterizing a single charging cycle. Let C_i denote the ith charging cycle of a charging station C. The interface function α is given in Eq. (A.10).

$$\alpha(C, t, \Delta t) = \begin{cases} 1 & \exists i : t^{C_i}_{on} \leqslant t < t^{C_i}_{off} \\ 0 & \text{else} \end{cases} \tag{A.10}$$

The charging cycle available at time t is written as C_t. The interface functions $s^{in}_{max}, s^{out}_{max}, \eta^{in}, \eta^{out}, \lambda_{lin}$ and c^{out} for the input $(C, t, \Delta t)$ are defined as the corresponding parameter of C_t in Table A.2 analogous to Eqs. (A.1) to Eq. (A.7) if $\alpha(C, t, \Delta t) = 1$, and zero otherwise. To consider the connection and disconnection of different electric vehicles in the state-of-charge variables, the external storage input function q_{ext} defined in Eq. (A.11) is used.

$$q_{ext}(C, t, \Delta t) = \begin{cases} \mathrm{soc}^{C_t}_{on} & t = t^{C_t}_{on} \\ \mathrm{soc}^{C_t}_{off} & t = t^{C_t}_{off} - \Delta t \\ 0 & \text{else} \end{cases} \tag{A.11}$$

Accordingly, the function soc_{max} is given by Eq. (A.12).

$$\mathrm{soc}_{max}(C, t, \Delta t) = \begin{cases} C^{C_t} & t^{C_t}_{on} \leqslant t < t^{C_t}_{off} - \Delta t \\ 0 & \text{else} \end{cases} \tag{A.12}$$

If charging cycles go beyond the optimization time frame, start and stop values for the state-of-charge are interpolated linearly between the connection and disconnection state-of-charge. For $t^{C_t}_{on} < \min \overrightarrow{t} < t^{C_t}_{off}$ the start state-of-charge $\mathrm{soc}_{start}\left(C, \overrightarrow{t}, \Delta t\right)$ is set to

$$\mathrm{soc}^{C_t}_{on} + \frac{\min \overrightarrow{t} - \Delta t - t^{C_t}_{on}}{t^{C_t}_{off} - t^{C_t}_{on}} \cdot \left(\mathrm{soc}^{C_t}_{off} - \mathrm{soc}^{C_t}_{on}\right). \tag{A.13}$$

otherwise it equals zero. Similarly, $\mathrm{soc}_{stop}\left(C, \overrightarrow{t}, \Delta t\right)$ defaults to zero except for $t^{C_t}_{on} < \max \overrightarrow{t} < t^{C_t}_{off} - \Delta t$. In that case it is given by

$$\mathrm{soc}^{C_t}_{on} + \frac{\max \overrightarrow{t} - t^{C_t}_{on}}{t^{C_t}_{off} - t^{C_t}_{on}} \cdot \left(\mathrm{soc}^{C_t}_{off} - \mathrm{soc}^{C_t}_{on}\right). \tag{A.14}$$

Table A.4
Parameters describing electric boilers.

Parameter	Default	Unit	Description
$\overrightarrow{L}^{\text{Boiler}}$		MW	Vector of domestic hot water loads
$P_{\text{in}}^{\text{Boiler}}$	0.0066	MW	Nominal input power
V^{Boiler}	300	L	Water storage volume
$T_{\text{min}}^{\text{Boiler}}$	40	°C	Minimum water storage temperature
$T_{\text{max}}^{\text{Boiler}}$	95	°C	Maximum water storage temperature
$T_{\text{room}}^{\text{Boiler}}$	20	°C	Surrounding room temperature for the water storage
$\eta_{\text{in}}^{\text{Boiler}}$	0.99		Charging efficiency
λ^{Boiler}	0.01	1/h	Linear water storage temperature losses

A.3. Heat pumps

Domestic heat pumps are characterized the nominal input power, temperature limits, a conversion factor, efficiencies, loss factors and the building's living area. Furthermore, a vector storing the outdoor temperature at each time step is required to calculate the building's temperature losses. Table A.3 lists all parameters describing heat pumps and their default values. The default values for $\text{cop}_{\text{lin}}^{\text{HP}}$, $\text{cop}_{\text{const}}^{\text{HP}}$, $\lambda_{\text{lin}}^{\text{HP}}$ and $\lambda_{\text{const}}^{\text{HP}}$ were derived using a linear regression on measured data for electric power, thermal power, indoor and outdoor temperature of a real heat pump. The interface functions overloaded for a heat pump H are given in Eqs. (A.15) to Eq. (A.20).

$$s_{\text{max}}^{\text{in}}(H,t,\Delta t) = P_{\text{in}}^{H} \tag{A.15}$$

$$\eta^{\text{in}}(H,t,\Delta t) = \eta_{\text{in}}^{H} \tag{A.16}$$

$$\phi(H,t,\Delta t) = \frac{A^H \cdot \phi^H}{\text{cop}_{\text{const}}^{H} + \text{cop}_{\text{lin}}^{H} \cdot T_{\text{out},t}^{H}} \tag{A.17}$$

$$\text{soc}_{\text{base}}(H,t,\Delta t) = T_{\text{out},t}^{H} \tag{A.18}$$

$$\lambda_{\text{const}}(H,t,\Delta t) = \lambda_{\text{const}}^{H} \tag{A.19}$$

$$\lambda_{\text{lin}}(H,t,\Delta t) = \lambda_{\text{lin}}^{H} \tag{A.20}$$

If the state-of-charge limits are fixed to T_{min}^{H} and T_{max}^{H}, the optimization model can become infeasible for extreme outdoor temperatures. Hence, they are adapted based on the outdoor temperature profile to ensure feasibility, respecting the provided temperature limits whenever possible. For this purpose, a functions $T_{\text{next}}^{\text{min}}$ and $T_{\text{next}}^{\text{max}}$ are introduced in Eq. (A.21), calculating the minimum and maximum potential indoor temperatures in the next time step.

$$T_{\text{next}}^{\text{min}}(H,T,t,\Delta t) = T - \Delta t \cdot \left(\lambda_{\text{const}}^{H} + \lambda_{\text{lin}}^{H} \cdot \left(T - T_{\text{out,t}}^{H}\right)\right) \tag{A.21}$$

$$T_{\text{next}}^{\text{max}}(H,T,t,\Delta t) = T_{\text{next}}^{\text{min}}(H,T,t,\Delta t) + \Delta t \cdot \frac{\eta_{\text{in}}^{H} \cdot P_{\text{in}}^{H}}{\phi(H,t,\Delta t)} \tag{A.22}$$

With these auxiliary functions, the generic interface methods for soc_{max} and soc_{min} are given in Eq. (A.23). Note that only t is explicitly written in the equations. The input parameters H and Δt are omitted.

$$\text{soc}_{\text{max}}(t) = \max\left\{T_{\text{max}}^{H}, T_{\text{next}}^{\text{min}}(\text{soc}_{\text{max}}(t-\Delta t), t-\Delta t)\right\} \tag{A.23}$$

$$\text{soc}_{\text{min}}(t) = \min\left\{T_{\text{min}}^{H}, T_{\text{next}}^{\text{max}}(\text{soc}_{\text{min}}(t-\Delta t), t-\Delta t)\right\} \tag{A.24}$$

Finally, the start and stop values for the state-of-charge are defined in Eq. (A.25).

$$\text{soc}_{\text{start}}\left(H,\overrightarrow{t},\Delta t\right) = \frac{T_{\text{max}}^{H} + T_{\text{min}}^{H}}{2} \tag{A.25}$$

$$\text{soc}_{\text{stop}}\left(H,\overrightarrow{t},\Delta t\right) = \text{soc}_{\text{min}}\left(\max \overrightarrow{t}\right) \tag{A.26}$$

A.4. Electric boilers

Electric boilers are characterized by a load profile for domestic hot water demand, the nominal input power and the charging efficiency.

Furthermore, the hot water storage is described by its volume, temperature limits and losses. The corresponding parameters are listed in Table A.4. With the approximate values for the density $\rho = 0.99\text{kg L}^{-1}$ and the specific heat capacity $c = 4.18\text{ J g}^{-1}\text{ K}^{-1}$ [42] of water, the interface functions for an electric boiler B are given in Eqs. (A.28) to (A.35).

$$s_{\max}^{\text{in}}(B, t, \Delta t) = P_{\text{in}}^{B} \tag{A.28}$$

$$\eta^{\text{in}}(B, t, \Delta t) = \eta_{\text{in}}^{B} \tag{A.29}$$

$$\phi(B, t, \Delta t) = \frac{c \cdot \rho}{3.6 \times 10^{6}} \cdot V^{B} \tag{A.30}$$

$$\text{soc}_{\min}(B, t, \Delta t) = T_{\min}^{B} \tag{A.31}$$

$$\text{soc}_{\max}(B, t, \Delta t) = T_{\min}^{B} \tag{A.32}$$

$$\text{soc}_{\text{base}}(B, t, \Delta t) = T_{\text{room}}^{B} \tag{A.33}$$

$$q_{\text{ext}}(B, t, \Delta t) = -\frac{\Delta t}{\phi(B, t, \Delta t)} \cdot L_{t}^{B} \tag{A.34}$$

$$\lambda_{\text{lin}}(B, t, \Delta t) = \lambda^{B} \tag{A.35}$$

A.5. Photovoltaic systems and non-flexible loads

PV systems are characterized by a schedule of production values $\overrightarrow{S}^{\text{PV}}$ in MW and a Boolean value δ^{PV} indicating if it is allowed to be curtailed. The only interface functions overloaded for a PV system P are given in Eq. (A.36).

$$s_{\max}^{\text{out}}(P, t, \Delta t) = S_{t}^{P} \tag{A.36}$$

$$s_{\min}^{\text{out}}(P, t, \Delta t) = \begin{cases} 0 & \delta^{P} = 1 \\ S_{t}^{P} & \delta^{P} = 0 \end{cases} \tag{A.37}$$

Non-flexible loads are described by a schedule of consumption values $\overrightarrow{S}^{\text{Load}}$ in MW. They do not offer any flexibility but are important to consider, because they affect the grid tariff, fees and surcharges if they share a grid connection point with other flexible devices. The interface functions defined for a non-flexible load L are given in Eq. (A.38).

$$s_{\max}^{\text{out}}(L, t, \Delta t) = S_{t}^{L} \tag{A.38}$$

$$s_{\min}^{\text{out}}(L, t, \Delta t) = S_{t}^{L} \tag{A.39}$$

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