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# On the Importance of Grid Tariff Designs in Local Energy Markets

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**Abstract:** Local Energy Markets (LEMs) were recently proposed as a measure to coordinate an increasing amount of distributed energy resources on a distribution grid level. A variety of market models for LEMs are currently being discussed; however, a consistent analysis of various proposed grid tariff designs is missing. We address this gap by formulating a linear optimization-based market matching algorithm capable of modeling a variation of grid tariff designs. A comprehensive simulative study is performed for yearly simulations of a rural, semiurban, and urban grids in Germany, focusing on electric vehicles, heat pumps, battery storage, and photovoltaics in residential and commercial buildings. We compare energy-based grid tariffs with constant, topology-dependent and time-variable cost components and power-based tariffs to a benchmark case. The results show that grid tariffs with power fees show a significantly higher potential for the reduction of peak demand and feed-in (30–64%) than energy fee-based tariffs (8–49%). Additionally, we show that energy-based grid tariffs do not value the flexibility of assets such as electric vehicles compared to inflexible loads. A postprocessing of market results valuing the reduction of power peaks is proposed, enabling a compensation for the usage of asset flexibility.

**Keywords:** local energy market; distribution grid; flexibility; electric vehicles; market design; linear optimization



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## 1. Introduction

The ongoing transformation of energy systems worldwide from several large-scale power plants to millions of Distributed Energy Resources (DER) implies major technical and regulatory challenges. In Germany, for example, a drastic increase of Photovoltaic (PV) installation capacity (5.8-fold, +268 GW), Heat Pump (HP) installations (11.9-fold, +13.1 million), Electric Vehicles (EVs; 21-fold, +24 million) and PV-Battery storage (51-fold, 66.1 GW) is projected in the next 15 years by the federal grid agency [1].

Introducing this large amount of small-scale DER mainly to distribution grids not only increases the demand for balancing measures such as energy storage but stresses the grid to its physical limits in times of peak feed-in from Variable Renewable Energies (VREs) or peak demand from EVs, HPs and other electric appliances [2].

Grid integration measures such as demand response, demand side management or time-of-use tariffs might help to keep required grid reinforcement costs low [3]; however, current regulatory frameworks do not substantially incentivize and integrate small-scale prosumers into the energy market [4]. One major reason is the price structure in retail energy markets, which is dominated by constant Regulated Electricity Price Components (REPCs). On the low-voltage level, each unit of bought energy in Germany is charged with 77% taxes, grid fees and levies, leaving only 23% for the actual price of energy [5], which could be used to incentivize a demand response from customers. Given the limited price elasticity of residential electricity consumers [6], common demand response patterns are not expected to lead to substantial adaptions of customer demand if not automated.

Local Energy Markets (LEMs) were recently proposed as a measure to integratively coordinate and incentivize DERs at the distribution grid level [7,8]. A variation of market designs for LEMs were proposed, ranging from purely decentral Peer-to-Peer (P2P) markets, e.g., [9–11], which do not rely on a central coordinator, to community-based approaches [12,13] with a market operator. Abrishambaf et al. show in a recent review paper [14] that a major focus of the current literature is the mathematical modeling of LEM simulation frameworks and market matching models. An important feature of LEMs, i.e., the benefit to the distribution grid, is identified as a research gap by the review of Tushar et al. [15], including the required adaption of REPCs to efficiently implement LEMs.

### 1.1. Related Work

There are several approaches to adjust grid tariffs to foster demand response and increase grid integration of DER. The temporal dynamization of retail prices, i.e., offering end customers a time-of-use tariff, is a typical approach to incentivize consumption in times of low market prices, e.g., a day–night tariff. Further dynamization is attempted by coupling residential prices to wholesale market prices on hourly or sub-hourly bases. Freier et al. [16] calculate such dynamic REPCs based on volatility indicators such as wholesale market prices, greenhouse gas emissions and the residual load.

Another approach recently introduced in Austrian regulations [17] is an absolute deduction of REPCs for electricity exchanged within the same renewable energy community located under the same substation. Buying one unit of electricity from a neighbor located under the same substation is hence reduced by a fixed share of REPCs. In [18], the authors demonstrate that such a topology-based reduction of REPCs can be integrated into the market matching algorithm of an LEM and reduce peak loads and feed-in from PV. However, only two example days and one LEM scenario with high shares of DER are simulated, reducing the generalizability of the found results.

Bjarghov et al. [19] propose a subscription-based tariff design for residential customers, penalizing demand over a certain subscribed level or limiting it to the level. They show that the annual costs stay almost stable while reducing peak loads in the grid.

In [20], Cramer et al. demonstrate the application of LEMs in different regions in Germany for a scenario of extensive EV deployment. They show that an introduction of LEMs decreases the annual power peaks substantially (17–39%), especially when introducing power fees.

The implementation of LEMs with regards to regulation in China is addressed by Lin et al. in [21]. They investigate the peak–valley pricing scheme, i.e., time-of-use tariff with peak prices for consumption between 08:00 and 20:00. They conclude that the peak–valley pricing scheme increases savings for consumers but reduces grid revenue. As shown by Li et al. [22], electricity markets are strongly effected by calendar effects. Hence, constant peak–valley tariffs might not be sufficient to account for the continuously changing patterns of the electricity market.

A recent paper by Maldet et al. [23] reviews regulatory frameworks for LEMs and energy communities in Austria, Ireland and Norway. It concludes that all investigated frameworks generate economic benefits, mainly by a reduction of energy fees. The authors highlight that power fee-based grid tariff designs contribute to keep grid expansion costs lower, especially when implemented with a virtual metering point for the whole LEM or energy community.

### 1.2. Scope and Contributions

While most works discuss specific grid tariff designs for specific grid setups (e.g., generic testcase setup) and considering specific assets, a consistent comparison of grid tariff designs for LEMs for a variety of detailed scenarios (rural, semiurban, urban) is missing. In particular, a detailed evaluation of the effect of grid tariff design on demand and feed-in peaks and the resulting financial effects on relevant asset types (PV, EV, HP, storage) are not covered.

In this paper we address this gap by introducing a linear optimization-based LEM market matching model that can incorporate a variety of grid tariff designs and adaptions of REPCs.

We subsequently derive simulation scenarios from publicly available benchmark grids [24], including a variation of grid types (rural, semiurban, urban) and four scenario years (2020, 2025, 2030, 2035). We then apply the four most common grid tariff designs for LEMs, i.e., purely energy-based fees (Flat scenario), reduced fees based on topology (Feeder scenario), time-variable fees (Variable scenario) and power fees (Power fee scenario) to the LEM model and compare the results to a Business-As-Usual (BAU) scenario without the introduction of an LEM.

Specific attention is paid to the explicit modeling of common flexible assets with major impact in the distribution grid in Germany, namely EVs, HPs, PV, and battery storage. For the different scenarios, both EV charging at home and at work is investigated. We especially concentrate on the tradeoff between the benefit of an LEM with regards to grid integration aspects and financial aspects of participant assets and the reduction of collected REPCs.

## 2. Method

### *2.1. Overview*

Figure 1 provides an overview of the proposed research method. In an initial step, simulation scenarios are generated for typical German Low Voltage (LV) distribution grids derived from the Simbench dataset [24]. The assumptions on installed assets within the respective grids are based on the Simbench dataset but updated to the grid development plan of the federal grid agency of Germany [25] for the scenario years 2020, 2025, 2030 and 2035. Thermal and electrical demand time series of residential and commercial grid users are obtained from the Simbench dataset, while EV charging time series are generated based on statistical data. The full process of scenario generation is described in Section 2.2.

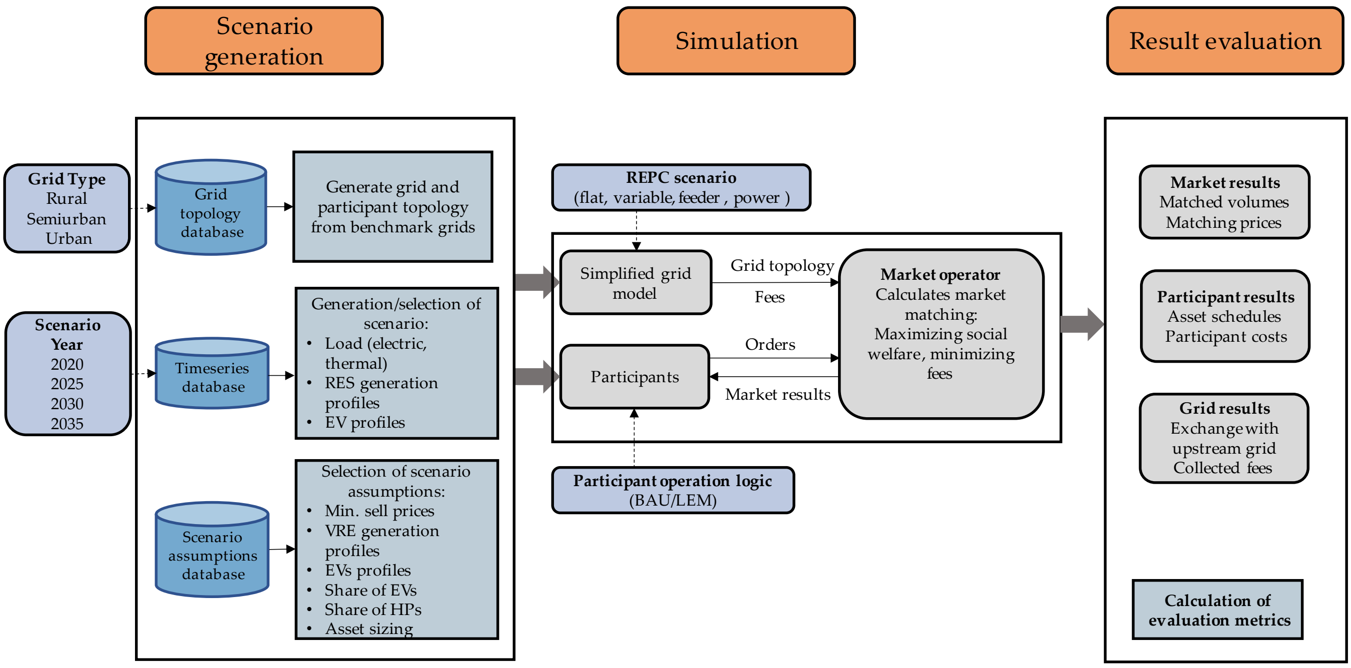



**Figure 1.** Overview of the methodology framework. VRE: Variable Renewable Energy, EV: Electric Vehicle, HP: Heat Pump, BAU: Business as usual, LEM: Local Energy Market, REPC: Regulated Electricity Price Component.

Details on the modeling approach for the market operator, market participants and assets can be found in Section 2.3. Section 2.4 covers the proposed operation scenarios of the local energy system.

Section 2.5 introduces evaluation metrics to compare the simulated scenarios with regards to the effect on the distribution grid, the asset schedules of participants, and the financial aspects of participants and collected REPCs.

The described mathematical models and simulation framework are implemented as an object-oriented software solution in Python 3.9.6. The optimization problem is formulated using the algebraic modeling language AMPL [26] and solved with the SCIP solver version 8.0 [27]. Pyscipopt [28] is used to provide the interface between Python and SCIP. The market matching in the simulation scenarios is performed daily, with a temporal resolution of 15 min assuming perfect foresight.

### 2.2. Scenario Generation

Baseline assumptions such as the number of grid connections and residential and commercial participants are derived from a rural, semiurban, and urban Simbench grid with the following identifiers (rural: LV2.101; semiurban: LV5.201; urban: LV6.201). Since the assumptions for the expansion of DERs in the Simbench grids are based on an older grid development plan, the assumptions are updated and linearly extrapolated from the Simbench baseline year 2016 with assumptions until 2035 from the grid development plan published in 2020. The adapted parameters include the rated power of PV, the share of HPs, the rated power of battery storage and the share of electric vehicles. The share of electric vehicles is further adapted with specific regional shares of vehicles per household based on [29], since the grid development plan does not provide a differentiation based on regions. Table 1 shows the scenario assumptions for the three different grid types for the scenario year 2035. Assumptions for other scenario years can be found in Appendix A, Tables A1–A3.

**Table 1.** Scenario assumptions for scenario year 2035, adapted from [24].

| | | **Rural** | **Semiurban** | **Urban** |
|---|---|---|---|---|
| **Parameter** | **Type/Unit** | | | |
| Grid connection points | Count (-) | 96 | 110 | 58 |
| Residential loads | Count (-) | 92 | 92 | 102 |
| Commercial loads | Count (-) | 7 | 12 | 9 |
| Photovoltaic systems | Rated power (kW) | 326.7 | 432.4 | 222.1 |
| | Count (-) | 19 | 30 | 19 |
| Heat pumps | Rated power (kW) | 138.1 | 100.9 | 63.4 |
| | Count (-) | 24 | 27 | 14 |
| | share | 24.2 | 26.0 | 12.6 |
| Electric vehicles | Rated power (kW) | 241.0 | 262.8 | 166.2 |
| | Count (-) | 33 | 35 | 17 |
| Battery | Rated power (kW) | 93.0 | 247.7 | 50.8 |
| | Count (-) | 8 | 15 | 7 |
| | Capacity (kWh) | 186.3 | 495.5 | 101.7 |
| Electric load | Energy (MWh) | 257.9 | 470.3 | 530.9 |
| Thermal load | Energy (MWh) | 159.5 | 166.9 | 102.0 |
| Electric load EV | Energy (MWh) | 111.2 | 90.6 | 62.0 |

Yearly simulation time series of relative PV generation, electric baseloads and electric loads of HPs are provided in the Simbench dataset and are respectively scaled to the rated power of the scenario in the case of PV systems. To explicitly model the flexibility of EVs, time series of the plug-state (on/off) and required State of Charge (SOC) at the start and end of a charging process are generated based on statistics. The basis for the generated time series is an extensive mobility survey in Germany [30] providing distributions for typical departure times to work or other trips, differentiated by region as well as typical distances traveled. Time series patterns are randomly generated for participants with

EVs charging at home and at work. A combination of both, i.e., a participant charging at home and/or at work, is not considered. Based on the traveled distance of a trip and the temperature-dependent consumption of the EV based on [31], the required charging demand after a trip is calculated. We assume that each charging process continues until the battery is fully charged. The flexible operation of HPs is modelled through decoupling the thermal demand curves of customers through thermal energy storages. Rated electrical power, temperature dependent Coefficient of Performance (COP) and thermal load profiles are derived from the time series and parameters provided in the Simbench dataset. It is assumed that the thermal storage is sufficiently sized to shift energy demand throughout one simulation day.

Price assumptions required for the generation of market orders (later described in Section 2.3) for buy-, sell- and storage-orders are based on the following assumptions. We assume that maximum buy prices, minimum sell prices and prices for the usage of battery storage can be derived from the respective opportunity costs.

For buying from the LEM, we hence assume the maximum buy price is equal to the best alternative, i.e., directly buying from an energy retailer. We assume an average buy price for households with a consumption of 3500 kWh of 31.37 ct/kWh in 2020 [5].

Minimum sell prices for PV are based on the feed-in tariffs of each individual power plant as the next best opportunity to sell. Feed-in tariffs in Germany are guaranteed for a period of 20 years. Throughout the years, the tariffs have drastically declined [32], which needs to be considered in the modeling of the scenario years. For PV plants with expired feed-in tariffs in a modeled scenario year, we assume a minimum sell price of the feed-in tariff of the particular year. We further assume the technical lifetime of PV panels to be 30 years. Based on the power plant registry of the German grid operators [33], we map 2.02 million PV plants (end of 2021) with their feed-in tariffs based on the their capacity and the commissioning date. This approach generates a distribution of feed-in tariffs for each scenario year. For each grid type and scenario year, we subsequently randomly draw a feed-in tariff for each PV plant in the scenario until the weighted average is reached within a deviation of 0.1%. Figure A1 in the Appendix B shows the development of weighted average feed-in prices for the scenario years.

For the usage of battery storage to provide flexibility to the LEM, we assume the revenue to be the daily arbitrage opportunity achievable on the wholesale market. An evaluation of the wholesale market prices of the region Germany-Luxembourg-Austria from 2016–2019 shows an average daily arbitrage opportunity of 2.87 ct/kWh.

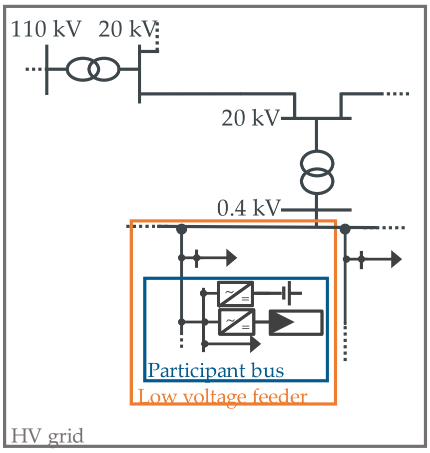
### 2.3. LEM Market Model

We propose a market matching algorithm based on a closed order book and linear optimization. Three order categories are introduced to capture the flexibility in demand, generation and battery storage. Table 2 provides an overview of the order types and their parameters based on [18,34]. The basic concept of the market model is that market participants not only submit tuples of demanded energy and a maximum price but include several technical parameters in the market order, which enables the market operator to consider specific flexibility options of assets. A buy-order for a charging process of an EV can, for example, be defined as a time series with the maximum charging power, the total charging demand over a specific time and a maximum buy price. The market operator can hence find the best possible time to begin and end the charging process based on the objective functions described below. With this approach, assets at the participant site can be anonymized and abstracted while enabling the market operator to optimally schedule flexibilities.

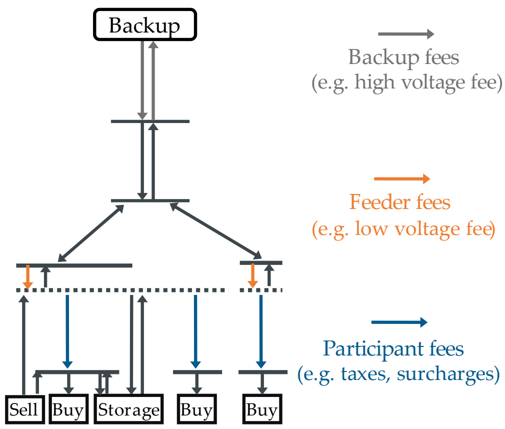
**Table 2.** Overview of parameters for market orders.

| Order | Parameter | Unit | Description |
|---|---|---|---|
| All | $T, t_{start}, t_{end}$ | (-) | Valid time period, start and end timesteps of order |
| Buy | $c^{b}_{max,t}$ | (ct/kWh) | Maximum buy price for each timestep |
| | $P^{b}_{max,t}$ | (kW) | Maximum power input for each timestep |
| | $E^{b}$ | (kWh) | Requested energy within time period $T$ |
| Sell | $c^{s}_{min,t}$ | (ct/kWh) | Minimum sell price for each timestep |
| | $P^{s}_{max,t}$ | (kW) | Maximum power output for each timestep |
| | $E^{s}$ | (kWh) | Offered energy within time period $T$ |
| Storage | $E^{st}_{max,t}$ | (kWh) | Storage capacity |
| | $E^{st}_{0}$ | (kWh) | Initial storage capacity |
| | $P^{st}_{max,ch,t}$ | (kW) | Maximum charging power |
| | $P^{st}_{max,dch,t}$ | (kW) | Maximum discharging power |
| | $\eta^{st}_{ch}, \eta^{st}_{dch}$ | (-) | Charge and discharge efficiency |
| | $c^{st}_{dch,min}$ | (ct/kWh) | Minimum discharge price |

The abstraction of participant assets and a simplified distribution grid topology is shown in Figure 2. To model a variation of grid tariff designs, a simplified grid topology, including nodes at the participant, feeder and substation is included in the LEM model. The example shows how a participant with an electric load, a PV plant and storage and two participants with inflexible load are modeled. The explicit modeling of the participant bus allows for a differentiation of self-consumed generation and a virtual splitting of storage assets. Storage can hence be utilized to increase self-consumption and, if economically viable, used to provide storage to other market participants. Modeling REPCs on different levels of the topology allows incentivization of trades with close electrical proximity. In the sample case (Figure 2b), selling generation from the PV panel would be charged only participant fees when bought by the participant at the same feeder; however, it would additionally be charged feeder fees when selling to a participant connected to another feeder. With this formulation, maximum prices for buy orders can be included as gross prices, and sell prices as net prices, since REPCs are directly assigned in the optimization problem.




(**a**) Simplified distribution grid model




(**b**) LEM model

**Figure 2.** Modeling simplification of distribution grid topology (**a**) within the LEM market matching model (**b**).

The formulation of the linear-optimization problem aims to minimize the following objective function (Equation (1)). A minimization of paid REPCs is combined with a maximization of Social Welfare (SW). For a set of buy-orders $B$, sell-orders $S$, storage-orders

$ST$, lines $L$, nodes $N$ and participants $P$, the linear, positive decision variables are the respective active powers of orders and flows over lines and nodes ($P^B, P^S, P^{ST}, P^L, P^N, P^P$):

$$\min_{(P^B,P^S,P^{ST},P^L,P^N,P^P)\epsilon R^+} (\mathrm{REPC} - \mathrm{SW}), \tag{1}$$

where $SW$ is the difference of costs for buy-orders per order per timestep and the costs for sell-orders and storage-discharge orders per order per timestep

$$SW = \left[\sum_{t\epsilon T} \Delta t \left(\sum_{b\epsilon B} P^b_{t,p} c^b_{max,t} - \sum_{s\epsilon S} P^s_{t,p} c^s_{min,t} - \sum_{st\epsilon ST} P^{st,ext}_{dch,t,p} c^{st}_{dch,min}\right)\right], \tag{2}$$

where $P^b_{t,p}$, $P^s_{t,p}$ and $P^{st,ext}_{dch,t,p}$ are the matched power of each buy-, sell- and storage order.

REPCs are split to energy ($f_e$) and power ($f_p$) related fees:

$$REPCs = f_e + f_p, \tag{3}$$

where energy related fees are the sum of power flows into a participant node ($P^p_{in,t}$) or over a feeder node ($P^n_{in,t}$), multiplied with their respective energy fees ($c^n_{e,t}$, $c^p_{e,t}$) (ct/kWh)

$$f_e = \sum_{t\in T} \Delta t \left(\sum_{n\in N} P^n_{in,t} c^n_{e,t} + \sum_{p\in P} P^p_{in,t} c^p_{e,t}\right). \tag{4}$$

Power fees are considered as

$$f_p = \sum_{l\in L} P^l_{p,j,k} c^l_p, \tag{5}$$

where $P^l_{p,j,k}$ is the maximum power flow over a line within the market interval and $c^l_p$ is the power price (ct/kW).

The constraint of internal power balance of a market participant $p$ is formulated as

$$\sum_{s\in S(p)} P^{s,int}_{t,p} + \sum_{b\in B(p)} \left(-P^{b,int}_{t,p} + P^{b,ext}_{t,p}\right) + \sum_{st\in ST(p)} (-P^{st,int}_{t,p,ch} + P^{st,int}_{t,p,dch}) = 0, \quad \forall\, p \in P, t \in T, \tag{6}$$

where $P^{b,int}_{t,p}$ and $P^{b,ext}_{t,p}$ are the internally and externally bought electricity of a buy-order $b$, $P^{s,int}_{t,p}$ is the internally sold electricity of a sell-order $s$, and $P^{st,int}_{t,p,ch}$, $P^{st,int}_{t,p,dch}$ are the internally charged and discharged power of a storage-order $st$. We subsequently formulate the internal feeder node balance as

$$\sum_{p\in P(n)} \left(P^p_{in,t} - P^p_{out,t}\right) - \sum_{st\in ST(P(n))} \left(P^{st,ext}_{dch,t} - P^{st,ext}_{ch,t}\right) + P^n_{in,t} - P^n_{out,t} = 0, \quad \forall\, n \in N, t \in T, \tag{7}$$

where $P^p_{in,t}$ is the sum of all buy-orders of a participant $p$, $P^p_{out,t}$ is the sum of all sell-orders of a participant $p$ that are not consumed internally, $P^{st,ext}_{dch,t}$, $P^{st,ext}_{ch,t}$ are the charge and discharge power of a storage $st$ that are not used for self-consumption, $P^n_{in,t}$, $P^n_{out,t}$ are variables describing in- and outflows of the feeder node $n$. The transport equation connecting nodes via lines is described as

$$P^n_{in,t} - P^n_{out,t} + \sum_{k=n}^{L} P^l_{t,j,k} - \sum_{j=n}^{L} P^l_{t,j,k} = 0, \quad \forall\, n \in N, t \in T \tag{8}$$

where $P^{l}_{t,j,k}$ is the power flow over a line ($l$) from node $j$ to node $k$. The following constraints apply on the order level limiting maximum power and energy amounts. For sell-orders $S$:

$$P^{s}_{t,p} = P^{s,int}_{t,p} + P^{s,ext}_{t,p}, \ \ \forall s \in S, t \in T, \tag{9}$$

$$P^{s}_{t,p} \leq P^{s}_{max,t}, \ \ \forall s \in S, t \in T, \tag{10}$$

$$\sum_{t=t_{start}}^{t=t_{end}} P^{s}_{t,p} \Delta t = E^{s}, \ \ \forall s \in S. \tag{11}$$

For buy-orders $B$:

$$P^{b}_{t,p} \leq P^{b}_{max,t}, \ \ \forall b \in B, t \in T, \tag{12}$$

$$\sum_{t=t_{start}}^{t=t_{end}} P^{b}_{t,p} \Delta t \leq E^{b}_{max}. \ \forall b \in B, \tag{13}$$

and for all storage-orders $ST$:

$$E^{st,int}_{t} + E^{st,ext}_{t} \leq E^{st}_{max,t}, \tag{14}$$

$$P^{st,int}_{t,p,dch} + P^{st,ext}_{t,p,dch} \leq P^{st}_{max,dch,t}, \tag{15}$$

$$P^{st,int}_{t,p,ch} + P^{st,ext}_{t,p,ch} \leq P^{st}_{max,ch,t}, \tag{16}$$

$$E^{st}_{t_{start}} = E^{st}_{0} = E^{st}_{t_{end}}, \tag{17}$$

$$\frac{E^{st,int}_{t} - E^{st,int}_{t-1}}{\Delta t} = P^{st,int}_{t,p,ch} \eta^{st}_{ch} - \frac{1}{\eta^{st}_{dch}} P^{st,int}_{t,p,dch}, \ \ \forall t \in T, t > t_{start}, \tag{18}$$

$$\frac{E^{st,ext}_{t} - E^{st,ext}_{t-1}}{\Delta t} = P^{st,ext}_{t,p,ch} \eta^{st}_{ch} - \frac{1}{\eta^{st}_{dch}} P^{st,ext}_{t,p,dch}. \ \ \forall t \in T, t > t_{start}. \tag{19}$$

where the separate storage balance Equations (18) and (19) allow for a virtual splitting of the storage capacity. Self-discharge of storage is neglected for the 24 h time horizon analyzed here. It is additionally assumed that all demand and generation that cannot be matched locally is supplied by a backup utility at a backup node outside of the considered grid (Figure 2).

### 2.4. Scenarios

Generally, two different operation scenarios are considered, which are introduced in the following subsections. Both scenarios share exactly the same installed assets, participant structure and distribution grid. The Business as Usual (BAU) scenario simulates the operation of each individual participant separately, while the LEM scenario assumes that the introduced market model is utilized to enable an optimal, cross-participant operation of the energy system.

#### 2.4.1. Business as Usual

The BAU scenario describes the benchmark operation of the energy system without the introduction of an LEM. Each energy system of each participant is operated based on rules. Flexible demand assets, i.e., HPs and EVs, are operated based on the following logic.

Heat pumps are operated based on the provided time series of the Simbench dataset. It is assumed that the SOC of the heat storage is kept at a minimum level of 50%, while heat demand is directly supplied from the storage. Once this level is undercut, the HP or electric boiler is used to fill the storage.

For EVs, it is assumed that the car is charged with full available capacity after plug-in until the maximum SOC is reached.

The operation of battery storage of participants with PV, storage and loads is evaluated iteratively for each timestep with a rule-based approach commonly found in the literature [35]. If local generation exceeds the sum of all demand assets and the SOC of the battery storage is not at 100%, the storage is charged with the residuum of generation and demand. If local generation is less than local demand, the residuum is supplied by the battery storage if it is not empty.

#### 2.4.2. LEM Scenarios

Figure 3 shows the analyzed LEM scenarios with a variation of grid tariff designs.

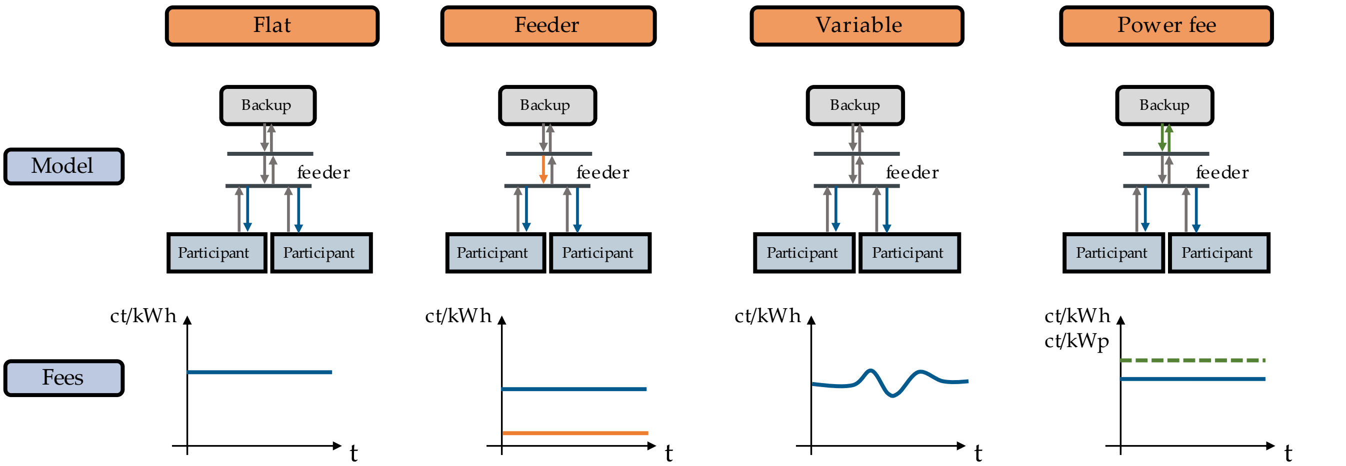



**Figure 3.** Overview of analyzed grid tariff models for LEMs. Lines and arrows: blue—participant energy fees ct/kWh; orange—feeder energy fees ct/kWh; green—power fees ct/kWp.

Grid tariff designs:

(a) **Flat:** In this scenario, the full REPCs (24.17 ct/kWh) are applied for each consumed kWh of a participant from outside the participant's energy system. This can be viewed as a benchmark case, without a reduction or adaption of grid tariff design.

(b) **Feeder:** This scenario describes a reduction of energy fees for trades within the same feeder. It is based on similar new regulations in Austria [17]; the height of the reduction is the reduction of the constant energy tax in Germany of 2.05 ct/kWh, including a reduction VAT. Participant energy fees (blue line) are set to 21.74 ct/kWh, and feeder fees (orange line) to 2.44 ct/kWh.

(c) **Variable:** An adaption of participant energy fees based on the time-variable Wholesale Electricity Market (WEM) is considered in this scenario. The fees are adapted using the following formula: $c_{p,t} = c_{p,base} + c_{p,variable}\frac{\lambda_{WM,t}}{\lambda_{WM,T}}$, with $\lambda_{WM,t}$ as the wholesale market price at timestep t, $c_{p,base}$ a constant base value (21.74 ct/kWh) and $c_{p,variable}$ as a variable adaption constant (2.44 ct/kWh).

(d) **Power:** This scenario combines a flat energy fee with power fees for demand and generation at a virtual connection point of the LEM to the backup energy supply. The overall paid power fees **over** the simulation horizon (one year) are distributed among the participants who contributed to the five highest peaks in a postprocessing step. A power fee of 3.7 €/kW is assumed based on [36] as well as an average connection capacity of 15 kW.

Table 3 provides an overview of potential advantages and disadvantages of the evaluated grid tariff designs.

**Table 3.** Overview of potential advantages and disadvantages of proposed grid tariff designs.

| | Grid Tariff Designs | | | |
|---|---|---|---|---|
| | **Flat** | **Feeder** | **Variable** | **Power** |
| **Advantages** | Low implementation effort | Incentives trades within close spatial proximity. Generates spatially resolved investment signals. | Allows market coupling with wholesale market. Incentivation of flexibility usage. | High incentivization to reduce demand and feed-in peaks. Allows for clear renumeration of flexibility provision. |
| **Disadvantages** | No incentivization of grid-friendly behavior | Moderate implementation efforts. | High implementation efforts. | High implementation efforts. |

### *2.5. Evaluation Metrics*

The focus of the evaluation is on the reduction of peak power (generation and feed-in) and the financial KPIs of participant assets and collected REPCs compared to the BAU scenario. The main metric for peak power reduction is the relative difference compared to the BAU case. To reduce the overestimation of single yearly peaks, we consider the N 5% highest peaks during a year:

$$\frac{1}{N}\sum_{n\in N} \underset{n}{max}\left(\frac{P_{\mathrm{BAU},n}-P_{\mathrm{LEM},n}}{P_{\mathrm{BAU},n}}\right), \tag{20}$$

where $P_{\mathrm{BAU},n}$ and $P_{\mathrm{LEM},n}$ are the daily demand or feed-in peaks in the BAU and LEM scenario $n$.

To calculate the relative benefit of a buy-order, we consider the difference between achieved prices in the LEM scenario compared to the prices in the BAU scenario ($\lambda^{b,\mathrm{BAU}}$):

$$\lambda^{b,\mathrm{BAU}} - \frac{\sum_{t\in T}\left(P^{b}_{t,p}\lambda^{b}_{t,p}\right)}{\sum_{t\in T}P^{b}_{t,p}}, \tag{21}$$

and for a sell-order $s$, with the reference price in the BAU scenario $\lambda^{s,\mathrm{BAU}}$:

$$\frac{\sum_{t\in T}\left(P^{s}_{t,p}\lambda^{s}_{t,p}\right)}{\sum_{t\in T}P^{s}_{t,p}} - \lambda^{s,\mathrm{BAU}}. \tag{22}$$

For storage-orders we directly consider the achieved discharge prices, since there is no possibility to externally market the flexibility of storage in the BAU case.

To compare the collected REPCs, we calculate the relative deviation as for a scenario $s$:

$$1-\frac{\mathrm{REPCs_s}}{\mathrm{REPCs_{BAU}}}, \tag{23}$$

where $\mathrm{REPCs_s}$ is the REPCs of the LEM scenario directly derived from the objective function, and the REPCs collected in the BAU case is

$$\mathrm{REPCs_{BAU}} = \sum_{t\in T}\sum_{p\in P}\Delta t c_e P_{bu,in,t,p}. \tag{24}$$

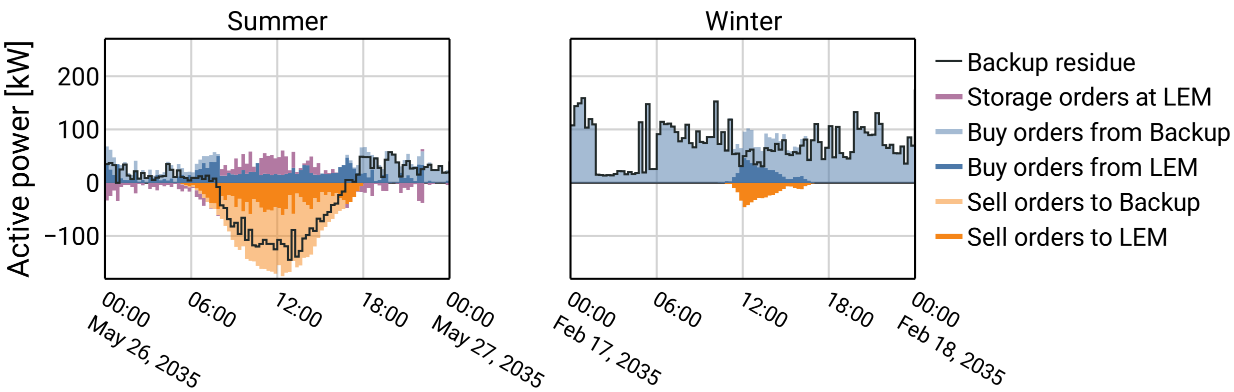
## **3. Results**

### *3.1. Examplary Operational Differences*

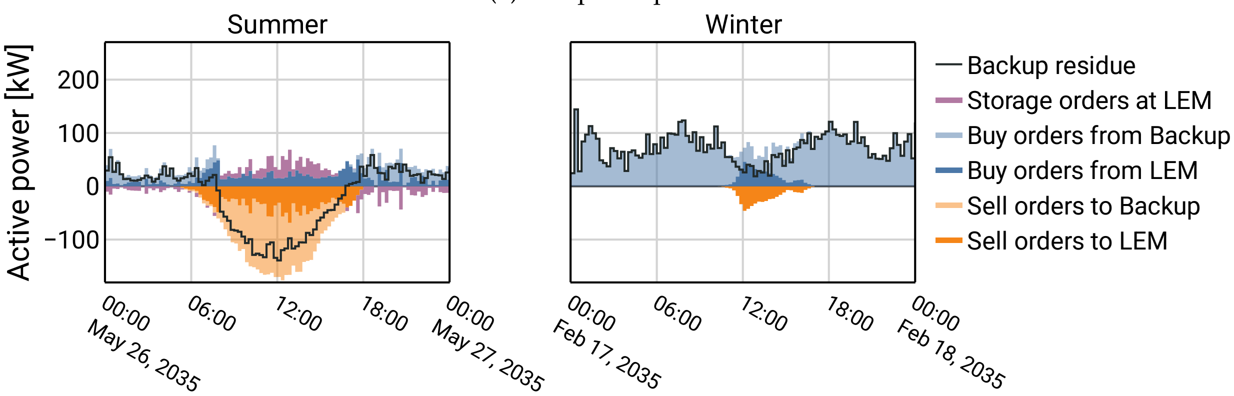
To gain a first overview of the differences in operation between the different grid tariff designs, Figure 4 shows the results of the market matching for a variation of scenarios (a–d). For each scenario, a day with high PV feed-in and low load during summer and a day with high load and low PV feed during winter are displayed. The figure shows the market balance, with matched buy-orders and storage charges on the positive $y$-axis. The negative $y$-axis shows matched sell-orders and discharged power of storage. Lighter opacity indicates buys and sells from and to the backup utility. The black line represents the residue of local demand and generation to the backup utility and is equivalent to the load at the substation.

Between the constant energy fee scenarios (scenario (a) and scenario (b)), the main difference is that the demand from buy-orders in the winter scenario is additionally distributed in the reduced feeder fee scenario (b). During the summer day, storage charges are arbitrary if there is an excess of sell-orders. The same operation can be observed for the summer day in the scenario with time variable fees (c). However, in the winter scenario, several drastic peaks during the morning can be observed. Scenario (d), which additionally applies power fees, shows a flat backup residue for the feed-in during midday in the summer scenario and a constantly flat line with a lower value than observed in the other scenarios.

Figure 5 shows the exemplary results of the same scenario on an asset level. It is clearly observable that the demand peaks in scenarios (a)–(c) clearly originate from the scheduling of the flexible loads (EVs and HPs). While the demand from HPs and EVs and the operation of the storage are well distributed over the winter day in scenario (d) with power fees, several peaks can be observed in other scenarios, especially in the scenario with variable fees. On the summer day, the charging of storage is scheduled to 11:00–13:00, with the highest PV feed-in during the day in the scenario with power fees. This reduces the overall feed-in to a constant limit of around 100 kW during midday, while other scenarios reach peaks up to 140 kW.

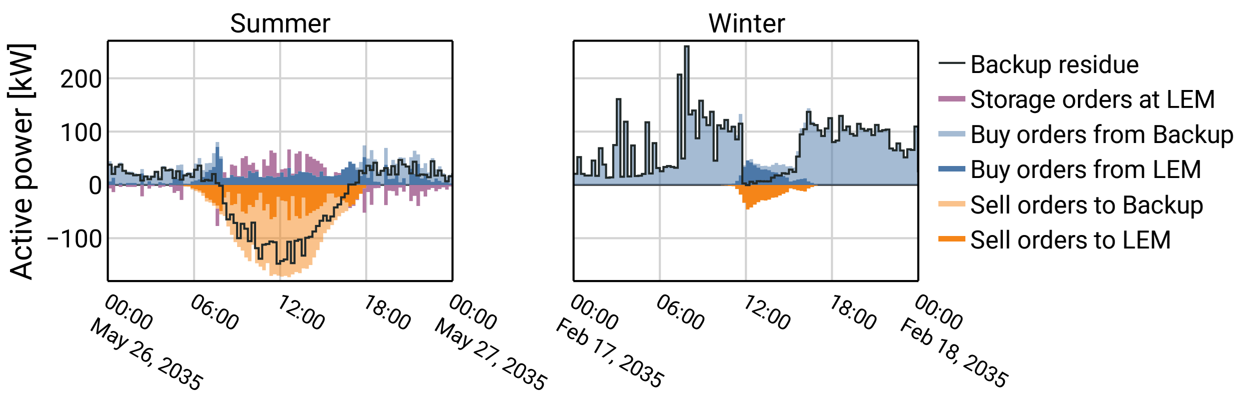



(**a**) Flat participant fees

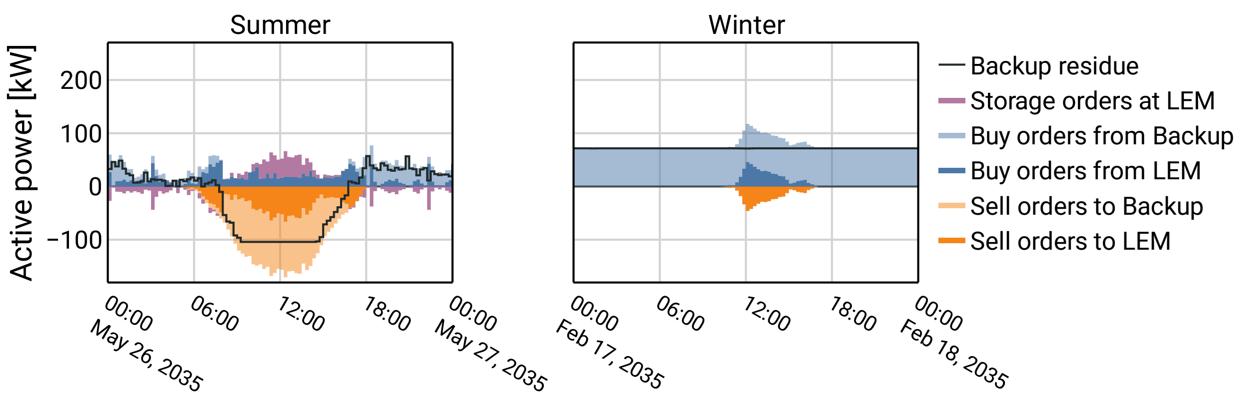



(**b**) Reduced feeder fees

**Figure 4.** *Cont.*




(**c**) Time variable fees

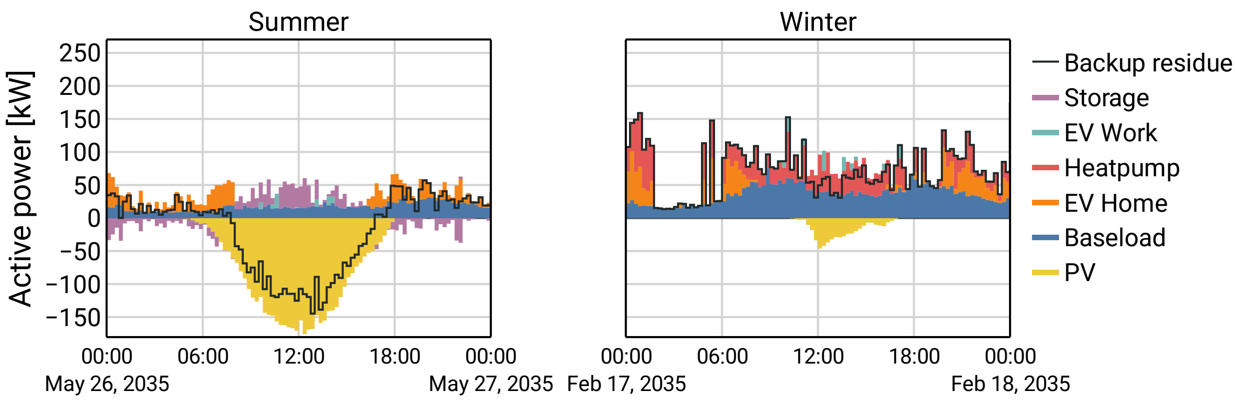



(**d**) Power fees

**Figure 4.** Market matching results of sample summer and winter days for a variation of grid tariff scenarios, the scenario year 2035 and the rural distribution grid.

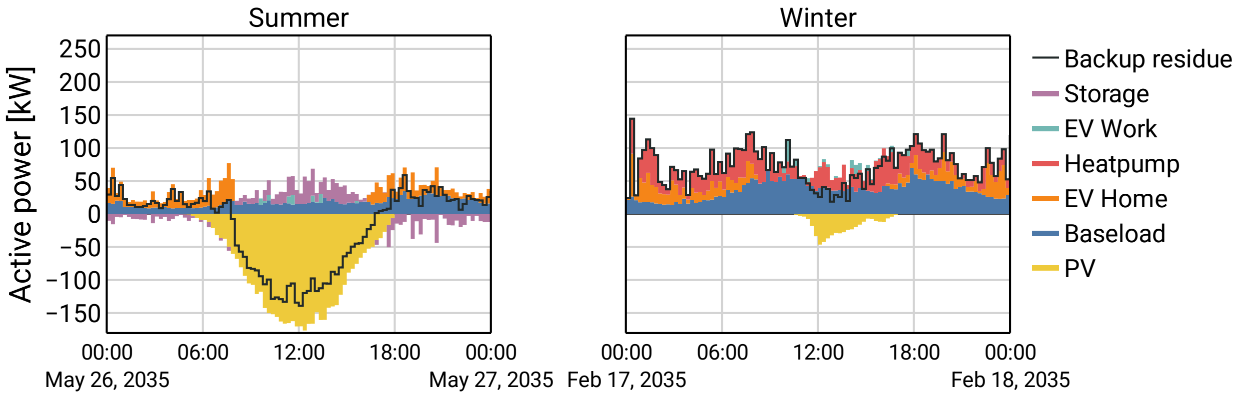
### 3.2. Comparison of Residual Load and Power Peaks

To analyze demand and feed-in patterns throughout the simulation years, scenarios of grid tariff designs are compared among each other and with the BAU scenario. Figures 6 and 7 show heatmaps of the residual load at the substation of the rural grid for the scenario year 2035. Positive values indicate an import from the upstream grid level. Negative values indicate an excess of feed-in and an export to the upstream grid level.

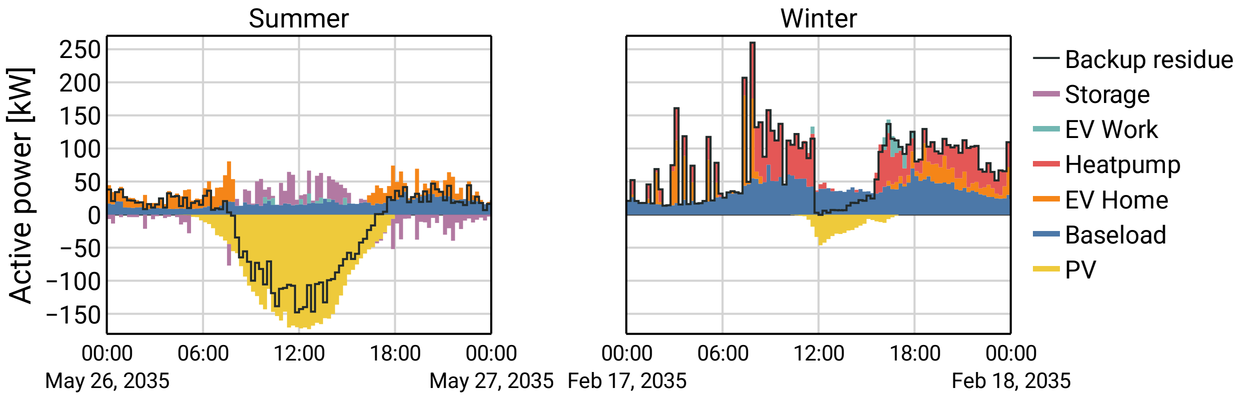



(**a**) Flat participant fees

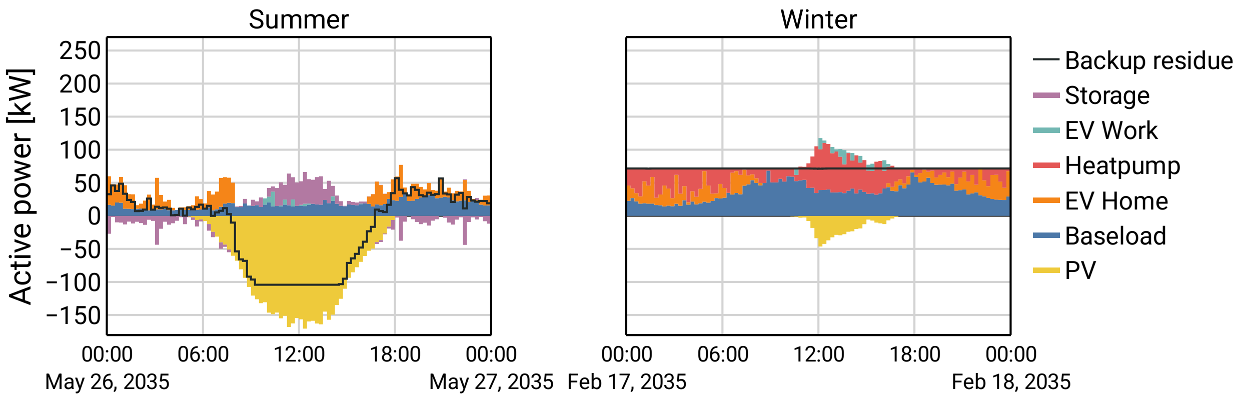
**Figure 5.** *Cont.*




(**b**) Reduced feeder fees




(**c**) Time variable fees




(**d**) Power fees

**Figure 5.** Market matching results on an asset level for sample summer and winter days and a variation of grid tariff scenarios, the scenario year 2035 and the rural distribution grid.

Figure 6 shows the operation of the energy system under the BAU scenario. Typical seasonal load patterns with increased electric demand during winter months and high feed-in during summer months can be observed. Daily patterns suggest that especially during early evening hours (16:00–19:00) on weekdays, increased overall demand over 200 kW can be observed due to EVs charging at home.

Applying an LEM scenario with time-variable fees (scenario (c)) results in the heatmap shown in Figure 7. While seasonal patterns of the residual load are comparable to the BAU case, the daily operation differs. Clear demand peaks resulting from EV charging in the evening are not observed. However, there are a few 15-min time intervals with increased demand, in the early morning hours or at specific timesteps in the evening. Heatmaps of the other scenarios can be found in Appendix C.

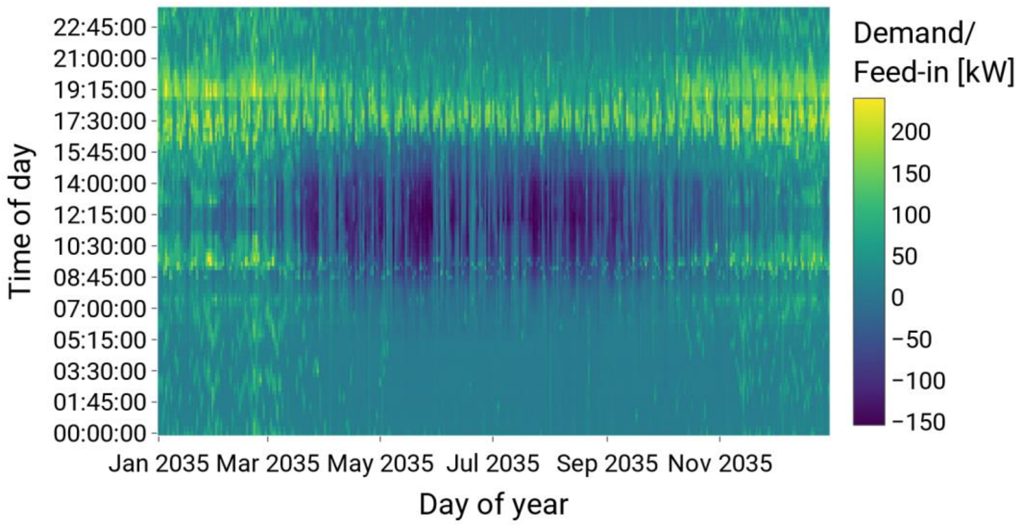



**Figure 6.** Heatmap of the electric demand (positive values) and feed-in (negative values) for the business-as-usual scenario, the scenario year 2035 and the rural grid.

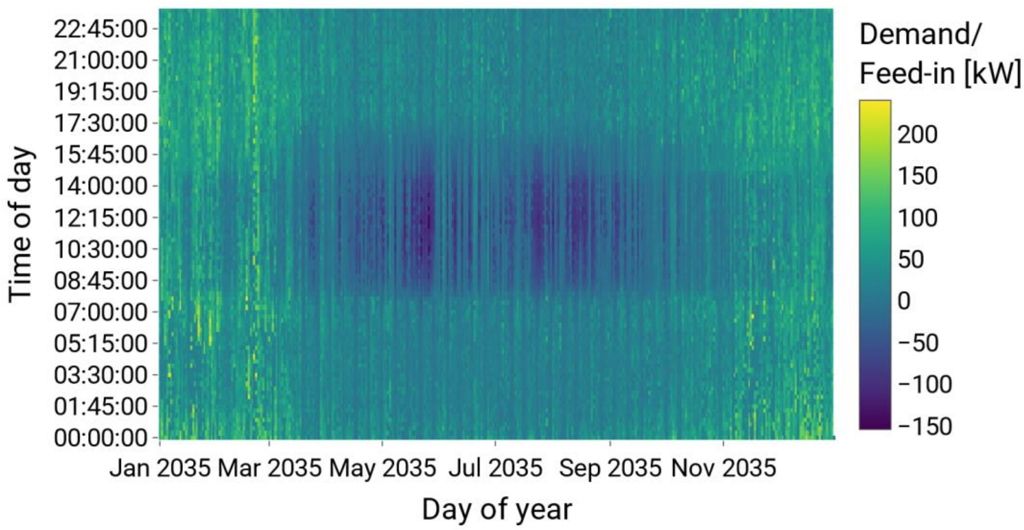



**Figure 7.** Heatmap of the electric demand (positive values) and feed-in (negative values) for the scenario with time variable fees, the scenario year 2035 and the rural grid.

The load duration curve of the same scenario (Figure 8) enables a more detailed comparison of the scenarios. From a first glance at the load duration curve of the full year (Figure 8a), a clear distinction between the BAU scenario and the LEM scenarios can be made. The BAU scenario shows a significant increase of timesteps with higher demand and feed-in compared to the LEM scenarios, while residues in the range of 0–50 kW are almost overlapping. A more detailed look at the highest feed-in and load peaks (Figure 8b,c) reveals a clearer picture. Although all LEM scenarios outperform the BAU scenario in terms of a reduction of the peak feed-in and demand, there are considerable differences within the different LEM grid tariff designs. For demand peaks (Figure 8c), all energy fee-based grid tariffs (scenarios (a)–(c)) have peak values above 200 kW, with the time-variable scenario closest to the BAU scenario, with the highest peak above 250 kW. The power fee scenario, however, allows reaching a peak demand as low as 100 kW. For the highest feed-in peaks, a similar pattern is reproduced. While the reduction achieved by the LEM scenarios with energy fees is generally higher compared to the demand peaks, the scenario applying power fees also reaches the lowest feed-in level.

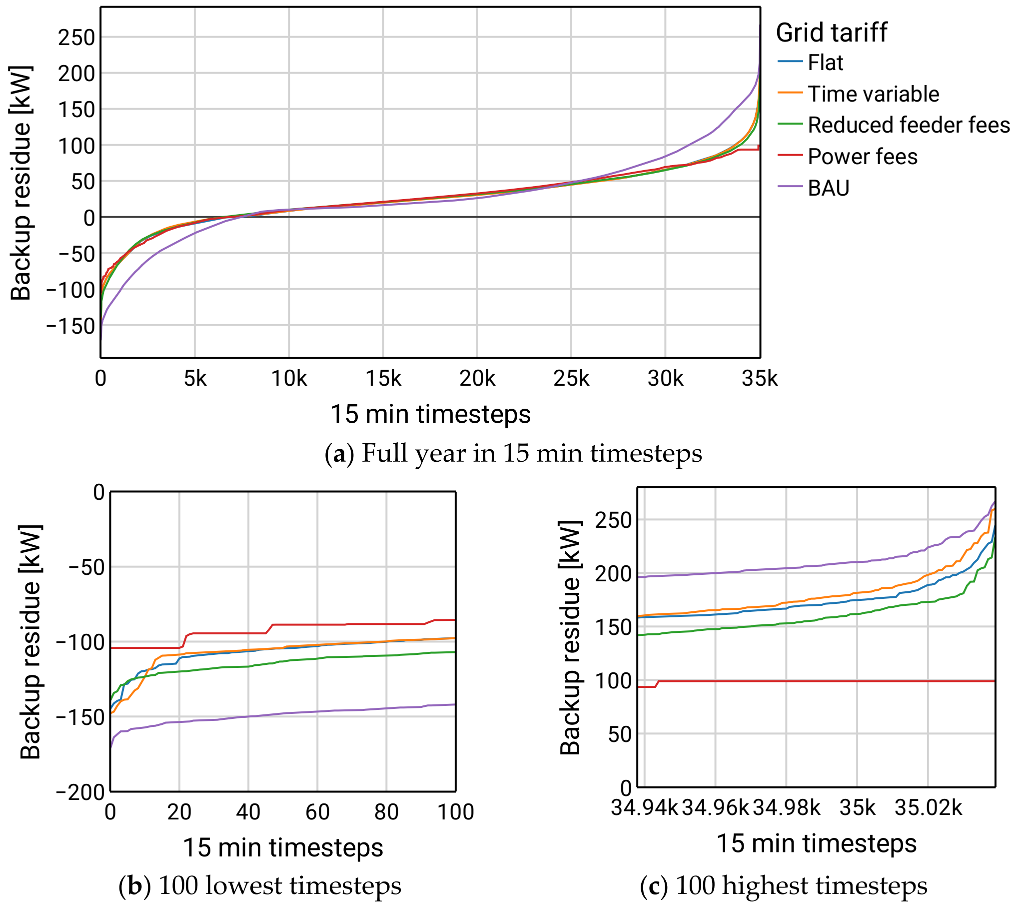



**Figure 8.** Load duration curves for a variation of grid tariff scenarios for a full simulation year (**a**), the 100 timesteps with lowest residual load (**b**) and the highest residual load (**c**). Data from scenario year 2035 and the rural distribution grid.

Figure 9 shows the relative peak deviations, comparing the LEM scenarios to the BAU scenario for demand and feed-in peaks. It shows the average deviation for the highest 5% of all scenario years ($x$-axis) and grid types (a)–(c). First observations from the load duration curve, i.e., that the highest reduction of demand and feed-in peaks is achieved in the power fee scenario, can be confirmed for all scenario years and grid types. Reductions for demand peaks in a range of 30–60% are achieved in the power fee scenario in the year 2035. The highest reduction of 60% is achieved in the rural grid case, with a high relative share of EVs charging at home. Reductions in the semiurban and urban case are around half of the reduction in the rural grid (30%). On the feed-in side, reductions range between 40 and 60%, with the highest reductions achieved in the urban and semiurban grids.

Energy-based fees achieve a consistently lower reduction, ranging from 8 to 22% for demand peaks in the scenario year 2035 and from 21 to 49% for feed-in peaks. Throughout the scenario years, a general trend of a reduction of power peaks can be observed. The power fee scenario already enables a significant reduction even for early scenario years (2020, 2025), while the energy fee–based scenarios might even show a relative increase of peaks for early scenario years, e.g., for the urban and semiurban grid.

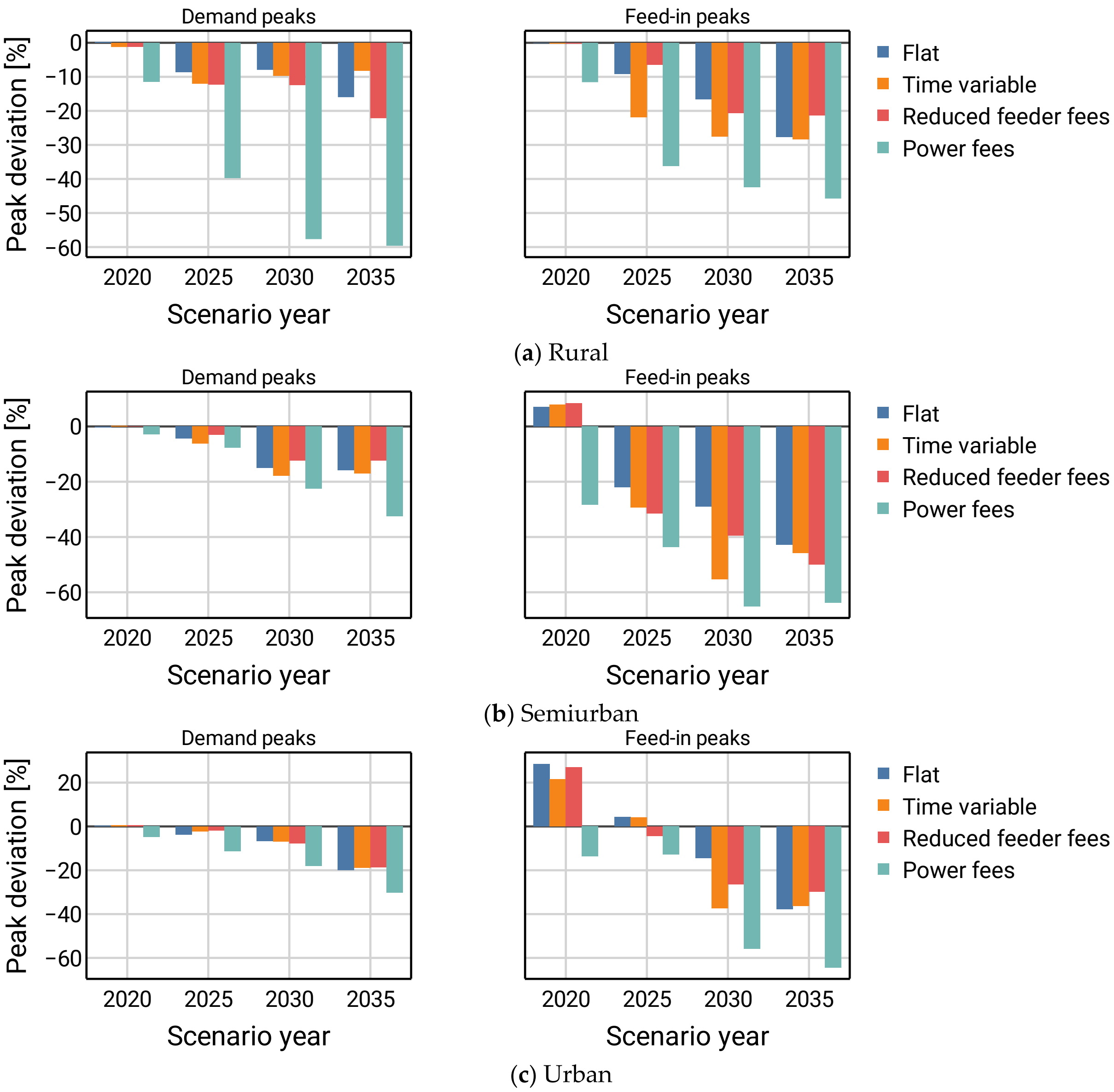
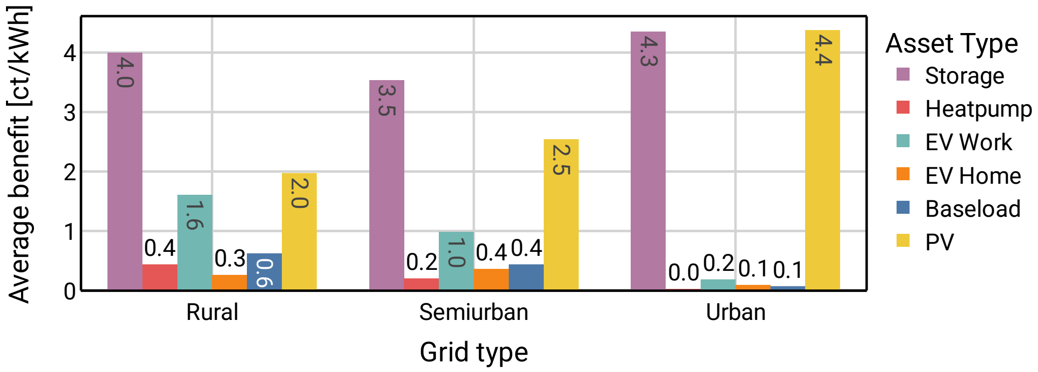



**Figure 9.** Relative deviation of demand and feed-in peaks for a variation of grid types (**a**–**c**) and scenario years and grid tariff designs. Deviation calculated using the 5% highest daily peaks of the business-as-usual scenario.

### *3.3. Evaluation of Financial Impacts*

Resulting LEM market prices, derived from the dual variables of the balance equations of market participants and nodes, enable an assessment of the benefit achieved for market participants and their respective assets.

Figure 10 shows a heatmap of the weighted average buy prices (gross prices) for the flat fee scenario 2035 in the rural grid. For times of excess local generation (midday in the summer months), prices are as low as 25 ct/kWh, while generation is sold at maximum prices (31 ct/kWh) during midday in winter months. Additionally, only summer days show market activity during night hours. During these days, excess PV generation is utilized to charge battery storage.



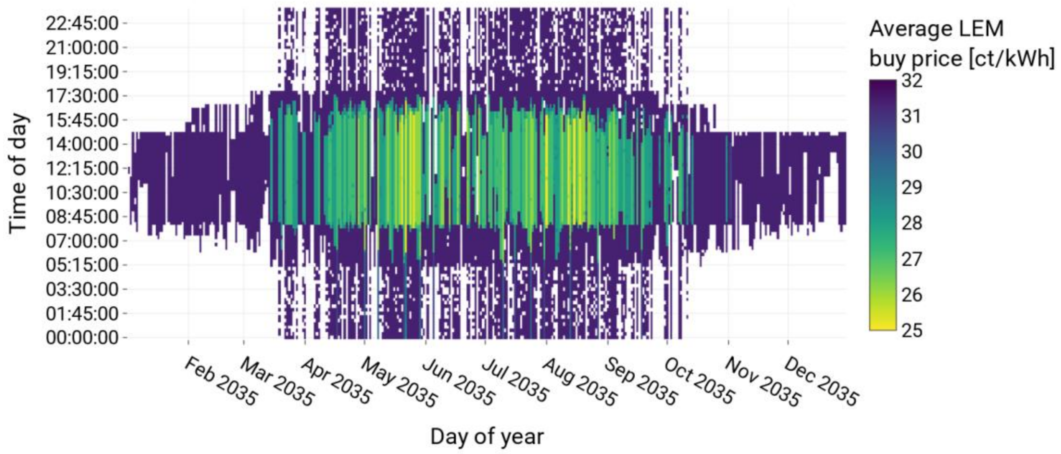




**Figure 10.** Heatmap of weighted average buy prices (gross) for scenario year 2035, the rural grid and the scenario with flat participant fees.

Since storage capacity and PV generation are limited, buy prices during night times converge to the maximum buy limit of demands in the system. During some days, there are no trades for several hours. In these cases, PV generation is completely self-consumed at participant sites.

Figure 11 condenses the average benefits of all asset types per grid type. Expectably, the highest benefit for generation is achieved in the urban scenario, where the ratio of installed PV capacity to demand is relatively low. Hence, generating assets as a scarce type set the price and reach the highest benefit (4.4 ct/kWh) compared to their opportunity costs. On the demand side, however, the relative benefit is comparably low (0–0.2 ct/kWh). In the rural and semiurban scenarios, the benefit of PV assets is reduced, while the benefit of demand assets is slightly increased. Higher benefits are reached for demand assets like EVs charging at work (1–1.6 ct/kWh), as their charging behavior correlates with excess PV generation during midday. An additional observation is that flexible demand assets like HPs and EVs charging at home have a lower benefit compared to simple baseload assets. Although these flexible assets might be utilized to reduce peak power, in this flat energy fee–based scenario, they are not monetarily incentivized accordingly.

Differences in calculated average asset benefit for a variety of grid tariff scenarios for scenario year 2035 and the semiurban grid are shown in Figure 12. Compared to the previously shown scenario with flat fees (scenario (a)), the energy-based tariff designs (time-variable scenario (b) and reduced feeder fee scenario (c)) reach a generally higher benefit for demand, generation and storage assets due to a reduction of REPCs. For the power fee scenario (d), demand assets contributing to high peaks (Baseload) have a lower benefit compared to flexible assets, which enable a reduction of peaks (EVs and HPs).

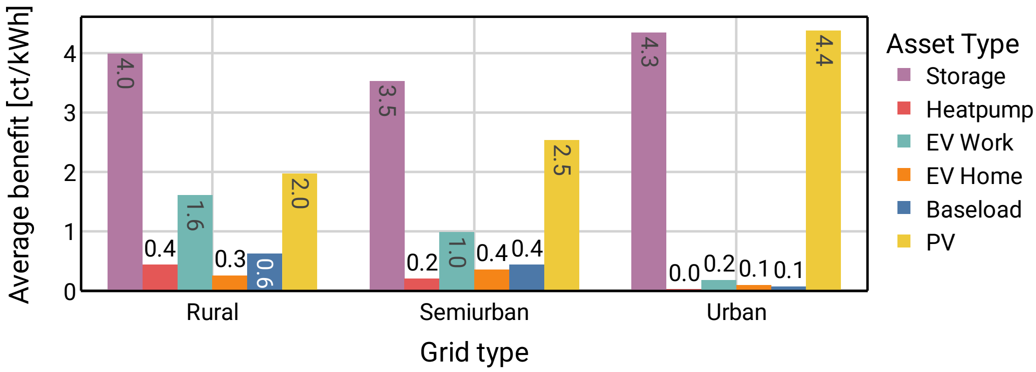



**Figure 11.** Average asset-specific benefit compared to business as usual for an LEM without a reduction of REPCs for a variety of grid types for the scenario year 2035.

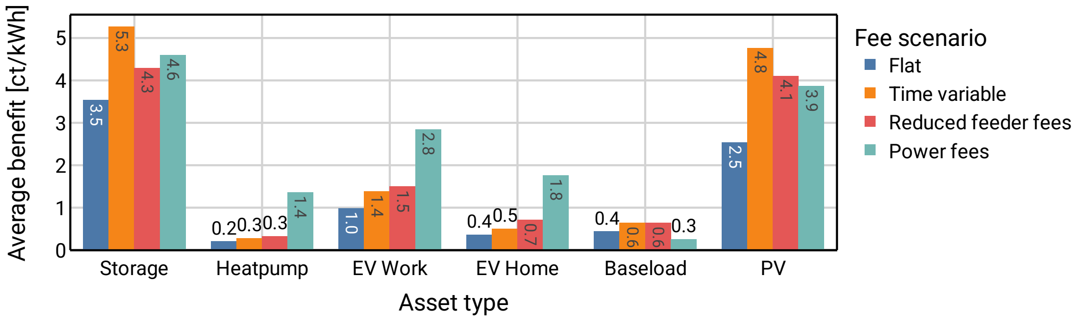



**Figure 12.** Average asset-specific benefit compared to the business-as-usual scenario for a variation of grid tariff designs/fee scenarios, the semiurban grid and the scenario year 2035.

The relative reduction of REPCs within scenarios (b)–(d) implies an overall reduction of collected REPCs. Figure 13 shows that this reduction is limited to below 5% compared to the collected fees in the BAU or the flat fee scenario (scenario (a)). More overall volume is traded at the LEM within rural and semiurban scenarios due to a higher share of local generation, resulting in an increased reduction of REPCs in these scenarios compared to the urban scenario. Overall, the highest reduction of REPCs is reached in the scenario with time-variable energy fees.

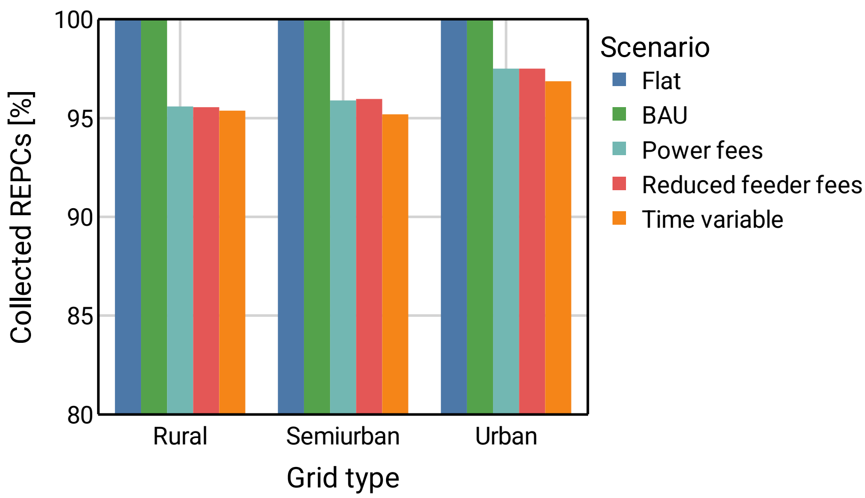



**Figure 13.** Comparison of collected regulated electricity price components for a variation of grid tariff scenarios for the scenario year 2035.

## 4. Discussion

The comparison of grid tariff designs for LEMs with regard to a reduction of demand and feed-in peaks showed that a major reduction in peaks is only achievable applying power fees at a virtual connection point to the upstream grid. With this approach, a reduction of 30–60% for demand peaks and 46–64% for feed-in peaks can be reached for a variety of grid types. These findings are consistent with conclusions drawn by Maldet et al. [23], who highlight the importance of power-based fees in the design of LEMs. Cramer et al. [20] draw similar conclusions, with an average reduction of 39% for an LEM scenario implementing power fees. The results additionally show that a power fee–based approach is able to reduce peaks in early scenario years 2020 and 2025, whereas other approaches show a considerable reduction only in the last scenario years (2030, 2035). It should be noted that an implementation of LEMs with power fees would require a more complex postprocessing and tracing of the contributions of each participant to the common power peaks as compared to a simple billing of consumed energy at the participant level. Time-variable fees based on wholesale market prices might, in early stages of implementation, i.e., as long as LEMs do not significantly influence wholesale market prices, lead to increased demand peaks compared to a solution with flat energy fees. This effect is mainly caused by flexible demand such as that of EVs, which simultaneously shift the charging process to a few hours of low wholesale market prices and are specifically profound in rural grids with a high share of EVs charging at home. Similar conclusions are drawn by Gemassmer et al. [37], who investigated the impact of EV charging under variable price scenarios.

The results on the reduction of power peaks must be interpreted as a theoretical maximum. Real applications might reduce the effects due to forecasting errors of demand and generation, which will lead to suboptimal solutions compared to the optimization results shown in this paper. Future research should hence address this issue, including an analysis of possible mitigation measures, such as short-term trading or aggregation of participant loads to increase forecast accuracy.

The analysis of market prices generated by the LEM shows that price signals are set in all scenarios, which might incentivize additional generation, demand and storage, depending on the grid type and the respective installed local generation. The urban grid, for instance, shows a significantly higher benefit for participants with local generation compared to the semiurban and rural grid with high installation rates of PV. Results of the asset-specific benefits show that renumeration for the usage of flexibility needs to be additionally incentivized in energy fee–based scenarios. Otherwise, participants might reduce their comfort level through a participation at an LEM (e.g., scheduling of charging processes for EVs in the night) without being specifically renumerated. In these cases, inflexible baseload demand achieves a similar or higher benefit compared to flexible demand from HPs and EVs. This might lead to a reduction of willingness to participate in an LEM. Postprocessing the market results in the power fee scenario to reduce REPCs for the usage of flexible assets incentivizes the reduction of peak power more adequately. An important aspect not covered in this paper is the coupling of LEMs with the wholesale market and cross LEM couplings, as analyzed, e.g., by Schmitt et al. in [38]. These aspects should be addressed in future research, especially regarding the coordination of grid services and peak power reduction.

Overall, regulators should consider the implementation of a power fee–based grid tariff design in combination with a regionally resolved reduction of energy fee components. This would not only lead to a large potential reduction of feed in peaks, but also incentivize the optimal usage of flexibilities (short-term). Additionally, the regionally resolved energy fee components might lead to clear investment signals for new generation in areas with high demand (long-term).

## 5. Conclusions

This paper addressed the issue of optimal grid tariff designs in LEMs to achieve a reduction of peak loads and feed-in and an adequate financial compensation of participants. To comprehensively evaluate a variation of tariff designs, we proposed a linear optimization-based market matching algorithm. The simulation of 60 yearly LEM scenarios varying grid types, scenario years and tariff designs showed that regulators should take careful consideration when designing tariffs for LEMs. Grid tariffs with a power fee have significantly higher potential for peak demand and feed-in reduction (30–64%) than energy fee–based tariffs (8–49%). The highest reduction potential is achieved in grids with a high share of EVs charging at home, i.e., rural distribution grids. In the power fee scenario, these flexible assets can be scheduled to times of low inflexible demand and hence reduce stress on the grid. Additionally, the evaluation of benefits on an asset level showed that the LEM approach might incentivize investments in generation and demand assets. Higher benefits for generating assets were, for instance, achieved in urban grids, with high demand incentivizing an expansion of this asset type. Comparing the benefit of demand assets, however, energy fee–based tariff designs were not suitable to incentivize the usage of flexible assets such as EVs and HPs. A postprocessing methodology was developed that values the usage of flexible assets to reduce peaks in the power fee–based scenario. With this approach, flexible assets are incentivized to be rescheduled and hence reduce peaks in the overall system. Across all scenarios, a reduction of regulated energy price components did not lead to a significant reduction (<5%) of collected fees, taxes and levies. Future research directions were identified, including the modeling of uncertainty in LEMs and the analysis of possible approaches to integrate LEMs within the overall energy system.

**Author Contributions:** Conceptualization, S.S. and S.T.; methodology, S.S.; software, R.S. and S.S.; validation, S.S. and R.S.; formal analysis, S.S.; investigation, S.S.; resources, R.S. and S.S.; data curation, S.S.; writing—original draft preparation, S.S.; writing—review and editing, R.S., S.T. and S.N.; visualization, S.S.; supervision, S.T. and S.N. All authors have read and agreed to the published version of the manuscript.

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**Conflicts of Interest:** The authors declare no conflict of interest.

## Appendix A

**Table A1.** Scenario assumptions for scenario year 2020, adapted from [2].

| Parameter | Type/Unit | Rural | Semiurban | Urban |
|---|---|---|---|---|
| Grid connection points | Count (-) | 96 | 110 | 58 |
| Residential loads | Count (-) | 92 | 92 | 102 |
| Commercial loads | Count (-) | 7 | 12 | 9 |
| Photovoltaic systems | Rated power (kW) | 185.7 | 202.7 | 93.8 |
| | Count (-) | 19 | 30 | 19 |
| Heat pumps | Rated power (kW) | 16.8 | 19.8 | 13.8 |
| | Count (-) | 5 | 5 | 3 |
| | share | 5.1 | 4.8 | 2.7 |
| Electric vehicles | Rated power (kW) | 22.0 | 29.2 | 0 |
| | Count (-) | 1 | 1 | 0 |
| Battery | Rated power (kW) | 20.7 | 55.0 | 11.3 |
| | Count (-) | 8 | 15 | 7 |
| | Capacity (kWh) | 41.4 | 110.1 | 22.6 |
| Electric load | Energy (MWh) | 257.9 | 470.3 | 530.9 |
| Thermal load | Energy (MWh) | 19.1 | 31.2 | 27.7 |
| Electric load EV | Energy (MWh) | 4.6 | 3.3 | 0.0 |

**Table A2.** Scenario assumptions for scenario year 2025, adapted from [2].

| Parameter | Type/Unit | Rural | Semiurban | Urban |
|---|---|---|---|---|
| Grid connection points | Count (-) | 96 | 110 | 58 |
| Residential loads | Count (-) | 92 | 92 | 102 |
| Commercial loads | Count (-) | 7 | 12 | 9 |
| Photovoltaic systems | Rated power (kW) | 236.0 | 284.8 | 139.6 |
| | Count (-) | 19 | 30 | 19 |
| Heat pumps | Rated power (kW) | 38.6 | 26.7 | 15.8 |
| | Count (-) | 6 | 7 | 4 |
| | share | 6.1 | 6.7 | 3.6 |
| Electric vehicles | Rated power (kW) | 80.4 | 91.3 | 82.3 |
| | Count (-) | 11 | 12 | 6 |
| Battery | Rated power (kW) | 46.5 | 123.9 | 25.4 |
| | Count (-) | 8 | 15 | 7 |
| | Capacity (kWh) | 93.2 | 247.8 | 50.8 |
| Electric load | Energy (MWh) | 257.9 | 470.3 | 530.9 |
| Thermal load | Energy (MWh) | 37.8 | 42.0 | 33.7 |
| Electric load EV | Energy (MWh) | 40.1 | 30.7 | 20.8 |

**Table A3.** Scenario assumptions for scenario year 2030, adapted from [2].

| Parameter | Type/Unit | Rural | Semiurban | Urban |
|---|---|---|---|---|
| Grid connection points | Count (-) | 96 | 110 | 58 |
| Residential loads | Count (-) | 92 | 92 | 102 |
| Commercial loads | Count (-) | 7 | 12 | 9 |
| Photovoltaic systems | Rated power (kW) | 286.4 | 366.8 | 185.4 |
| | Count (-) | 19 | 30 | 19 |
| Heat pumps | Rated power (kW) | 102.0 | 63.2 | 41.6 |
| | Count (-) | 13 | 15 | 8 |
| | share | 13.1 | 14.4 | 7.2 |
| Electric vehicles | Rated power (kW) | 157.1 | 175.2 | 122.4 |
| | Count (-) | 22 | 23 | 11 |
| Battery | Rated power (kW) | 72.3 | 192.7 | 39.5 |
| | Count (-) | 8 | 15 | 7 |
| | Capacity (kWh) | 144.9 | 385.4 | 79.1 |
| Electric load | Energy (MWh) | 257.9 | 470.3 | 530.9 |
| Thermal load | Energy (MWh) | 101.8 | 98.7 | 64.3 |
| Electric load EV | Energy (MWh) | 75.2 | 62.7 | 36.7 |

## Appendix B

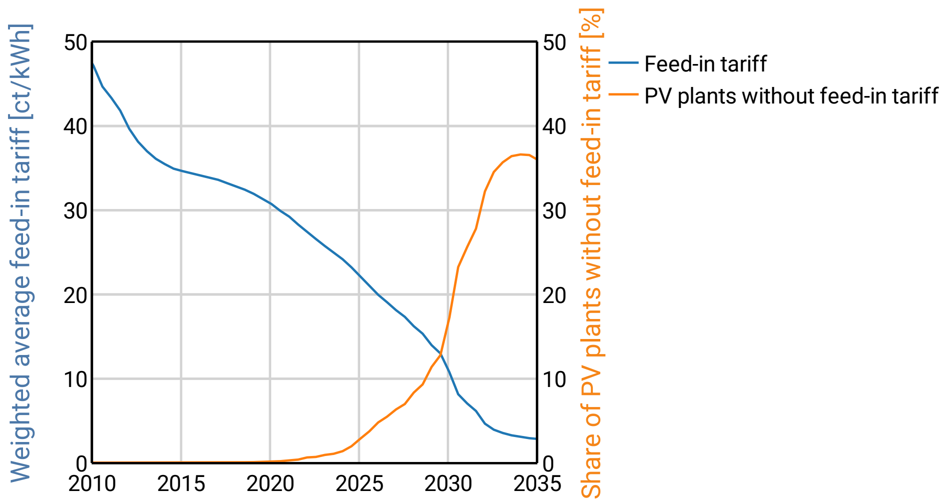


**Figure A1.** Development of weighted average feed-in tariffs for PV power plants and share of PV plants without feed-in tariffs in Germany. Data based on [33], extrapolated for years after 2021 using [25,39].

## Appendix C

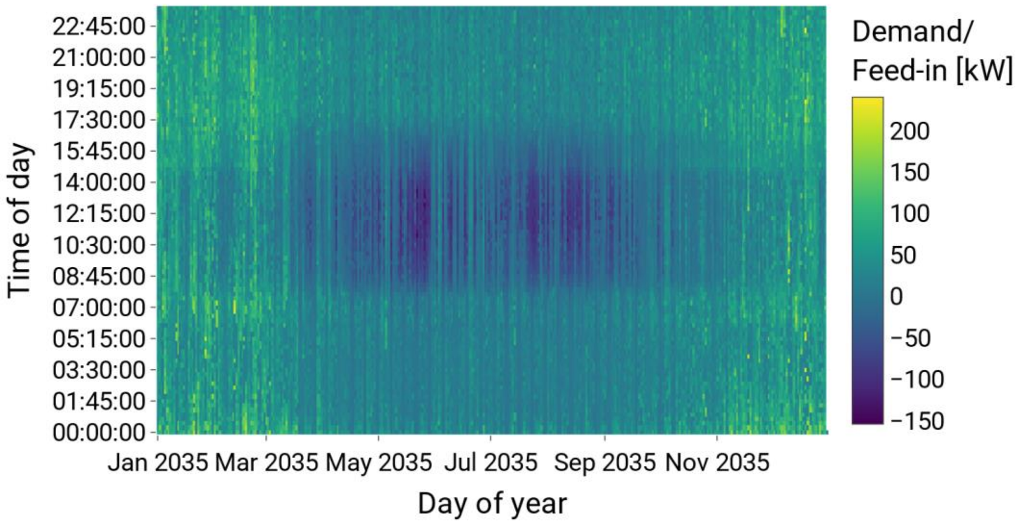


**Figure A2.** Heatmap of the electric demand (positive values) and feed-in (negative values) for the flat participant fee scenario, the scenario year 2035 and the rural grid.

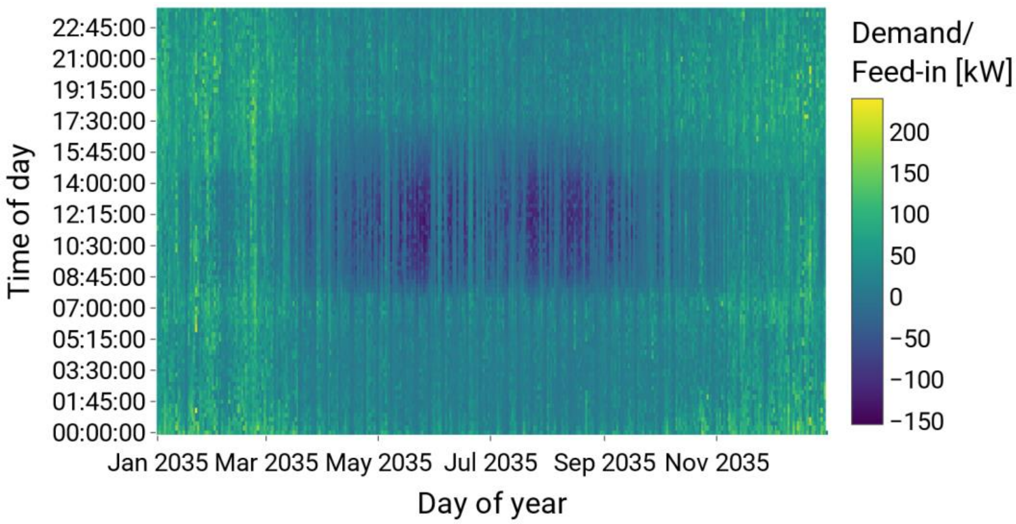


**Figure A3.** Heatmap of the electric demand (positive values) and feed-in (negative values) for the feeder fee scenario, the scenario year 2035 and the rural grid.

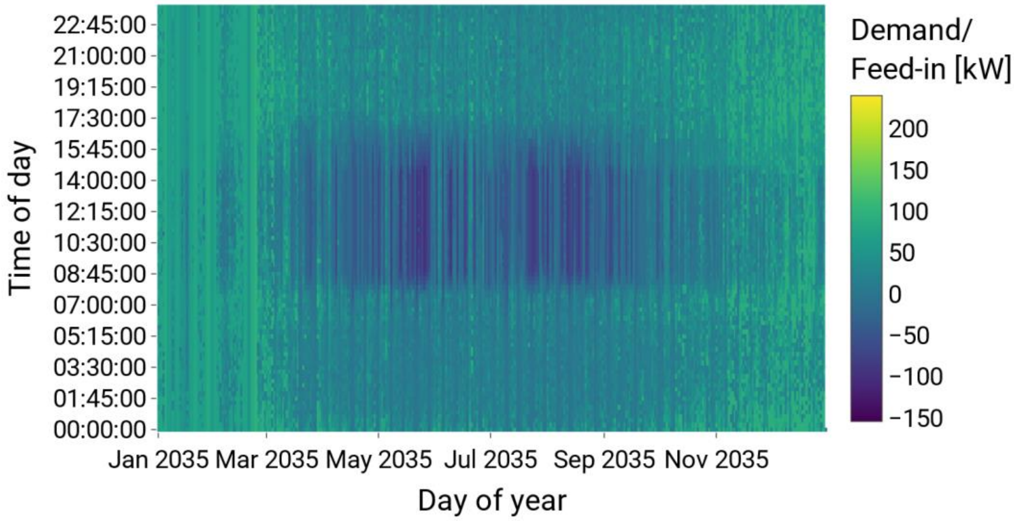


**Figure A4.** Heatmap of the electric demand (positive values) and feed-in (negative values) for the power fee scenario, the scenario year 2035 and the rural grid.

## References


1. Bundesnetzagentur. *Genehmigung Des Szenariorahmens 2023–2037/2045*; Bundesnetzagentur: Bonn, Germany, 2022.
2. Thormann, B.; Kienberger, T. Evaluation of Grid Capacities for Integrating Future E-Mobility and Heat Pumps into Low-Voltage Grids. *Energies* **2020**, *13*, 5083. [CrossRef]
3. Navigant Kompetenzzentrum Elektromobilität und RE-Xpertise. *Verteilnetzausbau für Die Energiewende–Elektromobilität im Fokus. Studie im Auftrag von Agora Verkehrswende, Agora Energiewende und The Regulatory Assistance Project (RAP)*; Agora Energiewende: Berlin, Germany, 2019.
4. Eid, C.; Koliou, E.; Valles, M.; Reneses, J.; Hakvoort, R. Time-Based Pricing and Electricity Demand Response: Existing Barriers and next Steps. *Util. Policy* **2016**, *40*, 15–25. [CrossRef]
5. BDEW Bundesverband der Energie-und Wasserwirtschaft e.V. *BDEW-Strompreisanalyse January 2020*; Haushalt und Industrie: Berlin, Germany, 2020.
6. Andruszkiewicz, J.; Lorenc, J.; Weychan, A. Demand Price Elasticity of Residential Electricity Consumers with Zonal Tariff Settlement Based on Their Load Profiles. *Energies* **2019**, *12*, 4317. [CrossRef]
7. Parag, Y.; Sovacool, B.K. Electricity Market Design for the Prosumer Era. *Nat. Energy* **2016**, *1*, 16032. [CrossRef]
8. Lezama, F.; Soares, J.; Hernandez-Leal, P.; Kaisers, M.; Pinto, T.; Almeida do Vale, Z.M. Local Energy Markets: Paving the Path Towards Fully Transactive Energy Systems. *IEEE Trans. Power Syst.* **2018**, *8950*, 4081–4088. [CrossRef]
9. Sorin, E.; Bobo, L.; Pinson, P. Consensus-Based Approach to Peer-to-Peer Electricity Markets with Product Differentiation. *IEEE Trans. Power Syst.* **2019**, *34*, 994–1004. [CrossRef]
10. Luo, F.; Dong, Z.Y.; Liang, G.; Murata, J.; Xu, Z. A Distributed Electricity Trading System in Active Distribution Networks Based on Multi-Agent Coalition and Blockchain. *IEEE Trans. Power Syst.* **2019**, *34*, 4097–4108. [CrossRef]
11. Morstyn, T.; McCulloch, M. Multi-Class Energy Management for Peer-to-Peer Energy Trading Driven by Prosumer Preferences. *IEEE Trans. Power Syst.* **2018**, *34*, 4005–4014. [CrossRef]
12. Liu, N.; Yu, X.; Wang, C.; Li, C.; Ma, L.; Lei, J. Energy-Sharing Model with Price-Based Demand Response for Microgrids of Peer-to-Peer Prosumers. *IEEE Trans. Power Syst.* **2017**, *32*, 3569–3583. [CrossRef]
13. El-Baz, W.; Tzscheutschler, P.; Wagner, U. Integration of Energy Markets in Microgrids: A Double-Sided Auction with Device-Oriented Bidding Strategies. *Appl. Energy* **2019**, *241*, 625–639. [CrossRef]
14. Abrishambaf, O.; Lezama, F.; Faria, P.; Vale, Z. Towards Transactive Energy Systems: An Analysis on Current Trends. *Energy Strategy Rev.* **2019**, *26*, 100418. [CrossRef]
15. Tushar, W.; Saha, T.K.; Yuen, C.; Smith, D.; Poor, H.V. Peer-to-Peer Trading in Electricity Networks: An Overview. *IEEE Trans. Smart Grid* **2020**, *3053*, 3185–3200. [CrossRef]
16. Freier, J.; Arnold, M.; Hesselbach, J. Introduction of an Approach to Develop Dynamic Electricity Prices for Residential Customers. In Proceedings of the 2019 16th International Conference on the European Energy Market (EEM), Ljubljana, Slovenia, 18–20 September 2019; pp. 1–6.
17. E-Control. *Federal Act Providing New Rules for the Organisation of the Electricity Sector (Electricity Act 2010—EIWOG 2010), BGB1.1 110/2012*; E-Control: Vienna, Austria, 2021.
18. Schreck, S.; Thiem, S.; Amthor, A.; Metzger, M.; Stefan, N. Analyzing Potential Schemes for Regulated Electricity Price Components in Local Energy Markets. In Proceedings of the International Conference on the European Energy Market, EEM, Stockholm, Sweden, 16–18 September 2020.

19. Bjarghov, S.; Farahmand, H.; Doorman, G. Capacity Subscription Grid Tariff Efficiency and the Impact of Uncertainty on the Subscribed Level. *Energy Policy* **2022**, *165*, 112972. [CrossRef]
20. Cramer, W.; Schumann, K.; Andres, M.; Vertgewall, C.; Monti, A.; Schreck, S.; Metzger, M.; Jessenberger, S.; Klaus, J.; Brunner, C.; et al. A Simulative Framework for a Multi-Regional Assessment of Local Energy Markets—A Case of Large-Scale Electric Vehicle Deployment in Germany. *Appl. Energy* **2021**, *299*, 117249. [CrossRef]
21. Wesseh, P., Jr.; Chen, J.; Lin, B. Peak-Valley Tariffs and Solar Prosumers: Why Renewable Energy Policies Should Target Local Electricity Markets. *SSRN Electron. J.* **2022**, *165*, 112984. [CrossRef]
22. Li, K.; Cursio, J.D.; Jiang, M.; Liang, X. The Significance of Calendar Effects in the Electricity Market. *Appl. Energy* **2019**, *235*, 487–494. [CrossRef]
23. Maldet, M.; Revheim, F.H.; Schwabeneder, D.; Lettner, G.; del Granado, P.C.; Saif, A.; Löschenbrand, M.; Khadem, S. Trends in Local Electricity Market Design: Regulatory Barriers and the Role of Grid Tariffs. *J. Clean. Prod.* **2022**, *358*, 131805. [CrossRef]
24. Meinecke, S.; Sarajlić, D.; Drauz, S.R.; Klettke, A.; Lauven, L.P.; Rehtanz, C.; Moser, A.; Braun, M. SimBench-A Benchmark Dataset of Electric Power Systems to Compare Innovative Solutions Based on Power Flow Analysis. *Energies* **2020**, *13*, 3290. [CrossRef]
25. Bundesnetzagentur. *Genehmigung Des Szenariorahmens 2021–2035*; Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen: Bonn, Germany, 2020.
26. Fourer, R.; Gay, D.M.; Kernighan, B.W. AMPL: A Mathematical Programing Language. In *Algorithms and Model Formulations in Mathematical Programming*; AT&T Bell Laboratories: Murray Hill, NJ, USA, 1989; pp. 150–151. [CrossRef]
27. Bestuzheva, K.; Besançon, M.; Chen, W.-K.; Chmiela, A.; Donkiewicz, T.; van Doornmalen, J.; Eifler, L.; Gaul, O.; Gamrath, G.; Gleixner, A.; et al. The SCIP Optimization Suite 8.0. *arXiv* **2021**, arXiv:2112.08872.
28. Maher, S.; Miltenberger, M.; Pedroso, J.P.; Rehfeldt, D.; Schwarz, R.; Serrano, F. PySCIPOpt: Mathematical Programming in Python with the SCIP Optimization Suite. In *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*; Springer: Berlin/Heidelberg, Germany, 2016; Volume 9725, pp. 301–307. [CrossRef]
29. Nobis, C.; Kuhnimhof, T. *Mobilität in Deutschland MiD Ergebnisbericht*; Studie von Infas, DLR, IVT und Infas 360 im Auftrag des Bundesministers für Verkehr und Digitale Infrastruktur (FE-Nr. 70.904/15); Bundesministers für Verkehr und Digitale Infrastruktur: Bonn, Germany, 2018; p. 135.
30. Infas; DLR; IVT; Infas 360. *Mobilität in Tabellen (MiT 2017)*; Dataset; Bndesministers für Verkehr und Digitale Infrastruktur: Bonn, Germany, 2017.
31. Schmidt, A. Flottenbetrieb von Elektrischen und Autonomen Serviceagenten im Städtischen Personennahverkehr. Ph.D. Thesis, Karlsruher Institut für Technologie, Karlsruhe, Germany, 2017.
32. Bundesnetzagentur. Archivierte EEG Vergütungssätze und Datenmeldungen. Available online: https://www.bundesnetzagentur.de/DE/Fachthemen/ElektrizitaetundGas/ErneuerbareEnergien/ZahlenDatenInformationen/EEG_Registerdaten/ArchivDatenMeldgn/artikel.html (accessed on 9 May 2022).
33. Übertragungsnetzbetreiber (DE) EEG-Anlagenstammdaten. Available online: https://www.netztransparenz.de/EEG/Anlagenstammdaten (accessed on 4 March 2022).
34. Schreck, S.; Thiem, S.; Amthor, A.; Metzger, M.; Niessen, S. Activating Current and Future Flexibility Potential in the Distribution Grid through Local Energy Markets. In Proceedings of the CIRED 2020 Berlin Workshop (CIRED 2020), Online, 22–23 September 2020; IET: London, UK, 2020. [CrossRef]
35. Bertsch, V.; Geldermann, J.; Lühn, T. What Drives the Profitability of Household PV Investments, Self-Consumption and Self-Sufficiency? *Appl. Energy* **2017**, *204*, 1–15. [CrossRef]
36. Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen; Bundeskartellamt. *Monitoringbericht 2021*; Monitoringbericht Gemäß § 63 Abs. 3 i.V.m. § 35 EnWG Und § 48 Abs. 3 i.V.m. § 53 Abs. 3 GWB; Bundesnetzagentur: Bonn, Germany, 2022.
37. Gemassmer, J.; Daam, C.; Reibsch, R. Challenges in Grid Integration of Electric Vehicles in Urban and Rural Areas. *World Electr. Veh. J.* **2021**, *12*, 206. [CrossRef]
38. Schmitt, C.; Samaan, K.; Schwaeppe, H.; Moser, A. Bottom-up Modeling of Local Energy Markets within a Pan-European Wholesale Electricity Market Model. In Proceedings of the 2020 6th IEEE International Energy Conference (ENERGYCon), Gammarth, Tunisia, 28 September–1 October 2020; pp. 631–636. [CrossRef]
39. Bundesminiterium der Justiz Gesetz für den Ausbau Erneuerbarer Energien. (Erneuerbare-Energien-Gesetz—EEG 2021)\S 49 Absenkung der Anzulegenden Werte für Strom aus Solarer Strahlungsenergie. In *EEG-Erneuerbare-Energien-Gesetz Kommentar*; Erich Schmidt Verlag: Berlin, Germany, 2018.