# Distributed Electric Vehicles Charging Management with Social Contribution Concept

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***Abstract*—This paper proposes a charging management of electric vehicles (EVs) with a newly presented EV social contribution. The EV charging problem is represented by a generalized Nash equilibrium game where each individual EV tries to minimize its charging cost while satisfying its own charging requirements and respecting the charging facility constraints. The individual EV features a social behavior to potentially contribute in shifting its charging schedule from specific intervals that have insufficient charging power. This shift in the EV schedule will allow more charging power to other EVs that admit stricter charging requirements, i.e., intervals and demands. In this way, the contributed EVs socially help others in reducing their charging costs which is particularly important during the overload cases in the system. The proposed solution is reached iteratively in a distributed way utilizing the consensus network and found based on the receding horizon optimization framework. Both simulation and experimental results demonstrate the effectiveness and correctness of the proposed social contribution in the charging management for reducing the charging cost of EVs.**

***Index Terms*—Distributed charging management, electric vehicle (EV), social contribution, game theory, multi-step optimization, overload control, consensus network.**

## I. Introduction

RENEWABLE energy sources and electrification of transportation have recently drawn an increasing interest due to the demand growth in energy and environmental concerns. Electric vehicles (EVs) have also received a notable attraction by industry and government and considered as promising automobiles for future transportation [1]. However, EVs face a prominent challenge to be re-charged periodically given the travel trips made by the EV drivers and the limited capacity of the EV on-board battery. This issue will largely affect the total load on the charging distribution system as the number of EVs increases. Therefore, uncontrolled EV charging can cause harmful load peaks especially when overloads the capability of the charging facility system [2]. This issue, together with charging requirements of individual EVs and constraints of charging facilities, makes the EV charging problem more challenging. These matters demonstrate the necessity to develop an effective charging management to improve the charging operation efficiency, to coordinate the charging schedules of individual EVs, and to reduce their charging costs.

There are two main classes of control architecture proposed in the EV charging problem namely centralized and distributed approaches. Ref. [3] proposed a centralized control approach to minimize the total charging costs of EVs considering two charging modes and time-of-use electricity price. In Ref. [4], a binary optimization method with convex relaxation was developed for EV charging scheduling. Ref. [5] applied an improved learning particle swarm optimization algorithm to optimize the power distribution with enhanced economic benefits. However, with a large number of EVs in the system, the centralized approaches encounter difficulties in collecting the information and applying the solution in a specified interval.

The distributed control, on the other hand, has recently received a notable attention because it allows scalability in real-time and lowers the computation and communication burden. It can also protect the privacy of the individual EVs by reaching the solution without revealing their private information. Ref. [6] proposed a distributed charging method for plug-in hybrid EVs (PHEVs). The objective of each individual PHEV user was to maximize its charging load at lower cost. The PHEV users could adapt their charging rates on the basis of dynamic pricing information and the optimal solution was iteratively reached at the so-called equilibrium price. Ref. [7] applied a noncooperative game theory into the EV charging problem. The proposed charging management is distributed in which each EV minimized its charging cost on the basis of pricing policy from a regional aggregation unit. A hybrid particle swarm optimization method was adopted to reach the solution. Ref. [8] focused on a valley-filling objective to the charging profile in the EV charging scheduling problem. The proposed iterative algorithm required each EV to solve its local problem of minimizing its charging cost only. In each iteration, EVs updated their charging profiles responding to a control signal broadcast by the utility company. Ref. [9] introduced a distributed charging management of EVs in which the objective was set to minimize the operation cost of the power grid network. The day-ahead iterative solution was reached by a partial decomposition method on the basis of the Lagrangian relaxation framework. Ref. [10] applied game theory into the EV fast charging station. The EV objective in this approach compromised between benefits from charging and reserves provision. The maximization of the proposed social welfare was emphasized without mentioning charging power distribution among EVs. In Ref. [11], the EV charging problem in a microgrid of buildings was formulated as a



Manuscript received April 12, 2019; revised July 29, 2019, and September 25, 2019; accepted October 20, 2019. *(Corresponding author: Chengbin Ma.)*

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Markov decision process. The objective was to maximize the profit of the building while reducing the charging costs of EV owners. The solution was heuristically proposed as a distributed simulation-based policy. Ref. [12] introduced a cooperative charging approach to minimize a common cost function of plug-in EVs (PEVs). This approach simplified the diversity of the cost functions of EVs and the cooperative approach can not be guaranteed to be existed between EVs since they basically have selfish charging nature. Moreover, The charging capability of the system was not considered nor its effect on the charging power distribution among EVs. Ref. [13] proposed a noncooperative game-theory-based charging control to minimize the charging cost of each individual PEV. Since the proposed method is a pure noncooperative, it lacks the ability to consider possible cooperation between EVs which may exist in practice. Moreover, the charging control did not show the effect of limited total power for charging on the power distribution among EVs and how each EV reduces and shifts its charging demand to other time accordingly. Unlike [12], [13], the proposed charging management in this paper steps closer to more realistic situations in terms of charging nature by adopting both noncooperative and cooperative approaches, and in terms of charging environment by addressing in detail the power distribution among EVs under cases of limited total power for charging.

This paper proposes a distributed charging management that reduces the charging cost of each individual EV based on a receding horizon optimization which is suitable for a dynamic charging environment, e.g., with weather forecast uncertainties and different EV driving pattern scenarios. The proposed strategy does not compromise the security of the charging network, i.e., does not reveal its individuals' private information comparing with [4], [5]. The approach considers a social behavior of EV defined by its contribution to assist in reducing the charging costs of others without sacrificing its own charging cost. This is possible if the EV has the ability to shift its charging power from certain times to others under the same electricity price. In this way, the total power for charging will be more available for EVs that admit stricter charging requirements, e.g., high charging energy demands and short charging intervals. The EVs here are assumed to feature a social contribution behavior by some motivations and incentives supported, for example, by the charging facility. The major work of this paper is summarized as follows:

1) The proposed charging management considers a dynamic charging capability constraint, i.e., a limited total available power for charging EVs, and couples it with the existing demand curtailment request and overload control [4], [13].
2) Different from the pure noncooperative methods in charging [10], [13], this paper attaches the selfish behavior with a social one. In this way, the proposed method minimizes the charging costs of individual EVs based on both a competitive manner and a cooperative assistance.
3) A social contribution behavior of EV is newly included in the charging management which is particularly important in the cases of limited total available power for charging, i.e., overload cases in the system, that lead to lowering the charging costs of EVs.

The rest of this paper is organized as follows. Section II models the test system including the EV charging problem. Section III develops the solution of the EV charging management with the proposed social contribution concept. Detailed simulation analysis is discussed in section IV. Experimental results are presented in section V followed by conclusion in section VI.

## II. System Model

As illustrated in Fig. 1, the test system is one node with a feeder of the distribution power network named as EV charging station (EVCS). This EVCS consists of a grid system (GS), a photovoltaic system (PVS), a battery energy storage system (BESS), a base load system (BLS), and a number of EVs ($\mathcal{N} := \{1, 2, \ldots, N\}$). Each system could be a group of systems with the same type. GS can give or receive power symbolized by GS$^+$ or GS$^-$, respectively. The model of PVS is derived as in [14], while the battery (i.e., BESS and EV on-board) is modeled by its equivalent circuit model [15]. The BESS is utilised to buffer the power between surplus and intermittent periods and mitigate the power and voltage fluctuations [16]. BLS represents the base demand load (i.e., non-EV demand). Besides of the aforementioned systems, there is an EVCS operator that handles the following missions:

1) Controls the power flow among GS, PVS, BESS, and BLS in a similar way in [16].
2) Announces the total available power for charging EVs and checks its violation.
3) Exchanges the shared (i.e., public) data between the connected systems.
4) Coordinates the charging of EVs over a multi-step charging interval $\mathcal{T} := \{1, 2, \ldots, T\}$.

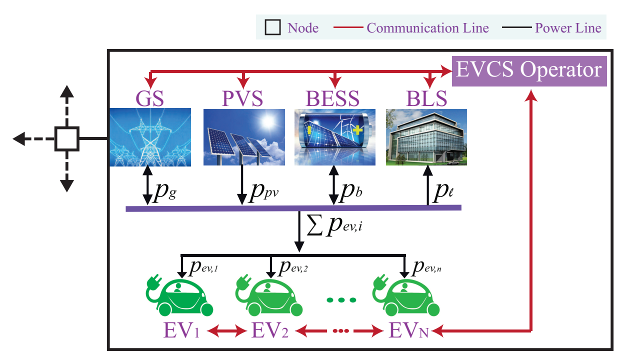


Fig. 1. Structure of the test system

### A. Available Charging Power Domain

The total available power for charging EVs $p_{ava,t}$ relies on the power flows of GS, PVS, BESS, and BLS, namely $p_{g,t}$, $p_{pv,t}$, $p_{b,t}$, and $p_{l,t}$, respectively. After supporting the demand of BLS, the total available power at any time $t$ can be calculated as

$$p_{ava,t} = p_{g,t} + p_{pv,t} + p_{b,t} - p_{l,t}, \quad \forall t \in \mathcal{T}. \tag{1}$$

By considering a maximum loading capability of the distribution power network feeder $P_g^{max}$ and an overload safety factor of EVCS $\eta_t(\leq 1)$ [13], the charging power capability of EVCS $P_{c,t}^{max}$ can be written as

$$P_{c,t}^{max} = \eta_t(P_g^{max} + p_{pv,t} + p_{b,t} - p_{l,t}), \quad \forall t \in \mathcal{T}. \tag{2}$$

Given that $p_{n,t}$ is the battery charging power of EV$_n$, the available charging power domain can be then written as

$$0 \leq \sum_{n\in\mathcal{N}} p_{n,t} \leq p_{ava,t} \leq P_{c,t}^{max}, \quad \forall t \in \mathcal{T}. \tag{3}$$

It is important to mention that (3) is the common constraint that couples the charging schedules of EVs and the overload cases are occurred when this constraint is violated at its upper bound.

### B. EV Charging Domain

The dynamic model of charging the EV on-board battery can be described by the linear model (4) in which $SoC_{n,t}$ is the state of charge of the EV$_n$'s battery at time $t$, $\eta_c \in (0, 1]$ is the charging efficiency, $I_{n,t}$ is the current cross the battery, $\Delta t$ is the time step, and $C_n$ is the battery capacity (Ah).

$$SoC_{n,t+1} = SoC_{n,t} + \frac{\eta_c I_{n,t}\Delta t}{C_n}. \tag{4}$$

Each EV$_n$ arrives EVCS at time $T_n^a$ with energy $E_n^a$ and needs to meet its demanded energy $E_n^d$ when it departures at time $T_n^d$. Hence, the total requested energy for charging in the interval $\mathcal{T}$ is $E_n^r$,

$$E_n^r = E_n^d - E_n^a = T\sum_{t\in\mathcal{T}} p_{n,t}. \tag{5}$$

Giving that $SoC_n^a$ is the state of charge of EV$_n$ at the arrival time to EVCS and $SoC_n^d$ is its state of charge at the departure time from EVCS, the following has to be held during charging

$$SoC_n^a \leq SoC_{n,t} \leq SoC_n^d. \tag{6}$$

### C. EV Charging Problem

Consider a noncooperative game-theoretic based charging management where each player, i.e., individual EV$_n$, has a preference to minimize its own charging cost under its charging requirements. If $S_n$ is the electricity price sensitivity ($\$/kWh^2$) of an EV$_n$, $P_{n,t}^{min}$ and $P_{n,t}^{max}$ are the lower and upper bounds of the charging power of EV$_n$, respectively, and $p_t^e$ is the electricity price ($\$/kWh$), the charging problem of each EV$_n$ can be then defined to minimize the following quadratic cost function along with its corresponding constraints,

$$\min_{p_{n,t}} \sum_{t\in\mathcal{T}} \left(\frac{1}{2}S_n\Delta t^2 p_{n,t}^2 + p_t^e\Delta t p_{n,t}\right) \tag{7}$$

$$\text{s.t.} \sum_{n\in\mathcal{N}} p_{n,t} \leq p_{ava,t}, \qquad \forall t \in \mathcal{T}, \tag{8}$$

$$P_{n,t}^{min} \leq p_{n,t} \leq P_{n,t}^{max}, \qquad \forall t \in \mathcal{T}. \tag{9}$$

It is known that representing a problem by a theoretic game means that its solution is called Nash equilibrium. Since the constraint (8) couples all the charging powers of EVs, the aforementioned charging problem is actually a generalized Nash equilibrium (GNE) problem [17].

The lower bound and the upper bound of the charging power of EV$_n$ are defined by the instantaneous power constraint (9). Since this paper discusses a uni-directional charging of EVs, the lower bound of the charging power is set to zero. However, the upper bound equals the EV$_n$'s charger power rate $P_n^r$ in times when it is plugged-in (i.e., the binary parameter $I_{n,t} = 1$) and zero otherwise,

$$P_{n,t}^{max} = \begin{cases} P_n^r & I_{n,t} = 1 \\ 0 & I_{n,t} = 0. \end{cases} \tag{10}$$

## III. Charging Management Principle

The proposed solution of the EV charging problem described in this section is based on a receding horizon optimization framework over $T$ time steps rather than a single time step [18]. However, only the first action of the optimal schedule will be applied at the current time step. The optimization will be carried out again in the following time step with a shifted horizon by one time step and with updated realization based on the newly available information. The realization results from several reasons such as weather forecast uncertainties and different EV driving pattern scenarios, e.g., a modified constraint of the departure time. This point makes the proposed optimization framework suitable in a dynamic environment. It is worth to mention that the advantage of the proposed charging management with the social contribution concept is still existed and its essence is not changed in both the deterministic and the stochastic information.

### A. Optimality Conditions

Based on the Karush–Kuhn–Tucker (KKT) conditions of optimality, the Lagrangian function of the aforementioned EV charging problem for each EV$_n$ after introducing its Lagrange multipliers $\lambda_{n,t}$, $\mu_{n,t}^{min}$, and $\mu_{n,t}^{max}$ can be given by

$$\begin{aligned} L_n =& \sum_{t\in\mathcal{T}} \left(\frac{1}{2}S_n\Delta t^2 p_{n,t}^2 + p_t^e\Delta t p_{n,t}\right) \\ &- \sum_{t\in\mathcal{T}} \lambda_{n,t}\left(\sum_{n\in\mathcal{N}} p_{n,t} - p_{ava,t}\right) \\ &+ \sum_{t\in\mathcal{T}} \mu_{n,t}^{min}\left(P_{n,t}^{min} - p_{n,t}\right) + \sum_{t\in\mathcal{T}} \mu_{n,t}^{max}\left(p_{n,t} - P_{n,t}^{max}\right). \end{aligned} \tag{11}$$

Consequently, by considering a bold style of a symbol as a $T \times 1$ vector of its quantity, i.e., values over $T$ time steps, the gradient condition of the KKT necessary optimality conditions is

$$\frac{\partial L_n}{\partial \boldsymbol{p_n}} = \left(S_n\Delta t^2\boldsymbol{p_n} + \boldsymbol{p^e}\Delta t\right) - \boldsymbol{\lambda_n} + \boldsymbol{\mu_n^{min}} + \boldsymbol{\mu_n^{max}} = \mathbf{0}. \tag{12}$$

Due to the convexity of this problem, i.e., convexity of the cost function along with linear inequality constraints, both the existence and the uniqueness of the GNE can be mathematically demonstrated. Thus, KKT necessary conditions are sufficient.

At the most socially stable equilibrium, i.e., $\overline{\boldsymbol{\lambda}}$, the optimal solution, i.e., the Nash equilibrium (NE), for each EV$_n$ holds the following [19],

$$\left(S_n \Delta t^2 \boldsymbol{p_n} + \boldsymbol{p^e} \Delta t\right) \doteq \overline{\boldsymbol{\lambda}}, \tag{13}$$

with $\boldsymbol{p_n}$ has not violated its lower and upper bounds [refer to (9)]. By introducing a projection operator $\mathcal{P}\,[.]$ of the argument into the feasible charging domain of EV$_n$ between $\boldsymbol{P_n^{min}}$ and $\boldsymbol{P_n^{max}}$, the optimal solution can be then uniquely represented in terms of $\overline{\boldsymbol{\lambda}}$ as

$$\boldsymbol{p_n} = \mathcal{P}\left[\frac{\overline{\boldsymbol{\lambda}} - \boldsymbol{p^e}\Delta t}{S_n \Delta t^2}\right]. \tag{14}$$

If a centralized control method is applied here, then assigning the charging power of each EV by (14) will be the responsibility of the centralized (i.e., global) controller. To this end, this global controller has to know all the information of EVs, such as $S_n$'s, to be able to find $\overline{\lambda}$ and then to reach the solution (14). However, after assuming the privacy of the EVs' local (i.e., private) information, the centralized control method usually becomes invalid. This assumption makes sense in practice, since each EV cares mainly about its local information, preference, and constraints, i.e., (7) and (9). Furthermore, the social contribution concept, which is proposed in the following section, is also a private issue for EV and can not be handled by a global controller. Moreover, after considering a large number of EVs in the EVCS, the centralized approach faces difficulties in gathering the information of EVs and applying the solution in a specified interval. Therefore, making the charging decisions of EVs by themselves is reasonable here, and thus a distributed charging management is proposed in the following section.

### *B. Distributed Management with Social Concept*

The aim here is to solve the EV charging problem, i.e., reaching (14), along with the influence of the proposed social concept in a distributed way, that is, without global controller and without revealing the EVs'private information. Note that the EVCS operator here is just a coordinator who handles a coordination task of announcing the total available power for charging EVs $\boldsymbol{p_{ava}}$ and checking its violation. As mentioned in the previous section, each EV is willing to set its own charging power decision $\boldsymbol{p_n}$ by itself, thus each EV is assumed to have a local controller that accesses only its local information and sets its own decision. However, handling the common constraint (8) and then reaching the solution (i.e., $\overline{\boldsymbol{\lambda}}$) requires communication between these local controllers and exchange to their public information, i.e., $\boldsymbol{p_n}$'s and $\boldsymbol{\lambda_n}$'s, as illustrated in Fig. 2. In this distributed structure, EVCS operator and EVs are represented by individual nodes connected by a network of links. Each EV node executes algorithm 1, which shows the proposed distributed charging management with social contribution (DCMSC) for an EV$_n$ in a single time step. This algorithm is initialized by setting the binary flag of social contribution $SC$ to one. For clarity, algorithm 1 is organised as three tasks, namely optimization, communication, and contribution, in which each task has a unique meaning and function as explained below.

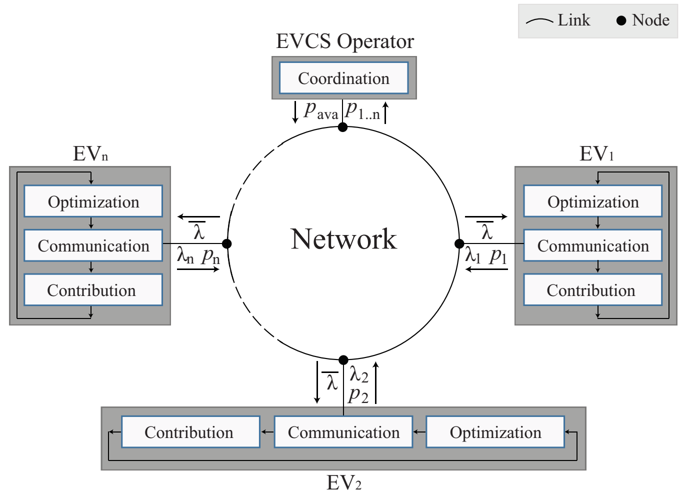


Fig. 2. The network of connected nodes with their tasks.

Firstly, optimization task means finding the optimal charging schedule, i.e., solving the charging problem, of each EV$_n$ over the time horizon individually with its own current constraints only [refer to line 2 in algorithm 1]. Note that here the maximum charging power of EV$_n$, $\boldsymbol{P_n^{max}}$, is dynamically changing, and the optimal outcomes are $\boldsymbol{p_n}$ and $\boldsymbol{\lambda_n}$. This is an important step to create the intended distributed structure and to emphasize the ability of each EV to make its initial charging decision. Thus in the first round of processing this task, no overload cases are yet addressed in the system. Note that executing this task only while dropping the other two tasks in the charging management will be named as method-1 [refer to the beginning of section IV].

Secondly, communication task means communicating between nodes to tackle the common constraint (8), i.e., overload control. In other words, it is the only task in which the nodes communicate to check the overload cases if they occur when violating (8) in any single time step over the time horizon [refer to line 3]. Algorithm 1 terminates at the Nash equilibrium if no overload cases are met or after handling them along with the contribution task. However, if any overload case is met, the binary flag of overload $OL$ is set to one. Hence, a compromised solution in this time step is expected to be reached between the nodes (i.e., EVs) by suppressing their charging powers currently demanded to meet the constraint (8). In other words, reaching the solution (14) requires converging all values of $\lambda_{n,t}$'s of the EV nodes to the global decision-making value $\overline{\lambda_t}$, an element of $\overline{\boldsymbol{\lambda}}$ as discussed in the follows. First, the power mismatch due to violating the common constraint will be assigned to $\Delta p_t$. This term is important to bring the power balance back into the system to meet the constraint (8) at its upper bound. In the distributed structure here, each EV local controller shares only its public information ($\boldsymbol{p_n}$ and $\boldsymbol{\lambda_n}$), and interacts iteratively with other neighboring local controllers. This interaction-based method is implemented by utilizing the consensus network concept [19]. To do so, each node updates its $\lambda_{n,t}$ utilizing the sum of the weighted differences between this node's $\lambda_{n,t}$ and that of its neighbors' $\lambda_{j,t}$'s and the weighted degree of

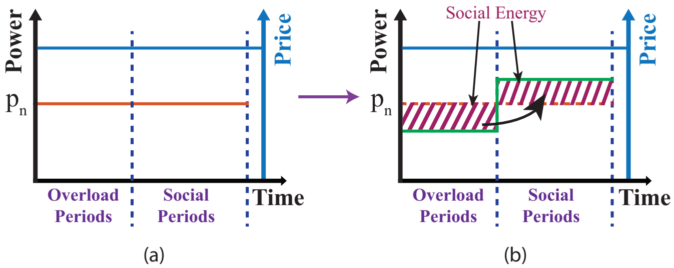


Fig. 3. Concept of the charging power of EV$_n$. (a) Without social contribution. (b) With social contribution.

violating the common constraint as well [refer to line 13]. $\beta_n$ and $\alpha_n$ are two weight parameters and $N_n$ is the neighbor's set of node $n$ [19]. As the convergence is accomplished, the new maximum charging power of EV$_n$, $\boldsymbol{P_n^{max}}$, can be calculated similar to (14) [refer to line 15]. Note that $\varepsilon_0$ and $\varepsilon_1$ are small user defined values. After addressing the overload case, EV$_n$ has to re-optimize its charging schedule with the new calculated value of the maximum charging power. Once handling the overload cases, the final task will be launched. It is noted that handling only the first two tasks in the charging management means addressing the optimal schedule of EV along with the overload control and this will be named as method-2.

Finally, the contribution task means the potential self-based modification made by the individual EV$_n$ on its charging power. The social contribution concept of EVs proposed here means that the contributed EV$_n$ can shift its charging schedule over several same electricity price periods since it has a loose charging requirement, i.e., a charging demand over long charging interval. As a result, this EV$_n$ can lower its charging demand by the amount named as social energy in a specific time $st \in \mathcal{T}_o$ during the overload periods $\mathcal{T}_o \subset \mathcal{T}$. This energy amount of EV$_n$ can be compensated in other periods named as social periods $\mathcal{T}_{n,st}$ and defined by (15) to be the time steps out of the overload times and with the same electricity price, to reserve the EV$_n$'s charging cost, when it is plugged-in.

$$\mathcal{T}_{n,st} = \{t \in \mathcal{T} \backslash \mathcal{T}_o \mid p_t^e = p_{st}^e,\ I_{n,t} = 1\}. \tag{15}$$

The concept of the social contribution on the charging power of EV$_n$ is illustrated for clarity in Fig. 3. On the other hand, there are some EVs having stricter charging requirements and may need to be charged over different electricity price times including the overload periods. Therefore, given the shifting demand by the contributed EV$_n$ from $\mathcal{T}_o$, the total available power for charging during $\mathcal{T}_o$ will be more available for these in-need EVs. In other words, the in-need EVs can increase their demands during $\mathcal{T}_o$ and lower them in the high electricity price periods, i.e., lower charging costs. In such a way, the EV$_n$ may socially help other EVs in reducing their charging costs. The aforementioned description about the social concept can be then formulated in algorithm 1 as follows. During the overload times $\mathcal{T}_o$, EV$_n$ will calculate its social energy $E_n^s$ which is still able to be charged during the social times $\mathcal{T}_{n,st}$. In other words, the weighted time sum of the differences between its maximum charging power and its calculated charging power [refer to line 23]. If the social energy is bigger than its threshold $E_n^{s,th}$, EV$_n$ can then contribute others by decreasing its maximum charging power according to its social energy value. However, the EV$_n$ will compensate the previous decrease by increasing its charging power during $\mathcal{T}_{n,st}$ later again in the optimization task. Finally, after addressing the overload cases (i.e., $OL = 1$) and the social contribution (i.e., $SC = 1$) by passing over the above described three tasks, algorithm 1 will terminate in line 4. The so-called method-3 means that the charging management runs the three above described tasks, i.e., the optimization, communication, and contribution tasks.

**Algorithm 1** DCMSC

***I. Initialization***
1: $SC = 1$
***II. Optimization Task***
2: $Solve\ (7)\ subject\ to\ (9)$
***III. Communication Task***
3: **if** $\left(\left|\sum_{n\in\mathcal{N}} \boldsymbol{p_n} - \boldsymbol{p_{ava}}\right| \leq \boldsymbol{\varepsilon_0}\right)$ & $(SC = 1)$ **then**
4: Terminate
5: **end if**
6: $SC = 0$
7: $OL = 0$
8: **for** $\forall t \in \mathcal{T}$ **do**
9: **while** $\sum_{n\in\mathcal{N}} p_{n,t} > p_{ava,t} + \varepsilon_0$ **do**
10: $OL = 1$
11: $\Delta p_t = \sum_{n\in\mathcal{N}} p_{n,t} - p_{ava,t}$
12: **while** $max(|\lambda_{n,t} - \lambda_{j,t}|) > \varepsilon_1$ **do** $\forall j \in \mathcal{N}_n$
13: $\lambda_{n,t} \leftarrow \lambda_{n,t} + \sum_{j\in\mathcal{N}_n} \alpha_n(\lambda_{j,t} - \lambda_{n,t}) + \beta_n \Delta p_t$
14: **end while**
15: $P_{n,t}^{max} = \mathcal{P}\left[\dfrac{\lambda_{n,t} - p_t^e \Delta t}{S_n \Delta t^2}\right]$
16: **end while**
17: **end for**
18: **if** $OL = 1$ **then**
19: Go back phase II
20: **end if**
***IV. Contribution Task***
21: **for** $\forall t \in \mathcal{T}_o$ **do**
22: $st = t$
23: $E_n^s = \mathcal{T}_{n,st} \sum_{t\in\mathcal{T}_{n,st}} (P_{n,t}^{max} - p_{n,t})$
24: **if** $E_n^s \geq E_n^{s,th}$ **then**
25: **if** $E_n^s \geq \Delta t p_{n,t}$ **then**
26: $P_{n,t}^{max} = 0$
27: $E_n^s \leftarrow E_n^s - \Delta t p_{n,t}$
28: **else**
29: $P_{n,t}^{max} = p_{n,t} - E_n^s/\Delta t$
30: $E_n^s = 0$
31: **end if**
32: Go back phase II
33: **end if**
34: **end for**
35: $SC = 1$
36: Go back phase II

## IV. Simulation results

The performance of the proposed algorithm has been evaluated by two case studies. The first is established with a small number of EVs charging during a specific interval of the day to show clearly the effect of the social contribution on the power distribution of EVs. While the second which adopts a large scale penetration of EVs charging throughout one day is illustrated to demonstrate the effect of the social contribution on the charging cost reduction. In both cases, the simulation configuration is set up as follows.

The pairs of the on-board battery capacity 22–242 Ah and the charger power rate 3.3–10 kW of EVs are selected randomly within the data bank in [20]. Meanwhile, the SoC values at the arrival and departure times are considered to follow a normal distribution, 0.2–0.6 and 0.7–0.9, respectively [21]. The EV arrival time to EVCS could be any time, however, there are two mean peak arrival times: one in the morning (08:30) when people come workplace and the other at night (17:30) when they return back home [13]. The EV departure time from EVCS is randomly set after considering its own realization, i.e., specifications and charging requirements. The solar irradiance and temperature data needed by PVS to generate the solar power is taken from [22]. The BLS load and the electricity price profiles are taken from [23], [24], respectively. The optimization time horizon is one day, and the sample-time is 15 minutes. The charging power capability of EVCS is considered in a similar way to the maximal charging capability in [13]. Note that method-1 and method-2 [13], [19], [25], which have been described in section III-B, are adopted to serve as comparison methods with the proposed charging management represented by method-3. The addressed issues by each method are summarised as follows:

1) *Method-1:* Optimizes the schedule of each EV but can not handle the overload cases in the EVCS, i.e., no overload control.
2) *Method-2:* Optimizes the schedule of each EV and handles the overload cases in the EVCS, i.e., overload control.
3) *Method-3:* Optimizes the schedule of each EV, handles the overload cases, and applies the social contribution.

### A. Small Scale–Specific Interval Case Study

Given the aforementioned simulation configuration, three EVs are chosen with different realizations listed in Table I that are charging in the specific interval 8:00–16:00. The electricity price is shown in Fig. 4 (a) and the results of the above three methods are shown in Fig. 4 (b)-(d).

TABLE I
Realizations of the example three EVs

| Target EV | $C_n(Ah)$ | $P_n^r(kw)$ | $T_n^a$ | $T_n^d$ | $SoC_n^a$ | $SoC_n^d$ |
|---|---|---|---|---|---|---|
| $EV_1$ | 48 | 3.3 | 8:30 | 13:10 | 0.21 | 0.90 |
| $EV_2$ | 51 | 3.3 | 8:35 | 13:20 | 0.23 | 0.89 |
| $EV_3$ | 54 | 3.3 | 8:40 | 15:52 | 0.32 | 0.85 |

As seen from the results of method-1 in Fig. 4 (b), all EVs are charged with their maximum charging powers at electricity price 0.160. Then, while $\text{EV}_3$ fulfilled its charging requirement at price 0.170, $\text{EV}_1$ and $\text{EV}_2$ are still charged with their maximum charging powers at it and fulfilled their charging requirements at price 0.240. It is noticed that SoCs of EVs start to increase beginning from their arrival values at their arrival times with the same rate of their charging powers until they meet their departure values at their departure times. It is known that the overload cases occur as the charging requirement of EVs, i.e., total charging power ($\sum_{n\in\mathcal{N}} p_{n,t}$), exceeds the charging capability. Since method-1 does not have overload control, one overload case is occurred in the period 11:00–13:10 with amount shaded in purple. Note that in the period 08:00–09:00 no overload is happened since the charging requirement of EVs is 3.3×3=9.9 kW and the charging capability is 10 kW. Since the overload is harmful and causes a load imbalance in the EVCS, the EVCS operator applies a penalty during this case such as increment on the electricity price [26]. This increment is assumed here to be 0.075 $\$/kWh$. Accordingly, the charging costs of each EV and of all EVs ($EV_{1-3}$) by method-1 are shown in Table II.

The results of method-2 in Fig. 4 (c) observe similar trends to that ones in method-1. However, in contrast to the results of method-1, no overload in the period 11:00–13:10 is occurred and the charging requirement has always respected the charging capability. Note that the charging power distribution among the three EVs during the overload period has followed the procedure mentioned in the communication task of algorithm 1. Due to the charging requirements (i.e., $SoC_n^d$ and $T_n^a$), $\text{EV}_1$ and $\text{EV}_2$ have to be charged in the high price period 09:00–11:00. However, since there is no overload here, i.e., no price penalty, the charging costs of EVs have decreased as listed in Table II.

The results of method-3 in Fig. 4 (d) match that ones in method-2 by respecting the charging capability, while show some differences because of the social contribution affect. $\text{EV}_3$ here has a late departure time and has also the ability to increase its charging power after the departure time of $\text{EV}_1$ (i.e., 13:10) because its charging power did not reach its charging power rate 3.3 kW. This condition gives $\text{EV}_3$ the ability to contribute to other EVs by decreasing (stopping here) its charging power in the lowest charging capability period 11:00–13:10. $\text{EV}_1$ and $\text{EV}_2$ get a chance, accordingly, to increase their charging powers from the $\text{EV}_3$'s share. This will help both $\text{EV}_1$ and $\text{EV}_2$ to decrease their charging powers during the highest price period 09:00–11:00. As a result, their charging costs, comparing to those in method-2, have decreased as recorded in Table II. Note again that $\text{EV}_3$ has fulfilled its charging requirement by increasing its charging power in the period 13:10–15:52 which admits the same price to that one it decreased its power at before, i.e., 0.170. This means that $\text{EV}_3$, comparing with method-2, has socially contributed, i.e., without harming or benefiting its charging cost, to decrease the charging costs of $\text{EV}_1$ and $\text{EV}_2$ by \$0.139 for each and a total by \$0.278. In other words, a charging cost reduction by 5.799 % and 5.753 % for $\text{EV}_1$ and $\text{EV}_2$, respectively, and a total by 4.268 %. It should be noted that the charging cost reduction can be much bigger with higher electricity price, different realizations, and larger penetration of EVs.

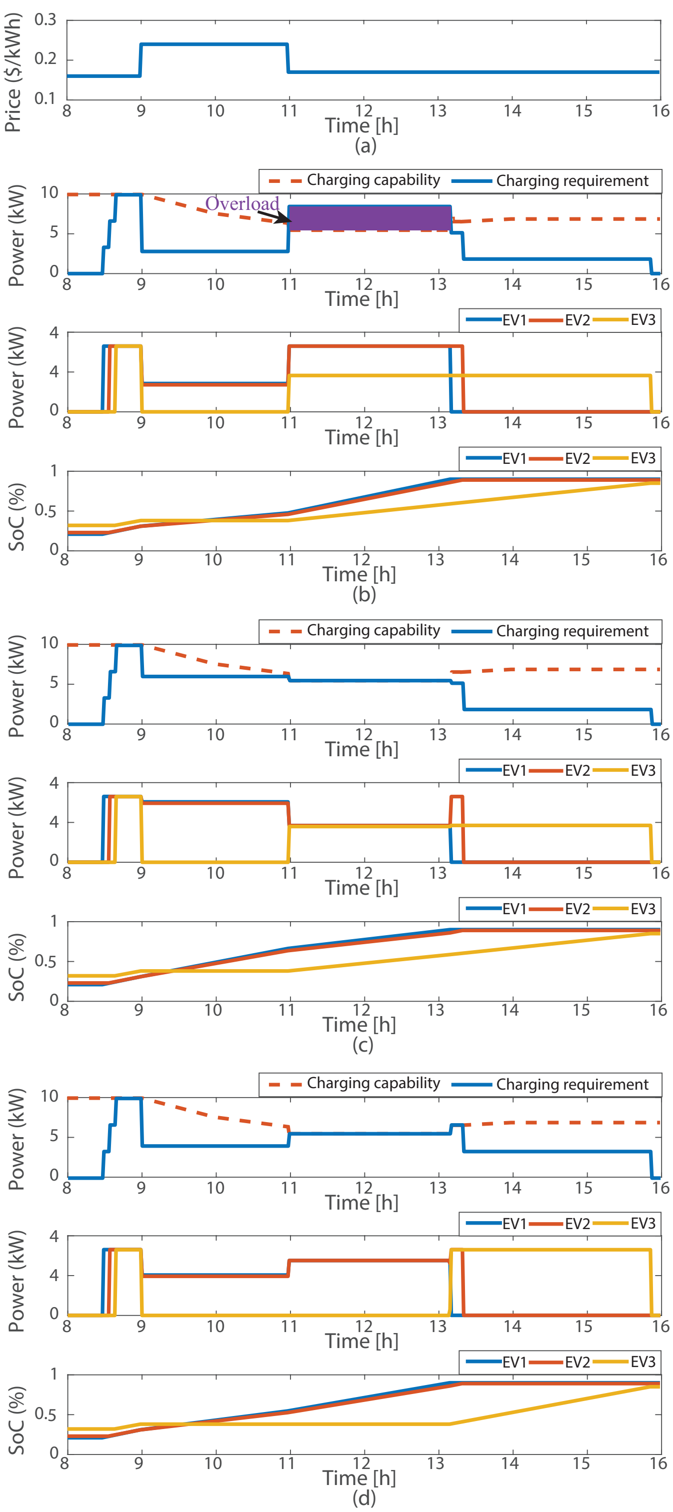


Fig. 4. (a) Electricity price profile. Charging capability, charging requirement, and EVs' responses of power and SoC in (b) Method-1. (c) Method-2. (d) Method-3.

TABLE II
EV CHARGING COSTS IN 8 HOURS.

| **Target EV** | $EV_1$ | $EV_2$ | $EV_3$ | $EV_{1-3}$ |
|---|---|---|---|---|
| **Method-1 ($)** | 2.673 | 2.693 | 1.976 | 7.342 |
| **Method-2 ($)** | 2.397 | 2.416 | 1.700 | 6.513 |
| **Method-3 ($)** | 2.258 | 2.277 | 1.700 | 6.235 |
| **Charging cost reduction ($)** | 0.139 | 0.139 | 0.000 | 0.278 |
| **Charging cost reduction (%)** | 5.799 | 5.753 | 0.000 | 4.268 |

It has to be mentioned that in real life EVs can not know or inform their exact arrival or departure times to EVCS because inaccuracy in their predicted values may occur, such as when using different map services. This error results in a time difference and then may lead to a mismatch in the current charging schedules and costs. To reflect the influences of these uncertain scenarios on the charging costs of the proposed charging management, i.e., method-3, an example of the result to speed profile deviations, i.e., time differences of $\pm 15$ and $\pm 30$ min, are applied on the $\text{EV}_1$ arrival and departure times mentioned in Table I. Here $\pm$ means after or ahead of the predicted time. As seen in Table III, a bigger time deviation will cause a bigger charging cost mismatch. Moreover, the charging cost mismatch of $\text{EV}_1$ caused by the deviation on the arrival time is bigger than that caused by the deviation on the departure time. It is because during the arrival time, $\text{EV}_1$ is having a better or worse chance in charging when the electricity price is the lowest and there is no overload occurred. On the other hand, due to the higher electricity price and the existence of the overload during the departure time deviation of $\text{EV}_1$, there is a cost mismatch in $\text{EV}_2$ too. Since $\text{EV}_3$ is mostly charging out of the plugged in time of $\text{EV}_1$ [refer to Fig. 4 (d)], it is not influenced by the time deviation of $\text{EV}_1$ and thus its charging cost remains the same. Deviations on the arrival and departure times of $\text{EV}_2$ and $\text{EV}_3$ will lead to similar observations.

TABLE III
INFLUENCES OF $\text{EV}_1$ ARRIVAL AND DEPARTURE TIMES.

| **Target EV** | | $EV_1$ ($) | $EV_2$ ($) | $EV_3$ ($) | $EV_{1-3}$ ($) |
|---|---|---|---|---|---|
| $T_1^a$ | $\pm$15 min | $\pm$0.066 | $\pm$0.000 | $\pm$0.000 | $\pm$0.066 |
| | $\pm$30 min | $\pm$0.126 | $\pm$0.000 | $\pm$0.000 | $\pm$0.126 |
| $T_1^d$ | $\pm$15 min | $\pm$0.057 | $\pm$0.009 | $\pm$0.000 | $\pm$0.066 |
| | $\pm$30 min | $\pm$0.115 | $\pm$0.018 | $\pm$0.000 | $\pm$0.133 |

### B. Large Scale–One Day Interval Case Study

Under the same aforementioned simulation configuration and comparison methods, the proposed charging management is tested with 50 EVs throughout one day with electricity price is shown in Fig. 5 (a) and results are shown in Fig. 5 (b)-(d). In method-1, after optimizing the charging schedules of EVs, the results suffer from three overload cases as depicted in Fig. 5 (b). This is because of the big number of EVs charging at the same time, i.e., peak charging times. However, EVs are not charged in the two locally high price periods, i.e., located during the charging intervals of some EVs, 09:00–11:00 and 18:00–20:00. Given the applied price penalty in the overload periods, the total charging cost of EVs is $102.921.

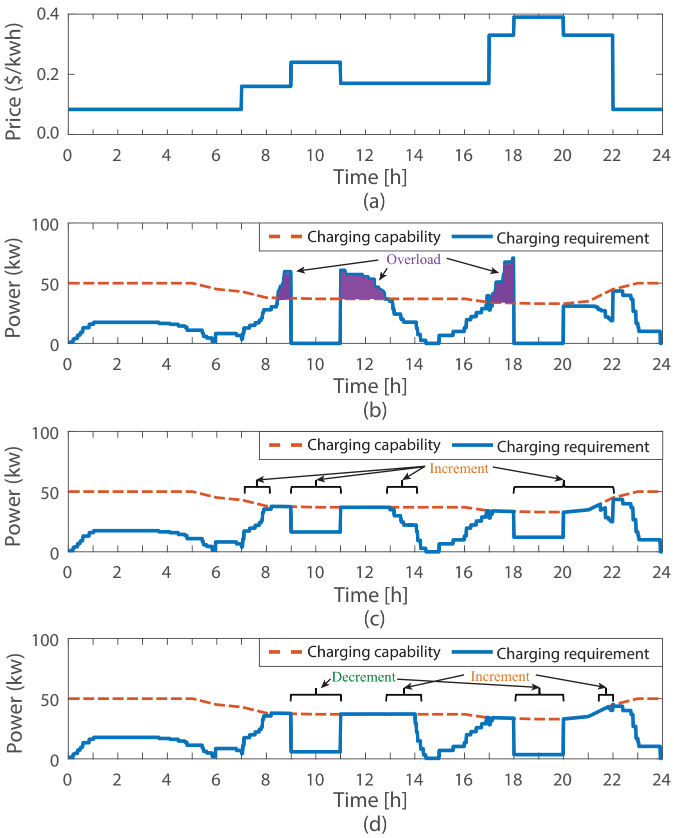


Fig. 5. (a) Electricity price profile. (b) Charging requirement of EVs by method-1. (b) Charging requirement of EVs by method-2. (c) Charging requirement of EVs by method-3.

Meanwhile in method-2, as expected and shown in Fig. 5 (c), the extra charging requirement beyond the charging capability is cut and added to other periods. Part of these additions will lead to increments happening in the aforementioned two locally high price periods. However, since no price penalty is applied here, the total charging cost of EVs has decreased to \$87.104 comparing with method-1. Finally, in method-3 and as illustrated in Fig. 5 (d), some EVs have socially contributed by shifting their charging times from the overload periods to others. This will decrease the charging requirement during the aforementioned two locally high price periods. As a result, the total charging cost of EVs has decreased by \$5.418 to become \$81.686, i.e., decrease by 6.220 %.

Apart from the above 50-EV scenario, by continuing to scaling up the penetration number of EVs in the distribution power network, the reduction on the charging cost will be much more bigger as listed in Table IV. This further demonstrates the effectiveness of the proposed EV social contribution in the charging management to reduce the charging costs of EVs.

TABLE IV
CHARGING COST REDUCTION BY SOCIAL CONTRIBUTION IN ONE DAY.

| **Penetration No. of EVs** | 250 | 500 | 1000 | 1500 |
|---|---|---|---|---|
| **Charging cost reduction (\$)** | 28.119 | 58.187 | 109.364 | 171.811 |
| **Charging cost reduction (%)** | 6.511 | 6.812 | 7.162 | 7.639 |

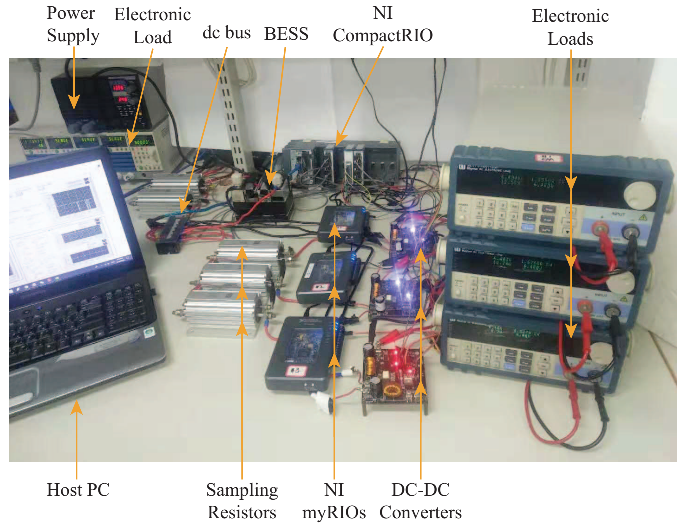


Fig. 6. Downscaled testbed.

## V. EXPERIMENTAL VERIFICATION

A downscaled testbed, 1:200 at power level, is setup to verify the distributed implementation of the proposed charging management. The EV charging facility and the hourly time step are also downascaled to three charging poles (CPs) and to minutely time step, respectively. A downscaled scenario compatible with that in section IV-B, i.e., runs over one-day interval, is then expected to be created. As illustrated in Fig. 6, PVS and $GS^+$ are combined together and emulated through a controllable power supply on the left side. While on the same side, an electronic load is used to emulate BLS and $GS^-$. The BESS is installed with actual cells and connected directly to the dc bus. Each charging pole includes a unidirectional buck dc-dc converter, electronic load to mimic the on-board battery dynamics, and a National Instruments (NI) myRIO as a local controller. All of the three dc-dc converters are controlled by PI (Proportional and Integral)-based Pulse-Width-Modulation (PWM). High-accuracy sampling resistors are used as current sensors. The aforementioned description about the testbest can be further represented by a functional block diagram as shown in Fig. 7. Note that here the host PC, who is analogous to the EVCS operator, collects and records all the experimental data. It controls the power supply and the left-sided electronic load through their RS232 serial communication ports. It also coordinates the local myRIO controllers and communicates with the NI CompactRI via Wi-Fi and Ethernet, respectively. The specifications for major components of the testbed are listed in Table V. The sample-time here is 15 seconds, and the latency of all the used communications is in the range of tens of milliseconds.

A scenario of nine EVs in which each three are orderly charging at a charging pole is considered here. The total charging costs of EVs by method-1, method-2, and method-3 are \$22.113, \$20.811, and \$19.770, respectively, which admit similar observations to that in sections IV-A and IV-B. To avoid redundancy, the focus here is only on the proposed method-3 and its implementable performance. Thus, a comparison between the simulation and the experimental results

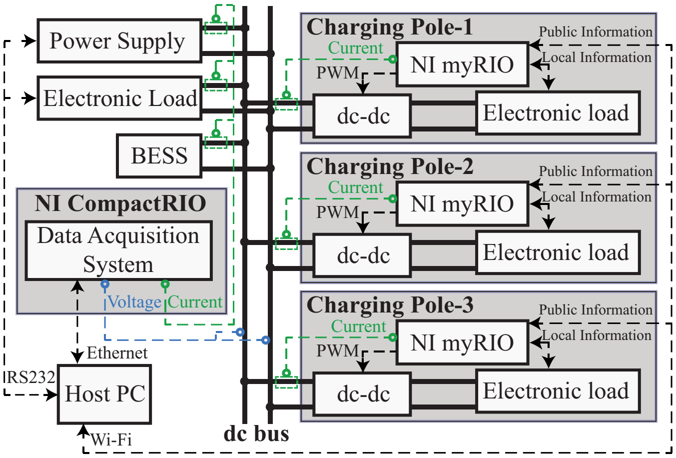


Fig. 7. Functional block diagram of the testbed.

TABLE V
SPECIFICATIONS FOR MAJOR COMPONENTS

| | |
|---|---|
| Power Supply (Takasago ZX-800L) | Max power: 800 W (0-80V, 0-80A) |
| Electronic Load [left] (1 Kikusui PLZ-50F/150U) | Max power: 600 W (1 PLZ-50F, 4 PLZ150USs with 1.5-150 V, 0-30 A each) |
| Electronic Loads [right] (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 (BESS) (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%) |

are shown in Fig. 8. Here, $EV_6$ reduced its charging power in the overload period 11:47–13:15 to help $EV_4$ and $EV_5$ in reducing their charging costs by lowering their charging powers in the locally high price period 09:00–11:00. Similarly, $EV_7$ reduced (stopped here) its charging power in the overload period 20:00–21:00 to help $EV_8$ and $EV_9$ in reducing their charging costs by lowering their charging powers in the locally high price period 18:00–20:00. As seen, the experimental charging powers of EVs well match the results in simulation. This validates the real-time implementation and correctness of the distributed charging management with the proposed social contribution concept.

## VI. CONCLUSION

EVs naturally feature a selfish behavior meanwhile scheduling their charging times. Given proper incentives, however, it is possible to motivate them to contribute in reducing the charging costs of other EVs. This paper has proposed a distributed charging management with an EV social contribution concept. The EV charging problem is represented by a generalized Nash equilibrium game. Each individual EV in this game has minimized its charging cost respecting its charging requirements and the charging facility constraints. The solution is iteratively reached in a distributed way and is constructed by three tasks that match three comparison methods. The proposed method has proofed effective results in optimizing the charging schedules of EVs, controlling the

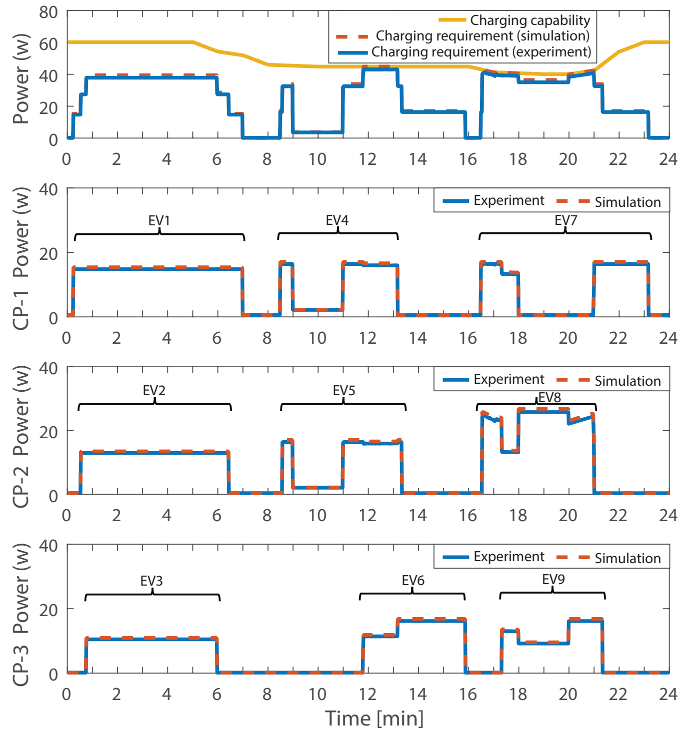


Fig. 8. Experimental versus simulation results (CP: charging pole).

overload cases in the system, and reducing the charging costs of EVs. The experimental results have well matched the findings in simulation and have further validated the real-time implementation and correctness of the proposed charging management. The proposed concept of EV social contribution has further extensions such as studying different types of EV contribution behavior in the charging management.

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