Distributed Charging Management of Electric Vehicles Considering Different Customer Behaviors

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Abstract—This paper proposes a charging management of electric vehicles (EVs) in a charging station taking into account different behavioral responses of EV customers. The EV charging problem is decomposed into two subproblems. The first subproblem is called the pricing game and it considers the charging price and the allowable requesting EVs for charging. Included in this subproblem three different EV customer responses to the charging price are developed. While the second subproblem is called the power distribution game and it tackles the charging power distribution among the plugged in EVs. Three different EV customer responses to the charging power are also proposed and included here. The proposed solution for each subproblem is reached iteratively in a distributed way. Detailed simulation, experiment, and comparison results are presented to verify the effectiveness and correctness of the proposed charging management with EV customer behaviors.

Index Terms—Distributed charging management, electric vehicle (EV), charging station, customer behavior, game theory.

I. INTRODUCTION

T HE increase in energy demand and the interest in environmental concerns have boosted the focus on the renewable energy sources and the electric vehicles (EVs). The number of EVs on streets are continuously growing, however, the limited capacity of their on-board batteries remains the big challenge for their widespread use. This issue requires EVs to be charged frequently to satisfy the charging requirements of their EV customers. However, the total charging load of EVs has to respect the charging capacity of the charging station to avoid overload cases, which may affect the distribution power network [1]. Addressing the matters related to the EV charging problem requires developing an appropriate charging management, i.e., control, of EVs in the charging station. This management is also important to provide a flexible and a scalable charging in a dynamic environment.

The EV charging problem was tackled in literature for different aspects including the control of the charging energy price and the charging power distribution of EVs. The control architecture here can be mainly classified into centralized and distributed approaches. Ref. [2] presented a centralized scheme to optimize the charging schedule of each EV while respecting the demand curtailment request from the utility. Ref. [3] developed a learning particle swarm optimization algorithm to optimize the power distribution with enhanced economic benefits. Ref. [4] introduced a four-stage optimization control algorithm to reduce the operational cost in an EV charging station and to balance the power supply and demand.

The distributed control has recently received a notable attention due to its scalability and reduced communication burden. Its importance is also because of the ability to secure the privacy of the customers by reaching the solution without revealing their private information. Ref. [5] applied game theory into an EV fast charging station in which EVs optimize the tradeoff between the benefits of charging and reserves provision. Ref. [6] presented a decentralized control method for charging stations. Two independent fuzzy logic systems were utilised to maintain the power balance stable among the charging station components. Ref. [7] developed a pricing scheme to minimize power distribution losses in plug-in EV (PEV) charging stations and to ensure system reliability.

On the other hand, treating the EV customers to have the same behavioral response model such as linear function, with respect to some charging quantities, e.g., charging price and charging power, is still the main trend in the EV charging literature. However, in practice the EV customers are more likely to have different behaviors, i.e., responses, and integrating them into the charging problem is becoming more attractive. The behavior could be basically modelled on the basis of survey questionnaire [8], historical data [9], or theoretical formulas [10].

Unlike the aforementioned literature, this paper develops an EV charging management, which addresses different preferences of charging station parties and different behaviors of EV customers. Note that EV customer, EV driver, and EV are used as alternatives in this paper. The EV charging problem is considered as two subproblems on the basis of the two distinct states of EV. By applying the suitable decision making tool of game theory, these two subproblems are considered as two games and named as pricing game and power distribution game. The solution of each game is reached in a distributed way to allow scalability and to secure the private information of EV customers. All simulation, experiment, and comparison are carried out to validate the proposed EV charging management and its real implementation. The major work of this paper is summarized as follows:

1) Whole operation management of EV charging station under conflicted preferences, utility functions, of charging station operator and EV customers, i.e., charging station

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parties. This management includes determination of the charging price, selection of EVs for charging, and distribution of power among the plugged in EVs.

- Dynamic determination of the charging price on the basis of the present electricity price and EV calls for charging.
- Power distribution control under the two realistic cases of sufficient and limited power for charging, i.e., no overload and overload, respectively.
- 4) Three different behavioral responses of EV customer to the charging price and power, on the basis of insights from social sciences and economics, are newly proposed and integrated into the EV charging management.

II. SYSTEM STRUCTURE AND MODEL

The studied EV charging station (EVCS), which represents one node with a feeder of the distribution power network, contains fixed and dynamic systems as illustrated in Fig. 1. The fixed systems include a grid system (GS), a photovoltaic system (PVS), a battery energy storage system (BESS), and a base load system (BLS). Each of them could be a group of systems with the same type. On the other hand, the dynamic systems consist of a number of requesting EVs for charging $(\mathcal{N}_r := \{1, 2, \dots, N_r\})$ and a number of plugged in EVs $(\mathcal{N}_p := \{1, 2, \dots, N_p\})$. The requesting EVs represent a group of needed EVs to be charged, which send charging calls to the EVCS. Once the charging calls are approved, the related EVs can come the EVCS, occupy the charging poles, and become plugged in EVs to be charged by power. Note that the numbers of requesting EVs and plugged in EVs are dynamic over time.

The GS can supply or receive power in the EVCS, thus symbolized by GS^+ or GS^- , respectively. The model of the PVS is derived as in [11], while the battery of BESS or plugged in EV on-board is modeled by its equivalent circuit model [12]. BLS represents the EVCS building load (i.e., non-EV load). Further to the aforementioned systems, there is an EVCS operator (CSO) whom handles the following missions:

- 1) Receives the charging calls from the requesting EVs and coordinates the charging of the plugged in EVs.
- 2) Determines the charging price.
- 3) Controls the power flow among the fixed systems including the regulation of the BESS power in relation to the GS power and PVS power. Since the focus of this paper is on charging EVs, this power flow is controlled in a similar way in [4].
- 4) Announces the charging capacity and checks its violation.

It has to be mentioned that due to the PVS intermittent nature, the amount of its generated power is uncertain. This dynamic power supply can be compensated by BESS and GS. During unfavorable weather conditions, the insufficient PVS power may potentially result in cases when the total power demand is bigger than the total power supply, i.e., overload cases. The proposed charging management tackles these challenging cases to efficiently distribute the present total available charging power among EVs, as discussed and validated in the following sections.



Fig. 1. Structure of the test system.

III. OPERATION MANAGEMENT OF CHARGING STATION

The whole operation of the EVCS is constructed on two tasks, i.e., subproblems, which are classified on the basis of the two distinct states of an EV. These two EV states are requesting for charging energy reservation when it is unplugged and seeking for charging power when it is plugged in. Each task is formulated on the basis of game theory, a suitable decision making tool, with a noncooperative type due to the selfish nature of the EV charging problem [5]. The first task is called the pricing game and it is excused at each time interval T_1 . While the second task is called the power distribution game and it is executed at each time interval T_2 . As shown in Fig. 2, T_1 is larger than T_2 , thus the results of each pricing game will obviously influence the outcomes of its subsequent power distribution games.



Fig. 2. Timing diagram of the two games of the charging station operation.

A. Pricing Game

This game addresses the EV charging calls, that is, the determination of the charging price and the allowable requesting EVs for charging along with their assigned energy demands. The charging call of each *n*-th EV ($n \in \mathcal{N}_r$) carries its original, i.e., physical, charging energy demand $E_n^o = E_n^c \times (SoC_n^e - SoC_n^s)$ with E_n^c is its on-board battery capacity as well as SoC_n^s and SoC_n^c are its state-of-charge (SoC) values at the start and end charging times, respectively. The involved parties in this game are the CSO and the requesting EVs whom have conflicting objectives as discussed below. EVs call the CSO to reserve charging price and the accepted, allowable, EVs for charging out of the requesting EVs. The interactions between these two parties are represented by a noncooperative Stackelberg game in which

CSO is assumed to be a leader and EVs are designated to be followers. In a market-oriented environment, usually the preference of CSO is to enlarge its own profit through selling energy to EVs, thus its utility function is defined to maximize (1).

$$u_{cso} = \sum_{t=t_0}^{t_0+T_1} \left(C_{ch,t} - C_{pv,t} - C_{b,t} - C_{g,t} - C_{l,t} \right)$$
$$= \sum_{t=t_0}^{t_0+T_1} \left(\sum_{n=1}^{N_r} \theta_{ch,t} E_{n,t} - \theta_{pv,t} E_{pv,t} - \theta_{b,t} E_{b,t} - \theta_{g,t} E_{g,t} - \theta_{l,t} E_{l,t} \right).$$
(1)

In the above equation, t_0 is the present time, and t is a specific time. $C_{ch,t}$, $C_{pv,t}$, $C_{b,t}$, $C_{g,t}$, and $C_{l,t}$ are the costs of charging EVs, PVS operation, BESS operation, energy supplied from/back the GS, and BLS operation during a specific time, respectively. $\theta_{ch,t}$, $\theta_{pv,t}$, $\theta_{b,t}$, $\theta_{g,t}$, $\theta_{l,t}$ are the unit costs of charging EVs (i.e., charging price), PVS operation, BESS operation, energy supplied from/back the GS (i.e., electricity price), and BLS operation, respectively. As seen, $\theta_{b,t}$ influences the profit of CSO. $E_{n,t}$, $E_{pv,t}$, $E_{b,t}$, $E_{g,t}$ and $E_{l,t}$ are the energies consumed or supplied by the *n*-th EV, PVS, BESS, GS, and BLS during a specific time.

On the other hand, naturally each n-th EV driver aims to meet his/her charging energy demand at a minimized expense, such as following the below utility function,

$$u_n^{\theta} = \sum_{t=t_0}^{t_0+T_1} \left(-\frac{1}{2} S_{n,t} E_{n,t}^2 + (\theta_{ch,n}^{max} - \theta_{ch,t}) E_{n,t} \right).$$
(2)

With $\theta_{ch,n}^{max}$ is the maximum charging price (cent/kWh) at which the EV driver begins to be unwilling to pay; $S_{n,t}$ is the EV driver energy-price sensitivity (cent/kWh²), i.e., sensitivity towards his/her required charging energy on the basis of the charging price. The utility function (2) reaches its maximum at each specific time when

$$E_{n,t} \doteq E_{n,t}^* = \frac{\theta_{ch,n}^{max} - \theta_{ch,t}}{S_{n,t}},\tag{3}$$

namely a preferred amount of charging energy, $E_{n,t}^*$, jointly determined by the dynamic charging price and the EV driver sensitivity. Thus the charging price and the EV driver sensitivity are obviously influencing the charging decision. In this paper, this EV driver sensitivity is related to the EV driver behavior in which three responses are proposed, namely high, mid, and low sensitivities to the charging price, and shown in Fig. 3. For reaching the same amount of charging energy, the relationships are different between the charging price and the required energy. Based on insights from social sciences and economics [13], these relationships are represented by exponential, linear, and logarithmic functions, and correspond to price high-sensitive driver (Pr-HSD), price mid-sensitive driver (Pr-MSD), and price less-sensitive driver (Pr-LSD). The logarithmic function displays a "risk-averse" (opening downward) behavior. It indicates a tendency to prioritize securing the charging energy as much as possible over the charging price. This behavior matches the Pr-LSD. Similarly, the exponential and linear functions show "risk-seeking" (opening upward) behavior (i.e., Pr-HSD) and "risk-neutral" behavior (i.e., Pr-MSD), respectively.



Fig. 3. Charging price vs. energy demand of EV driver under three different responses.

Thus the dynamic EV driver sensitivity can be accordingly defined as

$$S_{n,t} = \frac{S_n^{base}}{(1 - SoC_{n,t})R_{n,t}}.$$
(4)

In the above equation, $SoC_{n,t}$ is the present SoC of the *n*-th EV on-board battery. The behavioral response of the EV driver to the charging price is represented by $R_{n,t}$,

$$R_{n,t} = \begin{cases} \frac{e^{\alpha_{n,t}} - 1}{e - 1}, & \text{for } \Pr - \text{HSD} \\ \alpha_{n,t}, & \text{for } \Pr - \text{MSD} \\ ln[\alpha_{n,t}(e - 1) + 1], & \text{for } \Pr - \text{LSD}. \end{cases}$$
(5)

The parameter $\alpha_{n,t} \in [0,1]$, which is the same input of the three customer responses, reflects the ratio of the present charging price $\theta_{ch,t}$ to its EV driver maximum limit $\theta_{ch,n}^{max}$,

$$\alpha_{n,t} = max \left(1 - \frac{\theta_{ch,t}}{\theta_{ch,n}^{max}}, 0 \right).$$
(6)

Note that if $\theta_{ch,t}$ equals zero, naturally all $R_{n,t}$'s become identical, one, due to the "free" charging. From (4), obviously the static base sensitivity, S_n^{base} , equals $S_{n,t}$ when $R_{n,t}$ is one and $SoC_{n,t}$ is zero, i.e., EV on-battery is fully depleted. Thus S_n^{base} could be reasonably defined as [refer to (3) and Fig. 3]

$$S_n^{base} = \frac{\theta_{ch,n}^{max} - \theta_{ch,n}^{base}}{E_n^c}.$$
 (7)

Where $\theta_{ch,n}^{base}$ is a base charging price until which the EV driver will not compromise his/her original charging energy demand.

Due to the linearity of the CSO utility function, i.e., sum of linear functions, and the concavity of the EV driver utility function, both the existence and the uniqueness of the Nash equilibrium can be straightforwardly proven [14]. Algorithm 1 summarizes the iteration process to reach the Nash equilibrium, i.e., determination of the charging price and the allowable EVs for charging, following the above procedures [refer to (1)– (7)]. In the algorithm, k is the number of iteration, and $\Delta \theta_{ch}$ is a fixed step size to increase $\theta_{ch,t}[k]$. After considering a proper initialization, the algorithm works in a distributed manner as follows. First, CSO announces the modified charging price at the current iteration k as in line 6. Then, EVs respond to this price and calculate their current energy demands [refer to lines 7-9]. Consequently, CSO calculates its resulting profit as in line 10. The above process is constantly repeated as long as there is an increase in the CSO profit. The iteration stops when the CSO utility, u_{cso} , (i.e., its total profit) is maximized under a specific (i.e., final) charging price, $\theta_{ch,t}$. At this point, the *n*-th EV may have reduced its original energy demand to an assigned energy demand $E_n^a = \sum_{t=t_0}^{t_0+T_1} E_{n,t}^*$, which is determined based on its response (i.e., acceptance) to the final charging price. It is the truth that all $\theta_{ch,n}^{max}$'s of the allowable EVs for charging are larger than the final charging price. Note that under the iteratively distributed manner of the the algorithm, the assumed private information of EVs, such as $R_{n,t}$ and $SoC_{n,t}$, is not reveled to the leader CSO.

Algorithm 1 Pricing Game Management

I. Initializing Phase 1: k = 02: $\theta_{ch,t}[k] = \theta_{g,t}$ 3: Update $SoC_{n,t}$, $\forall n \in \mathcal{N}_r$ 4: Calculate S_n^{base} by (7), $\forall n \in \mathcal{N}_r$ $\forall n \in \mathcal{N}_r$ **II.** Updating Phase 5: k = k + 16: $\theta_{ch,t}[k] = \theta_{ch,t}[k-1] + \Delta \theta_{ch}$ 7: Calculate $R_{n,t}[k]$ by (5), $\forall n \in \mathcal{N}_r$ 8: Calculate $S_{n,t}[k]$ by (4), $\forall n \in \mathcal{N}_r$ 9: Calculate $E_{n,t}^*[k]$ by (3), $\forall n \in \mathcal{N}_r$ 10: Calculate $u_{cso}[k]$ by (1) III. Checking Phase 11: if $u_{cso}[k] < u_{cso}[k-1]$ then 12: Final $\theta_{ch,t} \leftarrow \theta_{ch,t}[k-1]$ Terminate 13: 14: else Go back phase II 15: 16: end if

B. Power Distribution Game

This game handles the power distribution among the plugged in EVs and it works as follows. After the settlement of the pricing game, the allowable (i.e., accepted) EVs will plug in for charging until they meet their assigned energy demands. The involved parties in this game are only the plugged in EVs, i.e., CSO here is just a coordinator. During charging, each EV tries to maximize its satisfaction, i.e., desire to have a specific amount of charging power. The interactions between EVs are represented by a noncooperative game in which the utility function of the *n*-th EV ($n \in \mathcal{N}_p$) for the charging power problem is defined as follows,

$$u_{n,t} = \vartheta_{n,t} \left(-\frac{1}{2} p_{n,t}^2 + P_n^d p_{n,t} \right),$$
 (8)

$$0 \le p_{n,t} \le P_n^d. \tag{9}$$

With $p_{n,t}$ is the actually acquired charging power of the *n*-th EV; P_n^d is its desired charging power, which may be not met such as due to limited total charging power, i.e., insufficient charging capacity; $\vartheta_{n,t}$ is a parameter to reflect the charging power anxiety (PA) of its driver. Obviously, the above utility function reaches its maximum when $p_{n,t}$ equals P_n^d , and its value is scaled by $\vartheta_{n,t}$, the power anxiety of the specific EV driver. The proposed concept of the power anxiety, analogous to the range anxiety concept in driving, is defined as the worry of the EV driver charging his/her EV that will run out of time before reaching his/her desired, assigned, energy demand. Thus PA represents the power excitement, $\beta'_{n,t} \in [0, 100]$, to make the desired charging power P_n^d matches the reference charging power $P_{n,t}^r$, i.e., ratio of the remaining energy demand over the remaining charging time. In other words, the higher the *n*-th EV power anxiety, the higher its ability to meet its energy demand at its preferable end charging time t_n^e .

$$\beta_{n,t}' = \frac{P_{n,t}^r}{P_n^d} = \frac{E_n^c(SoC_n^e - SoC_{n,t})}{(t_n^e - t)} \times \frac{1}{P_n^d}.$$
 (10)

Similar to section III-A, the PA is related to the EV driver behavior in which three responses are proposed, namely high, mid, and low sensitivities to the power excitement, a function to the reference charging power, and shown in Fig. 4. For reaching the same amount of charging power anxiety, the relationships are different between the power excitement and PA. Again, these relationships are represented by exponential, linear, and logarithmic functions, and correspond to power high-sensitive driver (Po-HSD), power mid-sensitive driver (Po-MSD), and power less-sensitive driver (Po-LSD). The logarithmic function displays a "risk-averse" (opening downward) behavior. It indicates a tendency to prioritize securing the charging power as much as possible over the charging time to avoid ending up without reaching the desired energy demand. This behavior matches the Po-HSD. Similarly, the exponential and linear functions show "risk-seeking" (opening upward) behavior (i.e., Po-LSD) and "risk-neutral" behavior (i.e., Po-MSD), respectively. Accordingly, and on the basis of $\beta_{n,t} = \beta'_{n,t}/100$, which is the same input of the three customer responses, the power anxiety $\vartheta_{n,t} \in [0,1]$ can be written as

$$\vartheta_{n,t} = \begin{cases} ln[\beta_{n,t}(e-1)+1], & \text{for Po} - \text{HSD} \\ \beta_{n,t}, & \text{for Po} - \text{MSD} \\ \frac{e^{\beta_{n,t}-1}}{e-1}, & \text{for Po} - \text{LSD.} \end{cases}$$
(11)



Fig. 4. Power excitement vs. power anxiety of EV driver under three different responses.

Solving the power distribution game looks clear by looking at (8) because each EV is willing to be charged at his/her desired charging power P_n^d . However, during charging in real environments there are various factors that can limit the power supply from the EVCS. These factors will dynamically influence the charging capacity $p_{ch,t}^c$, i.e., total available power for charging EVs, managed by the CSO. It is possible that the total sum desired charging power of EVs, charging requirement, may become larger than the charging capacity, i.e., overload case. Thus EVs must compromise their desired charging power demands to meet the EVCS charging capacity, constraint (12).

$$\sum_{n \in \mathcal{N}_p} p_{n,t} \le p_{ch,t}^c.$$
(12)

Since (12) couples all the charging power of EVs, the aforementioned charging power problem is actually a generalized Nash equilibrium (GNE) problem [14]. Since the proposed solution of this problem is based on the Karush–Kuhn–Tucker (KKT) conditions of optimality, the Lagrangian function of the *n*-th EV can be given as

$$L_{n} = \vartheta_{n,t} \left(\frac{1}{2} p_{n,t}^{2} - P_{n}^{d} p_{n,t} \right) + \lambda_{n,t} \left(\sum_{n \in \mathcal{N}_{p}} p_{n,t} - p_{ch,t}^{c} \right) + \mu_{n,t}^{min} \left(0 - p_{n,t} \right) + \mu_{n,t}^{max} \left(p_{n,t} - P_{n}^{d} \right).$$
(13)

With $\lambda_{n,t}$, $\mu_{n,t}^{min}$, and $\mu_{n,t}^{max}$ are the Lagrange multipliers of the *n*-th EV. Consequently, the gradient condition of the KKT necessary optimality conditions is

$$\frac{\partial L_n}{\partial p_{n,t}} = \vartheta_{n,t} \left(p_{n,t} - P_n^d \right) + \lambda_{n,t} + \mu_{n,t}^{min} + \mu_{n,t}^{max} = 0.$$
(14)

Both the existence and the uniqueness of the GNE can be mathematically proofed due to the convexity of this problem, i.e., convexity of (8) and linearity of (9) and (12), and thus KKT necessary conditions are sufficient. The most socially stable equilibrium, i.e., optimal solution, is of interest here and can be reached by demanding all $\lambda_{n,t}$'s of EVs to have a uniform value, $\overline{\lambda_t}$ [14]. Reaching this uniform value means that the *n*-th EV holds

$$\vartheta_{n,t}\left(p_{n,t} - P_n^d\right) \doteq -\overline{\lambda_t},\tag{15}$$

with $p_{n,t}$ has not violated its lower or upper bound in (9). This can be symbolised by $\mathcal{P}[.]$, a projection operator of the argument into the feasible charging domain between 0 and P_n^d . Hence the optimal solution can be uniquely represented as

$$p_{n,t} = \mathcal{P}\left[P_n^d - \frac{\overline{\lambda_t}}{\vartheta_{n,t}}\right].$$
 (16)

Again, the local information of EVs such as $\vartheta_{n,t}$ and $SoC_{n,t}$, are assumed to be secured from public, thus a centralized solution is invalid. Instead, after utilising the consensus network concept [15], the distributed algorithm 2 is proposed for a single control instant. Each EV here is assumed to have a local controller whom accesses only its information, seeks its desired charging power, shares only its control variables $(p_{n,t} \text{ and } \lambda_{n,t})$, and updates its demand iteratively until the uniform value $\overline{\lambda_t}$ is reached.

In the first phase of algorithm 2, an initialization to $\lambda_{n,t}$'s, and $p_{n,t}$'s, is performed with zero value and EV desired charging power, respectively, namely a preferred ideal case. In the checking phase, the common constraint (12) is checked. If the charging capacity $p_{ch,t}^c$ is sufficient to meet all $p_{n,t}$'s, the algorithm reaches the Nash equilibrium and terminates. Otherwise, a negotiating procedure among EVs is introduced to reach a compromised solution by suppressing the charging power of EVs currently demanded to meet the constraint as discussed in the next phase.

In the consensus phase, first the power mismatch due to violating the common constraint is assigned to Δp_t , managed by CSO. This term is important to bring the power balance back into the system to meet (12) at its upper bound. Second, converging all $\lambda_{n,t}$'s to a uniform one is performed. To this end, each EV updates its $\lambda_{n,t}$ utilizing the sum of the weighted differences between its $\lambda_{n,t}$ and that of its neighbors' $\lambda_{j,t}$'s and the weighted degree of violating the common constraint as well [refer to line 9]. Here, ω and ψ are two weight parameters and \mathcal{N}_n is a neighbor's set of the *n*-th EV [15]. When convergence is accomplished, the charging power of the *n*-th EV can be calculated [refer to line 11]. Finally, a return to recheck the the common constraint is applied. The algorithm will repeatedly iterate over the checking and consensus phases until the common constraint is satisfied. Note that ε_0 and ε_1 are small user defined values.

Algorithm 2 Power Distribution Game Management						
I. Initializing Phase						
1: $\lambda_{n,t} = 0$	$\forall n \in \mathcal{N}_p$					
2: $p_{n,t} = P_n^d$	$\forall n \in \mathcal{N}_p$					
II. Checking Phase						
3: if $\left \sum_{n\in\mathcal{N}_p}p_{n,t}-p_{ch,t}^c\right \leq\varepsilon_0$ then						
4: Terminate						
5: end if						
III. Consensus Phase						
6: while $\sum_{n \in \mathcal{N}_p} p_{n,t} > p_{ch,t}^c + \varepsilon_0$ do						
7: $\Delta p_t = \sum_{n \in \mathcal{N}_p} p_{n,t} - p_{ch,t}^c$						
8: while $max(\lambda_{n,t} - \lambda_{j,t}) > \varepsilon_1$ de	• $\forall n, j \in \mathcal{N}_p$					
9: $\lambda_{n,t} \leftarrow \lambda_{n,t} + \sum_{j \in \mathcal{N}_n} \omega(\lambda_{j,t} - $	$\lambda_{n,t}) + \psi \Delta p_t$					
10: end while						
11: $p_{n,t} = \mathcal{P} \left[P_n^d - \frac{\lambda_{n,t}}{\vartheta_{n,t}} \right]$	$orall n \in \mathcal{N}_p$					
12: end while						
13: Go back phase II						

IV. SIMULATION RESULTS AND ANALYSIS

The proposed management performance of the EVCS operation is evaluated by three parts. The first introduced a case study to assess the proposed pricing game management while the second presented another case study to assess the power distribution game management. Finally, the whole operation is conducted with comparison with another literature method. Overall, the simulation configuration is set up as follows.

The on-board battery capacity E_n^c 7.6–85 kWh and the desired charging power P_n^d 3.3–10 kW of EVs are selected

randomly within the data set in [16]. The SoC values at the start and end charging times SoC_n^s and SoC_n^e are considered to follow normal distribution 0.2–0.6 and 0.7–0.9, respective-ly [17]. The rest specifications of EVs including the EV driver behavioral response (RSPNS) are randomly generated within appropriate ranges to cover different situations. The solar irradiance and temperature data needed by PVS to generate the solar power is taken from [18]. The BLS load and the electricity price profiles are taken from [19], [20], respectively. Unit operation costs of EVCS systems are considered as in [4].

A. Pricing Game Evaluation

A case study of ten requesting EVs is introduced with specifications listed in Table I. The electricity price is assumed to be 6.344 (cent/kWh) in the requested charging durations of these EVs. Once the charging calls are delivered to CSO, algorithm 1 is executed. The CSO sets the charging price $\theta_{ch,t}$ to be 12.35 (cent/kWh) to guarantee a maximum profit up to 589.83 (cent). Consequently, as explained in section III-A and shown in Fig. 5, the assigned energy demands E_n^a 's of EVs are differently lower than their original demands E_n^o 's on the basis of their EV driver responses to the charging price. It can be observed here that the more sensitive EV driver is, the more energy difference (i.e., $E_n^o - E_n^a$) is. So, by listing EVs on the basis of this energy difference ascendantly starting from the left-hand side, EVs of Pr-LSD will be on the left, EVs of Pr-MSD in the middle, and EVs of Pr-HSD on the right. This is a reasonable result because EVs of Pr-LSD care less about the increase in the charging price, and thus are less willing to reduce their original energy demands. Similar conclusion can be drawn for EVs of Pr-MSD and Pr-HSD. Note that this energy difference still differs among EVs of the same behavioral response because it is also influenced by S_n^{base} . For example, EV₆ has a smaller energy difference than that one of EV₂ because its S_n^{base} is smaller than EV₂ one.

 TABLE I

 Specifications of the requesting EVs for charging.

SPEC	E_n^c kWh	P_n^d kW	$SoC_n^s \ \%$	$SoC_n^e \ \%$	S_n^{base} cent/kWh ²	RSPNS
EV_1	24.0	6.6	0.46	0.85	0.83	Pr/Po-HSD
EV_2	75.0	10.0	0.54	0.79	0.39	Pr/Po-LSD
EV_3	35.8	7.2	0.50	0.86	0.94	Pr/Po-HSD
EV_4	40.0	6.6	0.36	0.70	0.54	Pr/Po-MSD
EV_5	33.5	6.6	0.50	0.74	0.35	Pr/Po-LSD
EV_6	28.0	10.0	0.48	0.88	0.28	Pr/Po-LSD
EV_7	35.8	7.2	0.44	0.73	0.30	Pr/Po-LSD
EV_8	18.4	3.3	0.21	0.89	0.81	Pr/Po-HSD
EV_9	19.0	3.3	0.20	0.88	0.37	Pr/Po-LSD
EV_{10}	18.4	3.3	0.23	0.90	0.62	Pr/Po-MSD



Fig. 5. Results of the pricing game management.

B. Power Distribution Game Evaluation

The focus here is on the dynamic charging power curves of EVs. However, showing all EV curves could result in a messy figure and thus disturb the concerned focus. Hence a case study including the last three EVs of Table I is introduced, namely EV₈, EV₉, and EV₁₀. These EVs are assumed to start charging at $t_0=0$ (min) and to have the same preferable end charging time $t_n^e=180$ (min). To show the ability of algorithm 2 to control the power distribution among EVs under two realistic cases of no overload, i.e., $\sum p_{n,t} \leq p_{ch,t}^c$, and overload, i.e., $\sum p_{n,t} > p_{ch,t}^c$ is designed to be 12, 8, and 5 kW in the time intervals (0-60 min), (60-200 min), and (200-400 min), respectively, as shown in Fig. 6(a).

As shown in Fig. 6, during the first time interval 0-60 (min), as $p_{ch,t}^{c}$ (=12 kW) is larger than the charging requirement, i.e., sum of all the desired charging power of EVs, all of EVs are charged at that power, i.e., 3.3 kW. Thus their power anxieties equal zeros, i.e., no anxiety yet at this stage. From 60 (min), $p_{ch\,t}^{c}$ decreases to 8 kW, which is below the sum of the EV desired power, i.e., overload case. Thus overload control is applied and PAs of EVs start to have values bigger than zeros. As discussed in section III-B, the PA value depends on its EV driver behavior with higher value at higher sensitivity, i.e., PA of EV_8 is the highest and PA of EV_9 is the lowest. This results in a change on the power of each EV in proportion to its PA, i.e., the actual acquired power of EV₈ is the highest while the actual acquired power of EV_9 is the lowest [refer to line 11 in algorithm 2]. As long as the overload case exists (i.e., until 301 min), PAs of EVs dynamically increase up to their upper bounds, one, at the preferable end charging time, i.e., 180 (min). This means the EV power tends to have a uniform value, i.e., 2.6 or 1.6 kW when $p_{ch,t}^c$ (=8 or 5 kW), respectively, since $p_{ch,t}^c$ is evenly distributed among EVs. At time 293 (min) from which EV₈ is fully charged, i.e., its SoC reaches its SoC_n^e =0.89, $p_{ch,t}^c$ is then distributed evenly among the remaining EV_9 and EV_{10} to make the charging power of each equals 2.5 kW. At time 301 (min), when EV₈ is fully charged, $p_{ch,t}^c$ comes now back to be bigger than the desired charging power of the remaining EV_9 , i.e., no overload case. So, EV_9 is continuously charged with its desired power until it is fully charged at time 315 (min). Note that the dynamics of SoCs of EVs in Fig. 6(d) match their power dynamics in Fig. 6(c). Overall, given the same physical specifications and charging demands of EVs, the behavioral responses of EV drivers caused different charging durations of EVs. In other words, EV_8 (Po-HSD) is charged first, then EV_{10} (Po-MSD), then EV_9 (Po-LSD).

C. Whole Operation Evaluation and Comparison

As explained in section III, there are two time scales which need to be coordinated, one for the pricing game and another one for the power distribution game. It is known that the electricity price can be updated each hour, i.e., real-time price, and the charging power can be updated more frequently. Thus it is reasonable to set $T_1 = 1h$ and $T_2 = 15min$ [2], [3], to make the proposed charging management more efficient in a dynamic environment. For a better illustration, Fig. 5



Fig. 6. Results of the power distribution game management.

shows a flow chart of the timing-based coordination process to execute the two proposed algorithms, algorithms 1 and 2. Here, T_P and T_D are two indicators for the execution time of the two algorithms, respectively. It is worth to mention that the change in the electricity price, which is set by the utility (i.e., grid), is included in the pricing game (i.e., lines 2 and 10 of algorithm 1) to reflect its influence. The simulation time is conducted for one day with a total of 145 requesting EVs in the example EVCS which has a capacity of 20 charging poles.



Fig. 7. Timing-based coordination of executing algorithms 1 and 2.

For reference purposes, the proposed charging management (PCM) is compared with a norm method named as the basic charging management (BCM). In BCM method, CSO accepts the requesting EVs on the basis of their charging calls sequence, i.e., first come, first served, and agrees on their original energy demands, i.e., equal to the assigned energy demands [21]. Moreover, CSO treats the charging price as a levelized price, i.e., electricity price plus fixed operational unit cost such as 3.5 (cent/kWh) here [22].

To evaluate the performance of the two charging methods in terms of benefits for CSO and EV driver parties, five quantitative criteria are chosen, which have values in the range [0,1] with higher benefit at higher value. For CSO, a profit ratio (PR) is introduced, which means the CSO profit over the maximum resulting one by the two comparable methods. For EV drivers, an average satisfaction on the charging price (PS)is considered in a similar way to the behavior in Fig. 3, i.e., has zero value when the charging price is bigger or equal to the EV maximum price limit. Another criterion for EV drivers is an average satisfaction on the charged energy (ES), i.e., has one value when the assigned demand equals the original demand [10]. For both parties, an acceptance ratio (AR) is chosen, which represents the number of the accepted EVs over the total requesting EVs. To quantify the overall operation performance, a quality of service (QoS) is introduced, which represents the average of the previous criteria.

As seen from the results in Fig. 8, the charging price in PCM has less variance over its average 16.79 (cent/kWh) than that of BCM over its average 13.69 (cent/kWh). In other words, comparing with BCM, PCM tries to flatten the charging price, i.e., the difference between its charging price and the electricity price is more when the latter is low. This is because PCM tends to make the charging price close to the base charging price $\theta_{ch,n}^{base}$, which has an assumed average value here of 16 (cent/kWh). Thus PCM dynamically suits the charging price for a larger number of EV drivers corresponding to their behaviors, i.e., PS in PCM is higher than that of BCM. PCM may curtail the EV original energy demands [refer to section IV-A], while BCM does not, i.e., ES in PCM is lower than that of BCM. However, this gives PCM a larger time margin to accept more EVs for charging (i.e., 111) than BCM does (i.e., 91) especially at large number of requesting EVs with limited charging poles condition, thus PCM admits higher AR than BCM. Since PCM charges larger number of EVs with higher average charging price, its CSO profit, 174.51 $\times 10^2$ (cent/kWh), is higher than that of BCM, 146.82 $\times 10^2$ (cent/kWh). Thus PR in PCM is higher than that of BCM. Overall, PCM results in a more efficient performance, i.e., higher QoS, comparing with BCM.



Fig. 8. Results of the whole operation management and comparison.

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V. EXPERIMENTAL VERIFICATION

To validate the implementable operation of the proposed charging management, a downscaled testbed by 1:200 at power level is set up. The hourly time step and the EV charging facility are also downascaled to minutely time step and three charging poles (CPs), respectively. Note that the downscaling made here requires creation of a compatible operational scenario with that one in section IV-C. As shown in Fig. 9, the power sources PVS and GS⁺ are combined together and emulated by a controllable power supply. BLS and GS⁻ are also combined and emulated by electronic load on the left side, while BESS is set up with actual cells. Each charging pole consists of a unidirectional buck dc-dc converter, an electronic load to mimic the on-board battery dynamics, and a National Instruments (NI) myRIO as a local controller. The three dc-dc converters have efficiencies about 90% and are controlled by PI (Proportional and Integral)-based Pulse-Width-Modulation and the sampling resistors are used as current sensors. This testbest can be further represented by a functional block diagram as illustrated in Fig. 10. The host PC here, analogous to the EVCS operator, collects and records all the experimental data, controls the power supply and the left-sided electronic load through their RS232 serial communication ports, coordinates the local myRIO controllers via Wi-Fi, and communicates with the NI CompactRIO by Ethernet.

Power Supply Electronic Load dc bus BESS NI CompactRIO Electronic Loads



Host PC Sampling Resistors NI myRIOs dc-dc Converters

Fig. 9. Downscaled testbed.

A scenario of ten EVs are accepted for charging out of fourteen requesting EVs. A comparison between the simulation and the experimental results are shown in Fig. 11. As seen, the selection of EVs for charging and the dynamics of charging price and EV charging power admit similar observations to that ones in section IV-C. The first three EVs, EV_{1-3} , are charged with their full original demands since no other requesting EV calls have competed them during their charging durations. However, meanwhile the existence of the charging calls, the charging price increases, and thus EV_4 (Pr-HSD) reduces its charging demand and eventually terminates it in front of EV_7 (Pr-LSD). During the insufficient charging capacity time interval 18:00–20:00, EV_{8-10} are differently charged



Fig. 10. Functional block diagram of the testbed.

lower than their desired power in proportion to their PAs, i.e., EV_{10} (Po-HSD) has the most little decease. As seen, the experimental charging power of EVs well match the results in simulation. This validates the real-time implementation and correctness of the proposed distributed charging management with different EV customer behaviors for EVCS operation.



Fig. 11. Experimental versus simulation results.

VI. CONCLUSION

In order to handle the different behavioral responses of EV customers in the EV charging problem, it is broken down into two subproblems in which the EV customer behavior is included. Three behavioral response models of EV customer are proposed and named as high, mid, and low sensitive customers on the basis of charging price and charging power. The first subproblem is called the pricing game and is modeled as a noncooperative stackelberg game to set the charging price and the allowable requesting EVs for charging. The second subproblem is called the power distribution game and is designed as a generalized noncooperative game to conduct the power distribution among the plugged in EVs. Besides of the effective simulation results of the proposed charging management, it is benchmarked against a comparable method to further verify its performance. The implementable operation of the proposed behavior-based charging management is also proofed by experimental results.

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