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Decentralized V2G/G2V Scheduling of EV Charging Stations by Considering the Conversion Efficiency of Bidirectional Chargers

Jian-Tang Liao [1], Hao-Wei Huang [1], Hong-Tzer Yang [1,*] and Desheng Li [2,3]

[1] Department of Electrical Engineering, National Cheng Kung University, Tainan 701, Taiwan; z10408115@email.ncku.edu.tw (J.-T.L.); n28081056@ncku.edu.tw (H.-W.H.)
[2] State Key Laboratory of Automotive Safety and Energy, Tsinghua University, Beijing 100084, China; desheng.li@wanbangauto.com
[3] National Innovation Center of Energy and Information for N.E.V. Ltd., Nanjing 210000, China
* Correspondence: htyang@mail.ncku.edu.tw

Abstract: With a rapid increase in the awareness of carbon reduction worldwide, the industry of electric vehicles (EVs) has started to flourish. However, the large number of EVs connected to a power grid with a large power demand and uncertainty may result in significant challenges for a power system. In this study, the optimal charging and discharging scheduling strategies of G2V/V2G and battery energy storage system (BESS) were proposed for EV charging stations. A distributed computation architecture was employed to streamline the complexity of an optimization problem. By considering EV charging/discharging conversion efficiencies for different load conditions, the proposed method was used to maximize the operational profits of each EV and BESS based on the related electricity tariff and demand response programs. Moreover, the behavior model of drivers and cost of BESS degradation caused by charging and discharging cycles were considered to improve the overall practical applicability. An EV charging station with 100 charging piles was simulated as an example to verify the feasibility of the proposed method. The developed algorithms can be used for EV charging stations, load aggregators, and service companies integrated with distributed energy resources in a smart grid.

Keywords: battery degradation; charging and discharging scheduling; conversion efficiency; demand response; electric vehicle; optimization; vehicle-to-grid and grid-to-vehicle (V2G/G2V)

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1. Introduction

The rapid development of an electric vehicle (EV) industry has provided new economic and environmental benefits. However, the charging of numerous EVs undoubtedly imposes an additional burden on a power grid [1,2]. For a large-scale EV parking lot, solving problems of power usage security and cost management is crucial. Appropriate charging/discharging timing and quantity should be scheduled according to drivers' behavior to satisfy user demands and to prevent the violation of the contract capacity.

An EV parking lot that integrates numerous EVs is highly similar to an energy storage system (ESS), which can be used not only to select more economical charging periods but also to form an aggregator to participate in demand–response (DR) markets. The energy management system (EMS) of the aggregator should provide profits and assist power system operators in regulating system frequency through both vehicle-to-grid (V2G) and grid-to-vehicle (G2V) modes [3–6].

Some main problems, namely the collaboration of multi EVs, stochastic uncertainty, and integrated management with renewable energies (REs), must be overcome to resolve the charging and discharging scheduling of an EV parking lot. When only a few EVs are available, the scheduling problem is not substantially complicated. The owners of EV parking lots can earn profits by charging in low-price periods and discharging with higher price. However, when the number of EVs increases, the power rating of a power supply may exceed if all EVs charge or discharge simultaneously.

Methods for the charging/discharging scheduling of EVs can be divided into two categories, centralized [7] and decentralized management architectures [8]. In existing scheduling optimization algorithms, centralized scheduling methods are the most common, which are used to realize the coordination of multiple EVs. The results obtained from centralized scheduling methods are usually satisfactory when the overall system is considered. However, the dimensions of an optimal scheduling problem increase with the EV number leading to computational complexity. For example, assume that the duration of each time slot of the scheduling problem is 15 min, which means that there are 96 points of charging/discharging power at each time slot to be decided for one EV in the 24-h scheduling problem (worst case). Since the charging station considered in this paper has 100 charging piles, the dimension of the centralized architecture achieves 96 $\times$ 100 = 9600, namely, 9600 decision variables to be determined, which may result in the converging issues in the optimization process also with more computational time needed.

By contrast, the decentralized scheduling optimization method mainly adopts a multi-agent concept, which is used to make decisions based on the conditions of the dispersed environment and system parameters, such as the behavioral preferences of drivers and charging infrastructure. Thus, the problem of computational time can be effectively resolved. Based on the same condition of decentralized method with 100 charging piles, the charging and discharging power scheduling can be divided into 100 sub-optimization problems, each of which has 96 decision variables parallelly determined via the decentralized architecture. As the iteration is completed, only the system constraints are checked and moderate adjustments made. The optimization problem is thus greatly simplified with the computational time largely reduced.

In [7], the day-head, hourly, and real-time scheduling programs are integrated to manage the charging and discharging power of charging stations. Reference [9] adopts a multi-objective method to make the EV charging and discharging more cost-effective by considering both economy and user's preference. To further improve the operational profit of charging stations, reference [10] proposes the admission control mechanism and formulates the scheduling process as a deadline-constrained causal scheduling problem. In [11], a search-swapping algorithm (SSA) is proposed for optimal approximation. Besides, a single-round interactive protocol is designed for hierarchical coordinated framework for the power dispatch.

In addition, stochastic uncertainty is another problem faced during the scheduling of EV parking lots, including variations in the real-time electricity tariff and the arrival and departure times of EVs. Generally, an EMS depends on forecasting systems and schedule accordingly. Some EMSs of EV parking lots adopt day-head scheduling [12,13], which includes a cancelation penalty [12] for users to relieve the influence on profits caused by the uncertainty when users change their original arrival or departure schedules. Simultaneously, an event-driven [13] manner, which is used to reschedule the charging and discharging times only if a new task is activated or an original plan is changed, is proposed for overcoming the uncertainty problem. These types of approaches [12,13] remain considerably dependent on the prediction accuracy in practice. The scheduling performance may deteriorate if forecasting errors are large or an unexpected event occurs. In particular, some applications of EV parking lots are proposed recently, which have been integrated with REs [14–17] or used in the electricity market to provide ancillary services [18]. These uncertainties from REs and the electricity market may make this problem more serious.

An RE-integrated EMS employed in [14–17] has adopted the moving sliding-window concept, which is called receding horizon model predictive control (RHMPC) [16] or rolling horizon [17], to enhance the adaptability of scheduling algorithms. In the RHMPC, the scheduling window moves with time. Every time when the window moves, the scheduling algorithm is re-executed according to latest forecasting results to ensure that scheduling results satisfy the conditions of system operations to a possible extent.

In the discussion on structure of the optimization problem, reference [8] verifies the effectiveness of decentralized methods in saving computing burden. Additionally, reference [19] designs a hybrid centralized–decentralized charging control scheme which shows that the decentralized algorithm can lower the communication load between the EVs and the system controller. In [20], a new metric system is proposed to represent the EV user satisfaction fairness. A trade-off between the user satisfaction fairness and the total cost of electricity for charging can thus be achieved. Reference [5] introduces the concept of microgrid control, employing a decentralized method to set the suitable power point of individual EV to avoid violating the constraints of the low-voltage (LV) grids.

The application of moving sliding-window is necessary for the stochastic characteristics of vehicle drivers. The smaller is the moving step of sliding windows, which is usually a time slot, the higher is the real-time adaptability. However, the computational time of the scheduling algorithm must be less than that of the moving step; otherwise, the moving sliding-window approach cannot work. Consequently, the real-time adaptability of EMSs and EV amount, which can be simultaneously managed, conflict with each other.

Additionally, in the literature, the conversion efficiency of EV charging piles has been assumed to be a constant or has not been considered. The conversion efficiency of power electronic converter and its power output exhibit a nonlinear relationship [21,22]. The optimal conversion efficiency often occurs at 50–60% of the rated power. Therefore, when the conversion efficiency is not properly considered, additional losses may be caused. Moreover, the frequent charging/discharging of batteries may lead to battery degradation. Therefore, factors influencing the lifecycle of EV batteries should be evaluated. The modeling of battery degradation has been introduced in [23,24] and applied to the proposed optimization problem.

In addition, studies [25,26] have proposed a household energy-management system to dispatch renewable energy and EVs to participate in the DR market, which is beneficial to relieve the pressure of power systems and earn profits for users. EV charging parking lots have large-scale energy-storage resources until the number of idle vehicles present in the parking lot remains higher than a certain degree, which may provide a higher potential to earn profits by participating in the DR market.

In this study, an energy management algorithm was proposed for a large EV charging parking-lot with 100 charging piles. To reduce the unexpected cost caused by forecasting errors and the stochastic characteristics of users, the moving sliding-window method [27] was adopted to reschedule periodically according to the real-time information. The proposed method employed the decentralized scheduling optimization method to alleviate the computational complexity, achieve the power dispatch, and further reduce electricity cost by participating in the DR market. The proposed approach was used to substantially reduce the computational time to satisfy the operation requirements of the moving sliding-window model. In the proposed approach, each EV exhibited its own individual scheduling time window. The integration of decentralized optimization method and RHMPC concept [16] was thus beneficial for enhancing the real-time adaptability of EMSs and number of manageable EVs. In particular, the conversion efficiencies of EV charging piles were considered in scheduling optimization for improving total operational benefits.

The remainder of this paper is organized as follows. Section 2 introduces the overall system architecture. Section 3 presents the proposed scheduling strategy and optimization algorithm. Section 4 provides simulation results and associated discussions. Section 5 presents conclusions.

2. System Architecture and Operation

2.1. System Architecture

The scheduling scheme proposed for EV charging stations can be mainly divided into three levels, namely power utility level (PUL), central control level (CCL), and local control level (LCL) (Figure 1). The functions and operational contents of the three levels are as follows.

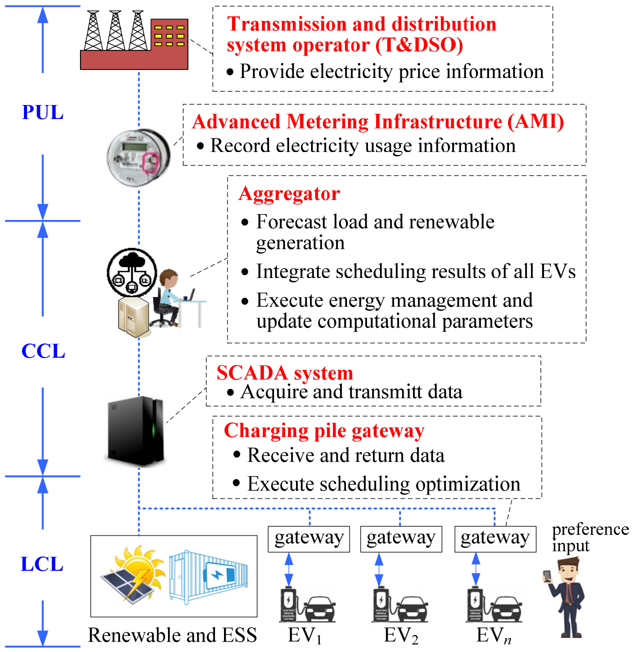

Figure 1. Architecture of an electric vehicle (EV) charging parking lot system.

PUL: A power system operator (SO) provides electricity pricing information based on the conditions of power system dispatch. If the power grid encounters an emergency event or peak-load periods, PUL can launch a DR event. The related information may be transmitted using an automated metering infrastructure (AMI) or internet communication system.

CCL: All EVs and other distributed energy resources at EV charging stations are mainly managed using aggregators. As the decentralized-management architecture was adopted in this study, the optimization program was not performed in the CCL but in gateways for the individual charging piles of LCL (Figure 1). Aggregators only determine the virtual pricing signals (VPSs) [28] according to the total scheduling results.

LCL: A user interface (UI) must be provided to drivers for setting their preferences, such as expected leaving time and desired state of charge (SOC). Based on these preferences and VPS from aggregators, LCL is used to perform optimization in gateways to minimize the electricity cost and return scheduling results to the aggregator.

2.2. Management and Operation Process

Figure 2 illustrates the operation process, which can be divided into five steps, of the proposed decentralized optimization strategy. The contents of each step are as follows.

Step 1: A charging station operator, namely, the aggregator present in the CCL, is used to collect related system parameters, such as electricity pricing information, load forecasting, and solar power generation forecasting results. Additionally, the gateway of an edge computing device in each charging pile is used to acquire a user preference from the UI.

Step 2: The aggregator is used to decide the VPS according to the electricity demand and available capacity. The time-of-use (TOU) tariff accepted from the PUL is usually adopted as the VPS unless aggregator used prefers to avoid excessive charging or discharging power in some certain time periods. For example, the CCL may be used increase the VPS of peak-load periods to make the LCL tend to reduce charging at this period.

The adjusted factor of the VPS can be calculated using the ratio of a system net load and contract capacity, as shown in (1). Accordingly, the VPS at time t is expressed as (2).

$$f_t = \frac{P_{\text{net},t}}{P_{\text{concap}}} \tag{1}$$

$$VPS'_t = f_t \cdot VPS_t \tag{2}$$

Step 3: The LCL is individually used to perform optimal power scheduling for each EV based on VPS_t and send the results to the aggregator.

Step 4: The aggregator is used to schedule the charging and discharging power of ESSs according to the scheduling results obtained from all LCL units. Subsequently, determine whether total power consumption violates the power security constrains. If yes, go back to Step 2 to adjust the VPS. Otherwise, the scheduling process ends.

Step 5: Move the sliding-window, and go back to Step 1 for the next scheduling round.

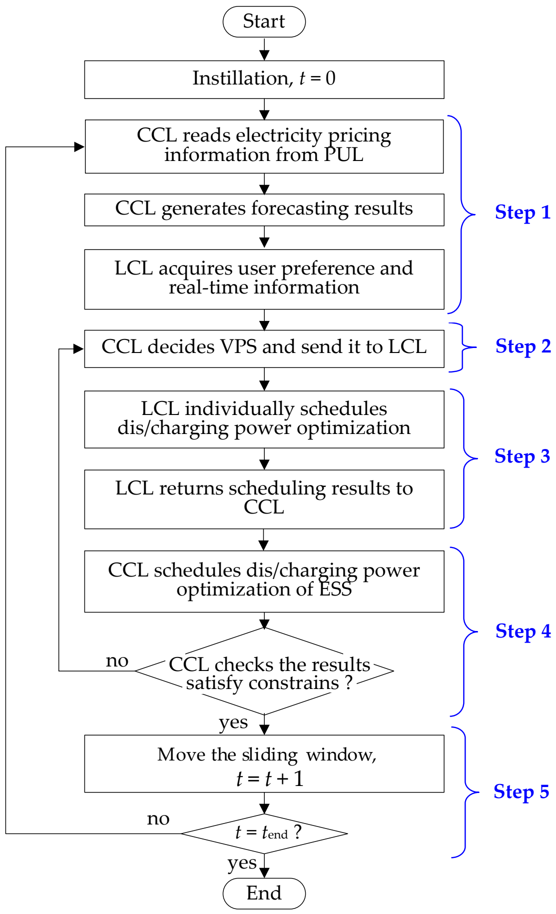

Figure 2. Flowchart of the proposed operation process.

2.3. *Moving Sliding Window of EVs*

As predicting the time of EV arrival is difficult, in this study, the moving sliding-window concept [21] was adopted to schedule EV charging and discharging power individually. The sliding window was used to move one time slot every time. At the beginning of each time slot, the control system was employed to confirm the EV number, the expected departure time of EVs, and their expected SOC. The optimization algorithm was then employed to schedule accordingly for each time slot.

Figure 3 illustrates the concept of moving sliding-windows. In the proposed method, the charging station does not predict the arrival time of EVs due to its uncertainty. However, once an EV arrives, the driver sets his/her expected departure time via a user interface. In this way, the EMS determines the scheduling time window, namely started from arrival time and ended at the expected departure time. The time windows are dynamically updated at each time step where the problem is re-scheduled as well. For example, the arrival and expected departure times of EV1 are at t = 28 and 33, respectively. Its scheduling dynamic window is thus represented as (28,33). When t = 29, the scheduling dynamic window of EV1 becomes as (29–33) and the optimization problem of power scheduling is re-executed again.

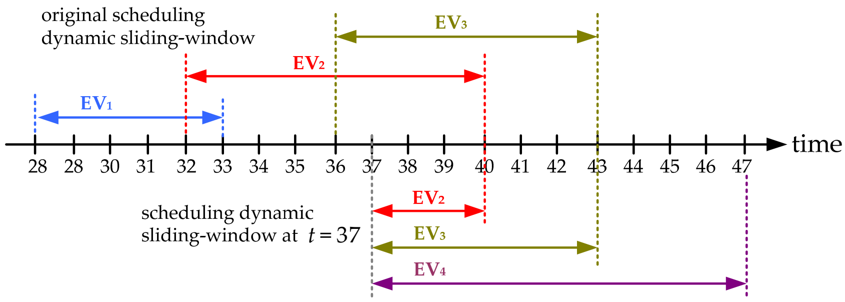

Figure 3. Moving sliding window at the 37th time slot.

Similarly, the original scheduling dynamic windows of EV2 and EV3 were set as (32, 40) and (36,43), respectively, according to Figure 3. When t = 37, the scheduling dynamic windows of EV2 and EV3 become as t_2 = (37,40) and t_3 = (37,43), respectively. At this moment, EV1 is not considered because left before. In addition, since EV4 arrives at t = 37, its scheduling dynamic window is set as (37,47) according to the expected departure time given by the driver.

2.4. Cash Flow of the Proposed Business Model

Figure 4 illustrates the relationship between the revenue and cost of the proposed scheme for EV charging stations. The aggregator was used to pay the electricity bill to power utility. If the aggregator participated in the DR market, it may obtain income from power utility. In addition, EV drivers should pay for charging piles. By contrast, if some drivers are willing to provide their EV batteries to the aggregator for participating in the related energy market as mentioned in [3–6]. the aggregator should share the profit with these EV drivers. Although payment from EV drivers to the aggregator may decrease because of the compensation from the aggregator, the additional cost of EV battery degradation may be caused by frequent charging and discharging operations. In the proposed method, the battery degradation cost was estimated and should be compensated using the aggregator.

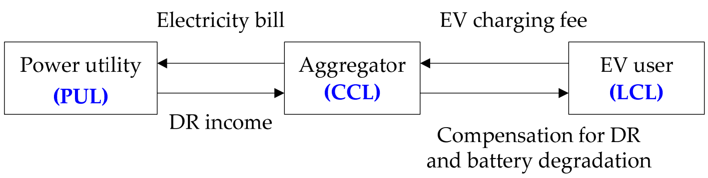

Figure 4. Cash flow of the proposed business model.

In addition to driver's incentives, there may still be some challenges when this business model is implemented, such as the credibility of power charging and discharging footprint, settlement, and the improvement of regulations, policies, and insurance. This article only conducts technical verification and discussion on the feasibility of the proposed method. In the future, progress and development at all aspects still require the cooperation of experts in various fields.

3. Proposed Scheduling Optimization Methods

3.1. Cost Minimization of EV in LCL

3.1.1. Objective Function

In this study, the decentralized optimization strategy was used and overall operational benefits were maximized from the perspective of the aggregator. An objective function, that is, to minimize the electricity cost of all EVs and consider the conversion efficiency of charging piles, is expressed in (3). The decision variable was the charging and discharging power, $p_{t,n}$, of the EV. Equations (4) and (5) express profits earned using the aggregator from users charging EVs and participating in the DR market, respectively.

The changing conversion efficiency of charging piles was considered. In addition, for encouraging users to participate in the DR market, aggregator was used to compensate the cost of battery degradation and share benefits earned from the DR market with users, as calculated in Equations (6) and (7) [5], respectively. The penalty factor is presented in (8) to prevent EV charging during DR periods.

$$\max \sum_{t}^{T} (I_{t,n}^{\mathrm{ch}} + I_{t,n}^{\mathrm{DR}} - C_{t,n}^{\mathrm{deg}} - C_{t,n}^{\mathrm{feedbk}} - C_{t,n}^{\mathrm{pen}}) \tag{3}$$

$$I_{t,n}^{\mathrm{ch}} = (\lambda_t^{\mathrm{chfee}} - \lambda_t^{\mathrm{TOU}}) \cdot p_{t,n}^{\mathrm{ch}} \cdot \eta \cdot \Delta t \tag{4}$$

$$I_{t,n}^{\mathrm{DR}} = \lambda_t^{\mathrm{DR}} \cdot p_{t,n}^{\mathrm{disch}} \cdot \eta \cdot \Delta t \tag{5}$$

$$C_{t,n}^{\mathrm{deg}} = C_n^{\mathrm{bat}} \cdot \left| \frac{m_n}{100} \right| \cdot \frac{p_{t,n}^{\mathrm{disch}} \cdot \Delta t}{B_n^{\mathrm{cap}}} \tag{6}$$

$$C_{t,n}^{\mathrm{feedbk}} = \lambda_t^{\mathrm{charfee}} \cdot p_{t,n}^{\mathrm{disch}} \cdot \Delta t \tag{7}$$

$$C_{t,n}^{\mathrm{pen}} = \lambda_t^{\mathrm{DR}} \cdot p_{t,n}^{\mathrm{ch}} \cdot \Delta t \tag{8}$$

3.1.2. Charging and Discharging Power Collaboration

With the adopted decentralized optimization architecture, the power input/output of EVs were scheduled individually. Thus, power security and reverse power-flow limitations may be violated because every EV user would charge or discharge power at their maximal convenience. In this study, to overcome these problems, EV charging and discharging priority indices, formulated as (9) and (10), were proposed. A higher value indicated a higher priority to charge or discharge. Accordingly, when the CCL determined total discharging power as negative (<0), the discharging power P_n^{disch} of each EV was assigned using (11).

3.1.3. Constraints

$$pri_{t,n}^{\mathrm{ch}} = \begin{cases} \frac{(SOC_n^{\mathrm{final}} - SOC_n^{\mathrm{ini}}) \cdot B_n^{\mathrm{cap}}}{(t_n^{\mathrm{dep}} - t_n^{\mathrm{arr}} + 1) \cdot \Delta t \cdot P_n^{\mathrm{max}}}, & \text{if } t_n^{\mathrm{arr}} \le t \le t_n^{\mathrm{dep}} \\ 0, & \text{other} \end{cases} \tag{9}$$

$$pri_{t,n}^{\mathrm{disch}} = \frac{1}{pri_{t,n}^{\mathrm{ch}}} \tag{10}$$

$$p_n^{\mathrm{disch}} = P^{\mathrm{V2G}} \cdot \frac{pri_{t,n}^{\mathrm{disch}}}{\sum_{n}^{N} pri_{t,n}^{\mathrm{disch}}} \tag{11}$$

The optimization of each EV scheduling problem must satisfy all the constraints expressed in (12)–(16). In (12), the property of EV power output indicates charging and discharging states. Moreover, the power output should be within security limits, as presented in (13). To avoid over-charge or over-discharge problems, the battery SOC was limited within an allowable range, as presented in (14). Furthermore, (15) shows that the SOC at any time slot should satisfy the physical behavior of batteries. Finally, the SOC at departure time should meet user preferences according to their requirements, as expressed in (16).

$$\begin{cases} p_{t,n}^{\text{ch}} = -p_{t,n}\ ,\ \text{if } p_{t,n} \leq 0 \\ p_{t,n}^{\text{disch}} = p_{t,n}\ ,\ \text{if } p_{t,n} > 0 \end{cases} \tag{12}$$

$$-P_n^{\max} \leq p_{t,n} \leq P_n^{\max} \tag{13}$$

$$SOC_n^{\min} \leq SOC_{t,n} \leq SOC_n^{\max} \tag{14}$$

$$SOC_{t+1,n} = SOC_{t,n} + \frac{p_{t,n}^{\text{ch}} \cdot \eta_n^{\text{ch}} \cdot \Delta t}{B_n^{\text{cap}}} - \frac{p_{t,n}^{\text{disch}} \cdot \Delta t}{B_n^{\text{cap}} \cdot \eta_n^{\text{disch}}} \tag{15}$$

$$SOC_{T,n} = SOC_n^{\text{final}} \tag{16}$$

3.2. Cost Minimization of ESS in LCL

3.2.1. Objective Function

The operational cost of the ESS was minimized based on the objective function, (17). Charging and degradation costs were calculated using (18) and (19), respectively. In this optimization problem, the output power, $p_{\text{ess},t}$, of the EV charging pile was the decision variable.

$$\min \sum_t^T (C_{\text{ess},t}^{\text{ch/disch}} + C_{\text{ess},t}^{\text{deg}}) \tag{17}$$

$$C_{\text{ess},t}^{\text{ch/disch}} = -\lambda_t^{TOU} \cdot p_{\text{ess},t} \cdot \Delta t \tag{18}$$

$$C_{\text{ess},t}^{\text{deg}} = C_{\text{ess}}^{\text{bat}} \cdot \left| \frac{m_{\text{ess}}}{100} \right| \cdot \frac{|p_{\text{ess},t}| \cdot \Delta t}{B_{\text{ess}}^{\text{cap}}} \tag{19}$$

3.2.2. Constraints of the BESS

The constraints of the BESS integrated with EV charging station observed in the power scheduling optimization problem are expressed as (20)–(24). The power output of the BESS, $p_{\text{BESS},t}$, was limited using (20), where a positive value indicated discharging and vice versa. Moreover, the SOC of BESS should satisfy the limits of (21) and (22). For easy comparisons, the final SOC was assumed to be consistent with the initial SOC, as expressed in (23). To maintain power usage security and prevent reverse power flow, the total power consumed using the grid of the whole EV parking-lot charging system should satisfy (24).

$$|p_{\text{ess},t}| \leq P_{\text{ess}}^{\max} \tag{20}$$

$$SOC_{\text{ess}}^{\min} \leq SOC_{\text{ess},t} \leq SOC_{\text{ess}}^{\max} \tag{21}$$

$$SOC_{\text{ess},t+1} = SOC_{\text{ess},t} + \frac{p_{\text{ess},t}^{\text{ch}} \cdot \eta_{\text{ess}}^{\text{ch}} \cdot \Delta t}{B_{\text{ess}}^{\text{cap}}} - \frac{p_{\text{ess},t}^{\text{disch}} \cdot \Delta t}{B_{\text{ess}}^{\text{cap}} \cdot \eta_{\text{ess}}^{\text{disch}}} \tag{22}$$

$$SOC_{\text{ess}}^{\text{ini}} = SOC_{\text{ess}}^{\text{final}} \tag{23}$$

$$0 \leq (p_{\text{L},t} - p_{\text{ess},t} - p_{\text{pv},t} - \sum_{n=1}^{N} p_{t,n}) \leq P_{\text{concap}}^{\max} \tag{24}$$

3.3. Compared Benchmark: Centralized Method

The objective function of the centralized method [7–19], which was used to schedule all EVs in a single optimization problem, is expressed as (25). The dimension of the decentralized optimization method was equal to the number of time slots, *T*. By contrast, the dimension of the centralized optimization method was (N + 1) × T. Although the centralized method may provide a more satisfactory solution because in this method overall conditions were considered, the dimension of the optimization problem substantially increased. The results of the proposed decentralized approach were compared with those of the centralized method and are presented in following sections.

$$\max\left[\begin{array}{l}\sum_{n}^{N}\sum_{t}^{T}\left(I_{t,n}^{\mathrm{ch}}+I_{t,n}^{\mathrm{DR}}-C_{t,n}^{\mathrm{deg}}-C_{t,n}^{\mathrm{feedbk}}-C_{t,n}^{\mathrm{penalty}}\right)\\+\sum_{t}^{T}\left(I_{\mathrm{ess},t}^{\mathrm{disch}}-C_{\mathrm{ess},t}^{\mathrm{ch}}-C_{\mathrm{ess},t}^{\mathrm{deg}}\right)\end{array}\right] \tag{25}$$

4. Simulation Results

4.1. Simulation System Parameters

To easily integrate with the operation of EMS system, the algorithm is developed by using Eclipse Java. In addition, because this paper considers the nonlinear conversion efficiency curve of a charging pile, the differential evolution (DE) algorithm [29] is used to solve the optimization problem, rather than the linear programming method. The simulation results were obtained on a personal computer with Intel Core i7-8700 CPU @ 3.20 GHz and 16-GB RAM.

Tables 1 and 2 present the parameters of the charging station and EVs, respectively. The probability distributions of the EV arrival and departure times and their SOCs are adopted to represent user behaviors, as shown in Figures 5 and 6 [30]. This paper considers an EV charging station equipped with 100 EV charging piles. The arrival and departure times of EVs at each charging pile are simulated according to the aforementioned probability distribution of user behavior. All the scheduling problems considered in this paper are for real-time operation with a time step of 15 minutes for sliding-window optimization.

Table 1. Parameters of EV charging station systems.

Parameters	Value
Contract capacity of the whole system	1000 kW
Number of DC charging piles	100
Capacity of ESS	50 kW/150 kWh
Efficiency of ESS	90%
Capital cost of ESS	172.45 USD/kWh
Life cycle of ESS	6400
Upper/lower SOC limits of ESS	20%/100%
Capacity of solar PV system	100 kWp

Table 2. Parameters of EV battery systems.

Parameters	Value
Initial investment cost	210.5 USD/kWh
Life cycle of EV battery	6400
Upper/lower SOC limits of EV battery	20%/100%
Rated power of DC charging pile	25 kW
Capacity of EV battery	42/62/100 kWh

Figure 7 illustrates the base-load and solar power generation of the EV charging station in a summer typical day. Table 3 presents the grid TOU parameters. Based on these probability distributions for EV, the simulation data are obtained via the Monte Carlo method to test and verify the effectiveness of the algorithm for dynamic charging/discharging scheduling. Therefore, to a certain degree, though the driver's habits, weather and meteorological conditions during the statistical period may influence both loading and fuel consumption, these factors have been comprised in the probability distribution functions.

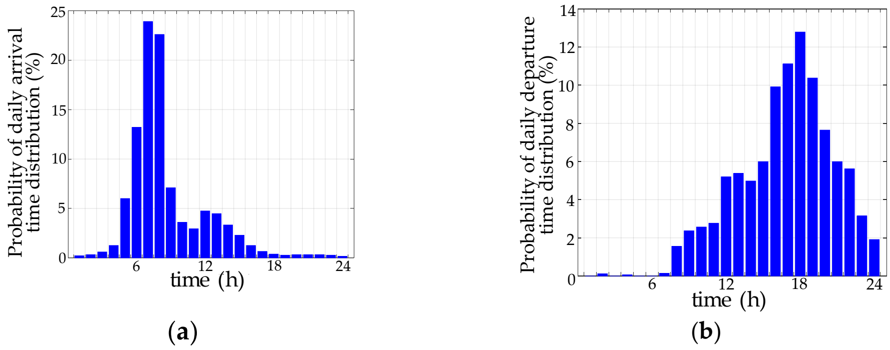

Figure 5. Probability distribution of daily (**a**) arrival and (**b**) departure times of EVs.

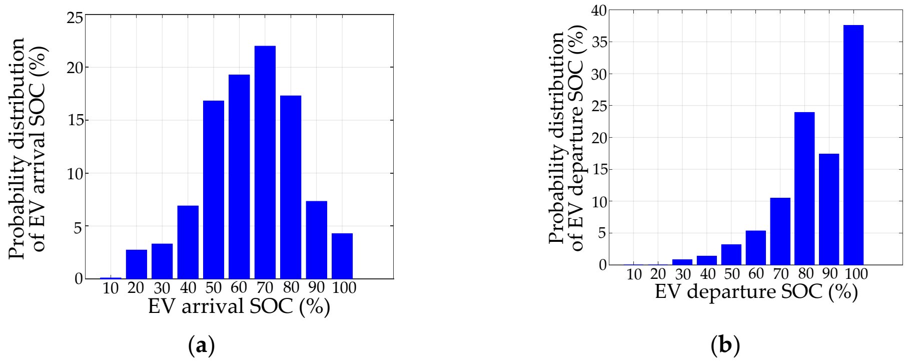

Figure 6. Probability distribution of SOC (**a**) arrival and (**b**) departure of EVs.

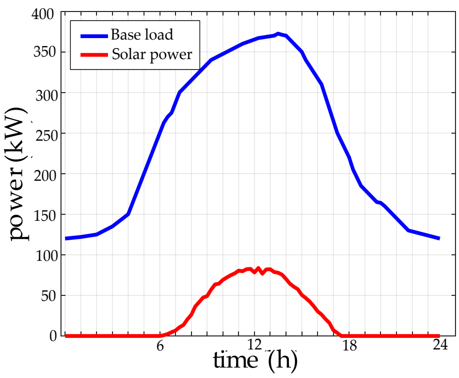

Figure 7. Commercial building load and solar power output of a summer typical day.

Table 3. Considered grid two-stage TOU electricity tariff.

Time	Tariff
Peak pricing (7:30 a.m.–10:30 p.m.)	0.12 USD/kWh
Off-peak pricing (10:30 p.m.–7:30 a.m.)	0.051 USD/kWh

4.2. System Simulation and Results

4.2.1. Scenario 1: Comparison between Centralized and Decentralized Optimization Methods

This section and Figure 8 present the comparison between decentralized and centralized methods. With different EV numbers, the computational time, optimized performance, and total profits varied accordingly. Although the total profit of the centralized method was slightly higher than that of the decentralized method, the computational time was considerably longer because of its higher dimension. In practical applications, the real-time computing ability of scheduling is vital to address the stochastic feature of users. Thus, in this study, the decentralized method was employed to solve the scheduling problem of EV charging stations.

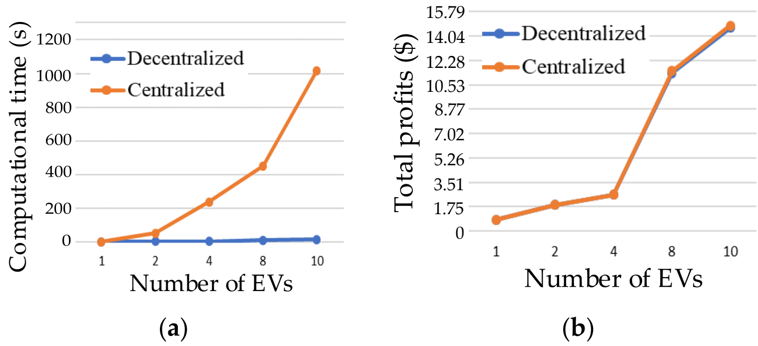

Figure 8. Comparison between decentralized and centralized method for (**a**) computational time and (**b**) total daily profit.

4.2.2. Scenario 2: Consideration of Conversion Efficiency

Similar to the other power converters and inverters, because the conversion efficiency of EV charging piles changes with varying load conditions, a fact which influenced the scheduling results. To the best of author's knowledge, no study has investigated the effect of the conversion efficiency of EV charging piles on EV charging/discharging scheduling. Figure 9 presents an example of a characteristic curve [4] of conversion efficiency $\eta(P)$ and load conditions P of a 25-kW DC-charging pile, where the blue crosses and red dotted line are the measured data and their fitted curve, respectively, which can be expressed as (26).

$$\eta(P) = 3.307 \times 10^{-4}\, P^3 - 0.0209\, P^2 - 0.3833\, P + 92.3373 \tag{26}$$

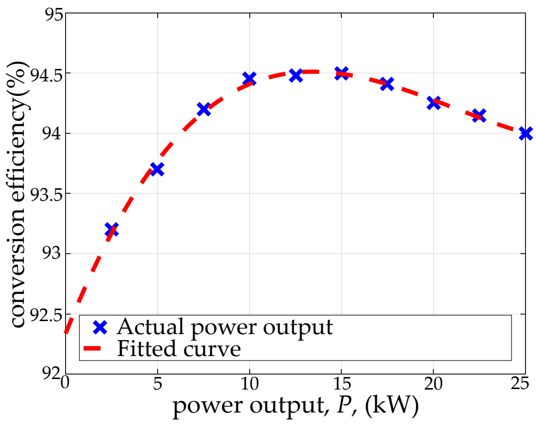

Figure 9. Conversion efficiency curve of a 25-kW DC-charging pile.

Table 4 shows the comparison of the proposed method and the one which only considers TOU tariffs without considering the conversion efficiency. The factors like climate and operating temperature may influence the conversion efficiency curve. However, the study in this paper assumes a conversion efficiency curve is given and known. It is observed that the proposed method can reduce the conversion loss by 49.8%. Accordingly, the total profit is thus increased by 3.5%. The proposed strategy is validated to provide the scheduling results with more total profits by setting the charging power output at high conversion efficiencies.

Table 4. Comparison of daily scheduling results conversion efficiency between EV charging piles with and without consideration. (Unit: USD).

Items	Based on Grid TOU Tariff Only	With Considering Conversion Efficiency
(1) Charging fee for EV users	264.93	265.1 (+0.06%)
(2) Total cost caused by conversion loss	17.20	8.63 (−49.83%)
(3) BESS electricity cost	−0.31	−0.32 (+3.23%)
Total profit of the charging station = (1) − (2) − (3)	248.04	256.79 (+3.53%)

Consider the 80th EV charging pile as an example. Figure 10 illustrates its charging power profile and corresponding SOC curve variations with the conversion efficiency consider or not. The results indicate that the EMS has the EV charged during the periods with lower electricity prices to meet the charging demand of EV. As the conversion efficiency is taken into account as shown in this figure, the EV charging power is set near as close as possible to the high-efficiency operation point, such as 15 kW.

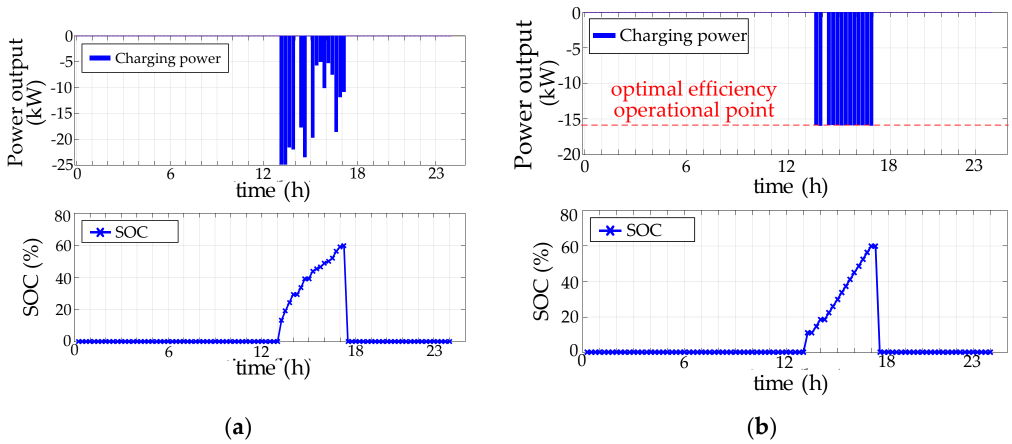

Figure 10. Daily Scheduling results of EVs (**a**) without and (**b**) with the consideration of variable conversion efficiency.

4.2.3. Scenario 3: Participate in the DR Program

The effect of the cost of DR compensation on the total revenue was analyzed. Table 5 presents the simulation results with different DR compensation prices. The total revenue increased with an increase in DR compensation prices. Moreover, higher DR compensation promoted the charging station systems to discharge at the DR period, which led to a slight increase in the conversion loss and electricity energy cost. Thus, the income from the DR program can be improved.

Table 5. Daily scheduling results of different DR compensation prices (Unit: USD).

Compensation of DR (USD/kWh)	Without DR	0.24	0.28	0.31	0.34
(1) Total revenue	265.10	265.13	247.70	247.51	247.56
(2) Conversion loss	8.63	8.80	9.76	9.78	9.79
(3) BESS electricity cost	−0.32	11.22	11.24	11.22	11.22
(4) Total income of DR	0	104.29	156.07	175.58	195.09
Total profit of charging station (1) − (2) − (3) + (4)	256.79	349.40 (+36.06%)	382.76 (+49.06%)	402.09 (+56.58%)	421.64 (+64.2%)

Figure 11 illustrates the load profiles of the EV charging station with a DR compensation price of 0.34 USD/kWh. Through the DR program, the charging system was used to discharge power during the DR period to shave a peak load. The simulation result indicated that the charging station system may be used to advance or delay the charging time for discharging power during the DR period and simultaneously satisfy user demands.

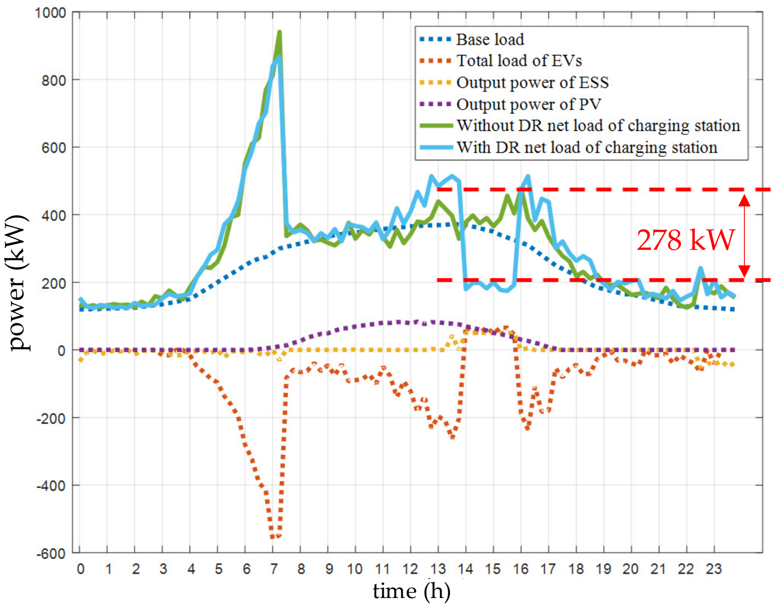

Figure 11. Daily load profile of the EV charging station with DR compensation price of 0.34 USD/kWh.

4.2.4. Scenario 4: Different Contract Capacities

This section mainly presents the effects of different contract capacities on the results. The contract capacities were considered to vary from 600 to 900 kW. Figure 12 presents the simulation results and indicates that the lower contact capacity may limit the profit of charging station systems. According to the stochastic user behavior model (Figure 5 [29]), most EVs arrived at 6–8 A.M. and left at 5–7 P.M. The schedule revealed that charging EVs arriving in the morning before 7:30 A.M., the boundary of peak and off-peak pricing, was more suitable to reduce the electricity cost. However, if the contract capacity was set lower, a part of energy must be shifted to the peak-pricing periods, resulting in a reduction of the total profit. Table 6 presents the related results.

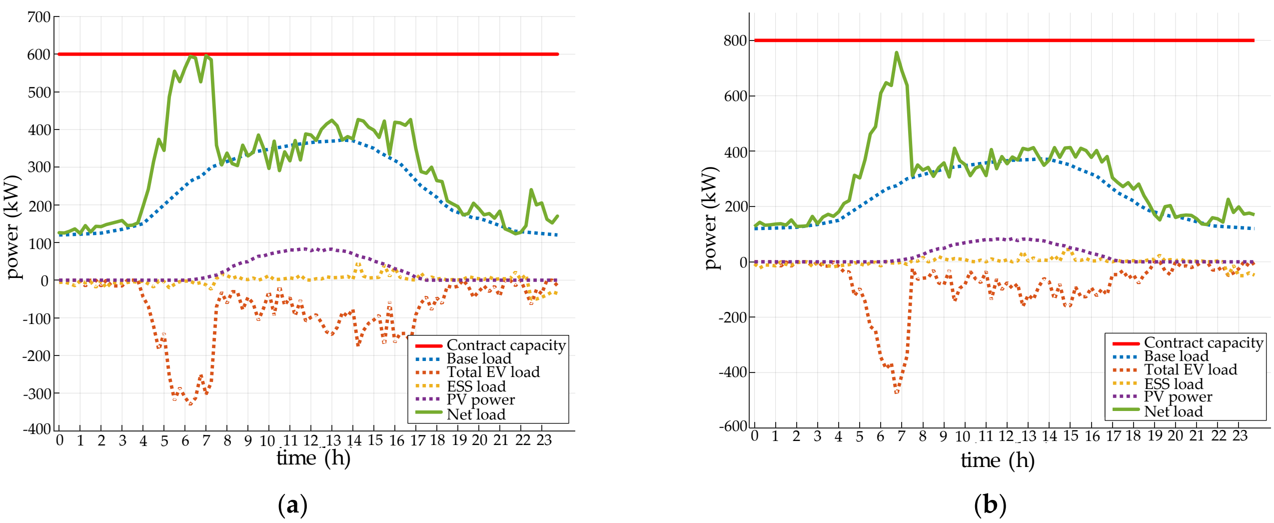

Figure 12. Daily power profiles with contract capacities of (**a**) 600 and (**b**) 800 kW.

Table 6. Comparison of daily scheduling results between contract capacities (Unit: USD).

Contract Capacity (kW)	500	600	700	800
(1) Total revenue	237.10	262.75	265.03	265.05
(2) Total conversion loss	10.30	9.07	8.81	8.79
(3) BESS electricity cost	−0.31	−0.32	−0.32	−0.31
Total profit (1)−(2)−(3)	227.11	254.00 (+11.84%)	256.54 (+12.96%)	256.57 (+12.97%)

5. Conclusions

In this study, the decentralized optimization architecture has been proposed for large-scale EV charging stations. The proposed approach was used to optimally schedule the charging and discharging power of EVs and ESSs to maximize the owner's profits of charging parking lot and satisfy the user's requirements. In the proposed method, the scheme of moving sliding-window was employed for periodical rescheduling to reduce the stochastic features of user charging behaviors. Moreover, in the decentralized method collaborated with edge-computing technologies, the computational time was substantially decreased, an advantage which highly improves the feasibility of real-time scheduling applications.

Most importantly, in the proposed method the conversion efficiencies of charging piles were considered, which have not been addressed in the literature. By reducing the power losses of the converters, total profits of the charging station were thus further increased. The simulation results proved that the sharing of EV battery capacities was beneficial to both the EV users and the charging station. Based on the proposed EMS strategies, EV charging stations can be used to not only participate in the DR program to earn more profits, but also improve the frequency regulation capability of the power system. The advantages thus achieved can be promoted in the power grid with high-penetrated renewable energy to enhance the system power quality and reliability.

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Abbreviations

f_t	the adjusted factor of the VPS at time t: VPS_t
$P_{\text{net},t}$	the net load of the whole parking lot system at time t
P_{concap}	the contract capacity
$p_{t,n}^{\text{ch}}$	the charging power outputs of nth EV at time slot t
$p_{t,n}^{\text{disch}}$	the discharging power outputs of nth EV at time slot t
$I_{t,n}^{\text{ch}}$	the profit earned using aggregator with user charging of nth EV
$I_{t,n}^{\text{DR}}$	the profit earned using aggregator with participating in the DR market of nth EV
$C_{t,n}^{\text{deg}}$	the cost of battery degradation during the DR periods of nth EV

$C_{t,n}^{\text{pen}}$	the cost of battery charging penalty during the DR periods of nth EV
$C_{t,n}^{\text{feedbk}}$	the compensation of nth EV from aggregator
λ_t^{chfee}	the user charging fee
λ_t^{TOU}	Time-of-use tariff
λ_t^{DR}	the DR compensation tariff
η	conversion efficiency
C_n^{bat}	the initial cost of nth EV battery
B_t^{cap}	the battery capacity of nth EV
m_n	the slope of lifecycle approximate curve
$p_{\text{pv},t}$	the power outputs of the PV at time slot t
$p_{t,n}$	the power outputs of the nth EV at time slot t
$P_{\text{ess}}^{\text{max}}$	the maximal power of BESS
$SOC_{\text{ess}}^{\text{max}}$	the upper SOC limits of BESS
$SOC_{\text{ess}}^{\text{min}}$	the lower SOC limits of BESS
C_n^{bat}	the initial cost of the nth EV battery
$p_{\text{ess}}^{\text{ch}}$	the charging power of BESS
$p_{\text{ess}}^{\text{disch}}$	the discharging power of BESS
$B_{\text{ess}}^{\text{cap}}$	the ESS capacity
$P_{\text{concap}}^{\text{max}}$	the contract capacity
$p_{\text{ess},t}$	the power output of the ESS at time slot t
C_n^{bat}	the initial cost of nth EV battery
$B_{\text{ess}}^{\text{cap}}$	the ESS capacity
m_{ess}	the slope of lifecycle approximate curve
$pri_{t,n}^{\text{ch}}$	the charging priority indices of nth EV at time slot t
$pri_{t,n}^{\text{disch}}$	the discharging priority indices of nth EV at time slot t
SOC_n^{ini}	the initial SOC of nth EV
SOC_n^{final}	the expected final SOC of nth EV
t_n^{arr}	the arrival time of nth EV
t_n^{dep}	the expected departure time of nth EV
P^{V2G}	the total discharging power
P_n^{max}	the rate power of nth charging plies

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