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Coordination Mechanism for PV Battery Systems with Local Optimizing Energy Management

Manuel Kersic ^{1,*} , Thilo Bocklisch ^{2,*}, Michael Böttiger ² and Lisa Gerlach ²¹ Belectric GmbH, Industriestraße 65, D-01129 Dresden, Germany² Chair of Energy Storage Systems, Institute of Power Engineering, Technische Universität Dresden, Helmholtzstraße 9, D-01062 Dresden, Germany; michael.boettiger@tu-dresden.de (M.B.); lisa.gerlach@tu-dresden.de (L.G.)

* Correspondence: manuel.kersic@belectric.com (M.K.); thilo.bocklisch@tu-dresden.de (T.B.); Tel.: +49-351-811296-1018 (M.K.); +49-351-46340270 (T.B.)

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Abstract: This publication presents a coordination mechanism for neighboring photovoltaic (PV) battery systems with local optimizing energy management (EM). The aim of this coordination is a high degree of self-sufficiency for the neighborhood while maintaining a high individual degree of self-sufficiency and relieving the grid. A financial incentive to increase the energy exchanged within the neighborhood is introduced. The local EM of the individual PV battery system uses model predictive control based on deterministic dynamic programming in order to minimize the individual economic costs and extreme grid power values. By using a coordination algorithm involving a central information processing unit, the neighboring PV battery systems are given information about the sum of the planned consumption and feed-in power profiles of the neighborhood, as well as the neighborhood tariffs. Based on these data, the PV battery systems successively optimize the operation of their batteries until either convergence or a maximum count of iterations is achieved. The operating principle of the distributed EM concept with coordination is demonstrated through a simulation of a residential neighborhood comprising eight households with different load profiles and varying PV peak powers and battery capacities. Its performance is compared with three EM concepts: two distributed concepts without coordination and another one with central optimizing EM representing ideal coordination. The resulting power flow distributions are analyzed, and the benefits and weaknesses of the developed coordination mechanism are discussed based on a number of evaluation criteria.

Keywords: distributed control; coordination; local trade; microgrid; energy management; lithium-ion battery; photovoltaic; optimization; model predictive control; dynamic programming

1. Introduction

The increasing number of generation units relying on intermittent renewable energy sources has led to a constantly growing temporal mismatch between production and consumption. Hence, innovative energy storage solutions (e.g., hybrid and decentralized energy storage systems [1–6]) are crucial to ensure the stability of the grid by balancing demand and supply. Decentralized residential storage, in particular battery storage, in private households, has the potential to increase the overall storage capacity significantly in the nearby future [7] and to thereby provide valuable flexibility for fluctuating renewable power plants, ideally in close proximity to the storage and loads. The number of households equipped with photovoltaic (PV) generators and battery storage has significantly risen in the past decade and is expected to increase further [8]. Until present, the energy management (EM) of such residential PV battery systems (see Figure 1a) has mainly focused on maximizing individual

self-consumption, which is related to the maximization of economic profit. Depending on their implementation, these PV battery systems with self-serving EM could lead to problematic grid states, (e.g., by simultaneously injecting power to the distribution grid in the middle of the day [7]). This could lead to a need for further grid expansion or limit the amount of feasible PV plants in the affected distribution grid segments.

Efforts have been made to develop EM for decentralized PV battery systems that reduce their negative impact on the grid [9–12]. However, many of these solutions focus on the control of individual PV battery systems (e.g., realizing individual peak shaving). This approach, however, is limited because it does not consider the other PV battery systems in the vicinity. By using control strategies that take into account a whole group of neighbored PV battery systems connected to one common grid connection point (see Figure 1b), it becomes possible to pursue this superordinate goal much more effectively [13,14]. Moreover, the total decentralized storage capacity could be used much more efficiently in this case, such as by making the unused storage capacity of an individual PV battery system available to the neighborhood. As the household inhabitants are generally the owners of the residential PV battery systems, it is desirable to maintain the local EM of the individual PV battery systems so that the owners maintain control of their equipment. In order to pursue superordinate goals, a coordination mechanism involving the local EM within a superordinate EM structure (see Figure 1b) is thus needed.

Figure 1. (a) Topology of a single PV battery system; (b) topology of a neighborhood of N PV battery systems (PV: photovoltaic, EM: energy management).

In this publication, a novel coordination mechanism for a group of neighbored PV battery systems is presented and investigated. Such aggregated PV battery systems form a special type of hybrid energy storage system. The coordination mechanism aims at a high degree of self-sufficiency of the neighborhood while retaining maximum individual degrees of self-sufficiency. Furthermore, it reduces stress on the grid that would otherwise be caused by peaks in the feed-in and consumption power. The desired individual operation is induced by means of a financial incentive for energy exchanged within the neighborhood. The coordination mechanism thereby enables individual households to trade their PV energy with each other under subsidized conditions. The results of simulation-based investigations show that the elaborated coordination mechanism reaches the highest degree of self-sufficiency for the neighborhood among the considered distributed EM concepts and thereby reaches its main target. In total, it can be shown that operating several PV battery systems together has a high potential to be beneficial for the local use of renewable energy and grid stress reduction compared to similar independent individual operations.

This paper is organized as follows: Section 2 gives an overview on the state of the art of EM for single PV battery systems, as well as the techniques for their coordination, and puts the elaborated coordination mechanism into the context of recent research. In Section 3, the model of a single PV

battery system and a neighborhood comprising several such systems are described, including their implementation in MATLAB. The working principle of the coordination mechanism is explained in Section 4. The financial incentive to increase the energy exchanged within the neighborhood is introduced, and the coordination algorithm, as well as the underlying local EM, are described. Section 5 presents the results of simulation-based investigations for an exemplary neighborhood. The proposed developed distributed EM concept with coordination is compared to two distributed EM concepts without coordination and a central EM concept representing ideal coordination. Finally, in Section 6, a summary and future outlooks are given.

2. State of the Art

2.1. Energy Management for Single PV Battery Systems

The primary aim of most EM concepts for decentralized PV battery systems is the maximization of self-sufficiency, which is related to electricity cost minimization. Further objectives can include the minimization of curtailment losses, grid feed-in power limitations, and increasing battery lifetime [9–11].

EM concepts can be categorized into rule-based and optimization-based strategies [1]. Rule-based EM concepts use rules with varying degree of sophistication to control battery storage; these concepts can be derived from expert knowledge or adaptive tuning. EM concepts that belong to this category are, for example, priority-based EM for self-sufficiency maximization [12,15], delayed charging concepts [15,16], concepts based on a fixed feed-in limitation [9], or concepts based on fuzzy logic [17,18]. Optimization-based EM concepts have the advantage that they allow diverse and complex criteria to be pursued directly. For online applications, model predictive control is mainly used. Here, forecasts to determine an optimal schedule for battery power are needed. To solve the optimization problem, several methods are utilized, such as linear programming [9,10,19,20], quadratic programming [21], deterministic dynamic programming [11,22–24], and stochastic dynamic programming [25].

In this paper, the local EM controlling a single PV battery system uses model predictive control based on a deterministic dynamic programming approach [11]. In this way, the non-linear objective function, which is necessary for the coordination mechanism, can be realized and calculated in a reasonable time. The local EM is described in detail in Section 4.2.

2.2. Coordination Mechanisms for PV Battery Systems

In order to operate PV battery systems collaboratively to achieve superordinate goals, a mechanism for the coordination of the local EM is needed. In general, the coordination of several decentralized energy systems with flexible loads and/or flexible generation can pursue grid-oriented or balanced (financial) objectives [26].

A superordinate EM structure describes how single EM units are organized and how they communicate and thereby defines their relation to each other [26]. The following superordinate EM structures can be distinguished (Figure 2) [13,26]:

- Centralized [27,28]
- Decentralized fully-dependent [28–30]
- Decentralized partially-independent [31,32]
- Decentralized fully-independent [33].

In a centralized structure, there exists a central information processing unit, which is the aggregator. By communicating with the local EM of the subordinate energy systems, the aggregator obtains the information needed to determine all set points, which are subsequently passed to the corresponding converters via the local (passive) EM. In a decentralized fully-dependent structure, the communication architecture is the same, but the decentralized energy systems determine the set points autonomously by their local EM. The aggregator enables the exchange of information between the subordinate decentralized energy systems and can induce the desired operation by giving

incentives, such as via time-variable price signals. A decentralized partially-independent structure features extended communication between the decentralized autonomous energy systems, while a decentralized fully-independent structure does not include an aggregator; further, decentralized autonomous energy systems coordinate via peer-to-peer communication. Especially for the latter structure, blockchain technology is receiving considerable attention [34].

Figure 2. Superordinate energy management (EM) structures: (a) centralized; (b) decentralized fully-dependent; (c) decentralized partially-independent; (d) decentralized fully-independent (adapted from [13]).

In the following section, some exemplary coordination mechanisms from the literature are presented. These methods apply the superordinate EM structures described above to decentralized energy systems comprising PV generation and battery storage or a flexible load. The examples exclusively considering a flexible load can generally be applied to PV battery systems as well because time-shiftable appliances can be interpreted as a special type of unidirectional energy storage. However, some adaptations concerning reverse power flow would need to be implemented in these cases.

In [27], a coordination mechanism based on a centralized EM structure is used. Mainly, PV battery systems are controlled by independent optimizing local controllers. The central controller monitors the state of the grid and only becomes active in a case of over-voltage issues, where it determines centrally optimized set points. If the adjustment of the battery's active power does not suffice to prevent over-voltage, the central controller additionally sets the reactive power of the PV inverters and the battery inverters.

An example of a decentralized fully-dependent EM structure is given in [28] and is compared to a centralized control. The considered decentralized energy systems include PV generators, battery storage systems, and flexible loads. By using an introduced incentive, the local exchange of energy between decentralized energy systems is financially favorable as decentralized energy systems feeding neighboring systems obtain a higher feed-in tariff for their exchanged energy. An aggregator forwards the predicted accumulated feed-in and consumption power profiles and further power values to the local EM of the decentralized energy systems. These systems minimize their costs and communicate their optimized power profiles back to the aggregator. This process is repeated until a maximum number

of iterations is reached. In comparison with a self-optimizing local EM, the distributed coordination mechanism results in less energy being consumed from the superordinate grid and a lower overall cost. With a central controller minimizing the total cost for the group of decentralized energy systems, the performance is further improved, but with the sacrifice of lacking an autonomous local EM. In [29], another coordination mechanism based on a decentralized fully-dependent EM structure is presented. These decentralized energy systems, comprising PV generation, battery storage and flexible load, collaborate to achieve minimal costs. They communicate their expected consumption power profiles to the aggregator, which in turn calculates an optimal data vector similar to a time-variable price signal. Based on this data vector, the decentralized energy systems optimize again for minimal cost, and this process is repeated until convergence is reached. A similar coordination mechanism is introduced in [30]. In this concept, a certain benefit is assigned to each flexible appliance. The aggregator purchases electricity on the wholesale market and determines real-time prices. Each local EM optimizes the total operation benefit of the flexible appliances in compromise with minimal energy cost. Based on the total demands' forecast, the aggregator updates the real-time price vector and the iterative process continues until convergence is achieved.

In [31], a distributed control strategy based on a decentralized partially-independent EM structure is presented. This strategy aims at minimizing the peak-to-average ratio of the aggregated demand profile of households with shiftable loads. For this purpose, the aggregator determines price signals and sends them to the households, which then optimize their operation. The households communicate their decisions to each other and determine the aggregated demand profile. This information is transmitted to the aggregator, which updates the price signals. This process is repeated iteratively until convergence is achieved. A similar approach is suggested in [32]. Here, the aggregator sends the price signal (which is proportional to the square of the aggregated demand profile) only once to the households. These households then initiate their economic optimization and broadcast their updated demand profiles to all the other households. When no household broadcasts updates anymore, it is assumed that convergence is achieved. The authors demonstrate analytically that by means of the quadratic cost function, the distributed optimization process always converges to a stable state; this state offers the global cost optimal solution for the whole neighborhood, as well as for all individual systems. Moreover, the peak-to-average ratio of the aggregated demand profile can be diminished substantially with this distributed control.

An example of a decentralized fully-independent EM structure is given in [33]. The objective is the coordinated control of the flexible appliances of households so that the energy costs are minimized and the aggregated demand profile is smoothed. Two distributed control strategies are presented: synchronous agreement-based and asynchronous gossip-based strategies. In both strategies, the households communicate with their geographically closest neighbors in order to determine the aggregated demand profile. Based on that information, the households optimize the schedule of their flexible appliances and pass the result to their neighbors.

The distributed control strategies described above could all be modeled as multi-agent systems, although only one publication [28] explicitly mentions this possibility. Moreover, game theory is often used for the design of the overall system's rules and the individual strategies implemented in the local EM [31–33]. Also, many publications induce the desired coordination by introducing local, partly time-variable, electricity tariffs [29–31,33]. Overviews on multi-agent systems and game theory applied to the electricity sector, as well as a review of local electricity markets, can be found in [35–37].

The coordination mechanism described and investigated in this publication is based on a decentralized fully-dependent EM structure similar to [28–30]. This structure was chosen because it requires the least amount of communication and thereby best maintains the privacy of individual energy systems (as long as the aggregator is trustworthy). The financial incentive for inducing the desired behavior of a PV battery system focuses on local trade similar to [28], where the costs for locally exchanged energy are reduced. Nevertheless, this price structure goes further as independent neighborhood tariffs for consumption and feed-in are introduced, which could even be time-variable.

The characteristic map was developed using an equivalent circuit model from [38]. The specifications of the modeled battery are given in Table 1. The battery inverter was modeled using a normalized efficiency curve scaled to the nominal power of the battery (5 kW) (Figure 5).

Table 1. Specifications of the modeled battery.

Technology	Nominal Capacity	Nominal Voltage	Nominal Power
Lithium nickel manganese cobalt	106 Ah	48 V	5 kW

Figure 5. Efficiency curve of the battery inverter.

3.2. Model of the Neighborhood of Coupled PV Battery Systems

The topology of a neighborhood of N coupled PV battery systems is presented in Figure 6.

Figure 6. Topology of the neighborhood model of PV battery systems.

All PV battery systems are intended to be in close vicinity and connected to a common low voltage network segment. They individually exchange power $P_{gr,n}$ with the grid. This power, which the whole neighborhood exchanges with the superordinate grid, is $P_{gr,nh}$. Network losses are neglected due to the immediate vicinity of the PV battery systems. A decentralized fully-dependent EM structure is modeled. The PV battery systems can exchange information with the aggregator. The relevant power flow definitions for the description of the neighborhood, as well as the overall EM concept, are listed in Table 2.

$$P_{f,n}(t) = \begin{cases} P_{gr,n}(t), & P_{gr,n}(t) > 0 \\ 0, & P_{gr,n}(t) \leq 0 \end{cases} \quad (2)$$

$$P_{c,n}(t) = \begin{cases} |P_{gr,n}(t)|, & P_{gr,n}(t) < 0 \\ 0, & P_{gr,n}(t) \geq 0 \end{cases} \quad (3)$$

$$P_{sf}(t) = \sum_{n=1}^N P_{f,n}(t) \quad (4)$$

$$P_{sc}(t) = \sum_{n=1}^N P_{c,n}(t) \quad (5)$$

$$P_{grnh}(t) = \sum_{n=1}^N P_{gr,n}(t) = P_{sf}(t) - P_{sc}(t) \quad (6)$$

$$P_{ex}(t) = \begin{cases} P_{sf}(t), & P_{sf}(t) \leq P_{sc}(t) \\ P_{sc}(t), & P_{sf}(t) > P_{sc}(t) \end{cases} \quad (7)$$

$$P_{fnh}(t) = P_{sf}(t) - P_{ex}(t) = \begin{cases} P_{grnh}(t), & P_{grnh}(t) > 0 \\ 0, & P_{grnh}(t) \leq 0 \end{cases} \quad (8)$$

$$P_{cnh}(t) = P_{sc}(t) - P_{ex}(t) = \begin{cases} |P_{grnh}(t)|, & P_{grnh}(t) < 0 \\ 0, & P_{grnh}(t) \geq 0 \end{cases} \quad (9)$$

Table 2. Relevant power flows of the neighborhood of PV battery systems.

Name	Equation
Individual feed-in power to the grid	(2)
Individual consumed power from the grid	(3)
Sum of individual feed-in power to the grid	(4)
Sum of individual consumed power from the grid	(5)
Aggregated grid power of the neighborhood	(6)
Power exchanged within the neighborhood	(7)
Neighborhood's feed-in power to the superordinate grid	(8)
Neighborhood's consumed power from the superordinate grid	(9)

The neighborhood model is implemented in MATLAB using object-oriented programming. A separate class is defined for the PV battery system and the aggregator. Therefore, the neighborhood can be scaled up to N PV battery systems by instantiating the desired number of PV battery system objects. The model calculations and the local EM are executed using the methods for the PV battery system objects. The data of the power flow distributions are saved as internal attributes for the PV battery system objects and the aggregator object. The communication between the PV battery systems and the aggregator is modeled using a simple transfer of variables.

4. Coordination Mechanism Including Local Optimizing Energy Management

4.1. Financial Incentive for Exchanging Energy Within the Neighborhood

Similar to the EM for single PV battery systems, the main objective of the coordination mechanism lies in maximizing the degree of self-sufficiency of the neighborhood $k_{SS\,nh}$. Nevertheless, the individual degrees of self-sufficiency for single PV battery systems $k_{SS,n}$ should not be significantly diminished compared to those of conventional EM concepts that maximize individual self-sufficiency. These aims are coupled with the minimization of individual and aggregated costs. In order to relieve the grid, another objective of coordination is the reduction of grid feed-in and consumption power peaks.

In order to induce an increase in the degree of self-sufficiency of the neighborhood, next to the regular pricing for individual private consumers with purchasing costs c_c (approx. 0.30 €/kWh in Germany) and feed-in tariffs c_f (approx. 0.10 €/kWh in Germany), a new pricing segment is introduced for the group of neighboring PV battery systems. The energy consumed from the grid when others in the neighborhood are simultaneously feeding energy into the grid is priced with $c_{c\ ex}$, which should be lower than the regular price c_c . Similarly, the neighbors, feeding energy into the grid while other participants are simultaneously consuming energy from the grid, receive a neighborhood feed-in tariff of $c_{f\ ex}$, which should be higher than c_f . This results in the following inequality:

$$c_c > c_{c\ ex} > c_{f\ ex} > c_f, \forall t. \quad (10)$$

As a consequence, the neighbors are induced to increase the energy exchanged within their neighborhood E_{ex} . The fact that the prices for consumption (index c) are higher than the feed-in tariffs (index f) guarantees that using the battery to increase individual self-consumption is still more profitable than using it to exchange energy within the neighborhood or with the superordinate grid. The gap Δc_{ex} between $c_{c\ ex}$ and $c_{f\ ex}$ could include the regulated cost elements for local trade, such as levies, taxes, and network charges. These could be significantly lower than the usual regulated cost elements, as proposed in [39].

A proportional source matching [28] method is applied to determine the amount of energy that can be billed with the neighborhood tariffs:

$$P_{c\ ex, n}(t) = \begin{cases} P_{s\ f}(t) \cdot \frac{P_{c, n}(t)}{P_{s\ c}(t)}, & P_{s\ f}(t) < P_{s\ c}(t) \\ P_{c, n}(t), & P_{s\ f}(t) \geq P_{s\ c}(t) \end{cases} \quad (11)$$

$$P_{f\ ex, n}(t) = \begin{cases} P_{s\ c}(t) \cdot \frac{P_{f, n}(t)}{P_{s\ f}(t)}, & P_{s\ c}(t) < P_{s\ f}(t) \\ P_{f, n}(t), & P_{s\ c}(t) \geq P_{s\ f}(t). \end{cases} \quad (12)$$

Thereby, the following equation is guaranteed to be satisfied:

$$P_{ex}(t) = \sum_{n=1}^N P_{c\ ex, n}(t) = \sum_{n=1}^N P_{f\ ex, n}(t), \forall t. \quad (13)$$

The costs for a single PV battery system n when billed with additional neighborhood tariffs (Index nht) will thus be

$$C_{nht, n} = \sum_t [(P_{c, n}(t) - P_{c\ ex, n}(t)) \cdot c_c - (P_{f, n}(t) - P_{f\ ex, n}(t)) \cdot c_f + P_{c\ ex, n}(t) \cdot c_{c\ ex} - P_{f\ ex, n}(t) \cdot c_{f\ ex}] \cdot \Delta t. \quad (14)$$

For the whole neighborhood, this results in the following aggregated costs:

$$\begin{aligned} C_{nht\ nh} &= E_{c\ nh} \cdot c_c - E_{f\ nh} \cdot c_f + E_{ex} \cdot \Delta c_{ex} \\ &= E_{s\ c} \cdot c_c - E_{s\ f} \cdot c_f - E_{ex} \cdot (c_c - c_f - \Delta c_{ex}). \end{aligned} \quad (15)$$

4.2. Local Energy Management

The local optimizing EM uses model predictive control based on deterministic dynamic programming [10]. The EM topology can be seen in Figure 7. For better readability, the index n for indicating a specific PV battery system is omitted.

Figure 7. Principle structure of the local EM of a single PV battery system, featuring communication with the aggregator.

The forecast module generates the forecast vectors of load and PV power $\underline{P}_{load\ fc}$ and $\underline{P}_{PV\ fc}$, with a prediction horizon T_p and a time resolution Δt_p . The underlined variables represent vectors of the form $[P(t_p = 0), \dots, P(t_p = m \cdot \Delta t_p), \dots, P(t_p = T_p - \Delta t_p)]$, where $m \in \{0, 1, \dots, \frac{T_p}{\Delta t_p} - 1\}$. The optimization module can determine an optimal control sequence for the grid power $P_{gr\ opt}$ using deterministic dynamic programming with the forecast data, including the latest SOC of the battery model and the data obtained from the aggregator. For this purpose, the optimization module uses a simplified battery model with ideal efficiencies and coulomb counting for SOC estimation and discretizes the SOC range to obtain a limited solution space. The optimization module can execute two different optimization procedures: independent optimization and coordinated optimization. The related cost functions ϕ_{ind} and ϕ_{coord} for the optimization are the following:

$$\phi_{ind}(t_p) = K_{cost\ reg}(t_p) + \alpha \cdot K_{grid}(t_p) \quad (16)$$

$$\phi_{coord}(t_p) = K_{cost\ nht}(t_p) + \alpha \cdot K_{grid}(t_p) \quad (17)$$

with:

$$K_{cost\ reg}(t_p) = [P_c(t_p) \cdot c_c - P_f(t_p) \cdot c_f] \cdot \Delta t_p / \text{€}, \forall t_p \quad (18)$$

$$K_{cost\ nht}(t_p) = [(P_c(t_p) - P_{c\ ex}(t_p)) \cdot c_c - (P_f(t_p) - P_{f\ ex}(t_p)) \cdot c_f + P_{c\ ex}(t_p) \cdot c_{c\ ex} - P_{f\ ex}(t_p) \cdot c_{f\ ex}] \cdot \Delta t_p / \text{€}, \forall t_p \quad (19)$$

$$K_{grid}(t_p) = [P_c(t_p)^2 + P_f(t_p)^2] / W^2, \forall t_p. \quad (20)$$

The cost function ϕ_{ind} for independent optimization considers the criteria of economic costs $K_{cost\ reg}$ when billed with regular tariffs and the weighted grid stress criteria, K_{grid} . No external information is necessary to calculate these values. The cost function ϕ_{coord} for coordinated optimization considers the cost criteria $K_{cost\ nht}$, as introduced in (14). For its calculation, information on the powers $\underline{P}_{sc}$ and $\underline{P}_{sf}$ of the neighborhood is needed to determine $\underline{P}_{c\ ex}$ and $\underline{P}_{f\ ex}$ (see (11) and (12)). The precise determination of $\underline{P}_{c\ ex}$ and $\underline{P}_{f\ ex}$ in the scope of the coordination algorithm is explained in Appendix A and is not included here to allow us to focus on the main principle. After $\underline{P}_{sc}$ and $\underline{P}_{sf}$, the neighborhood tariffs $c_{c\ ex}$ and $c_{f\ ex}$ are needed. This external information is obtained by communicating

with the aggregator. For both cost functions, the deterministic dynamic programming algorithm determines an optimal SOC-trajectory by minimizing the objective function:

$$J = \sum_{t_p} \phi(\text{SOC}(t_p), t_p). \quad (21)$$

The optimization, or more specifically the whole coordination algorithm (see Section 4.3), is executed every 15 min (Δt_{opt}); therefore, $P_{\text{gr opt}}$ is also updated in this cycle and passed to the grid controller. The grid controller generates a battery control signal $P_{\text{bat set}}$, which is applied to the PV battery system model. In this way, the forecast errors and model errors of the optimization module are compensated by the battery power.

4.3. Coordination Algorithm

With each optimization of a PV battery system, the planned powers $\underline{P}_{sc}$ and $\underline{P}_{sf}$ can change. This might have an effect on the optimal power flows of the other PV battery systems when using the coordinated cost function in the optimization. Therefore, these systems need to rerun the optimization using updated values for $\underline{P}_{sc}$ and $\underline{P}_{sf}$. As a result, the coordination algorithm leads to an optimal solution for the neighborhood in an iterative way. The qualitative program flow chart is given in Figure 8.

Figure 8. Program flow chart of the coordination algorithm.

First, all PV battery systems initialize their optimal power flows by executing independent optimization, and they pass $\underline{P}_{c,n}^{(j=1)}$ and $\underline{P}_{f,n}^{(j=1)}$ to the aggregator. The variable j indicates the iteration count. The aggregator determines the vectors $\underline{P}_{sc}^{(j=1)}$ and $\underline{P}_{sf}^{(j=1)}$ by adding up all individual planned consumption and feed-in power vectors. Subsequently, the iteration process begins, and for each iteration, the PV battery systems consecutively execute the coordinated optimization using the cost function ϕ_{coord} (17) with the obtained information of $\underline{P}_{sc}^{(j=1)}$, $\underline{P}_{sf}^{(j=1)}$, $c_{c \text{ ex}}$, and $c_{f \text{ ex}}$ from the aggregator. After each local optimization, the aggregator receives the optimization results $\underline{P}_{c,n}^{(j)}$ and $\underline{P}_{f,n}^{(j)}$ and updates the summated power vectors as follows:

$$\underline{P}_{sc}^{(j)} := \underline{P}_{sc}^{(j)} - \underline{P}_{c,n}^{(j-1)} + \underline{P}_{c,n}^{(j)} \quad (22)$$

$$\underline{P}_{sf}^{(j)} := \underline{P}_{sf}^{(j)} - \underline{P}_{f,n}^{(j-1)} + \underline{P}_{f,n}^{(j)}. \quad (23)$$

Therefore, the aggregator needs to save the individual optimization results of the previous iteration, namely $\underline{P}_{c,n}^{(j-1)}$ and $\underline{P}_{f,n}^{(j-1)}$. After each iteration, the algorithm checks if convergence or a

maximum number of iterations j_{lim} has been reached. In this context, convergence is defined as a state where the following inequality is satisfied for each PV battery system:

$$J_n^{(j_{\text{conv}})} - J_n^{(j_{\text{conv}}-1)} \leq \Delta J_{\text{conv}}, \forall n \in \{1, \dots, N\}, j_{\text{conv}} \in \{1, \dots, j_{\text{lim}}\}. \quad (24)$$

The convergence parameter ΔJ_{conv} takes the trade-off between convergence speed and accuracy of the determined solution into account. The higher the ΔJ_{conv} , the faster the convergence but with a risk of a larger distance to the global optimum.

Instead of keeping the neighborhood tariffs constant, one could also implement the time-variable neighborhood tariffs, $c_{\text{c ex}}(t)$ and $c_{\text{f ex}}(t)$. In that case, the aggregator would not just pass the same values for $c_{\text{c ex}}$ and $c_{\text{f ex}}$ to the PV battery systems but could determine the course of the neighborhood tariffs to induce the desired behavior of the PV battery systems. One straightforward approach would be to set the tariffs proportional to the negative of the aggregated grid power $\underline{P}_{\text{gr nh}}$. In this way, the incentive to increase consumption of energy from the neighborhood is larger during times when the surplus injected by the neighborhood is relatively high. On the other hand, the injection of energy into the grid is more profitable during times of high consumption in the neighborhood. This might lead to a higher degree of self-sufficiency of the neighborhood. However, during preliminary investigations, it became apparent that the variable price signals implemented in this manner increase complexity and reduce robustness without considerable improvements. Therefore, the scope of this publication is limited to constant neighborhood tariffs. Further information and investigations on time-variable neighborhood tariffs can be found in [6].

4.4. Evaluation Criteria

The criteria for evaluating the performance of the EM are given in Table 3. These criteria can be grouped into the categories of energy values (25)–(27), energy ratios related to load coverage (28)–(32), energy ratios related to PV generation allocation (33)–(37), costs (38)–(41), and battery stress (42)–(44). The relief of the superordinate grid is evaluated using duration curves of the aggregated grid power.

$$E_{\text{c nh}} = \int P_{\text{c nh}}(t) dt \quad (25)$$

$$E_{\text{f nh}} = \int P_{\text{f nh}}(t) dt \quad (26)$$

$$E_{\text{ex}} = \int P_{\text{ex}}(t) dt \quad (27)$$

$$k_{\text{SS},n} = \frac{E_{\text{load},n} - E_{\text{c},n}}{E_{\text{load},n}} \quad (28)$$

$$k_{\text{SS } \emptyset} = \frac{\sum_{n=1}^N (E_{\text{load},n} \cdot k_{\text{SS},n})}{\sum_{n=1}^N E_{\text{load},n}} = \frac{\sum_{n=1}^N E_{\text{load},n} - E_{\text{s c}}}{\sum_{n=1}^N E_{\text{load},n}} \quad (29)$$

$$k_{\text{NC},n} = \frac{E_{\text{c ex},n}}{E_{\text{load},n}} \quad (30)$$

$$k_{\text{NC } \emptyset} = \frac{\sum_{n=1}^N (E_{\text{load},n} \cdot k_{\text{NC},n})}{\sum_{n=1}^N E_{\text{load},n}} = \frac{E_{\text{ex}}}{\sum_{n=1}^N E_{\text{load},n}} \quad (31)$$

$$k_{\text{SS nh}} = \frac{\sum_{n=1}^N E_{\text{load},n} - E_{\text{c nh}}}{\sum_{n=1}^N E_{\text{load},n}} = k_{\text{SS } \emptyset} + k_{\text{NC } \emptyset} \quad (32)$$

$$k_{\text{SC},n} = \frac{E_{\text{PV},n} - E_{\text{f},n}}{E_{\text{PV},n}} \quad (33)$$

$$k_{SC \emptyset} = \frac{\sum_{n=1}^N (E_{PV,n} \cdot k_{SC,n})}{\sum_{n=1}^N E_{PV,n}} = \frac{\sum_{n=1}^N E_{PV,n} - E_{sf}}{\sum_{n=1}^N E_{PV,n}} \quad (34)$$

$$k_{NF,n} = \frac{E_{fex,n}}{E_{PV,n}} \quad (35)$$

$$k_{NF \emptyset} = \frac{\sum_{n=1}^N (E_{PV,n} \cdot k_{NF,n})}{\sum_{n=1}^N E_{PV,n}} = \frac{E_{ex}}{\sum_{n=1}^N E_{PV,n}} \quad (36)$$

$$k_{SC nh} = \frac{\sum_{n=1}^N E_{PV,n} - E_{fnh}}{\sum_{n=1}^N E_{PV,n}} = k_{SC \emptyset} + k_{NF \emptyset} \quad (37)$$

$$C_{reg,n} = E_{c,n} \cdot c_c - E_{f,n} \cdot c_f \quad (38)$$

$$C_{reg nh} = \sum_{n=1}^N C_{reg,n} = E_{sc} \cdot c_c - E_{sf} \cdot c_f \quad (39)$$

$$C_{nht,n} = (E_{c,n} - E_{cex,n}) \cdot c_c - (E_{fnh,n} - E_{fex,n}) \cdot c_f + E_{cex,n} \cdot c_{cex} - E_{fex,n} \cdot c_{fex} \quad (40)$$

$$C_{nht nh} = \sum_{n=1}^N C_{nht,n} = E_{c nh} \cdot c_c - E_{fnh} \cdot c_f + E_{cex} \cdot \Delta c_{cex} \quad (41)$$

$$k_{FC,n} = \frac{\int |P_{bat,n}(t)| dt}{2 \cdot E_{bat cap,n}} \quad (42)$$

$$k_{SOC>85\%,n} = \frac{T_{SOC>85\%,n}}{T_{sim}} \quad (43)$$

$$k_{SOC<15\%,n} = \frac{T_{SOC<15\%,n}}{T_{sim}} \quad (44)$$

Table 3. Definitions of the evaluation criteria.

Name	Equation
Energy consumed from the superordinate grid	(25)
Energy fed into the superordinate grid	(26)
Energy exchanged within the neighborhood	(27)
Individual degree of self-sufficiency	(28)
Mean individual degree of self-sufficiency	(29)
Individual neighborhood consumption ratio	(30)
Mean individual neighborhood consumption ratio	(31)
Degree of self-sufficiency of the neighborhood	(32)
Individual degree of self-consumption	(33)
Mean individual degree of self-consumption	(34)
Individual neighborhood feed-in ratio	(35)
Mean individual neighborhood feed-in ratio	(36)
Degree of self-consumption of the neighborhood	(37)
Individual costs with regular tariffs	(38)
Neighborhood's aggregated costs with regular tariffs	(39)
Individual costs with additional neighborhood tariffs	(40)
Neighborhood's aggregated costs with additional neighborhood tariffs	(41)
Number of battery full cycles	(42)
Duration ratio of SOC above 85%	(43)
Duration ratio of SOC below 15%	(44)

5. Simulation-Based Investigations

5.1. Simulation Setup

The simulation-based investigations aim at qualitatively analyzing the operating principle of the previously described coordination mechanism, including the local optimizing EM (hereafter shortened as CoordOpt) and to evaluate its performance in comparison to distributed EM concepts without coordination and a central EM. Thus, we investigate a residential neighborhood consisting of eight decentralized autonomous energy systems considered as households which partially own PV generators and battery storage. For each household, one specific load profile with a 1-min resolution from [40] is chosen. The corresponding annual energy consumptions can be seen in Table 4. Households H 1 to H 4 possess PV generators and battery storage, households H 5 and H 6 own only PV generators, and households H 7 and H 8 are just consumers. The PV peak power and battery capacity for households H 1 to H 6 are set based on the statistics from [8] to represent a scenario close to the present conditions and considering the available battery model (see Section 3.1). As households H 5 to H 8 do not possess battery storage that can be controlled, they are passive participants in the coordination algorithm. Nevertheless, these households still transmit their predicted power profiles $\underline{P}_{c,n}$ and $\underline{P}_{t,n}$, which, however, do not change over the course of one run of the coordination algorithm. The data for the PV power profile is obtained from measurements with a 1-min resolution at a reference object in Chemnitz, Germany, and is scaled to the corresponding PV peak power for each household.

Table 4. Characteristics of the households in the investigated neighborhood (H: household).

	H 1	H 2	H 3	H 4	H 5	H 6	H 7	H 8	Σ
Annual energy consumption in MWh	5.3	3.2	7.5	4.5	6.6	3.4	3.9	4.5	38.9
PV peak power in kWp	6	3	10	6	5	7	-	-	37
Battery capacity in kWh	5	5	5	5	-	-	-	-	20

The EM concept CoordOpt described in Section 4 is investigated considering constant neighborhood tariffs $c_{c\text{ ex}}$ and $c_{f\text{ ex}}$, with equivalent distances to c_c and c_f and with a constant gap $\Delta c_{\text{ex}} = 0.05 \text{ €/kWh}$ (see Table 5). For the first approach, ideal forecasts are used. This EM concept is compared with the following:

- *Distributed rule-based EM (RB)*: The battery power $P_{\text{bat}}(t)$ is set equal to the residual power $P_{\text{PV}}(t) - P_{\text{load}}(t)$; the battery can be charged as long as the maximum SOC value SOC_{max} is not exceeded and can be discharged as long as the battery state of charge does not fall below SOC_{min} . This control strategy aims at maximizing individual self-sufficiency.
- *Distributed independent optimizing EM (IndOpt)*: The local EM utilizes model predictive control, as described in Section 4.2, but without the coordination algorithm and instead only uses the independent cost function. Like CoordOpt, ideal forecasts are considered.
- *Central optimizing EM (CentralOpt)*: The whole neighborhood is considered as one PV battery system and is controlled by one central optimizing EM. The PV and load profiles, as well as the battery capacities and the battery inverters' nominal powers, are simply added up (see Table 4). The central EM uses the same control strategy as the local EM of IndOpt but is adapted to a higher battery capacity. In order to compare this EM with the distributed control strategies, the power flow of the virtually central 20 kWh battery is equally distributed to households H 1–H 4. One can interpret the distributed batteries as being centrally controlled and operating at the same SOC.

All parameters used for the simulation and optimization are given in Table 5. The weighting factor α is estimated by executing several simulations and choosing a value for α that results in the desired trade-off between cost minimization and grid relief.

Table 5. Simulation and optimization parameters.

Simulation Parameters		Optimization Parameters	
Simulation time T_{sim}	363 d	Prediction horizon T_p	36 h
Simulation time step Δt_{sim}	1 min	Prediction horizon time step Δt_p	15 min
Regular energy price c_c	0.30 €/kWh	Reoptimization time interval Δt_{opt}	15 min
Regular feed-in tariff c_f	0.10 €/kWh	Allowed range for SOC	10%–90%
Neighborhood energy price $c_{c \text{ ex}}$	0.225 €/kWh	SOC discretization ΔSOC	0.5%
Neighborhood feed-in tariff $c_{f \text{ ex}}$	0.175 €/kWh	Allowed range for P_{bat}	−2.5 kW–2.5 kW
Allowed range for SOC	10%–90%	Weighting factor α	10^{-9}
Allowed range for P_{bat}	−5 kW–5 kW	Maximum number of iterations j_{lim}	20
		Convergence parameter ΔJ_{conv}	0.001

5.2. Simulation Results

First, the qualitative operations of the three distributed EM concepts are evaluated by comparing the exemplary grid power profiles and SOC profiles of household H 1 (see Figure 9). CentralOpt is not considered here because its operation cannot be reasonably compared to the distributed EM concepts by examining only a single household. Nevertheless, its qualitative operation is basically the same as that of IndOpt but with the difference that it is applied to the whole neighborhood and considered as a single PV battery system.

Figure 9. Grid power profiles and SOC trajectories of household H 1 for two exemplary days in the summer.

For the EM concept RB, one can see that the battery is fully charged quickly and that the residual power with high peaks and large fluctuations (gray plot in Figure 9) is then fed into the grid. It should be mentioned that the residual power would equal the grid power in the case of no battery. The lower SOC bound is also reached here earlier than the other two EM concepts. This results in the battery remaining at its maximal and minimal SOC for a very long time. With IndOpt, the grid power profile is substantially smoothened, and the upper SOC bound is reached just before the battery is discharged

again for serving the load. Therefore, the duration of extreme SOC values is considerably reduced, which is a beneficial side effect of this control strategy concerning the battery stress. For qualitatively analyzing the operation of CoordOpt, the summated grid power of the neighbors ($P_{gr\ nh} - P_{gr,1}$) is additionally plotted in Figure 9. One can observe that, for CoordOpt, the course of the grid power and the SOC for household H 1 are generally similar to those of IndOpt. A major difference is that from $t = 7$ h until $t = 16$ h, the grid power is not kept predominantly constant but is instead adapted to the summated grid power of the neighbors. More precisely, household H 1 feeds more energy to the grid when its neighbors demand energy, e.g., at $t = 8$ h and $t = 10$ h. Another difference is that from $t = 16$ h until $t = 20$ h, household H 1 draws more energy from the grid. This energy draw keeps the battery at a high SOC and covers its load at night with the stored energy. This is presumably due to the fact that the neighbors continue to feed a PV surplus energy to the grid, which can be purchased at a lower price during this period of time than consuming energy at night for the regular consumption price.

After analyzing the qualitative operating principle of the three distributed EM concepts, their overall performance is evaluated and compared to the central optimizing EM based on simulations for one year. The definitions of the evaluation criteria are listed in Table 3, and the results for the whole neighborhood are given in Table 6.

Table 6. Comparison of the evaluation criteria of the four different EM concepts for the reference application (best values for the distributed EM concepts are underlined).

Evaluation Criteria	RB	IndOpt	CoordOpt	CentralOpt
Energy consumed from the superordinate grid $E_{c\ nh}$	21.8 MWh	21.7 MWh	<u>21.5 MWh</u>	21.4 MWh
Energy fed into the superordinate grid $E_{f\ nh}$	17.2 MWh	16.5 MWh	<u>16.3 MWh</u>	16.1 MWh
Energy exchanged within the neighborhood E_{ex}	2.8 MWh	3.5 MWh	<u>3.7 MWh</u>	6.7 MWh
Degree of self-sufficiency of the neighborhood $k_{SS\ nh}$	43.5%	43.7%	<u>44.2%</u>	44.5%
Degree of self-consumption of the neighborhood $k_{SC\ nh}$	51.0%	52.9%	<u>53.7%</u>	54.2%
Neighborhood's aggregated costs with regular tariffs $C_{reg\ nh}$	<u>5383 €</u>	5557 €	5576 €	6158 €
Neighborhood's aggregated costs with additional neighborhood tariffs $C_{nht\ nh}$	<u>4959 €</u>	5040 €	5020 €	5152 €

As expected, CoordOpt reaches the best values based on the amount of energy consumed from and fed into the superordinate grid and the energy exchanged within the neighborhood (only for the distributed EM concepts). Therefore, this EM concept also results in the highest degree of self-sufficiency and self-consumption of the neighborhood. Interestingly, the results of IndOpt always lie between RB and CoordOpt, presumably because individual grid power smoothing already results in an increased temporal match between consumption and feed-in compared to rule-based EM. The EM concept CentralOpt achieves the best values for all the criteria discussed above. Most notably, the energy exchanged between neighbors is the highest. CoordOpt can be seen as an ideal reference for distributed EM concepts, with selflessly acting households only serving this purpose for the whole neighborhood. Considering the aggregated costs, the EM concept RB results in the lowest values for both energy tariff designs. The reason for this is that the other EM concepts reduce the energy fed into the superordinate grid considerably more than the energy consumed from the superordinate grid. Thus, with RB, the neighborhood receives the greatest revenue from PV generation sold to the superordinate grid. However, CoordOpt results in lower costs than IndOpt when applying the neighborhood tariffs and thereby achieves its optimization goals. CentralOpt always results in the highest aggregated costs because it does not consider that the energy exchanged within the neighborhood is billed in both cases. If the exchanged energy were not billed at all ($\Delta c_{ex} = 0$), CoordOpt would result in the lowest overall costs.

In Figure 10 the share of coverage for the total neighborhood's demand is presented by source for the investigated EM concepts. In particular, the mean individual degree of self-sufficiency $k_{SS\ \emptyset}$, the mean individual neighborhood consumption ratio $k_{NC\ \emptyset}$ (summed up, these two values equal

the degree of self-sufficiency of the neighborhood ($k_{SS\ nh}$), and the share of consumption from the superordinate grid are illustrated.

Figure 10. Coverage of the total neighborhood's demand by source for the investigated EM concepts.

Here, it should be noted that the definitions of self-sufficiency and self-consumption in Table 3 assume that the stored energy that originates from the grid is completely used for one's own load and is never fed back to the grid (e.g., for arbitrage purposes). The EM concept RB does not violate this condition—neither do IndOpt nor CoordOpt because their objective functions do not aim at realizing arbitrage: the consumption price is always higher than the feed-in tariff, and the grid smoothing criteria K_{grid} (20) favors minimal energy exchange with the grid.

However, CentralOpt cannot guarantee that the above-mentioned condition is satisfied for individual self-sufficiency and self-consumption, as optimization is performed only in the scope of the whole neighborhood. Therefore $k_{SS,n}$, $k_{SS\ \emptyset}$, $k_{NC,n}$, $k_{NC\ \emptyset}$, $k_{SC,n}$, $k_{SC\ \emptyset}$, $k_{NF,n}$, and $k_{NF\ \emptyset}$ do not retain their intended conceptual contents when calculated for the results of CentralOpt. Nevertheless, the definitions for the whole neighborhood $k_{SS\ nh}$ and $k_{SC\ nh}$ are valid for CentralOpt as well. In practice, however, it also cannot be guaranteed that RB, IndOpt, and CoordOpt totally satisfy the aforementioned condition because of the settling times of controllers, forecast errors, model errors, and discretized optimization time series (15 min intervals). As these simulations assume ideally settled controllers and perfect forecasts, this effect is supposed to be insignificant.

In Figure 10, one can see that CoordOpt achieves the best results for the distributed EM concepts concerning the degree of self-sufficiency of the whole neighborhood because of increased energy exchange. Although the value for $k_{SS\ \emptyset}$ is the lowest, the sum of $k_{SS\ \emptyset}$ and $k_{NC\ \emptyset}$ results in the highest value for $k_{SS\ nh}$ for the distributed EM concepts. The share of consumption from the superordinate grid is only 0.3 percentage points lower when applying CentralOpt. The allocation of the total neighborhood's PV generation shows similar qualitative results and can be found in Figure A1 in the Appendix B. Note that in Figures 10 and A1, the percentage points don't sum up to exactly 100 % in all cases due to rounding.

When analyzing the individual degrees of self-sufficiency, $k_{SS,n}$, and neighborhood consumption ratios, $k_{NC,n}$, in Figure 11, it becomes apparent that with RB, $k_{SS,n}$ reaches the highest value, but $k_{NC,n}$ has the lowest value compared to the other EM concepts. Comparing IndOpt and CoordOpt, one can see that the values for $k_{SS,n}$ do not significantly diverge, but $k_{NC,n}$ increases for the households that possess battery storage (H 1–H 4). This effect can be observed especially for household H 2, which has the highest flexibility due to possessing the highest battery capacity relative to its annual energy consumption (see Table 4). It is notable that, when applying CentralOpt, the sums of $k_{SS,n}$ and $k_{NC,n}$ (meaning the coverage of individual demand by the total neighborhood's PV generation) converge to similar values between approximately 35% and 50% for all households. An analog figure showing $k_{SC,n}$ and $k_{NC,n}$ can be found in the appendix (Figure A2), where qualitatively similar observations can be made.

Figure 11. Individual degrees of self-sufficiency and neighborhood consumption ratios for the investigated EM concepts (In: IndOpt, Co: CoordOpt, Ce: CentralOpt, H: household).

The absolute values of the individual energy consumed from ($E_{c\ ex,n}$) and fed into the neighborhood ($E_{f\ ex,n}$) are illustrated in Figure 12. Summing up these values for all households, one obtains E_{ex} in both cases (see Table 6 for comparison). Regarding energy consumption from the neighborhood, it becomes apparent that households H 7 and H 8 reach the highest values for $E_{c\ ex,n}$ for all distributed EM concepts. Because they do not engage in PV generation, these households generally also consume energy from the grid during midday when the other households feed their PV surplus to the grid. Regarding the distributed EM concepts, household H 6 reaches the highest value for $E_{f\ ex,n}$, presumably because it has the highest PV peak power relative to its annual energy consumption. In general, the sum of these energy values increases from RB, IndOpt, and CoordOpt to CentralOpt. $E_{c\ ex,n}$ and $E_{f\ ex,n}$ are more equally distributed for CentralOpt.

Figure 12. Energy consumed from the neighborhood ($E_{c\ ex,n}$) and energy fed into the neighborhood ($E_{f\ ex,n}$) by each individual household (H: household).

In Figure 13, the individual costs when billed with regular tariffs ($C_{reg,n}$) and when billed with additional neighborhood tariffs ($C_{nht,n}$) are illustrated. One can see that $C_{nht,n}$ is always lower than $C_{reg,n}$ for each household, as expected. Generally, for households owning a PV generator and battery storage, $C_{reg,n}$ increases from RB to IndOpt to CoordOpt to CentralOpt because of an increase in the

energy exchanged with the individual grid connection ($E_{c,n}$ and $E_{f,n}$). The individual costs $C_{nht,n}$ show similar qualitative results, with the difference that CoordOpt leads to lower values than IndOpt. The other households without battery storage (H 5 to H 8) also benefit financially from additional neighborhood tariffs and coordination by CoordOpt and CentralOpt, although they do not actively take part in the coordination as they cannot adapt their individual grid power profiles. This result can be seen particularly for household H 6 in Figure 13. This raises the question if billing with neighborhood tariffs would be fair considering individual financial benefits relative to the provision of flexibility for superordinate goals.

Figure 13. Individual costs when billed with regular tariffs ($C_{reg,n}$) and when billed with additional neighborhood tariffs ($C_{nht,n}$) (In: IndOpt, Co: CoordOpt, Ce: CentralOpt, H: Household).

By comparing the individual battery stress parameters in Figure 14, it becomes apparent that RB leads to a significantly lower number of full cycles than the optimizing EM concepts. This might be the reason for the highest value of $k_{SS \emptyset}$ for RB in Figure 10, as lower battery full cycles correlate with lower battery losses. With the exception of household H 3, CentralOpt results in the highest number of full cycles. Therefore, CentralOpt leads to the lowest unused battery capacity, which seems reasonable, as all batteries always operate to serve the whole neighborhood. The fact that CoordOpt results in higher battery full cycles than IndOpt for all households can be explained with the same reasoning.

Considering the durations of the high and low SOC values, RB leads to the worst results—as expected based on the observations made in Figure 9. CoordOpt shows slightly worse behaviour than IndOpt for all households. The values of $k_{SOC>85\%,n}$ and $k_{SOC<15\%,n}$ for CentralOpt are the same for all households and approximately amount to the mean of CoordOpt's values.

Regarding the duration curves of the aggregated grid power in the consumption ($P_{c,nh}$) and feed-in direction ($P_{f,nh}$), in Figure 15, it becomes apparent that RB results in the highest stress on the superordinate grid for both power flow directions. IndOpt and CoordOpt almost result in the same duration curves, with considerably lower power values than RB. The only difference is that $P_{f,nh}$ has some marginally higher values when CoordOpt is applied, presumably due to its individual adaption to the aggregated grid power observed and analyzed in Figure 9. CentralOpt results in the lowest values for $P_{c,nh}$ and generally also leads to the best results for $P_{f,nh}$, except for some rare peaks that are slightly higher than the maximal power values for IndOpt and CoordOpt. As the batteries operate at the same SOC when CentralOpt is applied, they simultaneously reach the upper SOC bound in the case of a full charge. All battery powers are then set to 0 by the internal controllers of the batteries,

and the aggregated grid power equates the sum of all individual residual powers, which results in the abovementioned rare peaks of $P_{f,nh}$. By setting the upper SOC bound of the optimization lower than the upper SOC bound of the internal controllers of the batteries, this issue could be solved. Overall, these results are reasonable because CentralOpt is the only EM concept that directly pursues a reduction of peaks in the aggregated grid power profile. IndOpt and CoordOpt, on the other hand, reduce the peak power in the scope of individual grid connections.

Figure 14. Battery stress criteria for the investigated EM concepts (In: IndOpt, Co: CoordOpt, Ce: CentralOpt, H: household).

Figure 15. Duration curves of the power consumed from the superordinate grid (left) and the power fed into the superordinate grid (right).

6. Summary and Outlook

The developed and implemented coordination mechanism for PV battery systems (CoordOpt) is based on a decentralized fully-dependent EM structure including a local optimizing EM for each PV battery system, as well as an aggregator. This mechanism involves proposed neighborhood energy tariffs to financially induce the energy exchange between neighboring PV battery systems. The general working principle of CoordOpt was demonstrated and analyzed in simulation-based investigations for an exemplary neighborhood comprising eight households with diverging PV generator and battery storage dimensions and varying load profiles.

Compared to the two control strategies without coordination, distributed conventional rule-based EM (RB) and distributed independent optimizing EM (IndOpt), CoordOpt reached the highest degree of self-sufficiency for the neighborhood, as well as the highest amount of energy exchanged within the neighborhood, considering a simulation for a full year. Interestingly, IndOpt obtained better results for these criteria than RB by simply reducing the individual grids' power peaks. As a reference for ideal coordination, a centrally optimized EM (CentralOpt) was also developed and simulated. This EM leads to the highest amount of energy exchanged within the neighborhood. Nevertheless, the degree of self-sufficiency for the neighborhood is only marginally increased compared to CoordOpt.

Regarding the costs in the case of billing with neighborhood tariffs, RB leads to the lowest total costs. Although IndOpt, CoordOpt, and CentralOpt increase the energy exchanged between neighbors, which is financially beneficial, RB remains the best because it has the highest individual degrees of self-sufficiency. Nevertheless, CoordOpt decreases the total costs compared to IndOpt and, therefore, operates as expected. Concerning the individual costs, all households, including the inflexible ones without battery storage, benefit from the neighborhood tariffs. Actual billing with neighborhood tariffs is, therefore, problematic considering the fairness of the realized financial benefits relative to the provision of flexibility. Alternatively, neighborhood tariffs could be implemented only as technical signals to enable coordinated operation. In that case, the individual financial costs would have to be determined in a different manner, such as by means of a constant financial incentive for actively taking part in the coordination mechanism.

With respect to the battery stress, CoordOpt leads to slightly higher full cycles than IndOpt, as the batteries are utilized to increase the energy exchanged within the neighborhood in addition to the maximization of individual self-consumption. The same applies to durations of high and low SOC values, which are still considerable shorter than the ones resulting from RB. In future investigations, the effects of the different EM concepts on the lifetime of the batteries should be analyzed in detail by means of a comprehensive ageing model.

This study shows that the peaks of the aggregated grid power for consumption and feed-in direction are considerably reduced by CoordOpt in comparison with RB. Nevertheless, CentralOpt achieves a significant improvement, especially in its consumption direction, because it is the only EM concept that actually pursues the minimization of extreme values for the aggregated grid power in contrast to CoordOpt and IndOpt, which minimize only the individual extreme grid power values. An alternative version of CoordOpt, where all PV battery systems aim at minimizing the extreme values of the aggregated grid power (which could be called, e.g., *coordinated peak shaving*) instead of the individual grid power could, therefore, achieve significantly better results for grid relief and should be analyzed in future investigations.

In conclusion, the simulations with ideal forecasts demonstrated the theoretical potential of the developed coordination mechanism to increase the degree of self-sufficiency of the neighborhood while minimizing stress on the grid compared to conventional charging strategies. In subsequent investigations, benefits should be evaluated by utilizing more realistic forecast methods. Regarding the coordination algorithm, it would be interesting to investigate the fairness of the optimization order of PV battery systems. More precisely, it should be determined if the last optimizing PV battery system has a benefit compared to the other systems. Moreover, variations in pricing, such as time-variable neighborhood tariffs optimized by the aggregator, external time-of-use tariffs, and a discontinuation

of external fixed feed-in tariffs, could be analyzed. In general, it would also be possible to integrate different and more complex decentralized energy systems, such as those comprising heat pumps and heat storage, charging infrastructure for electric vehicles, or a hydrogen storage path in addition to the PV generator and the battery storage. Lastly, the integration of a supplementary community energy storage into the neighborhood's topological and coordination mechanism (e.g., for seasonal storage) could be beneficial.

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Appendix A

$\underline{P}_{c\ ex,n}^{(j)}$ and $\underline{P}_{f\ ex,n}^{(j)}$ in (19) are determined as follows:

$$P_{c\ ex,n}^{(j)}(t_p) = \begin{cases} P_{s\ f\ new,n}^{(j)}(t_p) \cdot \frac{P_{c,n}^{(j)}(t_p)}{P_{s\ c\ new,n}^{(j)}(t_p)}, & P_{s\ f\ new,n}^{(j)}(t_p) < P_{s\ c\ new,n}^{(j)}(t_p) \\ P_{c,n}^{(j)}(t_p), & P_{s\ f\ new,n}^{(j)}(t_p) \geq P_{s\ c\ new,n}^{(j)}(t_p) \end{cases} \quad (A1)$$

$$P_{f\ ex,n}^{(j)}(t_p) = \begin{cases} P_{s\ c\ new,n}^{(j)}(t_p) \cdot \frac{P_{f,n}^{(j)}(t_p)}{P_{s\ f\ new,n}^{(j)}(t_p)}, & P_{s\ c\ new,n}^{(j)}(t_p) < P_{s\ f\ new,n}^{(j)}(t_p) \\ P_{f,n}^{(j)}(t_p), & P_{s\ c\ new,n}^{(j)}(t_p) \geq P_{s\ f\ new,n}^{(j)}(t_p) \end{cases} \quad (A2)$$

with:

$$P_{s\ c\ new,n}^{(j)}(t_p) = P_{s\ c}^{(j)}(t_p) - P_{c,n}^{(j-1)}(t_p) + P_{c,n}^{(j)}(t_p), \quad \forall t_p \forall j \quad (A3)$$

$$P_{s\ f\ new,n}^{(j)}(t_p) = P_{s\ f}^{(j)}(t_p) - P_{f,n}^{(j-1)}(t_p) + P_{f,n}^{(j)}(t_p), \quad \forall t_p \forall j. \quad (A4)$$

Appendix B

Figure A1. Allocation of the total neighborhood's PV generation for the investigated EM concepts.

Figure A2. Individual degrees of self-consumption and neighborhood feed-in ratios for all households (In: IndOpt, Co: CoordOpt, Ce: CentralOpt, H: household).

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