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Research Article

Optimal Framework to Maximize the Workplace Charging Station Owner Profit while Compensating Electric Vehicles Users

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Electric vehicles (EVs) are one promising technology for an improved sustainable transportation sector, particularly when they are charged with electricity from renewable energy sources. However, the EV user behaviour uncertainties as well as the fluctuating generation of renewable energy sources make the interaction between these technologies challenging. In this work, a new approach to coordinate the charging process of multiple EVs parked at workplace charging station (WCS) equipped with Photovoltaic panels (PV) is proposed. Considering the PV incremental cost and the day-ahead electricity price (DAEP), an optimal framework is introduced to maximize the WCS owner profit while compensating the EV users for discharging their EVs' battery. The EV user behaviour uncertainties are modeled by probability distribution functions, and the PV generation is forecasted by the backpropagation neural network model (BPNN). The optimization problem is solved by mixed-integer linear programming (MILP) while the Monte Carlo sampling methods have been applied to handle the EV user behaviour uncertainties. The results show that the proposed method increases the WCS owner profit and the EV user compensation by 54% and 50.7%, respectively, compared to uncoordinated charging. Moreover, the estimated WCS owner profit and the EV user compensation generated by coordinated charging are 1.72% and 1.35%, respectively, higher than the profits based on real user behaviour data.

1. Introduction

Electric Vehicles (EVs) are becoming popular due to their potential for reducing air pollution, dependence on oil consumption, and ability to promote the penetration of renewable energy sources into the transport sector [1, 2]. Nevertheless, with the large scale of EVs connected to the power grid, the distribution network load profile will be extremely changed, which can lead to voltage fluctuations, power losses, and incremental overloads. Besides, there are environmental controversies about the EVs' charging, since the reduction of CO_2 vehicle emission might be followed by increasing the emissions in power generation. Therefore, the EVs can be beneficial for the environment only if the electrical energy used to charge their batteries is coming from renewable sources [3], such as photovoltaic panels (PV), concentrated solar power, and hydraulic and wind systems.

1.1. Literature Review. The concept of integration of PV with EV charging infrastructure attracts huge researchers' attention in recent years. In [4], a classification scheme of EVs in PV charging station (PVCS) has been studied to reduce the total cost of energy trading of the PVCS. A real-time price based on automatic demand response strategy is proposed in [5] for PVCS, which intends to minimize the electricity cost, to mitigate the peak charging demand, and to improve the PV self-consumption. In [6], a close-to-optimal algorithm based on the Lyapunov optimal is developed to improve the PVCS owner profit. A rule-based decision-making algorithm is applied in [7] to manage EVs charging based on PV generation and electricity time-of-use tariffs. A rule-based decision-making method that makes the solid state transformer-based PVCS can dynamically participate in the ancillary service of smart grid is presented in [8]. A new architecture for a PVCS with a hybrid control strategy is proposed in [9] to minimize the charging cost and to increase the PV self-consumption. Two optimization algorithms have been applied in [10] to minimize the EVs charging cost and to maximize the PV self-consumption for three EV fleet categories which are commercial (night charging), commuter (long day charging), and opportunity (short day charging). The authors in [11] developed a model to maximize the PVCS owner profit while considering the grid constraints, and results show that the PVCS owner profit is increased by 10% and the peak load is decreased by 40%. An energy management framework has been formulated for a university campus microgrid to coordinate the EVs' charging and maximize the PV self-consumption [12]. Based on the EVs' energy demand and the electricity price, a fuzzy logic power-flow controller has been designed in [13] to decrease EVs' charging cost at workplace parking garage equipped with PV panels. A Stackelberg game is designed in [14], where the PVCS operator acts as a leader and the EV users as followers. Soares et al. [15] developed an optimization model to minimize the operational cost of an eco-district microgrid with EV and PV systems compared with uncoordinated scenario; the operational costs are decreased by 70%. The authors in [16] propose an optimization problem to coordinate 6 EVs at workplace charging station (WCS) supplied by PV and grid.

1.2. Contributions and Novelty of This Research. Relying on our scientific knowledge, designing an EVs' charging strategy to maximize the WCS owner profit while compensating the EV users for discharging their EVs' battery is not proposed in those previous works. In other words, in this paper, the PV power generation is forecasted by the back-propagation neural network. Besides, based on the day-ahead electricity price (DAEP), the EV user behaviour and the PV incremental cost of an optimal charging strategy are proposed to maximize the WCS owner profit and to compensate the EV users for using their EVs' battery to supply the grid. The optimal charging strategy implemented in this work satisfied the PV system constraints, the EVs' constraints, and the grid constraints. Moreover, this paper presents a method to calculate EVs' initial state of charge (SOC_0) based on their daily driving mileage. In this case, the WCS would not need to collect the SOC_0 of the EVs from the users, which could help the WCS to predict the EVs' energy demand. Furthermore, the EV user behaviour has been modeled by probability distribution functions while Monte Carlo sampling methods (MCS) have been applied to handle EV user behaviour uncertainties. Hence, the contribution and novelty of the paper can be presented as follows:

(i) Presenting an optimal charging strategy that maximizes the WCS profit while compensating EV users for discharging their EVs' battery

(ii) Modeling EV user behaviour by probability distribution functions

(iii) Applying the MCS to handle EV user behaviour

1.3. Paper Organization. The paper is organized as follows. Section 2 provides the problem formulation. The PV power forecasting model is described in Section 3. The modelization of EV user behaviour by probability distribution functions is formulated in Section 4. The MCS, the proposed algorithm, and the optimization parameter value are presented in Section 5. To assess the effectiveness of the proposed optimal charging strategy, the results are compared with the uncoordinated charging scenario in Section 6. Finally, the conclusion of the paper is given in Section 7.

2. Problem Formulation

2.1. EV Charging Model. EVs park at the workplace for a sufficiently long time during the day [1]. For this reason, the concept of WCS with a fleet of EVs, PV panels on the roof, and bidirectional grid connection is studied in this paper. It is assumed that the WCS owner pays the EV users when their EVs supply the grid. As shown in Figure 1, there are two kinds of connection, energy and information connection. The optimal charging strategy resides in three steps. In the first step, an EVs' charging control center (EVs CCC) is supposed to collect the day-ahead electricity price from the electricity operator to forecast the PV power generation and the EV user behaviour. In the second step, an optimal charging strategy is implemented by CCC to maximize the WCS owner profit while compensating the EV users for discharging their EVs. Finally, the EVs CCC broadcast the information to the EVs, PV, and grid to exchange the energy between them.

In this work, we aim at designing a smart charging strategy scheme to maximize the WCS owner profit while compensating the EV users for discharging their EVs, where the EVs' constraints, the PV system constraints, and the grid constraints are fulfilled. The charging scheduling optimization problem for the WCS might be formulated as follows:

$$\min \sum_{t=1}^{T}\sum_{i=1}^{N}\Big[\lambda_{\mathrm{PV2}V,t}P^{i}_{\mathrm{PV}-V,t}+\lambda_{G2V,t}P^{i}_{\mathrm{grid}-V,t} -\left(\lambda_{V2G,t}-C_{\deg}\right)P^{i}_{V-G,t}-\lambda_{\mathrm{PV2}G,t}P_{\mathrm{PV}-G,t}\Big]\Delta t. \tag{1}$$

The objective function is subject to the following constraints.

(A) EVs constraints:

$$0\le P^{i}_{\chi-V,t}\le u^{i}_{t}\cdot P^{i}_{\max},\quad \forall t,i, \tag{2}$$

$$0\le P^{i}_{V-G,t}\le v^{i}_{t}\cdot P^{i}_{\max},\quad \forall t,i. \tag{3}$$

Each EV has its own limitation of charging and discharging power, as presented in (2) and (3).

$$u^{i}_{t}+v^{i}_{t}\le 1,\quad \forall t,i. \tag{4}$$

Equation (4) is necessary to prevent the EV contemporaneous charging and discharging, where u^{i}_{t} is the binary variable that states whether the EV labelled i is charging (1) or not (0) at time t and v^{i}_{t} represents the binary variable that states whether the ith EV is discharging (1) or not (0).

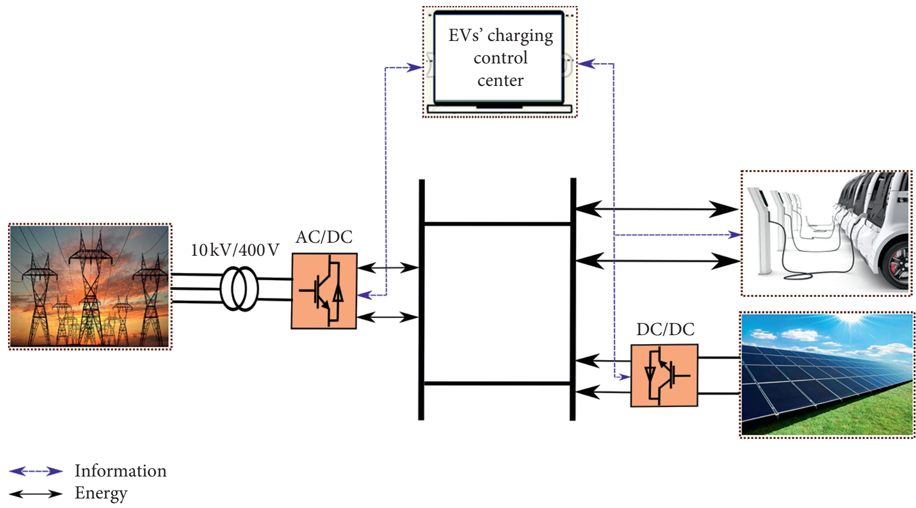

FIGURE 1: System model for charging/discharging EVs at WCS.

The power received by each EV at time t ($P^i_{EV,t}$) can be calculated according to equation (5). Subsequently, we can track the battery's state of charge (SOC) during the whole simulation time by (6), where SOC^i_{t-1} indicates the state of charge of the ith EV at time $t-1$, Δt represents the time step (in hour), and C^i_{max} is the EV maximum capacity. The restriction in (7) guarantees that the EV labelled i is fully charged at the end of charging period T. To avoid impacting the battery states of health due to overcharging and deep discharging, partial states of charge (SOC^i_t) must be constrained between certain boundaries, as in (8), where SOC_{min} and SOC_{max} are the minimum and the maximum constraints, respectively, imposed to all partial states of charge.

$$P^i_{EV,t} = \eta_{ch} \cdot P^i_{\chi-V,t} - \eta_{dis} \cdot P^i_{V-G,t}, \quad \forall t,\ i, \tag{5}$$

$$SOC^i_t = SOC^i_{t-1} + \frac{P^i_{EV,t} \cdot \Delta t}{C^i_{max}}, \quad \forall t, i, \tag{6}$$

$$SOC^i_T = SOC_{max}, \tag{7}$$

$$SOC_{min} \leq SOC^i_t \leq SOC_{max}, \quad \forall t, i. \tag{8}$$

(B) PV system constraints:

It has been assumed that the PV plant is equipped with a DC-DC converter with Maximum Power Point Tracker (MPPT), which has efficiency $\eta_{MPPT} = 0.98$ [17]. Furthermore, to allow the smart charging strategy to curtail PV power, equation (9) has been introduced:

$$\sum_{i=1}^{N} \eta_{MPPT} \cdot P^i_{PV-V,t} + \frac{P_{PV-G,t}}{\eta_{MPPT}\eta_{inv}} \cdot \leq P^{max}_{PV,t}, \quad \forall t,\ i. \tag{9}$$

(C) Grid constraints:

The charging/discharging power drawing from the grid or feeding into the grid is limited by the following equations:

$$\begin{aligned} &0 \leq P^i_{grid-V,t} \leq w^i_t \cdot P^{max}_{grid}, \quad \forall t, i \\ &\sum_{i=1}^{N} P^i_{V-G,t} + P_{PV-G,t} \leq \left(1 - w^i_t\right) \cdot P^{max}_{grid}, \quad \forall t, \end{aligned} \tag{10}$$

where w^i_t represents the binary variable that prevents drawing power from the grid while feeding power into grid $\{0, 1\}$.

3. Forecast Model for PV Power

In order to achieve the goal of this work which is forecasting the WCS profit while compensating the EV users for discharging their EV batteries, PV power generation needs to be predicted day-ahead. Many techniques have been devoted to predict PV power generation [18], for instance, statistical, persistance, hybrid technique, and machine learning. The machine learning technique includes Artificial Neural Network (ANN) which is one of the most widespread models among literature studies. ANN can learn, memorize, and build a system model through manipulating external information to get the predicting capabilities. However, ANN is underperformed by SARIMA at the highest temporal resolution (i.e., 5 minutes) [19]. In this work, the PV power forecasting is considered based on 1 hour temporal resolution. Besides, BPNN showed a successful result at lower temporal resolution (i.e., 1 hour) [20], which is why BPNN is used as the model to forecast PV power generation.

The predicting accuracy is influenced by meteorological factors, for instance, solar irradiance and ambient temperature. Hence, these parameters are chosen as basic elements of a feature vector to obtain similar days; equation (11) presents the coefficient of similarity:

$$\Theta = \left|\theta_f - \theta_h\right|, \tag{11}$$

where θ_f is the forecast day feature vector composed of solar irradiance and ambient temperature. θ_h is the feature vector of the historical day. The smallest Θ value explains the higher similarity between corresponding historical PV power generation data and the forecast day. The D historical days with the smallest coefficient of similarity will be chosen as the training input of the BPNN, where D is the size of input data.

3.1. BPNN Training Structure. The BPNN selected in this paper consists of three layers: the input layer, the hidden layer, and the output layer, as shown in Figure 2.

The input node number is 30, of which 15 nodes are the hourly PV power of an identical day that has the smallest similarity coefficient, and 15 other nodes are the characteristic vector elements of the identical days and the forecast day. The number of output nodes is 15, indicating the PV power generation output. A trial-and-error method [21] has been chosen to determine the appropriate number of hidden layers. Furthermore, the tangent sigmoid-function is used as the activation functions of the hidden layer and output layer, respectively.

3.2. Data and Error. This paper considers a charging station located in an industrial zone on sunny days. The PV power generation data has been collected from an actual PV plant with a rated capacity equal to 30 kW [22]. Fifty historical days with the smallest similarity coefficient in the past three months are chosen as the training input of the BPNN.

To define the prediction accuracy correctly, the forecast error is presented as follows:

$$\varepsilon = \frac{\sum \left| e_{\mathrm{pv}}^{\mathrm{ac}} - e_{\mathrm{pv}}^{\mathrm{fr}} \right|}{\sum e_{\mathrm{pv}}^{\mathrm{ac}}}, \tag{12}$$

where $e_{\mathrm{pv}}^{\mathrm{ac}}$ is the actual PV output energy and $e_{\mathrm{pv}}^{\mathrm{fr}}$ is the forecast output energy of PV.

4. EV User Behaviour Model

A survey has been conducted in Beijing on car user driving behaviour [23]. The data recorded by the global positioning system installed on 112 cars from June 2012 to March 2013 has been selected in this paper. According to the survey, the distributed percentages revealed that the mileage for each trip is significantly concentrated in 3 to 30 km range. The average travel time during workdays is 0.6 h [23]. Based on the work in [2], it has been assumed that the EV users arrive at WCS after 0.6 h from their home departure time, and they leave the WCS after 8 hours from their arrival time. Hence, the traveling periods of the EV users to WCS during workdays are concentrated between 07:36–10:36 (at the morning). To improve the Monte Carlo sampling credibility, the EVs' traveling behaviour statistics has been fitted by different probability distribution functions (PDFs); to find the best PDF that fits the data the maximum likelihood estimates (MLE) is adopted to obtain the selected PDF parameters.

4.1. The Arrival Time of EVs. The average travel time per trip during workdays is 0.6 h. It has been presumed that the EV users make one trip from home to WCS. To determine the EVs' arrival time at WCS, the EVs' departure time from home in [2] has been adopted.

The EVs' departure time from home follows the t location-scale distribution presented in (13) [24], where $g(\cdot)$ is the t location-scale PDF, $\Gamma(\cdot)$ represents the gamma function, σ is the scale parameter, μ is the location parameter, and ν is the shape parameter. Based on MLE, $\mu = 8.30$, $\sigma = 1$, and $\nu = 2.12$.

The statistical curve and the location-scale distribution fitting curve of the EVs arrival time to WCS are shown in Figure 3:

$$g(x \mid \mu, \sigma, \nu) = \frac{\Gamma(\nu + 1/2)}{\sigma\sqrt{\nu\pi}\,\Gamma(\nu/2)} \left[\frac{\nu + (x - \mu/\sigma)^2}{\nu}\right]^{-(\nu+1/2)}. \tag{13}$$

4.2. The Daily Driving Mileage. The daily driving mileage of each trip follows Birnbaum–Saunders distribution, as presented in (14) [25], where$g(\cdot)$ is the Birnbaum–Saunders PDF, γ represents the shape parameter, and β is the scale parameter. Based on MLE, $\gamma = 0.95$ and $\beta = 10.15$.

The statistical data and the Birnbaum–Saunders fitting data are shown in Figure 4:

$$\begin{aligned} g(x \mid \beta, \gamma) = {} & \frac{1}{\sqrt{2\pi}} \left\{ \exp\left[-\frac{((\sqrt{x/\beta}) - (\sqrt{x/\beta}))^2}{2\gamma^2} \right] \right\} \\ & \cdot \frac{((\sqrt{x/\beta}) + (\sqrt{x/\beta}))}{2x\gamma}. \end{aligned} \tag{14}$$

4.3. EVs' Initial State of Charge. The SOC_0 that will be needed to track the battery's state of charge can be calculated by equation (15), where C_{arr}^i represents the arrival capacity of the i th EV, d is the daily driving mileage (km), and ξ^i is the consumption of the i th EV (kWh/km).

The SOC_0 has the same probability distribution function as the daily driving mileage, with $\gamma = 0.95$ and $\beta = 90.48$.

Figure 5 illustrates the real data curve and the Birnbaum–Saunders fitting curve:

$$\begin{aligned} C_{\mathrm{arr}}^i &= C_{\max}^i - d * \xi^i, \quad \forall i, d, \\ \mathrm{SOC}_0^i &= \frac{C_{\mathrm{arr}}^i}{C_{\max}^i}, \quad \forall i, d. \end{aligned} \tag{15}$$

4.4. EVs' Energy Demand. The EVs' energy demand may be forecasted based on the EV owners' behaviour. Nevertheless, the EV owners' behaviour is a random factor. Hence, the good knowledge of this factor gives more reliability to the predicted EVs' energy demand. For this reason, the EVs' arrival/departure time and the EVs' daily driving mileage have been presented and fitted by different PDFs. Therefore, the estimated energy demand

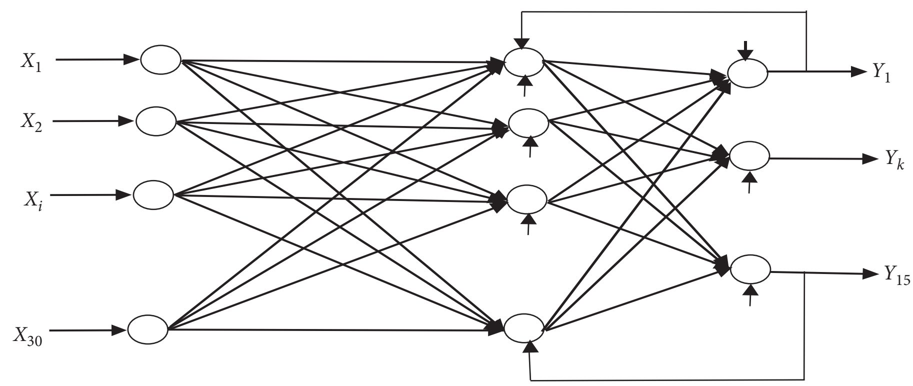

Figure 2: Training BPNN structure.

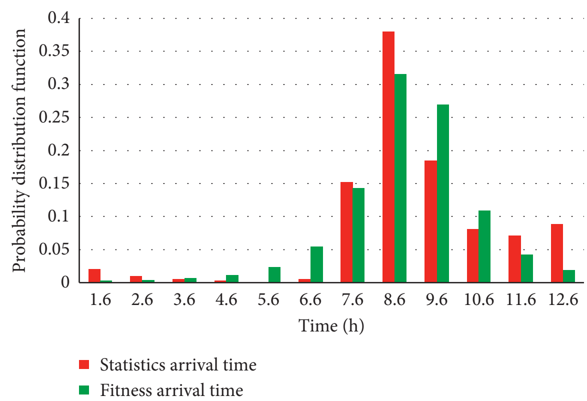

Figure 3: The EVs' arrival time at WCS.

may be calculated based on the fitness data, as well as the statistical data can be used to calculate the real energy demand.

The EVs' energy demand is calculated by equations (16)–(18) for both cases, where d is the travel distance (km):

(i) The EVs' number that travels the distance (d) is

$$N_d = N * g_d(x \mid \beta, \gamma), \quad d = 3, 6, 9, \ldots, 78. \tag{16}$$

(ii) The EVs' number that arrives at WCS at time t is

$$N_t = N_d * g_t(x \mid \mu, \sigma, \nu), \quad t = 1.6, 2.6, \ldots, 12.6. \tag{17}$$

(iii) The EVs' energy demand at time t is

$$E_d = N_t * d * \xi^i, \quad \forall d, t. \tag{18}$$

Figures 6 and 7 show the EVs' estimated and real energy demand. The peak energy demand corresponds to 8.6 h, as most EVs arrive to WCS at this time. The power demand value during the peak is equal to 3.48 kW and 4.24 kW for the estimated and the real energy demand, respectively; this difference is due to the error between the fitness and statistical data.

5. Implementation of the Optimization

5.1. Monte Carlo Sampling Methods. The Monte Carlo sampling methods (MCS) are a stochastic simulation method used for simulating the behaviour of uncertain parameters. This method can provide highly accurate results by giving a large sample size. In the MCS method, K variables $[y_1, y_2, \ldots, y_K]$ are selected randomly, and the average output value is calculated:

$$\widehat{y_K} = \frac{1}{K}\sum_{j=1}^{K} y_j. \tag{19}$$

For those uncertainties parameters described in Section 4, we use MCS to predict the WCS owner and the EV user profits and then compare them with the profits generated by using the real parameters.

5.2. Solving the Optimization Problem. The problem is nonconvex due to integer variables, and some constraints

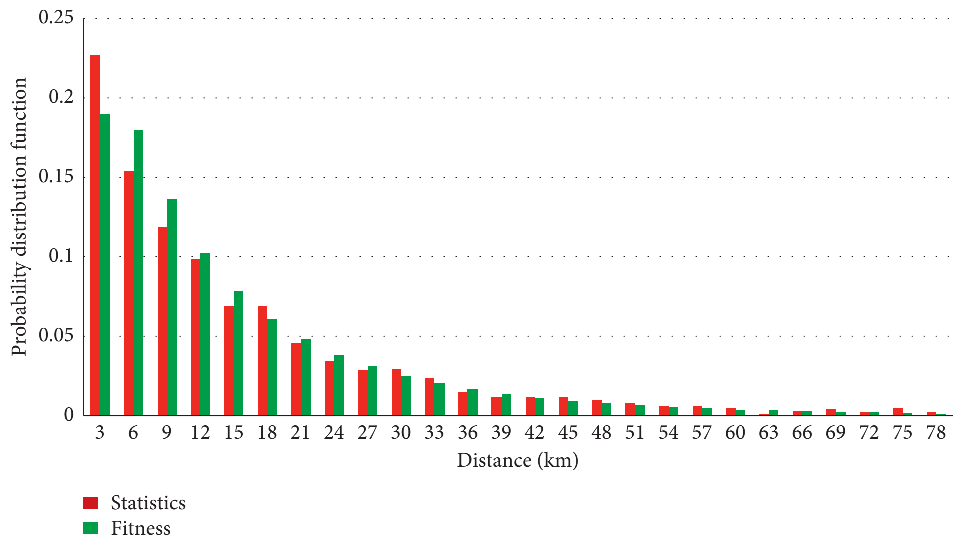

FIGURE 4: EVs' daily driving mileage per trip (km).

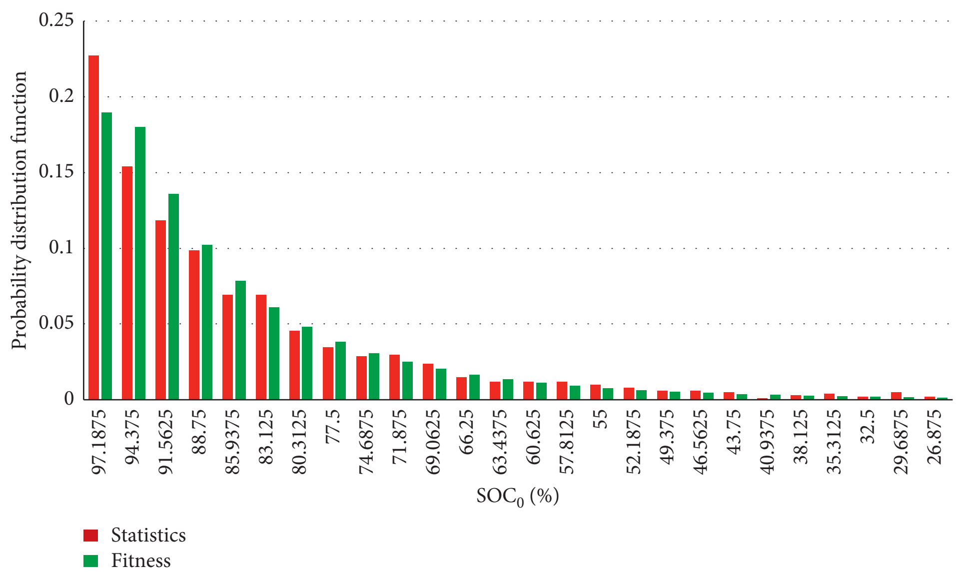

FIGURE 5: EVs' initial state of charge.

include binary variables. For this reason, mixed-integer linear programming (MILP) is chosen to solve the optimization problem. The Intlinprog tool provided by MATLAB has been used to solve the optimization problem in equation (1). Moreover, the Monte Carlo sampling methods have been applied to handle the arrival, departure time, and SOC_0. The optimal charging algorithm explains in more detail the process of the proposed strategy (Algorithm1).

5.3. Basic Data. The proposed optimization model has been examined under many uncertainties, such as EVs' arrival time at the WCS, EVs' departure time from the WCS, initial state of charge, and EVs' energy demand described in Section 4. The MCS is applied to handle the EV user behaviour uncertainties. Besides, the optimal strategy is compared to the uncoordinated charging, which still is the standard in many countries; hence, comparison between the proposed optimization model and the status quo will provide a clear view on the profit that the WCS owner can expect. Furthermore, realistic input parameters and appropriate price mechanisms need to be selected, which is the reason why the UK DAEP for January workday from [26] is adopted in the simulation. We also assume that the $\lambda_{V2G,t}$ and $\lambda_{\mathrm{PV2G},t}$ are 10% lower than $\lambda_{G2V,t}$ [16, 27]. Moreover, we defined $\lambda_{\mathrm{PV2V},t}$ in the objective function implying that PV power generation is not free. However, most works have ignored $\lambda_{\mathrm{PV2V},t}$ under the assumption that it is the incremental cost [28, 29]. Therefore, $\lambda_{\mathrm{PV2V},t}$ is assumed to be close to zero in this paper ($\lambda_{\mathrm{PV2V},t} = 0.097$ €/kWh [22]). The battery degradation price has been taken from the measurement-based prediction laboratory [30], and it is

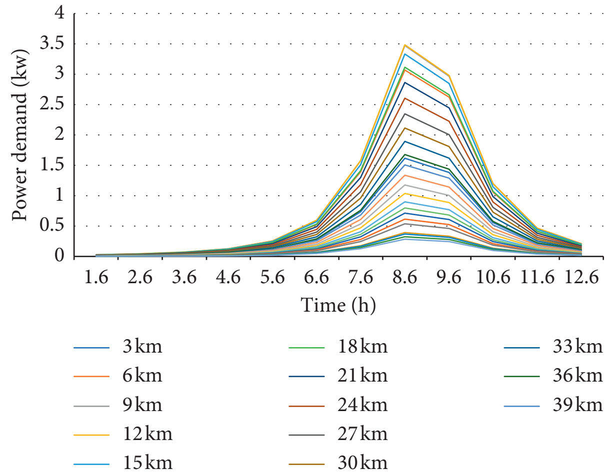

Figure 6: EVs' estimated energy demand.

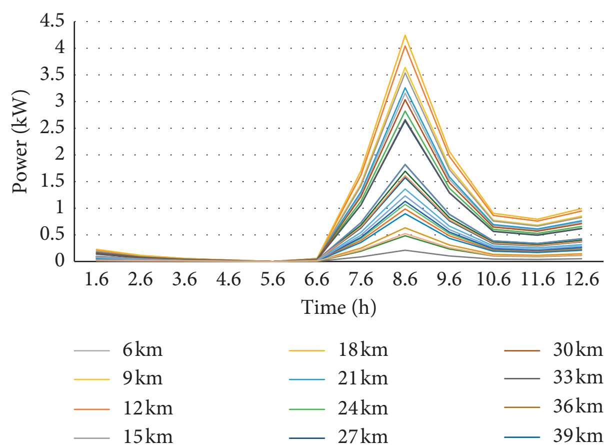

Figure 7: EVs' real energy demand.

equal to 0.032 €/kWh. The other parameter values applied in the optimization model are listed in Table 1.

6. Results

Figure 8 shows the PV forecasted energy, actual energy, and predicted error. It can be noticed that the generated error using the BPNN is small enough to adopt the PV forecasted power into the simulation.

To evaluate the efficiency of the proposed optimal charging algorithm, two scenarios have been considered, including uncoordinated and coordinated charging. It has been assumed that the PV power system and the grid are the principal suppliers to the WCS for both scenarios. The EVs' arrival, departure time, EVs' SOC_0, and EVs' energy demand have been presented in Section 4.

Figures 9 and 10 present the results of the uncoordinated charging policy and the optimal charging strategy proposed in this paper, respectively. There are at least three points of interest. First, the EVs charge their batteries as soon as they arrive at WCS and discharge at the time where the electricity price is low in the uncoordinated case. This is the opposite of what can be considered optimal charging. Hence, the WCS profit will be decreased. Second, we can see from Figure 10 that the EVs have discharged when the electricity price is high and charged when the DAEP is low. Therefore, we can conclude that the proposed algorithm plays alongside the WCS owner and increase the WCS profit. Finally, the PV power generation surplus during the day is fed into the grid, consequently, increasing the WCS profit. The estimated results of the WCS owner profit and the EV user compensation for uncoordinated and coordinated charging are illustrated in Table 2. The WCS owner profit and the EV user compensation have been increased by 54% and 50.7%, respectively, compared with uncoordinated charging.

To assess the credibility of the proposed algorithm, the real and the estimated results have been evaluated, where the fitted data of EV user behaviour has been exploited in the estimated results, while the real results have used the statistical data of the EV user behaviour. Figures 9 and 11 illustrate the estimated and real results of uncoordinated charging, and it can be noticed that the EVs charge their batteries in the morning and discharge it when the electricity price is low. The values of the EVs' charging/discharging

(1) **INPUT**: The utility begain by:
Forecasting the PV power generation.
Acquire t_{arr}, $C^i_{\max}$, d, ξ^i, $C_{\deg}$, N, $P^i_{\max}$, $P^{\max}_{\text{grid}}$, λ_{PV2V}, λ_{G2V}, and the number of MCS iteration K.
(2) OUTPUT: At each time step $t = 1, 2, 3, \ldots, T$ the power output profile
$\mathbf{P_{PV-V}} = (P_{PV-V,1}, P_{PV-V,2}, \ldots, P_{PV-V,T})$
$\mathbf{P_{grid-V}} = (P_{\text{grid}-V,1}, P_{\text{grid}-V,2}, \ldots, P_{\text{grid}-V,T})$
$\mathbf{P_{V-G}} = (P_{V-G,1}, P_{V-G,2}, \ldots, P_{V-G,T})$
$\mathbf{P_{PV-G}} = (P_{PV-G,1}, P_{PV-G,2}, \ldots, P_{PV-G,T})$
(3) **PROCEDURE:**
(4) **for** $i = 1$ to N **do**
(5) Pick t_{arr}
(6) **for** $j = 1$ to K **do**
(7) $C^i_{\text{arr}\,j} = C^i_{\max} - \xi * d_j$
(8) $\text{SOC}^i_{0j} \longleftarrow (C^i_{\text{arr}\,j}/C^i_{\max})$
(9) **Optimize**
(10) $\min \sum_{t=1}^{T} \sum_{i=1}^{N} [\lambda_{PV2V,t} P^i_{PV-V,t} + \lambda_{G2V,t} P^i_{\text{grid}-V,t} - (\lambda_{V2G,t} - C_{\deg}) P^i_{V-G,t} - \lambda_{PV2G,t} P_{PV-G,t}]\Delta t$

$$\text{s.t.} \begin{cases} \text{EVs constraints} \\ \text{PV system constraints} \\ \text{Grid constraints} \end{cases}$$

(11) **end for**

$$\begin{cases} P^i_{PV-V,t} = (1/K)\sum_{j=1}^{K} P^j_{PV-V,t} \\ P^i_{G-V,t} = (1/K)\sum_{j=1}^{K} P^j_{G-V,t} \\ P^i_{V-G,t} = (1/K)\sum_{j=1}^{K} P^j_{V-G,t} \\ P_{PV-G,t} = (1/K)\sum_{j=1}^{K} P^j_{PV-G,t} \end{cases}$$

(12) **end for**
(13) $\mathbf{P_{PV-V}} \longleftarrow \sum_{i=1}^{N} P^i_{PV-V,t}$
(14) $\mathbf{P_{G-V}} \longleftarrow \sum_{i=1}^{N} P^i_{G-V,t}$
(15) $\mathbf{P_{V-G}} \longleftarrow \sum_{i=1}^{N} P^i_{V-G,t}$
(16) $\mathbf{P_{PV-G}} \longleftarrow P_{PV-G,t}$

Algorithm 1: The optimal charging algorithm.

Table 1: The optimization model parameters.

Parameters	Symbol	Value
EVs' number	N	50
Battery degradation cost	C_{bat}	0.032
DAEP	$\lambda_{G2V,t}$	Dynamic
Electricity price from EV to grid	λ_{V2G}	Dynamic
Electricity price from PV to grid	λ_{PV2G}	Dynamic
The incremental cost of the PV	λ_{PV2V}	0.097
Maximum EVs' charger	$P^i_{\max}$	6.6
EV charging and discharging efficiency	$\eta_{\text{ch}}, \eta_{\text{dis}}$	90, 90
EVs' maximum capacity	$C^i_{\max}$	24
Maximum state of charge	$\text{SOC}_{\max}$	80
Minimum state of charge	$\text{SOC}_{\min}$	20
DC-DC converter efficiency	η_{MPPT}	98
Inverter efficiency	η_{inv}	98
Maximum power transfer from the grid to the EVs	$P^{\max}_{\text{grid}}$	200
EVs' consumption	ξ^i	0.17
The number of MCS iteration	K	5000

power and the grid-EVs' power in Figure 9 are different from those in Figure 11. Furthermore, Figures 10 and 12 show the estimated and the real results of the coordinated charging, where the real results are slightly different from the estimated results. The difference between the estimated and the real results for both uncoordinated and coordinated charging is due to the error generated by fitting the EVs user behaviour data.

In Table 2, the EV user compensation and the WCS profit for uncoordinated and coordinated EVs' charging are shown. The estimated EV user compensation and WCS profit generated by uncoordinated charging are 1.4% and

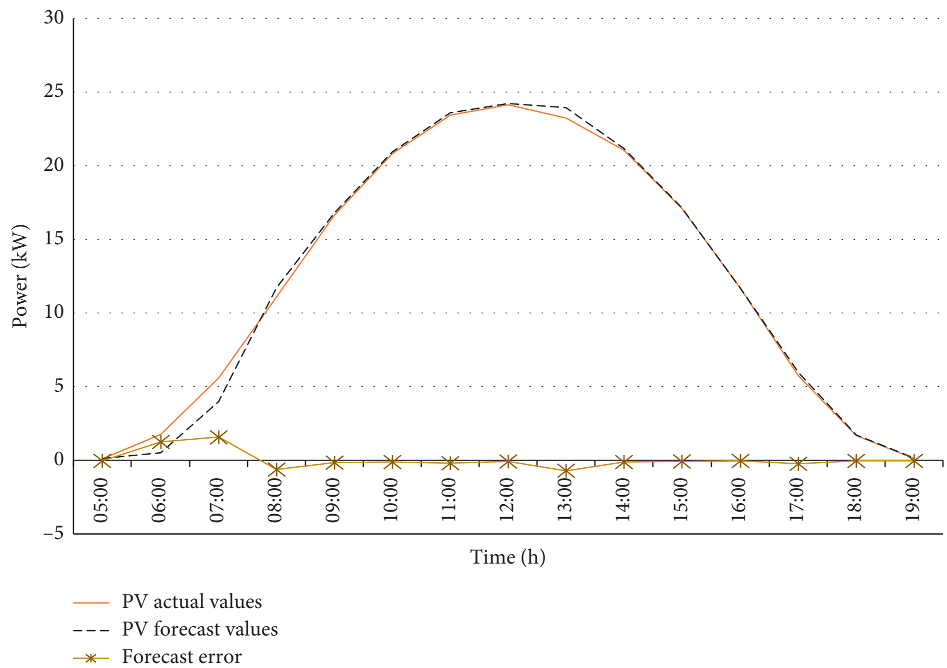

FIGURE 8: Forecasted and actual PV power generation.

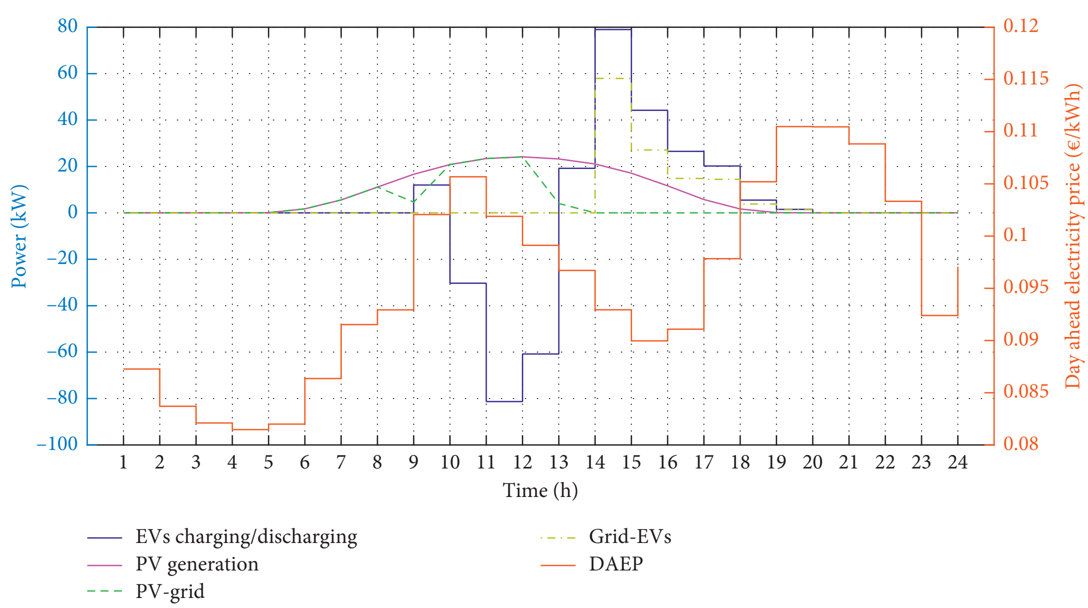

FIGURE 9: Uncoordinated EVs' charging with PV power generation (estimated results).

9.27%, respectively, higher than the profits using the real user behaviour data. However, the estimated EV user compensation and WCS profit generated by coordinated charging are 1.35% and 1.72%, respectively, higher than the profits using the real user behaviour data. The error generated by using the fitness data and the statistical data of the EV user behaviour for the proposed optimal charging strategy is small. Therefore, the WCS owner can apply the optimal charging strategy proposed in this paper with the EV user behaviour fitness data to have a clue about the profit that can make and the EV user compensation.

7. Conclusion

In this work, we proposed an optimal charging strategy in mixed-integer linear programming (MILP) framework, which allows to plan the EVs' power allocation for each hour while taking the EV user behaviour into account. The aim is to maximize the WCS owner profit while compensating the

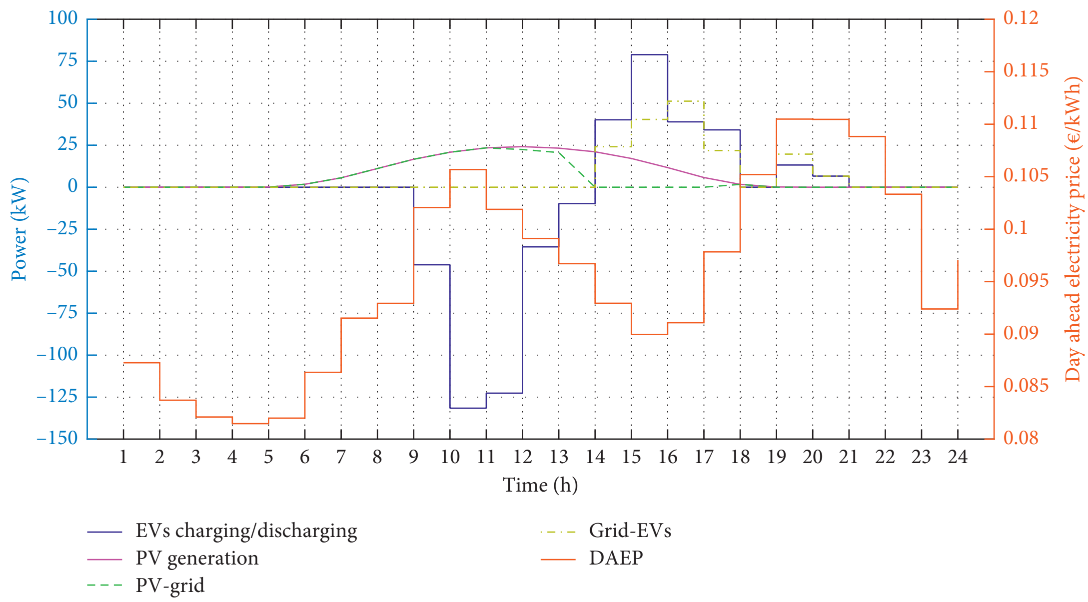

FIGURE 10: Coordinated EVs' charging with PV power generation (estimated results).

TABLE 2: EV user compensation and WCS owner profit by coordinated and uncoordinated charging.

	EV users Profit (€)	WCS profit (€)
Estimated uncoordinated charging (MCS)	5.45	12.51
Real uncoordinated charging	5.37	11.35
Estimated coordinated charging (MCS)	11.06	27.31
Real coordinated charging	10.91	26.84

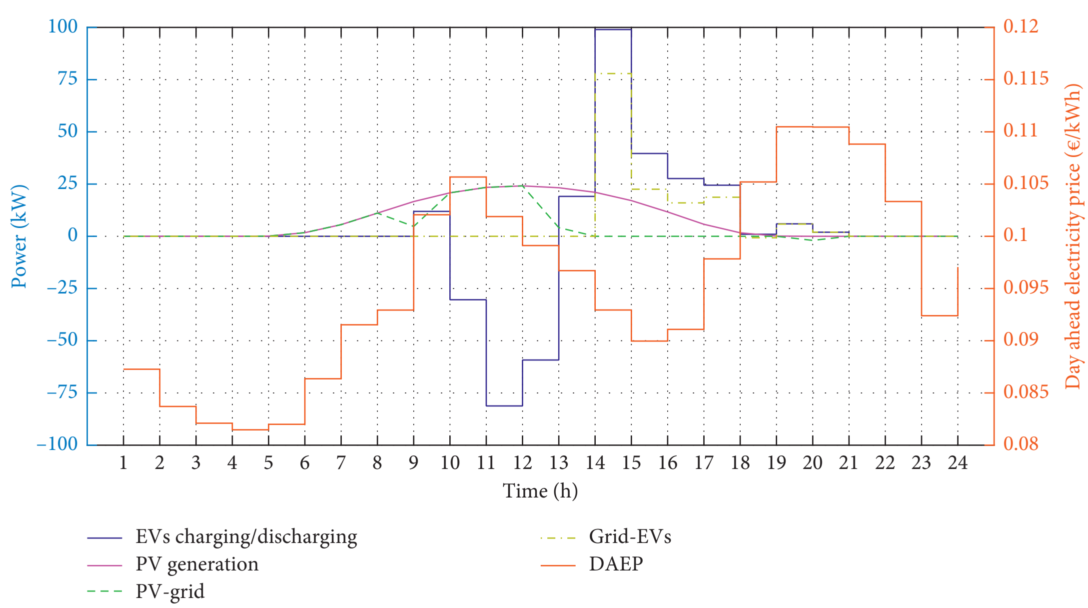

FIGURE 11: Uncoordinated EVs' charging with PV power generation (real results).

EV users for discharging their EVs. The PV power generation has been predicted by the backpropagation neural network model, and the EV user behaviour uncertainties are modeled with parametric probability density functions, while Monte Carlo simulation methods have been applied to handle the EV user behaviour uncertainties. The results

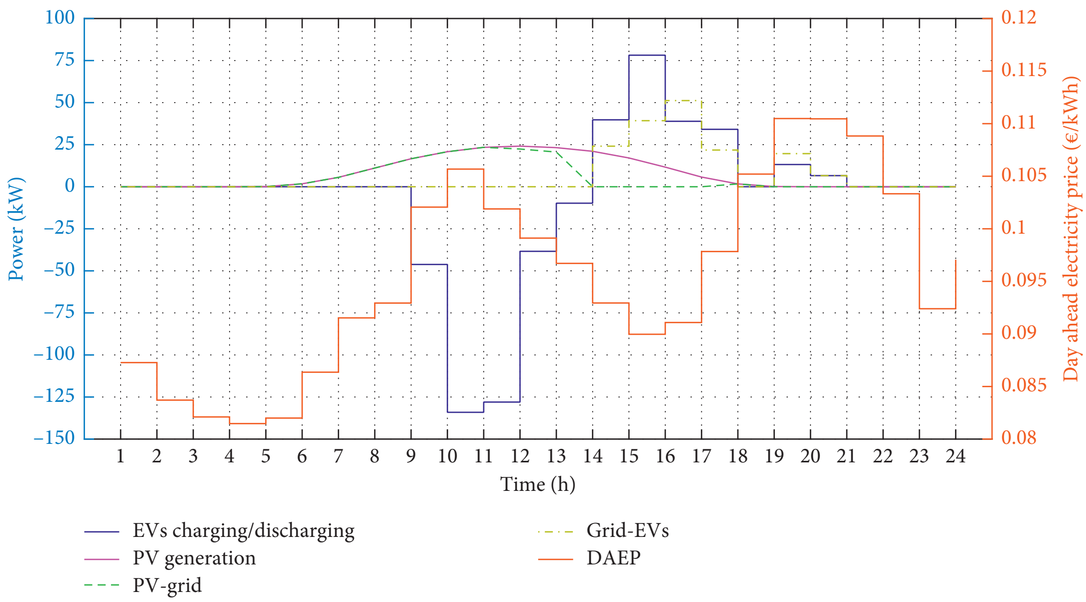

Figure 12: Coordinated EVs' charging with PV power generation (real results).

illustrate that the proposed optimal charging strategy increases the WCS owner profit and the EV users compensation by 54% and 50.7%, respectively, compared with uncoordinated charging. Moreover, the estimated WCS owner profit and the EV user compensation generated by coordinated charging are 1.72% and 1.35%, respectively, higher than the profits using the real user behaviour data. The error generated by using the fitted data and the statistical data of the EV user behaviour for the proposed optimal charging strategy is small. Hence, the WCS owner can apply the optimal charging strategy proposed in this work with the EV user behaviour fitted data to predict the profit that can make and the EV user compensation.

The following step in our research is to forecast the electricity price. Furthermore, as the output of any PV system is inherently uncertain, probabilistic PV power generation forecasting has to be considered. Incorporating these assumptions, the WCS owner profit and the EV user compensation would be accurately predicted. Moreover, the energy storage system might be included which will raise the WCS owner profit.

Nomenclature

T: Set of time period, $t \in T$
N: Set of electric vehicles
K: Set of Monte Carlo simulation
i: Number of EVs available for charging/discharging, $i \in N$
j: Number of Monte Carlo simulation iteration, $j \in K$
$P^i_{\max}$: Maximum EV charger power labelled i
$P^{\max}_{\text{grid}}$: Maximum power transfer from the grid to EVs (kW)
$\text{SOC}_{\max}$: Maximum state of charge (%)
$\text{SOC}_{\min}$: Minimum state of charge (%)
$\eta_{\text{ch}}, \eta_{\text{dis}}$: EV charging and discharging efficiency, respectively (%)
η_{MPPT}: DC-DC converter efficiency (%)
η_{inv}: Inverter efficiency (%)
C_{deg}: Battery degradation cost in (€/kWh)
$C^i_{\max}$: EVs' maximum capacity (kWh)
ξ^i: EVs' consumption (kWh/km)
$\lambda_{\text{PV2}V,t}$: Incremental cost of the PV energy at time t (€/kWh)
$\lambda_{G2V,t}$: Day-ahead electricity price (€/kWh)
$\lambda_{V2G,t}$: Electricity price of the power transferred from i th EV to grid (€/kWh)
$\lambda_{\text{PV2}G,t}$: PV energy cost transferred from PV to the grid (kWh)
$P^i_{\text{PV}-V,t}$: PV power transferred to i th EV during time t (kW)
$P^i_{\text{grid}-V,t}$: Power transfer from the grid to the EV labelled i (kW)
$P^i_{V-G,t}$: Power transferred from i th EV to grid (kW)
$P_{\text{PV}-G,t}$: Power transfer from the PV system to the grid during time t (kW)
$P^i_{\chi-V,t}$: Power transfer from the PV or the grid to the i th EV at time t (kW)
u^i_t: Binary variable that states whether the EV labelled i is charging (1) or not (0) at time t
v^i_t: Binary variable that states whether the i th EV is discharging (1) or not (0)
w^i_t: Binary variable that prevents drawing power from grid while feeding power into grid $\{0, 1\}$.

Data Availability

All data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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