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A decentralized power dispatch strategy in an electric vehicle charging station

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Abstract

In this study, a decentralized power dispatch in a charging station serving electric vehicles (EVs) is discussed. The power dispatch problem is solved through a Stackelberg game in real time. In this game, the leader is the EV charging station (EVCS) while the followers are EVs. The preferences of the EVCS are designed as being self-sufficient, providing charging services to the EVs, and maintaining the energy level of the battery energy storage system (BESS), which are described through different utility functions. In addition, the preferences of followers are to maximize their EV charging powers. The learning algorithm utilizes the consensus network to reach the generalized Stackelberg equilibrium as the power dispatch among EVs in an iterative decentralized manner. Both the static and dynamic case studies in the simulation verify the successful implementation of the proposed strategy, the flexibility to uncertainties and the re-configurability to the number of EVs. It also has an excellent performance compared with the centralized benchmark strategy with criteria, that is, the average EV charging time, the number of charge and discharge rate of the BESS and energy exchange to the grid. Finally, a down-scaled experiment implementation is set up to validate the functionality and the effectiveness of the game theory-based strategy.

1 | INTRODUCTION

With the interests in the distributed renewable energy sources and the concerns on air pollution, electric vehicles (EVs) have been intensively investigated in recent years [1, 2]. As a promising solution for the urban transportation, EVs have been widely applied in both public buses [3] and private passenger cars [4]. Considering the limited capacities of the batteries in EVs, EVs have to be charged at the service stations if the energy levels of the batteries are below the allowed ones. To this end, developing public EV charging station (EVCS)s is becoming an important demand for these concerns [5]. On the other hand, an EVCS itself can be a potential threat for the stability of the main grid because of the irregular charging schedules of EVs, that is, charging EVs simultaneously [6]. One of the possible solutions to stabilize the power flow of the charging stations is to utilize renewable energy such as photovoltaic (PV) energy to support charging EVs, namely, a PV-based EVCS [7]. Usually, the PVs are utilized together with battery energy storage systems (BESSs) because of the unpredictable solar irradiation. The BESS here can smoothen the PV power, provide a continuous charging service to EVs, and be the backup energy source. With the help of PVs and BESSs, the EVCS may work under the islanded state, that is, the main grid does not need to provide energy to the EVCS until it becomes a necessity. One of the questions here is, the sizing and placement design problem of an EVCS, which have been widely discussed [8–10]. In an EVCS, numbers of heterogeneous energy sources, with different preferences, are required to support the EV charging together where uncertainties in PVs and system configuration may exist. These concerns indicate that a comprehensive and flexible strategy should be designed to fulfil the above requirements.

The existing EV charging systems can be categorized into three levels [11], that is, slow charging (the charging power is lower than 3.7 kW, quick charging (the charging power ranges between 3.7 kW and 22 kW), and fast charging (the charging power is higher than 22 kW) [12]. Due to the public charging requirement, only the quick and the fast charging is considered in this study. In addition, the incoming EVs may have different battery capacities, state of charges (SoCs), and arriving time. These uncertainties are all related to the satisfaction levels of the EVs and thus designing a strategy becomes a critical problem. The present strategies can be categorized into centralized and decentralized ones. Centralized strategies in EVCSs are popular and can be classified into rule-based strategies and prediction based ones. For the rule-based strategies, a classical rule-based strategy implemented in an EVCS focuses on reducing the battery switch time and provide battery switch service in all working hours [13]. [13] designs a strategy with pre-defined rule where heuristic structure is utilized. The objective is designed to minimize the threat to the main grid. Similarly, [14] provides an online scheduling strategy with the same objective, that is, minimizing the threat to the main grid. For the prediction-based strategy, [15] gives a cooperative strategy among EVs.

In the meantime, decentralized strategies are considered as another possible solution toward the strategy problem in the EVCSs. In real applications, there could be unpredictable and changing number of the EVs in an EVCS. The types and the characteristics of EVs may also be quite different. Synergy, flexibility, and scalability are required when discussing a proper power dispatch strategy for the EVCS. This further adds difficulty in the power dispatch problem among EVCS and EVs. In this case, comparing with centralized strategies, decentralized strategies are more flexible in communication, reconfigurable in system topology, and robust to single point of failure. Due to the uncertainties existed in the EVCS system, decentralized control can fulfil the satisfaction level of EVs better. [12] provides a decentralized strategy to achieve efficient charging services through regulating the voltage of the direct current (dc) link. [16] utilizes a decentralized fuzzy logic control to the keep a stable power balance between EVs and EVCS. To the best knowledge of the authors, there is no literature modelling the EVs to be selfish, that is, maximize its preference without caring other EVs, and taking the non-cooperative characteristics into EVs charging strategy. In terms of decentralized decision-making, game theory is a well-known way to deal with the non-cooperative situations among selfish agents [17]. This aspect is, especially, useful to autonomously update the strategy when a system is reconfigured. In the game theory, the Stackelberg game is one of the famous games where one of the player is the 'leader' and others are the 'followers'. This aspect well matches the decentralized nature of the present power dispatch problem among EVCS and EVs. In this regard, a Stackelberg game is utilized to model the power dispatch problem among EVCS and EVs and then solves the power dispatch problem through reaching the Stackelberg equilibrium in a decentralized manner.

This study solves the power dispatch problem through a decentralized strategy utilizing game theory. This strategy should be fully decentralized and be adapted to uncertainties, that is, various EV capacities, SoCs, arriving times, and weather conditions. In this study, an EVCS with 20 charging places has been discussed in simulation and EVCS with three places in a down-scaled experimental real-world implementation. In addition, the power dispatch problem is represented as a Stackelberg game, in which the EVCS and EVs are treated as players. Since players are treated as selfish and individual ones, each player maximizes its utility function. Based on the learning algorithm, the players will communicate and negotiate with each other and then finalize to a Stackelberg equilibrium utilizing consensus network. This can be utilized as a solution for the power dispatch problem. This equilibrium can be reached under different uncertainties and system typologies. Finally, the performance and functionality of the proposed strategy is validated through both simulations and experiments.

- The strategy is fully decentralized and thus can avoid single point of failure
- The strategy can reserve player's local information, for example, SoC of EV battery
- The strategy is flexible to uncertainties and reconfigurable to the system topology
- The strategy is compared with centralized strategy to verify the performance
- The strategy has been validated in a down-scaled real-time experiment test bench

2 | COMPONENTS AND PREFERENCES

2.1 | EV charging station

As an extension of the previous work, [17], in this study, an EVCS possessing N charging places ($N = 20$) is utilized as an example to facilitate the following discussions. The EVCS shown in Figure 1 consists of PV panels, a BESS, a commercial load, and multiple EVs. There is a shared dc link connecting all the major sub-systems. For security enhancement, a power management system can reach the power flows and voltages while the private data of the EVs, such as SoCs of their on-board batteries are not available. Applying the proposed strategy, it sends commands to the converters and inverters to implement the power management, namely a real-time power dispatch.

- PV panels: The PV panels can work in one of the three modes, current control mode, voltage control mode, or standby mode. They are the main power sources for the present example EVCS. Therefore, the PV panels are designed to work in the current control mode during daytime. The well-known maximum power point tracking is usually applied through the dc-dc converter control. It should be, especially, noted that the power generation from them highly depends on weather conditions, namely a source of uncertainty in the system
- BESS: Similar to the PV panels, the BESS can work in either current control mode, voltage control mode, or standby mode. Except when its SoC is too low or high, the BESS is expected to mostly work in the voltage control mode in order to stabilize the dc-link voltage and smoothen the active power generated by PV panels. With this BESS control mode, the EVCS will be under islanded state. If the

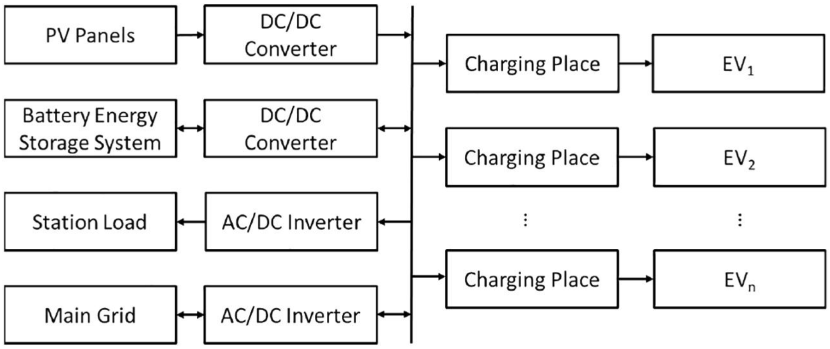

FIGURE 1 System configuration of an example EVCS with multiple EVs; EV, electric vehicle; EVCS, EV charging station; PV, photovoltaic

SoC of the BESS reaches its lower limit, the BESS will switch to the standby mode or current control mode for being charged by the main grid. On the other hand, with this BESS control mode, the EVCS will be under grid connected state

- Main grid: The EVCS is expected to mostly operate under its islanded state. However, the EVCS can be reconnected back to the main grid. With well-designed sizing and proper power dispatch strategy, the EVCS can be in a standby mode in most cases, while, as a backup generator, it can switch to current control mode or voltage control mode
- Commercial load: A typical office load is considered to be a typical commercial company profile in this study. The station load, here, only receives power according to the load profile and thus no control variable is designed for the load

For the power management in the EVCS, its major purposes are to

1. Be self-sufficient within an EVCS
2. Meet the charging needs from EVs
3. Maintain a proper SoC of the BESS

In this study, the EVCS is modelled as one single player. Its first objective is to be self-sufficient, i.e. to minimize the power flow between the EVCS and the main grid. The reasons for this objective is: (1) to fully utilize the renewable energy, and thus realize a 'green energy' based EVCS, and (2) to reduce the dynamic power influence from the renewable energy sources to the main grid. The second objective is to provide EV charging services as much as possible which is the basic function of the EVCS. At last, the third objective is to keep the BESS SoC in a proper range in order to provide the EV charging services when there is no PV power. Thus, the utility function of the EVCS, namely a quantification of its preference, can be defined as follows:

$$u_s(j) = -\mid p_{total,j} - \sum_{i=1}^{n} p_{ev,i,j} \mid, \tag{1}$$

and

$$0 \leq p_{total,j} \leq p_{pv,j} + p_{b,j} + p_{g,j} - pl, j, \tag{2}$$

where, $p_{total,j}$ is the total available charging power for EVs at time j. The symbols, $p_{pv,j}$, $p_{b,j}$, and $p_{g,j}$ are the supplied powers from the PV panels, BESS, and main grid, respectively; $p_{l,j}$ is the power consumed by the commercial load; n is the current EVs count in charging places. Note that $p_{g,j}$ is expected to be zero in the most cases. It could also become negative when the BESS SoC reaches the upper limit.

2.2 | Electric vehicles

As discussed above, there is usually a constraint on the total available charging power, $p_{total,j}$. It may be imposed by the system sizing, unfavourable weather conditions, and capacity of the main grid connection. Therefore, in the present EVCS, each EV may not be charged following its preferred charging profile. Compromises must be made to properly share the limited total charging power among all the plugged in EVs, which may have different capacities and SoCs of the on-board batteries. For an effective charging power management, it is important to quantify the preferences of plugged in EVs. The satisfaction level for charging could be enhanced by improving battery cycle life [18,19], saving charging cost [20], and increasing the sum of battery SoCs of all the plugged in vehicles. In this study, the utility functions of the EVs are defined to maximize their distributed charging power and be weighted by SoCs and capacities of the on-board batteries:

$$u_{i,j} = \frac{P_i^*}{SoC_{i,j}} \ln\left(p_{i,j} + 1\right), \tag{3}$$

and

$$\sum_{i=1}^{n} p_{i,j} \leq p_{total,j}, \tag{4}$$

$$0 \leq p_{i,j} \leq P_i^*, \tag{5}$$

where, P_i^* is the maximum charging power determined by battery type and capacity of the i-th EV. The lower and upper bounds of $p_{total,j}$ are $p_{min,s} = C_{max} V_{bus} N$ and $p_{max,s} = 2C_{max} V_{bus} N$, respectively. C_{max} is the maximum allowed EV battery capacity while V_{bus} is the nominal voltage of the EV battery.

3 | PROBLEM FORMULATION AND SOLUTION

3.1 | A leader-follower game

The two types of players, that is, the EVCS and EVs, have quite different utility functions (i.e. preferences) to maximize [refer to Equations (1) and (3)]. The EVCS is the single provider of the charging power, namely a dominant role. Thus, in this study, the EVCS is treated as the leader in the game while the EVs are designated to be the followers. The power dispatch problem then becomes a leader-follower game, that is, the Stackelberg game [21]. The solution of the charging power distribution is divided into two stages:

1. The first stage: The EVCS determines a virtual limitation on the total available charging power, $p_{total,j}$, which is a common constraint for the EVs [refer to Equation (4)];
2. The second stage: The plugged in EVs negotiate to determine a balanced charging power dispatch, that is, $p_{i,j}$'s, in a decentralized manner.

In the EVCS stage, the EVCS would first check the $SoC_{b,j}$. If the $SoC_{b,j}$ is out of the boundary, the EVCS will reconnect to the main grid. Otherwise, the EVCS will work under islanded state. Note that the EVCS would work under Islanded state for most of the time in order to satisfy the first objective of the EVCS. Then, the $p_{total,j}$ can be determined based on the current SoC of the BESS. This is because the second objective of the EVCS is designed to give charging power services to the EVs and the third objective is to keep the SoC of the BESS in a proper range. Meanwhile, the $p_{total,j}$ is utilized to reflect the current SoC status of the BESS. If the $p_{total,j}$ is large, it means the EVCS has enough energy so that it can provide more energy to the charging services, and vice versa. To this end, a rule-based strategy, that is, $p_{total,j}$ is proportional to $SoC_{b,j}$, that is, the SoC of the BESS, is applied as follows,

$$p_{total,j} = \begin{cases} +\infty, & SoC_{b,j} < SoC_{b,min} \text{ or } > SoC_{b,max} \\ p_{min,s}\left(1 + SoC_{b,j}\right), & \text{otherwise} \end{cases} \tag{6}$$

where, maximum number of the charging places is represented as N. C_{max} is the upper boundary of the C rate among batteries of EVs allowed in this EVCS. $SoC_{b,min}$ and $SoC_{b,max}$ are the minimum and maximum boundary of the SoC of the BESS.

Once $p_{total,j}$ is determined, the EVs start to seek a balanced power dispatch at the second stage. Through Karush-Kuhn-Tucker (KKT) conditions, the solution that maximizes the $u_{i,j}$ can be found [22]. Combining $u_{i,j}$ and constraint in Equation (4) gives Lagrangian function $L_{i,j}$,

$$L_{i,j}(p_{i,j}, \lambda_{i,j}) = u_{i,j} + \lambda_{i,j} G(p_{i,j}, \overline{\mathbf{p}}_{-\mathbf{i},\mathbf{j}}), \tag{7}$$

where,

$$G(p_{i,j}, \overline{\mathbf{p}}_{-\mathbf{i},\mathbf{j}}) = \sum_{i=1}^{n} p_{i,j} - p_{total,j}. \tag{8}$$

$\overline{\mathbf{p}}_{-\mathbf{i},\mathbf{j}}$ represents the power dispatch of the other followers' decision variables. $\lambda_{i,j}$ is the Lagrange multiplier. Note that the constraint (5) will be reflected in the following consensus network approach. Because of the concavity of (7), the existence and uniqueness of the so-called generalized Nash equilibrium is proofed by the KKT conditions. At the Nash equilibrium, no single player can benefit from unilaterally changing its decision while the other players maintain their previous decisions [18]. The KKT conditions of the i-th EV can be written as follows:

$$\frac{\partial L_{i,j}}{\partial p_{i,j}} = \frac{a_{i,j}}{p_{i,j} + 1} + \lambda_{i,j} = 0, \tag{9}$$

$$a_{i,j} = \frac{P_i^*}{SOC_{i,j}}, \tag{10}$$

$$G(p_{i,j}, \overline{\mathbf{p}}_{-\mathbf{i},\mathbf{j}}) \leq 0. \tag{11}$$

It is known that for the most socially stable generalized Nash equilibrium, the KKT conditions should satisfy the below relationship among the Lagrange multipliers [20, 23],

$$\lambda_{1,j} := \lambda_{2,j} := \ldots := \lambda_{n,j} := \overline{\lambda_j}. \tag{12}$$

3.2 | Consensus network approach

From Equation (9), it can be seen that each EV needs a common $\overline{\lambda_j}$ to determine its shared charging power. In the conventional centralized control scheme, there is a controller to collect all the necessary information, both local (P_i^* and $SOC_{i,j}$) and global ones ($p_{total,j}$, $p_{i,j}$, and n), and calculate the optimized charging power distribution under the KKT conditions.

However, in real applications, it is usually advantageous to protect the local information and provide flexibility and scalability when operating in a dynamic environment. Consensus network is applied to determine the common $\overline{\lambda_j}$ in a decentralized manner [24]. As shown in the Algorithm 1 below, this approach only requires global information. In order to protect the privacy and avoid single point failure, a consensus network technology is applied into learning algorithm. Thus, through utilizing $\overline{\lambda_j}$, the local charging power solution can be assigned. To this end, the consensus variable is suggested to be $\lambda_{i,j}$ for the ith EV through which the EV can access the global information. $\lambda_{i,j}$

will be shared with nearby players based on consensus network learning algorithm. Due to the common constraint (4), another consensus variable, that is, δp_j, is utilized to guarantee that each player will follow the constraint. Note that due to the leader–follower relationship, the $p_{i,j}$s are available to the EVCS and thus δp_j can be directly sent to each follower.

Algorithm 1 *Learning Algorithm*

1. **Initialization**
   $\lambda_{i,j}(0) = \frac{a_{i,j}}{P_i^*+1}$
   $\Delta p_j(0) = \sum p_{i,j}(0) - p_{total,j}$
2. **Consensus phase**
   while $\max(|\lambda_{x,j}(k) - \lambda_{y,j}(k)|) > \varepsilon_2, \forall x, y \in n$
   $\delta p_j(k) = \sum_{i=1}^{n} p_{i,j}(k) - p_{total,j}$
   $\lambda_{i,j}(k) = \lambda_{i,j}(k) + \sum_{m=1}^{n} w_{im,j}[\lambda_{m,j}(k) - \lambda_{i,j}(k)] + \eta\delta p_j(k)$
   $p_{i,j}(k) = \frac{a_{i,j}}{\lambda_{i,j}(k)} - 1$
   $p_{i,j}(k) = min\{max[p_{i,j}(k), P_i^*], 0\}$
   end while
3. **Check phase**
   if $|\delta p_j(k)| < \epsilon$ **then**
   Terminate
   else
   Continue $k++$
   end if
4. **Go back to step 2**

The proposed consensus algorithm is shown in Algorithm 1. In the initialization phase, $\lambda_{i,j}(0)s$ and $\Delta p_j(0)$ are determined as,

$$\lambda_{i,j}(0) = -\frac{a_{i,j}}{P_i^* + 1}, \tag{13}$$

$$\Delta p_j(0) = \sum p_{i,j}(0) - p_{total,j}(0). \tag{14}$$

Note that only $\lambda_{i,j}(0)$, instead of P_i^* and $SoC_{i,j}$, is being publicized among the players, that is, the EVs. The second step is the consensus phase where the EVCS and each EV updates δp_j and $\lambda_{i,j}$ following the rules,

$$\delta p_j(k) = \sum p_{i,j}(k) - p_{total,j}(k), \tag{15}$$

$$\lambda_{i,j}(k) = \lambda_{i,j}(k) + \sum_{m=1}^{n} w_{im,j}\left[\lambda_{m,j}(k) - \lambda_{i,j}(k)\right] + \eta\delta p_j(k), \tag{16}$$

where $w_{im,j}s$ are connectivity strengths and η is the step size for the $\delta p_j(k)s$. In order to guarantee that δp_j and $\lambda_{i,j}$ can converge to the average values of all the nodes, $w_{im,j}s$ are designed as $1/n$. Note that the communication network among EVCS and EVs are assumed to be a group in which any two players are connected with a bidirectional path. Firstly, the EVCS will tune its $\delta p_j(k)$ according to the difference between the $\sum p_{i,j}(k)$ and $p_{total,j}(k)$, shown in Equation (15). Then EVs will update $\lambda_i(k)$ according to Equation (16) with which $p_{i,j}(k)s$ can be calculated as follows:

TABLE 1 Specifications of the electric vehicle charging station

Parameters	Value
Capacity of the battery energy storage system	3000 kWh
Maximum power of PV panel system	1200 kWh
Rated power of the grid-connected system	1 MW
Maximum number of charging places	20

$$p_{i,j}(k) = \frac{a_{i,j}(k)}{\lambda_{i,j}(k)} - 1, \tag{17}$$

$$p_{i,min} \le p_{i,j}(k) \le p_{i,max}. \tag{18}$$

where, $p_{i,min}$ and $p_{i,max}$ are lower and upper boundaries of the EV charging powers. $p_{i,j}(k)s$ will be bounded according to $p_{i,min}$ and $p_{i,max}$. Finally, it returns to the beginning of step two unless the variation of $\lambda_{i,j}(k)s$ is less than a user-defined threshold value.

The third step is the check phase, it would check whether the $\sum p_{i,j}(k)s$ are close enough to the $p_{total,j}(k)$. If $\sum p_{i,j}(k)s$ and $p_{total,j}(k)$ satisfy the terminating condition, the algorithm would stop and each EV can update its charging power based on the $\lambda_{i,j}(k)$ and its charging power boundaries. Otherwise, the algorithm would jump back to step 2 and continue.

Note that if the charging power reached in Equation (17) is larger or smaller than the boundary values, the EVs will choose the boundary value as the solutions. The proposed strategy will determine the power dispatch once any EV joins or leaves the EVCS. If there is no EV joining or leaving the EVCS, the strategy will start every 10 min.

4 | SIMULATION RESULTS

4.1 | Example scenario

Here, a scenario with 20 charging places is taken as an example. A proper sizing is the base for discussing any strategy scheme. As listed in Table 1, since the EVCS is designed to work under islanded state, the size of the BESS and the PV panel system is designed based on the number of total incoming EVs, average capacity and SoCs of the EV battery. As shown in Table 2, the uncertainties of both EVs and PV panels are given. Here battery capacities of EVs follow normal distributions ranging from 65 to 83 kWh considering the ageing issue of the batteries. Again, the SoC of the EV batteries when the EVs stop at the charging place are designed as normal distributions with boundary from 0.2 to 0.5 and EVs will leave the EVCS when their BESSs are fully charged. The total number of the EVs which will stop at the charging station in a working day is designed as 100 to 130 depending on different scenarios. In addition, the EV charging power is determined from 1 C to 2 C since a quick or fast charging technology is utilized, where C is the charging current rate to fully charge the battery in 1 h. The incoming EVs are assumed to join the EVCS following Poisson distributions

TABLE 2 Uncertainty models in EVs and PV panel system

Uncertainty	Model	Mean	Standard deviation
EV arriving time	Poisson distribution	12:28 PM	209.58 (min)
SoC of EV battery	Normal distribution	0.35	0.075
Capacity of EV battery	Normal distribution	75 (kWh)	5 (kWh)
PV output power	Scaled profile and white noise	181.97 (kW)	258.69 (kW)

Abbreviations: EV, electric vehicle; PV, photovoltaic; SoC, state of charge.

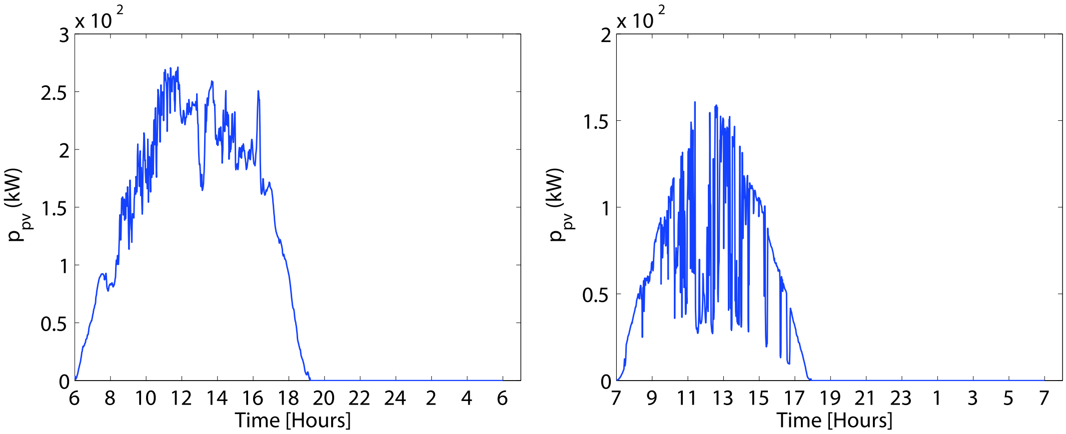

FIGURE 2 A typical summer day (left) and a typical winter day (right)

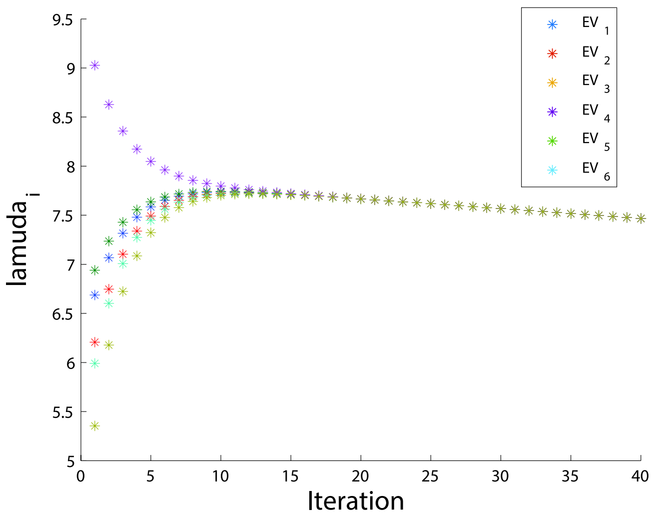

FIGURE 3 $\lambda_{i,30}$ map at 30 (min); EV, electric vehicle

considering a 12 h EVCS working time and the total incoming EVs number. Note that the proposed game theory-based strategy can be implemented with any sizing of the EVCS. The selected EVCS specification can be treated as an example. In addition, the PV output power profile is calculated based on the PV irradiation data from [25] and model from [13]. Then the profile is scaled with the maximum power of the PV panel system listed in Table 1. The uncertainties of the PV panel system are modelled by the white noise to emulate the sampling errors and weather uncertainties. Two example summer day and winter day PV output power profiles are shown in Figure 2.

4.2 | Static power dispatch

The static case study validates the performance of the proposed strategy and learning algorithm in a static case. A static case where there are six EVs in the EVCS is selected as an example, that is, $j = 30$ (min). As shown in Figure 3, with a given $p_{total,j}$ from the EVCS, the $\lambda_{i,j}$s from EVs can converge after several iterations which validate the efficiency of the learning algorithm. After the $\lambda_{i,j}$s stabilize, charging places are able to charge their connected EVs with the charging power given by (17) and (18). The example power dispatch for six EVs case is listed in Table 3. Since the existing EVs need to determine the power dispatch within $p_{total,j}$ and the PV output power is not sufficient, all EVs are charged according to their current SoC and P_i^*. In addition, the simulation results also suggest that the EV with highest capacity is able to have the largest charging power, that is, EV_5.

4.3 | Dynamic power dispatch

Further to the static case study, a complete procedure of the charging responses in a sunny summer day is presented here. According to the PV profiles, no radiation can be observed after 7 PM, the EVCS will stop acquiring power from PV after 7 PM. The power supply can only be acquired from BESS and grid.

As designed in Table 1, there are totally 100 incoming EVs, the entire power dispatch is over complicated and the dynamic responses are also over complicated to be shown in one figure. In this case, the entire power dispatch during charging of the first five EVs are picked up to verify the performance of the proposed strategy.

TABLE 3 The power dispatch at 30 (min)

Time (min)	p_1 (kW)	p_2 (kW)	p_3 (kW)	p_4 (kW)	p_5 (kW)	p_6 (kW)
30	154	141	153	160	156	144
p_b (kW)	SoC_1	SoC_2	SoC_3	SoC_4	SoC_5	SoC_6
704	0.52	0.37	0.52	0.29	0.30	0.32
p_{total} (kW)	C_1 (kWh)	C_2 (kWh)	C_3 (kWh)	C_4 (kWh)	C_5 (kWh)	C_6 (kWh)
908	76.9	70.4	76.7	80.1	78.1	71.9

Abbreviation: SoC, state of charge.

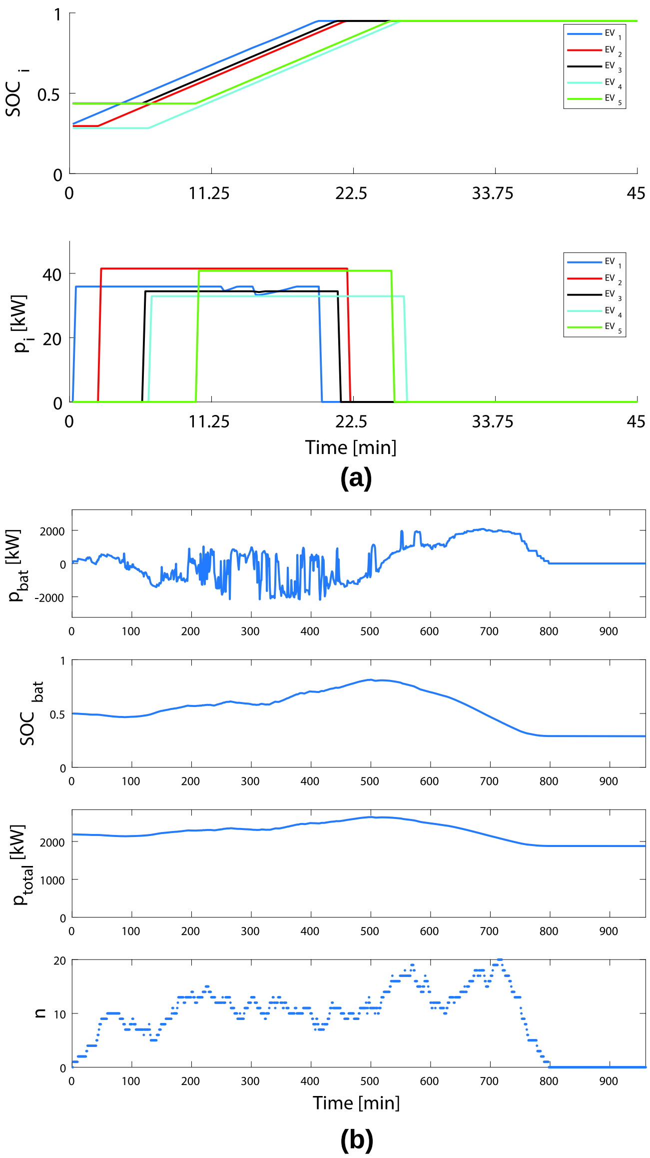

FIGURE 4 (a) The charging power and SoC responses of five selected EVs. (b) Power response of the BESS, SoC response of BESS, $p_{total,j}$ response, and number of coming EVs to the EVCS; EV, electric vehicle; EVCS, EV charging station; PV, photovoltaic; SoC, state of charge

It can be observed in Figure 4a that when EVs come in or leave the EVCS, the power dispatch will be re-arranged according to the preferences of the existing EVs in the EVCS like the example given in static case study. This result verifies that the proposed game theory-based strategy can be implemented with different system topology and uncertainties. In addition, with different initial EV SoC, all EVs will be fully charged before leaving the EVCS.

The power dispatch and SoC response of the BESS in the EVCS is shown in Figure 4b. During the entire simulation, the BESS has absorbed most of the dynamic power while the SoC of the BESS stays within the defined working range. This verifies that the utility function of the EVCS is well fulfilled and the capacity of the BESS is well designed. In addition, the $p_{total,j}$, is proportional to SoC_b, following the pre-defined solution of the EVCS. Besides, Figure 4b also verifies that the existing EVs in the EVCS can be any number less than 20 (the number of the charging places), which verifies that the dynamic case study has covered different cases including the EVCS has empty charging place and non-empty charging place cases.

4.4 | Comparison with centralized-based strategy

In order to verify the performance of the proposed game theory-based strategy, the proposed strategy is compared with an strategy that only maximizes the charging power of EVs, that is, $p_i = P_i^*$. This comparison is designed to verify that the GT-based strategy can provide a balanced EV charging power solution. The criteria in this comparison are E_{grid}, that is, the energy exchange from the main grid, n_{rate}, that is, the number of rate change from charge to discharge and from discharge to charge, $p_{b,charg}$, that is, the average charge power of the BESS, $p_{b,discharg}$, that is, the average discharge power of the BESS, and t_{EV}, that is, the average charging time for EVs, shown as follows,

$$E_{grid} = \sum_{j=1}^{T} \left(p_{b,j} + p_{PV,j} + \sum_{i=1}^{n} p_{i,j} + p_{l,j} \right), \tag{19}$$

$$p_{b,charg} = -\sum_{j=1}^{T} p_{b,j}, \text{ for } p_{b,j} < 0 \tag{20}$$

$$p_{b,discharg} = \sum_{j=1}^{T} p_{b,j}, \text{ for } p_{b,j} > 0 \tag{21}$$

$$t_{EV} = \frac{\sum t_{EV,i}}{n}, \tag{22}$$

TABLE 4 The simulation comparison results

Cases	$n = 100$	$n = 110$	$n = 120$	$n = 130$
[GT-based:]				
E_{grid} (MJ)	0	0	1932	6403
n_{rate}	30.51	31.81	32.63	32.95
$p_{b,charg}$ (MW)	0.24	0.22	0.21	0.20
$p_{b,discharg}$ (MW)	0.21	0.23	0.24	0.25
t_{EV} (min)	18.56	18.80	18.52	20.02
[Centralized-based:]				
E_{grid} (MJ)	0	492	2409	8776
n_{rate}	30.4	31.72	32.08	32.51
$p_{b,charg}$ (MW)	0.24	0.22	0.21	0.20
$p_{b,discharg}$ (MW)	0.22	0.23	0.25	0.26
t_{EV} (min)	18.48	18.47	18.45	18.43

where $t_{EV,i}$ is the charging time for ith EV and n is the number of EV, and T is the total simulation time. Note that these two criteria are directly related to the utility functions of the EVCS and EVs, respectively.

The simulation results are shown in Table 4 with different total incoming EVs cases, i.e. n. Due to the existing uncertainties, i.e. EV SoC, capacity, and arriving time, the simulation is run 1000 times for each case. After 1000 times of simulation run, t_{EV} for EVs utilizing the proposed strategy is comparable against the centralized one while the E_{grid} is much smaller under $n = 110$, $n = 120$ and $n = 130$ cases. In addition, the $p_{b,charg}$ for the GT-based strategy is almost the same as that for the centralized-based strategy while the $p_{b,discharg}$ for the GT-based strategy is larger than that for the centralized-based strategy under all three cases. These results suggest that (1) the centralized-based strategy have a larger energy exchange than the GT-based one which verifies the result from E_{grid}; and (2) with centralized-based strategy, the BESS will be out of power earlier than the BESS with GT-based strategy. Besides, the n_{rate}s for two strategies are almost the same, which proves the randomness for the uncertainties of both PVs and EVs. The n_{rate}s also increase with larger n, which means the more EVs come to EVCS the more frequently the BESS will change from charge to discharge and vice versa. These comparison results suggest that the GT-based strategy provides two benefits against the centralized-based strategy: (1) the GT-based strategy provides a more balanced solution among the preferences of EVs and EVCS; and (2) the GT-based strategy does not share the local information of EVs to the EVCS through using consensus network approach.

4.5 | Scalability analysis

Because of the decentralized manner of the proposed strategy, the convergence speed of the learning algorithm with more and more EVs involved becomes a considerable problem. Thus, it is necessary to have a scalability analysis for the game theory based power dispatch strategy. Based on the proposed the simulation system, the maximum number of EVs is 20. In the scalability analysis, the number of iterations needed to converge is recorded with different number of EVs ranged from 3 to 100. As shown in Figure 5, the computation burden is proportional to number of EVs. Since there is no exponential increase or other specific increase for the iterations toward the number of EVs, it can be concluded that when the number of EVs increases, the proposed power dispatch strategy is scalable [24].

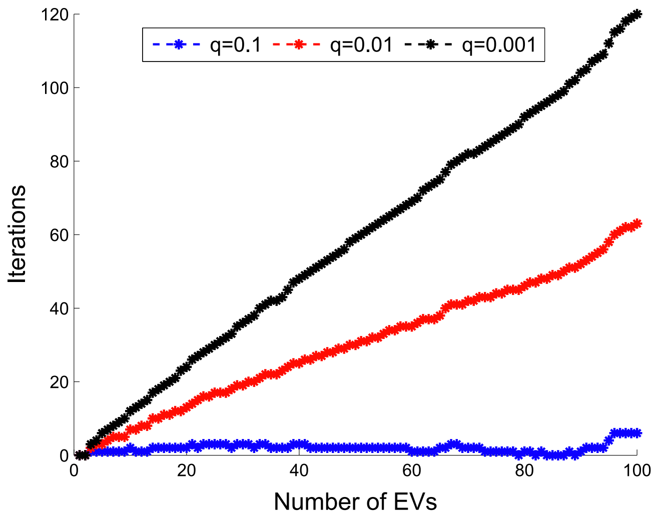

FIGURE 5 The relationship between iterations of the learning algorithm and number of EVs; EV, electric vehicle

As shown in Figure 5, the threshold value for the stop condition of the learning algorithm, that is, q ranges from 0.1 to 0.001. It can be observed that there is a trade-off between the convergence accuracy and the number of iterations. The q can be designed as different value based on the calculation ability of the controller where the proposed power dispatch strategy is implemented.

5 | EXPERIMENTAL RESULTS AND ANALYSIS

Figure 6 and Table 5 show the down-scaled test bench and specifications of the experimental system. An EVCS with three charging places is utilized to verify the functionality and effectiveness of the proposed game theory-based strategy. Note that from the strategy point of view, there is no difference between an EVCS with three charging places and an EVCS with 20 charging places. The EVs and charging places are emulated through three electronic loads and buck converters. Note that the electronic load is working in constant voltage mode in order to model a real EV battery while the buck converter is implemented to control the charging power. The charging power is controlled by an individual National Instruments (NI)-myRIO, which samples the charging power

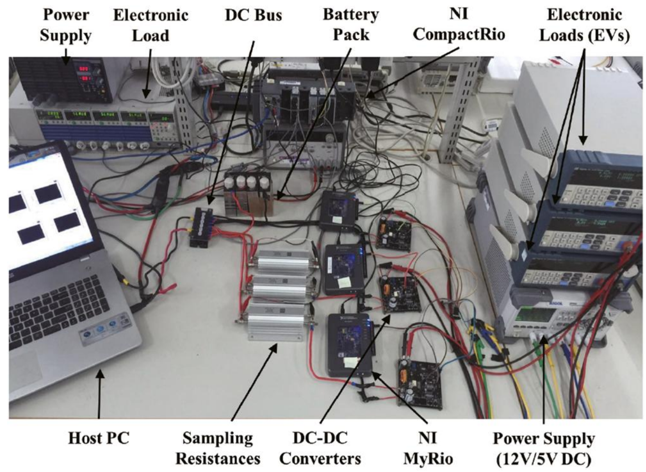

FIGURE 6 Down-scaled test bench

TABLE 5 The parameters of EVs

EV_i	1	2	3	4	5	6	7	8	9	10
P_i^* (W)	12	12	10.75	11.5	12.75	10.75	10.75	10.75	13.75	13
SoC_i	0.34	0.31	0.44	0.23	0.31	0.29	0.21	0.20	0.35	0.41

Abbreviations: EV, electric vehicle; SoC, state of charge.

and performs the pulse-width-modulation wave to the buck converter. Three proportional-integral (PI) controllers are implemented in the NI-myRIOs to control the charging powers. The PV-panels and station load are emulated through a power supply and an electronic load programmed by LabVIEW in a host personal computer (PC). Note that the power supply and electronic loads are connected to the host PC through RS-232 port. A NI-CompactRIO is utilized to sample the power flow of the BESS. Thus, the NI-CompactRIO together with the host PC can be treated as the EVCS strategy centre. Since the BESS with converter works in voltage mode, it is emulated through a real battery directly connected to the dc-bus for simplicity proposes. Five 0.01 Ω high-accuracy sampling resistors are utilized to measure the currents of the EVs, station load, and PV panels.

Note that the rated power and capacity are also scaled down to the test bench level. The total incoming EV number is scaled down to 10 while the total simulation time is scaled down to 1440 s. Since there is nearly no energy exchange in the last 440 s, the experimental results only show the responses within the first 1000 s. The PV power profile will also be scaled down accordingly. Following the power profile of the PV-panels system and station load, the reference power can be directly sent to the power supply and electronic load. The communication among EVs and charging station is designed utilizing shared variables in LabVIEW program through Wifi communication. Similar to the simulation, the EVs will leave the EVCS when they are fully charged.

As shown in Figure 7a, the power dispatch of 10 EVs with three charging places verify the effectiveness of the proposed

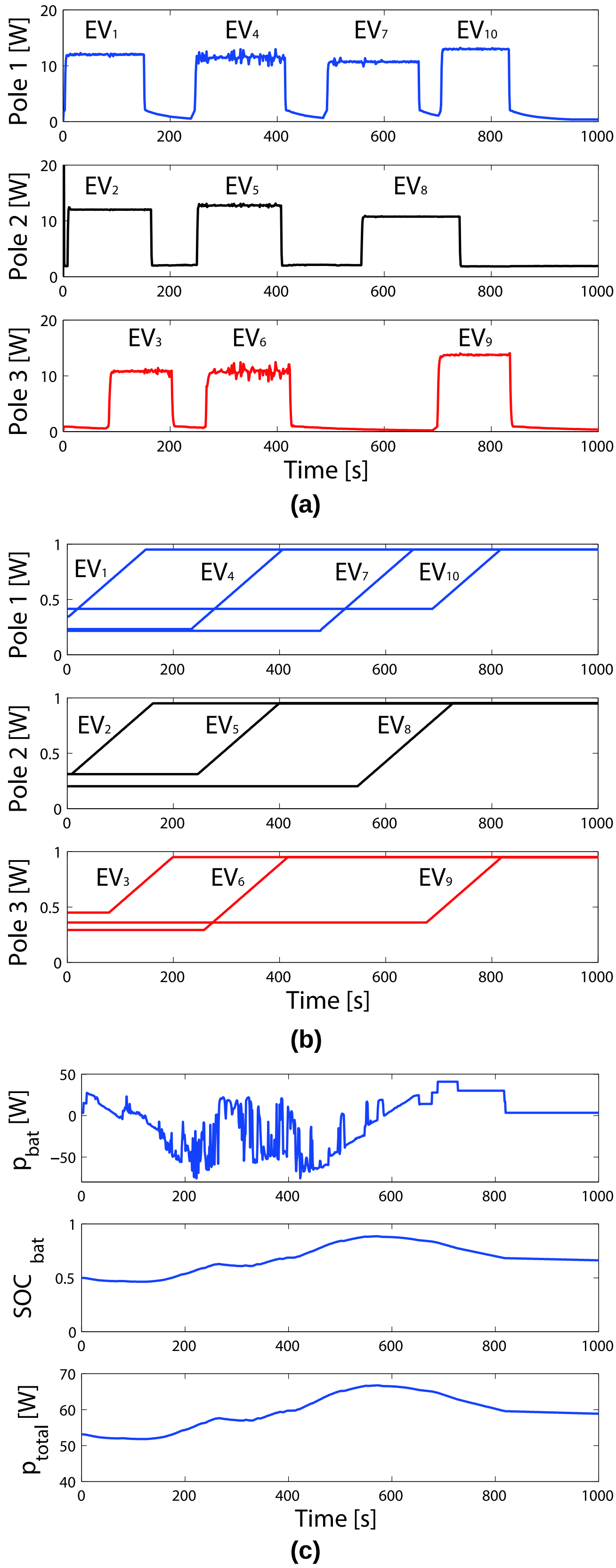

FIGURE 7 (a) EV charging power response. (b) EV SoC response. (c) Battery power response, SoC response of BESS, and p_{total} in experiment; EV, electric vehicle; SoC, state of charge

TABLE 6 Specifications for major components

BESS	Lishen LP2770102AC,
Four cells	12.5 Ah/cell
EVs	Lishen LP2770102AC
Two cells	12.5 Ah/cell
(Emulated through electronic loads)	
Power supply	Takasago ZX-800L
Max power: 800 W	(0–80 V, 0–80 A)
Electronic load	Kikusui PLZ-50 F/150U,
Max power: 600 W	4 PLZ150Us with 1.5–150 V, 0–30 A
dc-dc converters	Design/fabricate in house
Switch frequency: 20 kHz	Efficiency: > 90%
High-accuracy sampling resistor	PCN Corporation RH series
Five RH250M4 0.01 Ω (±0.02%)	

Abbreviations: AC, alternating current; BESS, battery energy storage system; EV, electric vehicle.

strategy, that is, the power dispatch follows the P_i^* and SoC_i given in Table 6. For example, the charging powers of EV_1 and EV_2 are higher than the charging power of EV_3 due to the higher P_i^* and lower SoC_i. When the total available charging power is sufficient, for example, only two EVs are in the EVCS and p_{total} is high enough at 600 s, EVs can be fully charged. The fluctuations in the charging power responses are caused by the sampling errors and response time of the PI current controllers. It can be observed that EVs come to the EVCS in sequence following the Poisson distribution. The initial SoCs of EVs are determined through normal distribution, shown in Figure 7b and Table 6. All EVs are fully charged when they leave the charging station. As shown in Figure 7c, the power response of the BESS shows a similar dynamic response, which verify the smooth and stabilizing function of the BESS. As shown in Figure 7c, the SoC response of BESS verifies the sizing of the EVCS, that is, the BESS has never been over charged or over discharged. Similar to the simulation results, the p_{total} follows the same track of the SoC response of the BESS.

6 | CONCLUSIONS

This study designs and develops a decentralized power dispatch strategy in EVCSs. The power dispatch problem is converted into a Stackelberg game, in which the EVCS and EVs are modelled as individual players. Each player possesses a utility function representing its preference, that is, being self-sufficient, providing charging power services to the EVs, maintaining the SoC of the BESS, and maximizing the EV charging power. Through a learning algorithm utilizing consensus network, the generalized Stackelberg equilibrium is iteratively reached as a solution for the charging power dispatch problem. The simulations in both static and dynamic case studies give an improved performance, reconfigurablility, and scalability with the game theory-based strategy. Finally, a down-scaled real-world test bench is utilized to validate the real-world implementation and the effectiveness of the proposed decentralized strategy.

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