A Two-Stage Scheme for Both Power Allocation and EV Charging Coordination in A Grid Tied PV-Battery Charging Station

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***Abstract*—Charging station that incorporates renewable energy resource and energy storage is a promising solution to meet the growing charging demand of electric vehicles (EVs) without the need to expand the distribution network. The aggregation of multiple energy resources and EVs requires an efficient and flexible energy management strategy. This paper presents a two-stage scheme to solve the power allocation and charging coordination of plugged-in EVs. Game theory based control is utilized to address the interaction among different components for respecting their individual preferences. The first stage determines the power allocation of PV, battery and the grid as well as total charging power for EVs. In the second stage, charging power dispatch among individual EVs is coordinated based on the available total charging power determined in the first stage. As a result, the two energy management problems of charging station are addressed sequentially. The proposed solution is validated via simulation and experiment, and the comparisons with benchmarks show its advantages.**

***Index Terms*—Charging coordination, charging station energy management, energy storage, game theory, renewable energy.**

I. INTRODUCTION

THE electric vehicle (EV) and renewable energy generation have achieved considerable development due to the growing energy demand and scarcity in fossil fuels [1]. At the same time, EVs consume a huge amount of electricity when they are clustered in a charging station, which may significantly impact the operation of the grid [2]. Therefore, deploying renewable generation and battery energy storage on the charging station side is regarded as a promising win-win solution.

A. Motivation and Incitement

By integrating renewable energy and battery, charging stations can greatly reduce the consumed energy from the grid and thus suppress the required grid capacity [3]. On the other hand, this energy mixing complicates the configuration and management of the charging station. Especially, renewable energy power generation is known to be intermittent, and the charge and discharge capability of the battery usually changes over time and is affected by the state of charge (SOC). Under constantly changing charging power provision, the charging of EVs should also be controlled to avoid undesired overload. These problems pose challenges to the energy management of the charging stations, because the stations must coordinate both the charging power dispatch of EVs and the power allocation among photovoltaic panels (PV), battery and the grid.

B. Literature Review

Recently, the energy management of charging stations have been extensively explored [4]–[7]. A charging mechanism was introduced in Ref. [4] to determine the energy generation and EV charging strategy based on the predicted PV generation power and EV arriving/departure time. In Ref. [5], a power dispatch and charging strategy was developed for a PV based battery swap station considering PV energy utilization and swapping service availability. A day-ahead scheduling framework was studied in [6] which aimed to optimize the operation scheduling for both a microgrid and EV battery swapping station. Chance constrained optimization based approach was suggested in [7] to optimize the operational cost of the charging station using PV and battery powers. Ref. [8] formulated a multi-objective optimization problem, which was solved by stochastic dynamic programming. But the transition probability of all the uncertainties was required in advance. In addition, robust and nonlinear energy management strategies were adopted to obtain the optimal demand and electricity procurement under predicted uncertainties sets [9], [10]. It should be noted that implementation of the above proposed methods is highly dependent on the forecasting of uncertainties, such as in the EV charging demand, renewable generation, and electricity price [11]. Therefore, these time-ahead methods may lead to suboptimal or even be impractical to directly apply to actual cases.

In addition, the above existing methods are all centralized solutions. Difficulties will arise when the number of EVs and distributed energy resources increases [12]. Besides, considering that the charging station aggregates multiple energy sources and different types of EVs, it is usually more suitable to adopt a distributed and flexible control scheme. To address the given problem in a distributed manner, Ref. [13] introduced a distributed control based EVs charging scheduling. But PV and battery were not included, and the focus was

Manuscript received July 30, 2020; revised November 5, 2020; accepted January 11, 2021. *(Corresponding author: Chengbin Ma.)*

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mostly on utilizing the charging flexibility of EVs while ignoring the different charging requirements. Game theory based approaches have been widely used to reflect the individual characteristic and distributed nature of the above control problem [14]–[16]. Stackelberg game was used in Ref. [14], [15] to model the interaction between the charging station and EVs and thus determine a charging price to influence the charging demand. The price is only one of the factors to impact the EV charging decisions, and the total available charging power has to meet the physical constraints, especially for the charging stations using PV and battery powers. The power allocation on the energy supply side was not discussed in detail in Ref. [16]. The order of energy use in the existing schemes mentioned in Ref. [17], [18] was renewable, battery and the grid to save the grid energy consumption. But this may cause the battery to quickly run out of energy, and the grid must provide all the load alone. The battery originally equipped to reduce the burden on the grid cannot be fully utilized.

It should be noted that the previous literature did not take into account the power shortage in which the power supply is insufficient to meet the demand. In fact, the available energy supply of charging stations is likely to change over time (i.e., time-varying), especially when those stations are partly powered by the integrated PV and battery. For such cases, there is currently few solutions to allocate the power among PV, battery and the grid, when the power shortage happens. In addition, due to the insufficient total supply, the original charging of EVs will be affected. Thus, a new charging dispatch must be considered. To address the above problems, in this paper we propose a two-stage energy management scheme. In the first stage, based on the charging needs of the EVs, the charging station has the right to first determine the available total charging power as well as the power allocation among PV, battery and the grid. The second stage coordinates the EV charging power distribution under the limitation of the total available charging power determined in the first stage. This two-stage scheme continues over time, during which the decisions are made in turn. Since each stage involves multiple players with their own competitive decision-making, it is natural to use game theory as an effective tool to express the respect for each player's unique preference.

C. Contribution and Paper Organization

The main contributions of this paper are summarised as follows:

1) Proposing a two-stage scheme to solve both the power allocation among PV, battery and the grid, and the coordination of EVs charging under insufficient and time-varying power supply;
2) Extending the use of game theory in the energy management of charging stations, not only for EVs charging dispatch but also for power allocation among PV, battery and the grid;
3) Determining directly the total charging power for EVs taking into account the physical constraints, which is different from the previous work using pricing mechanism to indirectly affect the charging load [14], [15];
4) Studying the two-stage scheme under both grid-tied mode and islanded mode, while most previous work has focused only one single mode.

The rest of this paper is organized as follows. Section II describes the configuration of the charging station. Section III and IV formulate the first stage power allocation problem and second-stage EV charging dispatch problem, respectively. Detailed simulation results are discussed in Section V. Experimental results are presented in Section VI followed by conclusion in Section VII.

II. System And Problem Overview

The studied EV charging station is equipped with PV and battery, and it also connects with the grid. And various EVs can stochastically and dynamically arrive and charge at the charging station. As shown in Fig. 1, arrival EVs send their desired charging requirement signal $\sum_{i\in\mathcal{I}} p_{e,i}^{req}$ to charging station. As the energy supply, charging station provides the total charging power for EVs. Here the total charging power is supplied by a combination of PV, battery and grid. How to determine their respective supplied power is very important. It should note that considering the limited power capacity, charging station might not be able to meet the desired charging requirements of EVs. This aspect is different from the traditional scenario in which the supplied power should meet the demand. In addition, given the low battery SOC and low or no PV power, the total available charging power of the EVs should be reduced accordingly. Therefore, the charging station has the right to first determine its charging power provision, i.e., p_l in Fig. 1 in the first stage. p_l is directly affected by the PV power, battery power and grid power determined in the first stage. Then, based on the information of p_l published by the charging station, the second stage is to determine the share of this insufficient total charging power p_l among individual EVs. Again, because each of the above stages contains multiple players, it is effective to apply the game theory reflecting the competitive decision-making of the players. The two stages continue over time, and their decisions are made by turns. And considering the role of charging station and EVs are nonsymmetric, that is why we adopt the decoupled structure [14]–[16]. The proposed two-stage energy management scheme will be detailed in section III and IV, respectively. The scheme can be used for other types of energy storage and renewable energy sources by introducing their utility functions.

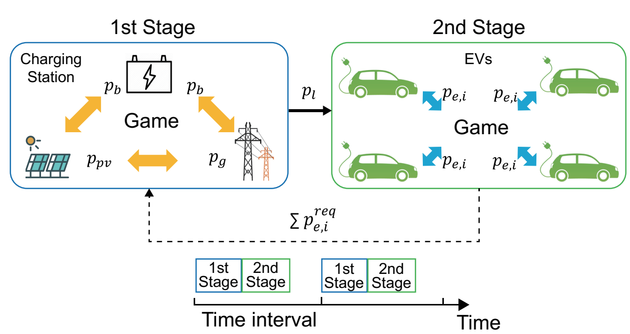

Fig. 1. The proposed two-stage energy management scheme for charging station.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TII.2021.3054417, IEEE Transactions on Industrial Informatics

III. Power Allocation–The 1st Stage

The purpose of the the 1st stage is to determine the power allocation among the PV, battery, grid. The power allocation problem is mathematically formulated as a noncooperative game. The heterogeneous energy sources: the PV, battery and grid are treated as three individual players in the formulated game, and they are assumed to be selfish and attempt to maximize their own utilities.

A. Utility Functions

Utility function is widely used to quantify the satisfaction level or preference of an individual agent for the action it takes [14], [15]. A quadratic form cost function is used to quantify the objective of each player. Note that quadratic form functions have been widely used to model player preference in energy system and economics [14], [19].

1) Battery: Here, the lithium-ion battery is used as an energy storage device. The stationary storage battery is to serve as an energy buffer for the PV and the grid. The battery SOC should be maintained at a specific preferred level. Therefore, the battery can quickly deliver or absorb power and thus provide a sufficient regulation margin for the possible fast adjustment. In this regard, the behavior of the storage battery equipped in the charging station is different from that of the on-board EV battery. Note that due to the focus on EV charging, the dynamics of the EV battery in this paper is mainly represented as a charging load. Then, the utility function of the battery u_b is defined as follows [19]:

$$u_b = -\frac{1}{2}(p_b - p_{bf})^2, \tag{1}$$

where the preferred p_{bf} is directly related to the battery SOC as follows

$$p_{bf} = \left(\frac{soc_b(t) - soc_{bf}}{(soc_{b,max} - soc_{b,min})/2}\right) p_{b,max}. \tag{2}$$

where $[soc_{b,min}, soc_{b,max}]$ and $[p_{b,min}, p_{b,max}]$ are the battery permitted SOC and power operation range, respectively. Assuming an equal possibility of charge and discharge, preferred SOC soc_{bf} is designed targeting 50%.

Since battery can either discharge or charge, here $p_b > 0$ means battery is discharging and $p_b < 0$ means charging. Because of the battery physical constraints, the battery power p_b and SOC soc_b should satisfy the following inequality constraints at any time:

$$soc_{b,min} \le soc_b \le soc_{b,max}, \tag{3}$$

$$p_{b,min} \le p_b \le p_{b,max}, \tag{4}$$

The evolution of battery SOC is related to its output power

$$soc_b(t+1) = \begin{cases} soc_b(t) - p_b(t)\Delta t/E_b/\eta_d, & \text{if } p_b(t) > 0; \\ soc_b(t) - p_b(t)\Delta t \eta_c/E_b, & \text{otherwise.} \end{cases}, \tag{5}$$

$$soc_b(0) = soc_{b,ini}, \tag{6}$$

where E_b, η_d, η_c, and $soc_{b,ini}$ are the battery normal energy, battery discharge efficiency, charge efficiency, and initial SOC value, respectively.

2) PV: In general, PV panels are assumed to be working at the maximum power point tracking (MPPT) mode, and the corresponding power p_{mp} can be roughly estimated by

$$p_{mp} = G_i A_{pv} \eta_{pv}, \tag{7}$$

where G_i is the solar irradiance, A_{pv} is the installed PV panels surface area, and η_{pv} is the conversion efficiency.

Although PV generation can reduce the energy from the power system, the rapid fluctuation of solar power could cause unexpected voltage violation [20]. Then, it is necessary to impose PV power ramping restriction $p_{pv,rp}$ as follows

$$p_p(t) - p_p(t-1) \le p_{pv,rp}. \tag{8}$$

where $p_p(t)$ is the PV power at time t. However, the ramping restriction inevitably results in PV curtailment from forgone energy usage. Thus, the utility function of the PV u_p is defined to emphasize providing the power as close as possible to p_{mp} that minimize the curtailment loss [21]. Here, u_p is defined as

$$u_p = -\frac{1}{2}(p_p - p_{mp})^2, \tag{9}$$

And p_p satisfies the following

$$0 \le p_p \le p_{mp}, \tag{10}$$

3) Grid: The utility function of the grid u_g is defined to emphasize the economy, namely reduction of the electricity consumption from the grid. Similar to the utility functions of battery and PV [22], we have

$$u_g = -\frac{1}{2}(p_g - p_{g,opt})^2, \tag{11}$$

where $p_{g,opt}$ means the preferred output power of grid, here it is zero, i.e., zero energy consumption of the grid. According to this function, the utility function u_g is maximized when there is no power output from the grid, while a large amount of grid output power is undesirable. The grid should meet the power capacity limits and ramping power limits

$$0 \le p_g \le p_{g,max}, \tag{12}$$

$$|p_g(t) - p_g(t-1)| \le p_{g,rp}, \tag{13}$$

where $p_{g,max}$ and $p_{g,rp}$ are the maximum permitted deliver power and ramping power.

4) Modified Utility Functions: Ideally EV charging station should satisfy EVs charging power requirement. However, due to the limitation of charging station capacity, it is possible that charging station cannot provide that required amount of charging power. For instance, when there is no PV power at night and battery SOC is low, the grid power with physical capacity limit may be lower than the required charging power of EVs $\sum_{i\in\mathcal{I}} p_{e,i}^{req}$. $p_{e,i}^{req}$ is EV i's desired charging power requirement sent to charging station, where $\mathcal{I}$ denotes the set of plugged-in EVs. Let $p_l^* = \sum_{i\in\mathcal{I}} p_{e,i}^{req}$ and p_l denote the actual provision total charging power determined by PV, battery and grid, i.e.,

$$p_l = p_p + p_b + p_g. \tag{14}$$

And p_l and p_l^* have the following relationship

$$p_l \le p_l^*. \tag{15}$$

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Then, charging station should maximize the following utility function u_l as much as possible:

$$\begin{aligned} u_l &= -\frac{1}{2}(p_l - p_l^*)^2 \\ &= -\frac{1}{2}(p_p + p_b + p_g - p_l^*)^2 \end{aligned} \tag{16}$$

As seen, the utility function u_l is maximized when the supplied power is exactly equal to the required power of EVs. In addition, u_l is also affected by the strategy of each player. Therefore, a possible solution is to combine the utility function u_l with those of other players. Thus, the final form of the utility function of each player is modified as follows:

$$u_{p,l} = u_p + w_{l,p} u_l, \tag{17}$$

$$u_{g,l} = u_g + w_{l,g} u_l, \tag{18}$$

$$u_{b,l} = u_b + w_{l,b} u_l, \tag{19}$$

where $w_{l,p}$, $w_{l,g}$, $w_{l,b}$ are weight coefficients with bigger and positive values, such that the last term of each modified utility function is treated as penalty term. Therefore, the physical meaning of the above mentioned final form of the utility function is that each energy source, i.e., PV, battery and grid, works to maximize its own utility. Meanwhile, it is required to contribute to minimizing the shedding of total charging demand as much as possible.

In addition, the above three weights adaptively vary based on the total charging demand p_l^*, as shown in the following equation. When p_l^* increases, the weights $w_{l,p}, w_{l,g}, w_{l,b}$ decrease correspondingly. This results in less emphasis on meeting the charging demand, and thus accordingly impacts the peak load. The quasi-pricing mechanism is similar to the pricing mechanism described in Ref. [14], [15].

$$\begin{aligned} w_{l,p} &= w_{l,p}^{max}(1 - p_l^*/p_{evcs}), \\ w_{l,g} &= w_{l,g}^{max}(1 - p_l^*/p_{evcs}), \\ w_{l,b} &= w_{l,b}^{max}(1 - p_l^*/p_{evcs}), \end{aligned} \tag{20}$$

where coefficients $w_{l,p}^{max}, w_{l,g}^{max}, w_{l,b}^{max}$ are bigger and positive values, p_{evcs} is the maximum available total charging power of the charging station. The above three weights are equivalent to the role of the charging price.

B. Noncooperative Game

A noncooperative game is then set up at each control time instant. It is represented in the strategic form

$$G_{cs} = \{(P, G, B), \{p_p, p_g, p_b\}, \{u_{p,l}, u_{g,l}, u_{b,l}\}\}, \tag{21}$$

where the game players, namely the PV "P", the grid "G" and battery "B", are assumed to be selfish. Each player attempts to maximize its own utility function. However, the utility function value of an individual player depends not only on its own control variable but also on the decision of other player and required charging power of EVs. Since these three independent players are selfish, a balanced allocation settles down under the so-called Nash Equilibrium (NE) [23]. Under NE, if one of the players unilaterally changes its decision variable (i.e., p_p, p_g, p_b), the cost of all three players cannot be improved at the same time. Thanks to the concavity of the utility functions $u_{g,l}$, $u_{g,l}$ and $u_{b,l}$, the existence and uniqueness of NE can be proved by solving the following best response (BR) functions:

$$BR_p : \frac{\partial u_{p,l}}{\partial p_p} = 0,\ BR_g : \frac{\partial u_{g,l}}{\partial p_g} = 0,\ BR_b : \frac{\partial u_{b,l}}{\partial p_b} = 0, \tag{22}$$

then we can obtain

$$\begin{aligned} BR_p : p_p &= \frac{p_{mp} - w_{l,p}(p_g + p_b - p_l^*)}{1 + w_{l,p}}, \\ BR_g : p_g &= \frac{-w_{l,g}(p_p + p_b - p_l^*)}{1 + w_{l,g}}, \\ BR_b : p_b &= \frac{p_{bf} - w_{l,b}(p_p + p_g - p_l^*)}{1 + w_{l,b}}. \end{aligned} \tag{23}$$

The Hessian (H) of each utility function is

$$\begin{aligned} H_{p,l} &: -(1 + w_{l,p}) < 0, \\ H_{g,l} &: -(1 + w_{l,g}) < 0, \\ H_{b,l} &: -(1 + w_{l,b}) < 0, \end{aligned} \tag{24}$$

which is always negative definite. Thus, the solutions in BR_p, BR_g and BR_b are global minimum points that determine an optimal power allocation.

Algorithm 1 Power allocation for charging station

1: **Initialization** $p_{p,last} \leftarrow p_{p,t-1}$, $p_{g,last} \leftarrow p_{g,t-1}$, $p_{b,last} \leftarrow p_{b,t-1}$.
2: **repeat**
3: solve p_g via BR_g using $p_{b,last}$ and $p_{p,last}$ and check (12-13).
4: solve p_p via BR_p using $p_{g,last}$ and $p_{b,last}$, and check (8-10).
5: solve p_b via BR_b using $p_{g,last}$ and $p_{p,last}$ and check (3-4).
6: **Check convergency:**
7: **if** $|p_p - p_{p,last}| \le \varepsilon$ and $|p_g - p_{g,last}| \le \varepsilon$ and $|p_b - p_{b,last}| \le \varepsilon$ **then**
8: terminate
9: **else**
10: $p_{p,last} \leftarrow p_p$, $p_{g,last} \leftarrow p_g$, $p_{b,last} \leftarrow p_b$.
11: **end if**
12: **until** convergence
13: solve p_l via (14) and send p_l to the second stage.

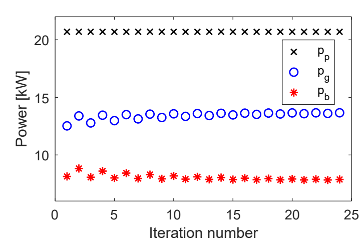

Fig. 2. An example iterative convergence of decisions of the three players.

Given the BR_p, BR_g and BR_b, the developed algorithm for power allocation of charging station is shown in Algorithm 1. Initially, the PV, grid and battery player share their decisions made at the last time instant, i.e., $p_{p,t-1}, p_{g,t-1}$ and $p_{b,t-1}$ [see line 1]. For the grid, to maximize its utility $u_{g,l}$, its decision p_g is solved through BR_g, where $p_p = p_{p,t-1}, p_b = p_{b,t-1}$, and then updates its new decision $p_{g,t-1}$ [see line 3]. The same procedure can be repeated for PV and battery players to obtain their response decisions using BR_p and BR_b [see line 4-5]. Once the convergence of p_p, p_b and p_g iteratively achieves, namely the NE of the game is found [see line 6-12 and Fig. 2]. Further, the final total available charging power p_l can be calculated by (14) and the signal will be sent to the second stage for EV charging coordination [see line 13]. The players only share their control variables (i.e., p_p, p_b, p_g) and the total required charging command (p_l^*) from the EV charging side through the environment, thus the players' local privacy information is well preserved internally.

IV. EV Charging Coordination–The 2nd Stage

Based on the total charging power p_l determined by the first stage, each EV should determine its shared portion of p_l in the second stage, namely EV charging coordination. EV charging coordination should consider the diversities. For instance, the required charging power of EVs differs each other. The preference of individual EV charging requirement is also different, which is reflected in that some EVs are urgent for charging quickly regardless of the higher electricity price, while other EVs have no particular requirement and can be parked for a long time. Those characteristics require flexible charging coordination. The advantage of applying game theory to solve the present charging coordination problem is its distributed nature and full respect of the preference of individual players. Here, EVs are modeled as independent players in the noncooperative game and they are competing for the published total charging power p_l.

A. Utility Function for EV Charging

For each EV player $i \in \mathcal{I}$, its charging utility function is defined by $U_{e,i}(p_{e,i})$ which represents the level of satisfaction for the obtained charging power $p_{e,i}$ for the ith EV,

$$U_{e,i}(p_{e,i}) = Q_{e,i} \cdot p_{e,i}^{req} \cdot \ln(p_{e,i} + 1), \tag{25}$$

where the natural logarithm $\ln(\cdot)$ has been extensively used for designing the utility and has also been shown to be suitable for designing the utility for the load [24], [25]. $p_{e,i}^{req}$ is the required charging power of the ith EV. $Q_{e,i}$ is a parameter defined to address the various preferences of EVs on charging requirement according to the following: Bigger $Q_{e,i}$ means EVs are urgent and willing to charge quickly. And EVs with smaller $Q_{e,i}$ have no particular requirement and are willing to donate portion of limited charging resource to contribute to other EV with urgent charging response. The final charging power $p_{e,i}$ is affected by $Q_{e,i}$ since an EV with bigger $Q_{e,i}$ has a higher marginal utility. Therefore, it needs to obtain more charging power to reach its maximum satisfaction level. In the game, each player, i.e., individual EV, seeks to maximize its own utility.

In addition, all EV players compete the total charging power p_l determined by the first stage, thus they need meet

$$\sum_{i\in\mathcal{I}} p_{e,i} = p_l. \tag{26}$$

The dynamics of the ith EV battery, in terms of its SOC $soc_{e,i}$, is described as follows,

$$soc_{e,i}(t+1) = soc_{e,i}(t) + p_{e,i}(t)\Delta t \eta_{c,i}/E_{e,i}, \tag{27}$$

where $p_{e,i}$ is the battery charging power, $E_{e,i}$ is the battery capacity, and $\eta_{e,i}$ is the charging efficiency.

B. Generalized Nash Equilibrium

Due to (26) couples all of charging powers of EVs, the charging power dispatch game problem turns to generalized Nash equilibrium (GNE) problem [26]. The compromised charging power of the ith EV can be obtained through solving (25) subject to (26). In order to study the existence of a socially stable solution to the game, based on the Karush-Kuhn-Tucker (KKT) conditions of optimality, the Lagrangian function of the ith EV is given by

$$L_i = -\,Q_{e,i} \cdot p_{e,i}^{req} \cdot \ln(p_{e,i} + 1) + \lambda_i\Big(\sum_{i\in\mathcal{I}} p_{e,i} - p_l\Big) \tag{28}$$

Then the gradient condition of the KKT necessary optimality conditions is

$$\frac{\partial L_i}{\partial p_{e,i}} = -\frac{Q_{e,i} \cdot p_{e,i}^{req}}{p_{e,i} + 1} + \lambda_i = 0 \tag{29}$$

Due to the convexity of this problem, the existence and the uniqueness of GNE can be proved mathematically. Thus, KKT necessary conditions are sufficient. At the most socially stable equilibrium point, $\overline{\lambda}$ for each EV holds the following [26],

$$\frac{Q_{e,i} \cdot p_{e,i}^{req}}{p_{e,i} + 1} = \overline{\lambda}. \tag{30}$$

It can be seen that $\overline{\lambda}$ is a positive value. Then the optimal charging power of ith EV can be uniquely determined based on $\overline{\lambda}$ by

$$p_{e,i} = \frac{Q_{e,i} \cdot p_{e,i}^{req}}{\overline{\lambda}} - 1. \tag{31}$$

In addition, the charging power of EV has to be limited by its allowable domain

$$0 \leq p_{e,i} \leq p_{e,i}^{req}. \tag{32}$$

If a centralized approach is applied here, then assigning the charging power for each EV by (31) will be the responsibility of the centralized controller. However, such a centralized controller has to know all information of EVs, e.g., $Q_{e,i}$ and $p_{e,i}^{req}$, to find $\overline{\lambda}$ and then to reach an equilibrium solution (31). This centralized approach is less flexible and not suitable for privacy preserving [21]. Therefore, a flexible distributed EV charging coordination algorithm is proposed in the following section.

C. Distributed Implementation

Here a consensus network based distributed algorithm is proposed to solve the charging coordination problem as shown in Algorithm 2. When EVs connect to the charging station, each EV should first publish the necessary communication information λ_i and $p_{e,i}^{req}$ [see line 1]. Since EV is assumed to be selfish, such characterisation naturally enables it to send its maximum charging power, which can be obtained by solving (25) subject to (32). Then, an initial λ_i value is generated under (30). Similarly, other plugged-in EVs also generate λ_i and $p_{e,i}^{req}$. This signal $p_{e,i}^{req}$ is shared to the charging station for Algorithm 1 while λ_i is shared among its neighbor EVs through the communication network. EVi can access the shared information of its neighbors, i.e., $\lambda_j, j \in \mathcal{N}_i$, which is the set of the neighbors of EVi. Once EVs receive the p_l

information, the distributed charging coordination computation is started.

At the 2nd stage, two situations need to be discussed [see line 2]. If there is only one single EV, then $p_{e,i} = p_l$ is the optimal dispatched charging power [see line 13]. The other situation is the general situation that includes at least two EVs. Under this situation, p_l needs to be allocated to each EV based on (31). First, according to the shared information ($p_{e,i}$ and p_l), the power mismatch, i.e., $\Delta p = \sum p_{e,i} - p_l$, will be checked whether the system power balance condition is met [see line 3]. If not, a switch variable LK is set to be 1 [see line 4], and all EVs start the consensus network to interact with their neighbors and update λ_i in the following way [see line 5-7]

$$\lambda_i \leftarrow \lambda_i + \sum_{j \in \mathcal{N}_i} w_{ij}(\lambda_j - \lambda_i) + \alpha \Delta p, \tag{33}$$

where w_{ij} is the connectivity strength which can be chosen from $0 \leq w_{ij} \leq (\max_{i=1 \dots N} |N_i|^{-1})$. Through several iterations, all λ_i will quickly converge to a same value [see Fig. 3] and satisfy $\max(|\lambda_i - \lambda_j|) \leq \varepsilon_1$, and then LK is set to be 0 [see line 8].

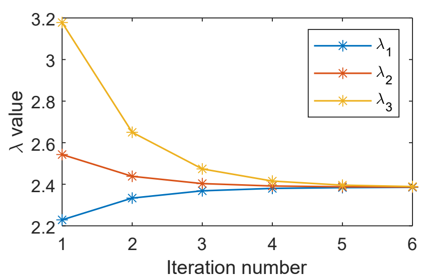

Fig. 3. An example iterative convergence of λ_i

The EV uses this new value λ_i to update its decision $p_{e,i}$ [see line 10]. The power mismatch Δp condition is checked again, and when Δp is small enough $\Delta p \leq \varepsilon_0$, the GNE of the original problem is found [see line 11]. Otherwise, the consensus algorithm will be repeated again until GNE is reached. Also, $p_{e,i}$ should be checked for constraint violation (32) on each iteration. Note that since charging coordination is dynamic over time, the above process is repeated at each control time instant. Through the algorithm, the coordinated charging is solved locally using local information.

Algorithm 2 Distributed EV Charging Coordination

1: **Initialization:** The plugged-in EVs initialize $p_{e,i}^{req}$ and λ_i independently and receive p_l sent by charging station.
2: **if** EV charging number $N_{ev} \geq 2$ **then**
3:   **while** $\Delta p = |\sum p_{e,i} - p_l| > \varepsilon_0$ **do**
4:     LK = 1
5:     **Consensus phase:** set up the consensus network
6:     **while** $(\max(|\lambda_i - \lambda_j|) > \varepsilon_1$ or LK=1) **do**
7:       $\lambda_i \leftarrow \lambda_i + \sum_{j \in \mathcal{N}_i} w_{ij}(\lambda_j - \lambda_i) + \alpha \Delta p$
8:       LK = 0
9:     **end while**
10:     $p_{e,i} = \frac{Q_{e,i} \cdot p_{e,i}^{req}}{\lambda} - 1$, and check (32)
11:   **end while**
12: **else**
13:   $p_{e,i} = p_l$, and check (32)
14: **end if**

V. Simulation Results and Discussion

In this section, simulation results are presented for assessing the performance of the proposed two-stage scheme for a considered charging station.

A. System Setup

There are six chargers in the charging station, and each of them is with maximum power 30 kW. The rated PV capacity $p_{pv,rate}$ is 70 kW. The grid power capacity is $p_{g,max}$ =100 kW less than the maximum total charging power p_{evcs} 180 kW. Grid ramping $p_{g,rp}$ is 1% of $p_{g,max}$, and $p_{pv,rp}$ is 10% of $p_{pv,rate}$ [20]. The parameters of battery are $E_b = 180$ kWh, $p_{b,max} = 90$ kW, $p_{b,min} = -90$ kW, $soc_{bf} = 0.5$, $soc_{b,ini} = 0.5$, $\eta_c/\eta_d/\eta_{e,i} = 0.95$. Considering uncertainties, two different PV power profiles are considered: one is with high PV power and the other low. The daily arrival EVs number are also different in two days. Each EV battery capacity is distributed within [40, 60] kWh, their start charging SOCs are randomly generated from [0.2, 0.5], and their target charging end SOCs are set as 0.95. Total simulation time are 2 days with 1 minute time interval. The weight coefficients $w_{l,p}^{max}, w_{l,g}^{max}, w_{l,b}^{max}$ are set as 10.

B. Power Allocation

Fig. 4 shows the two different days' operation results of power allocation among PV, battery and grid as well as the final coordinated EVs charging power at each minute. It could be found that both the fluctuation of PV power and total charging power are very intensive. If there is no energy storage, then the grid has to balance the system power, which will inevitably cause the grid power to vary drastically. Under the proposed strategy, the undesired situation is avoided by exploiting battery to bear the fluctuation and share the power demand. As a result, the grid power exhibits a smooth profile, and the maximum power is less than the peak charging demand. The proposed scheme slowly changes the battery SOC and keeps it near the intermediate level, which ensures the battery has sufficient margin to discharge and charge. In addition, the PV power curtailment mainly occurs when there is less charging demand. The sum of PV, battery and grid powers constitutes the total charging power provided to EVs. Then EVs compete and share the charging power based on Algorithm 2.

Besides, it is worth noting that the allowable total charging power is not fixed but dynamically changes over the time as shown in Fig 5. Most ratios of the actual provided total charging power to the required one are greater than 0.8, which means most charging demand is met. The above ratios in the first day are obviously lower than those in the second day. This is because the first day has higher charging demand. Thus, the peak load is more suppressed according to the developed quasi-pricing mechanism. Meanwhile, lower charging demand obtains the higher ratios in the second day. The results show the impact of the developed quasi-pricing mechanism on the peak load. The red circle area has extreme low ratios because at that time the battery SOC almost reaches its lower bound, PV power is less, and the required charging power exceeds the

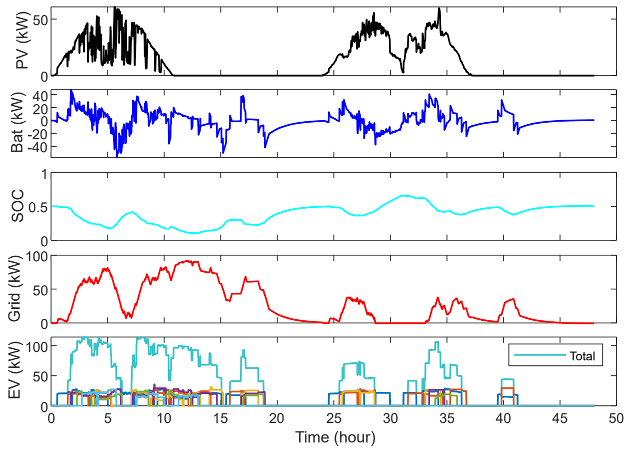

Fig. 4. Power allocation and battery SOC response.

power capacity of charging station corresponding to Fig. 4. Therefore, the supplied total charging power is a compromise result of the game among PV, battery and grid.

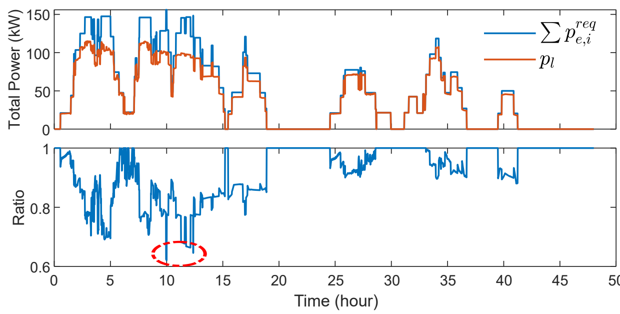

Fig. 5. The actual and required total charging power and their ratios.

C. Performance Comparison on Power Allocation

For reference purposes, the proposed two-stage scheme (i.e., TS#2 below) is compared with other three approaches:

(1) The conventional rule based strategy (RBS) [17], [18]: When there is surplus power, the excess energy is stored in the ESS, and when there is a shortage of power, the battery discharges, or distribution grid provides the power.

(2) The pricing scheme (PS) in Ref. [14], [15]: The EV charging demands are pricing sensitive and impacted by the price determined by the charging station.

(3) The proposed two-stage based scheme but without considering grid ramping and quasi-pricing scheme in (20) (TS#1).

(4) The proposed two-stage based scheme (including grid ramping and quasi-pricing scheme in (20)) (TS#2).

Fig. 6 shows that the grid power profiles of the four schemes. Under RBS and PS, the abrupt changes in the grid power are observed, which is due to the control logics. The RBS and PS schemes require the grid to bear the most of the charging demand alone. Meanwhile, the grid power profile under TS#2 is the smoothest. Comparing TS#1 with TS#2, the fluctuation in TS#2 is greatly alleviated because of the included grid ramping constraint, and battery better works to absorb the fluctuation. Note that frequent power fluctuation is undesired for the grid, which may reduce the power quality and adversely affect system performance. In addition, thanks to the developed quasi-pricing scheme to restrict the peak charging demand, both PS and TS#2 enable lower grid peak power without reaching the upper limit of grid output.

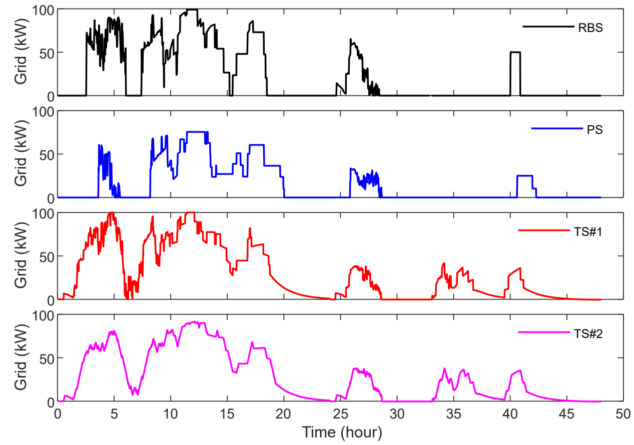

Fig. 6. Comparison results of grid power.

Fig. 7 depicts the battery power and SOC response. Due to the battery capacity is limited, the battery energy is quickly drained under RBS and PS, and the effective working time of battery is relatively short. While developed TS scheme can keep battery with sufficient margin for discharging and charging to share the burden of grid. Thus, RBS and PS is suitable for applications with large battery capacity, and the proposed strategy could save the battery capacity. Comparing with RBS and PS, TS#1-2 can recover to the starting SOC of battery at the end of a day. This makes the same dispatch flexibility at each day. In addition, TS#1-2 let battery withstand the frequent power fluctuations and reduce the impact on the grid.

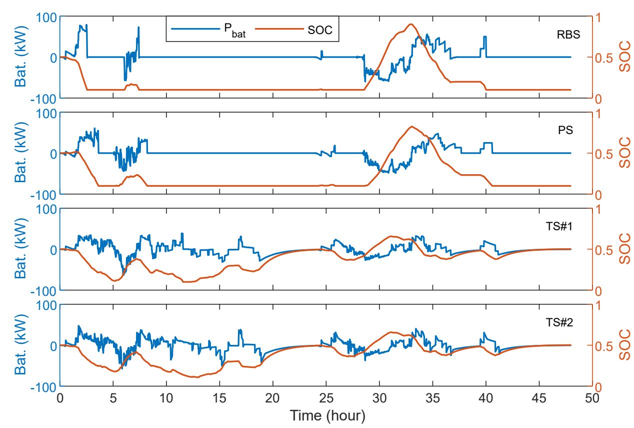

Fig. 7. Comparison results of battery SOC response.

Table I compares the results of RBS, PS, and TS#1-2 in terms of the following six criteria: battery maximum power, battery working time, grid peak power, grid peak-to-average ratio (PAR), grid power fluctuation and number of served EVs. A lower PAR is preferable for the grid as it indicates improved peak load regulation and the overall load on the grid is flattened. Although PS has the lowest grid peak power, it significantly reduces the EV charing demands, thereby further extending the EV charging time. This in turn causes less served

EVs due to the long occupation of the EV chargers. Comparing with other three schemes, the proposed TS#2 demonstrates a balanced and improved performance.

TABLE I
COMPARISON AMONG THE FOUR SCHEMES.

	Bat. max.(kW)	Bat. working time(Hours)	Grid Max.(kW)	PAR	Grid fluctuation max.(kW)	Served EVs
RBS	79	15	100	4.54	50	55
PS	61	19	75.5	5.14	32.2	45
TS#1	64	48	100	3.47	17.4	59
TS#2	57	48	91.6	3.3	2.4	57

D. Performance Comparison on EV Charging Coordination

EV players need compete the limited total charging power determined by charging station according to the algorithm 2. Taking the first coming 7 EVs in Fig. 4 for example, here they are assigned the same required charging power $p_{e,i}^{req} =$ 20 kW for comparison convenience. Two cases with different $Q_{e,i}$ settings are compared. In Case 1, seven EVs have the same $Q_{e,i}$ values of 2. In Case 2, the $Q_{e,i}$ value from EV1 to EV7 are intentionally set from 2 to 7, with an interval of 0.5, meaning they have different preferences.

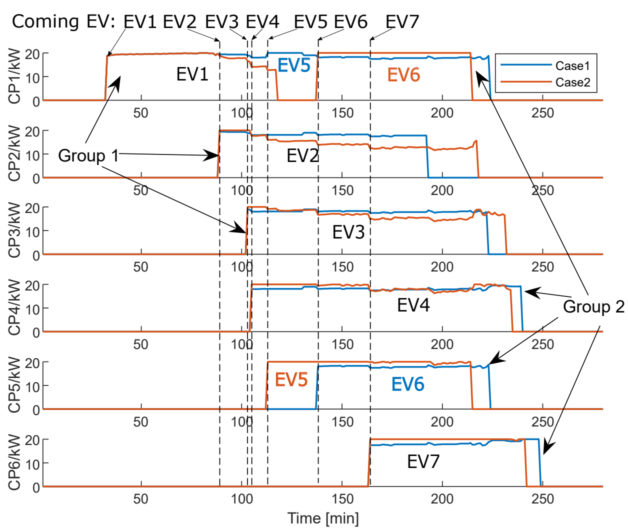

Fig. 8. Charging coordination comparison of Case 1 and 2.

Fig. 8 shows the dispatched charging power of each EV. For Case 1, when multiple EVs are charged at the same time, the plugged-in EVs obtain the equal charging power because of their equal $Q_{e,i}$. However, for Case 2, their dispatched charging power are changed since their $Q_{e,i}$s are different. Particularly, in Case 2, since EV2 with lower $Q_{e,i}$ has longer cross-charging interval with others, its charging power is curtailed, thereby its total charging time is extended by 11.3%. In contrast, the EV4-7 obtain larger charging power and complete their charging tasks in advance. Moreover, when each EV with higher $Q_{e,i}$ joins such as EV5-7 , charging power of EV2 is reduced accordingly.

Here EV1-3 are classified as Group 1, and the remaining EVs are classified as Group 2. The charging completion time of EVs of Group 1 is delayed. Conversely, EVs of Group 2 in Case 2 obtain more power, and shorten their charging completion time. Therefore, this mechanism is very helpful for EVs with urgent charging tasks (e.g. EVs with extremely low SOC). Facing the limited total charging power, the proposed scheme provides a viable solution to coordinate the charging power among EVs considering their different preferences.

E. Islanded Operation

The proposed two-stage scheme is also tested in the case of electricity outage, namely an islanded operating mode. Under this case, there is no grid connection and hence the on-site PV and battery jointly supply all the charging power for EVs. The results are shown in Fig. 9. Due to the insufficient power supply, the stored battery energy is quickly consumed comparing with the grid-connection operation in Fig. 4. Meanwhile, more PV power is utilized. Under the present scenario, the EV charging mainly occurs when PV power generation is available. Overall, electricity outage worsens the charging power provision but with the proposed two-stage scheme, the charging station can still maintain its basic charging ability through the PV and battery.

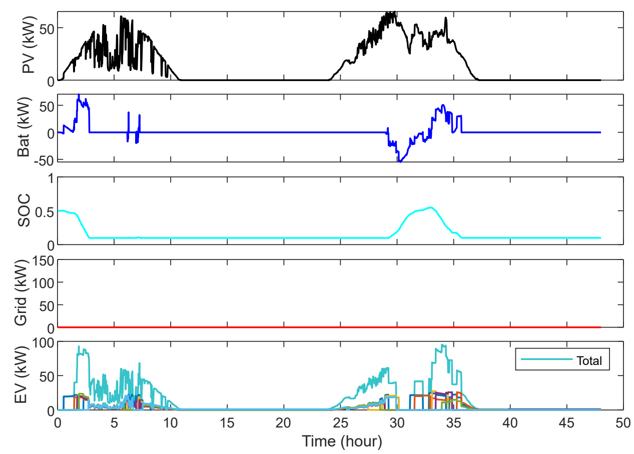

Fig. 9. Power allocation and battery SOC response under islanded mode.

F. Main Achievements

Here we briefly summary the obtained results and main achievements based on the above simulation results and comparisons. In order to respond to the EV charging demand, the first stage of the proposed scheme determines the outputs of PV, battery and the grid, and eventually the associated compromised total charging power, namely performing the power allocation. As a result, battery is properly utilized to provide long-lasting service and sufficient regulation margin for fast adjustment, thereby reducing the burden on the grid. Meanwhile, the developed quasi-pricing scheme effectively reduced the peak charging demand. For the EV charging coordination, i.e., in the second stage, the proposed scheme gives a compromised solution for the EV charging power dispatch under limited total charging power. The dispatch results also reflect the charging preferences of individual EVs, in which an EV with urgent charging requirement obtains more charging power.

VI. EXPERIMENTAL VERIFICATION

A reduced-scale testbed, 1:1000 at power level, is setup to validate the implementation of the proposed two-stage scheme. The EV charging station and the hourly time step are also downscaled to three chargers and to minutely time step, respectively. As shown in Fig. 10, PV and grid are combined together and emulated through a controllable power supply on the left side. The battery is set up using actual cells and connected directly to the dc bus. The emulated EV chargers are on the right side and each one contains its own unidirectional buck dc-dc converter. Electronic load mimics the on-board battery dynamics, and a local National Instruments (NI) myRIO as a local controller. All of the dc-dc converters are controlled by PI (Proportional and Integral)-based Pulse-Width-Modulation. The high-accuracy sampling resistors are used as current sensors. The host PC collects and records all the experimental data as well as communicates with the NI CompactRIO and NI myRIOs via Ethernet and Wi-Fi, respectively. It also controls power supply through its RS232 serial communication ports. The specifications for the major components of the testbed are listed in Table II.

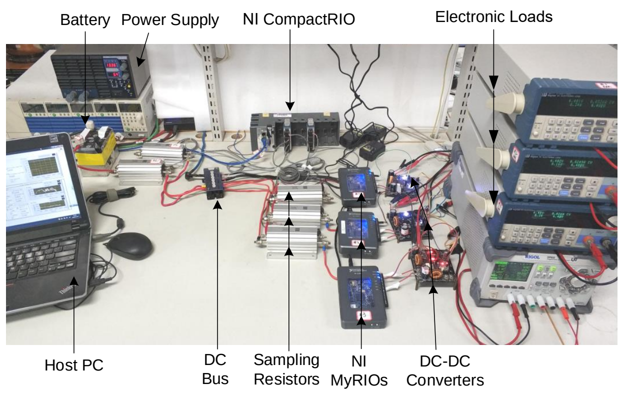

Fig. 10. Reduced-scale testbed.

A scenario of five EVs is considered here of which except $Q_{e,i}$ other parameters such as battery capacity, SOC, required charging power are same. A comparison between the simulation and the experimental results are shown in Fig. 11. Here, battery undertakes the power fluctuation arising from intermittent PV power generation. For EVs, EV1 has smaller $Q_{e,i}$ than EV2 and EV3, and thereby its charging power is reduced and its charging time is extended. Once EV2 and EV3 leave, EV1 obtains higher charging power. Similarly, the situation is similar for EV4 and EV5. As seen, the experimental charging powers of EVs well match the results in simulation. This validates the real-time implementation and correctness of the proposed energy management.

TABLE II
SPECIFICATIONS FOR MAJOR COMPONENTS.

Power Supply (Takasago ZX-800L)	Max power: 800 W (0-80V, 0-80A)
Electronic Loads (3 Maynuo M9711)	Max power: 150 W each (0-150 V, 0-30 A each)
DC-DC Converters (Design/fabricated in house)	Max power: 100 W each Switch Frequency: 20 kHz
Li-ion Battery Pack (Lishen LP2770102AC)	Four cells (series), 12.5 Ah/cell, 3.2 V/cell (nominal voltage)
High-accuracy Sampling Resistors (PCN Corporation RH series)	RH250M4 0.01 Ω (± 0.02%)

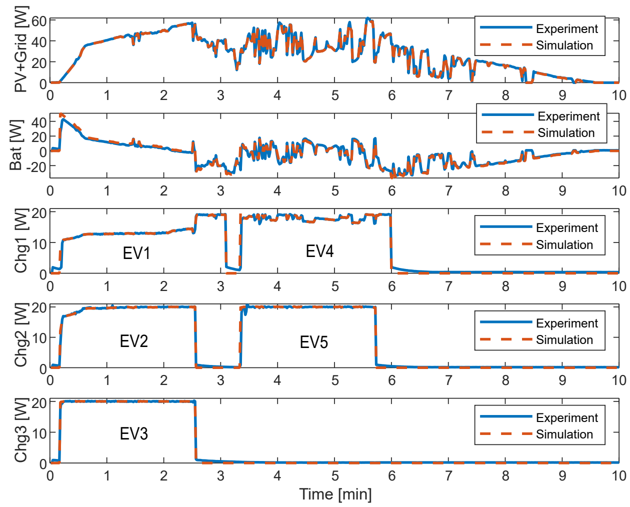

Fig. 11. Experimental versus simulation results.

VII. CONCLUSION

This paper presented a two-stage scheme for the power allocation of charging station and coordination of EVs charging. The power allocation among PV, battery and the grid as well as the available total charging power was solved in the first stage. Game theory was applied to deal with the different preference of each component, and its Nash equilibrium was directly solved based on the best response strategy. Then, the determined total charging power published to the second stage as coupled constraint. The EV charging coordination problem was solved by considering their unique individual charging requirements. And it was implemented in a distributed manner. Finally, the proposed scheme was evaluated through simulation and experiment. Comparing with conventional RBS, the proposed scheme could continuously maintain the battery SOC in an intermediate level, and make the grid power profile smooth as well as with lower PAR and peak power. The numerical results and comparison with benchmarks confirmed the effectiveness of the proposed solution.

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