Distributed Charging Management of Electric Vehicles with Charging Anxiety for Charging Cost Reduction

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***Abstract*—This paper proposes a charging management of electric vehicles (EVs) considering a charging anxiety behavior of EVs. A charging anxiety term is included in the objective function of EV which seeks to reduce its charging cost. This term is represented by the EV's parameters; capacity, state-of-charge, charging power rate, demanded energy and departure time. The charging anxiety can let the related EV shifts (if possible) its charging time slots to others without deteriorating its own changing cost to support other in-need EVs to charge. In such a way, EVs may socially help each others in reducing their charging costs. This is particularly important in cases of limited available power for charging in the system. The EV charging problem is treated as a generalized Nash equilibrium problem and the solution is found based on receding horizon optimization framework. Moreover, the solution is reached in a distributed way by utilizing the consensus network. The simulation results proof the effectiveness of the proposed distributed charging management in reducing the charging cost of EVs.**

***Index Terms*—Distributed charging management, electric vehicle, charging anxiety, game theory, consensus network.**

I. Introduction

The interest in renewable energy sources (RESs) and electrification of transportation have been increased due to the demand growth in energy and the environmental concerns. Hence, electric vehicles (EVs) have received a notable attraction by industry and government. Up to 35 % of the total vehicles in USA will be EVs by 2020 according to the electric power research institute [1]. However, due to the low capacity of the EV on-board battery, EVs have to be charged constantly. With the potential large charging demand of an EV, the overall load of EVs will increase the peak load of the power distribution system at the charging site/station (CS). Thus, uncontrolled EV charging can cause power flow fluctuations and create harmful load peaks especially when overloading the capacity of the charging facility system [2]. Considering the previous issue with the charging cost reduction aim of EVs will make the EV charging problem more challenging. Therefore, it is necessary to develop an efficient charging management to coordinate the charging behaviors of EVs. This charging management is expected to improve the charging operation efficiency and reduce the charging costs paid by EVs.

The EV charging problem to coordinate the charging schedules of EVs has been vastly discussed in literature in both centralized and decentralized control approaches. Ref. [3] minimized the total charging costs in a time-of-use (ToU) tariff through a centralized scheduling control. While Ref. [4] proposed a centralized scheme that considered the plug-in EV (PEV) route and ToU. However, here, the constraints in the system were not properly considered. Ref. [5] presented a collaborative energy management to fill the charging demands of plug-in hybrid EVs (PHEVs) and to provide a balanced network load. The objective was to optimize the power distribution and reduce the operation costs.

In recent years, the decentralized control has received a notable attention because it allows flexibility and scalability as well as lowers the computation and communication burden. Moreover, the decentralized control can protect the privacy of the EV drivers since it allows reaching the solution without revealing the private information. In Ref. [6], a bi-level optimization problem introduced to model the fast charging station and the EVs. The EV objective compromised between benefits from charging and reserves provision. In Ref. [7] the power distribution losses in PEV charging stations have been minimized by an inverse leader-followers game to ensure system reliability. The objective of PEV owner is set to satisfy his/her charging demand with minimized cost. Ref. [8] presented a decentralized cooperative charging approach to reduce the charging cost of PEVs while considering the limitations of charging PEVs and infrastructure. Ref. [9] proposed a noncooperative game based distributed method for charging PEVs in a distributed network. Though some papers handled the overload in the system, the solutions during these cases were simple and did not consider possible cooperations between EVs. This is mainly because they treated the objective functions of EVs to be formulated only in a self-interest way.

This paper introduces a distributed charging management that reduces the charging cost of each EV. Unlike [9] and [10], this paper tackles the cases of limited (insufficient) available power for charging which is more challenging than the system capacity and the demand curtailment request from utility.

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Moreover, this proposed management allows a chance (if possible) for some EVs to assist in reducing the charging costs for others without sacrificing their own charging costs. To this end, a charging anxiety term is created and included in the objective function of EV to make the decision on the availability and the value of this assistance. The resulting decrement in charging is called a social charging cost reduction.

II. System Model

The EV charging system network here is considered to be a charging station (CS) as an example. This CS consists of a photovoltaic system (PVS), a battery energy storage system (BESS), a base load system (BLS), a grid system (GS) and a number of EVs $\mathcal{N} := \{1, 2, \ldots, N\}$ for charging as illustrated in Fig. 1. The PVS is modeled as in [11] while BESS is modeled by its equivalent circuit model [12]. BESS is utilised to buffer the power between surplus and intermittent periods and mitigate the power and voltage fluctuations [13]. BLS represents the base demand load (i.e., non-EV demand). GS gives/receives power during the lack/extra generation periods of PVS. Moreover, there is an EV aggregator that

1) Coordinates the charging of EVs over a multitime charging interval $\mathcal{T} := \{1, 2, \ldots, T\}$.
2) Announces the available power for charging EVs ($p_{ava,t}$).
3) Exchanges the shared data between the connected systems.

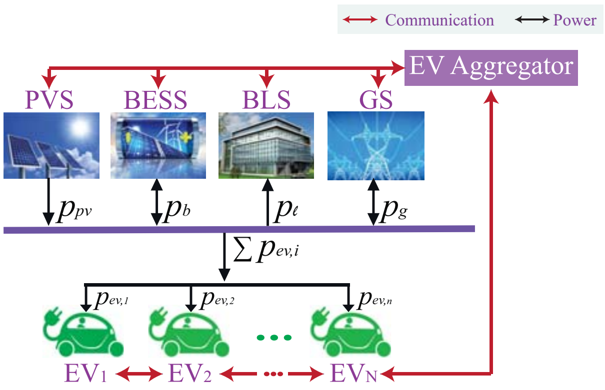

Fig. 1. Structure of the example charging station

A. Available Charging Power Domain

The total available power for charging EVs at any time t is calculated by

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

where $p_{pv,t}$, $p_{b,t}$, $p_{l,t}$, and $p_{g,t}$ are the powers of PVS, BESS, BLS, and GS. By considering the maximum loading capacity P_{cs}^{max} of the charging station, the following has to be held

$$p_{ava,t} \leq \eta_{cs} P_{cs}^{max}, \quad \forall t \in \mathcal{T}, \tag{2}$$

with $\eta_{cs} (\leq 1)$ is the overload control threshold of the charging station [14].

B. EV Charging Domain

Since this paper focuses on charging of EVs, the dynamic charge of each EV_n can be described by the linear model

$$SoC_{n,t+1} = SoC_{n,t} + \frac{\eta_c \Delta t p_{n,t}}{C_n}, \tag{3}$$

where $SoC_{n,t}$ is the state of charge of the EV battery at time t, $\eta_c \in (0, 1]$ is the charging efficiency, $p_{n,t}$ is the battery charging power, Δt is the time step, and C_n is the battery capacity.

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

$$E_n^r = E_n^d - E_n^i = T \sum_{t \in \mathcal{T}} p_{n,t}. \tag{4}$$

If $E_{n,t}$ $(= SoC_{n,t} C_n)$ is the energy of EV_n at time t, then, the following has to be respected

$$SoC_n^i \leq SoC_{n,t} \leq SoC_n^d, \tag{5}$$

with SoC_n^i $(= E_n^i / C_n)$ is the state of charge of EV at the arrival time to CS and SoC_n^d $(= E_n^d / C_n)$ is the state of charge of EV at the departure time from CS.

C. EV Charging Problem

Each EV cares about minimizing its own charging cost under its charging demands. Thus, the objective function of each EV_n can be represented as

$$\min_{p_{n,t}} \sum_{t \in \mathcal{T}} \frac{1}{\vartheta_{n,t}} \left(\frac{1}{2} S_n \Delta t^2 p_{n,t}^2 + pr_t \Delta t p_{n,t} \right) \tag{6}$$

$$\text{s.t.} \sum_{n \in \mathcal{N}} p_{n,t} \leq p_{ava,t}, \quad \forall t \in \mathcal{T} \tag{7}$$

$$P_n^{min} \leq p_{n,t} \leq P_n^{max}, \quad \forall t \in \mathcal{T} \tag{8}$$

In (6), S_n is the charging price sensitivity and pr_t is the charging price. $\vartheta_{n,t} \in [0, 1]$ is the charging anxiety (CA) that represents the degree of competing behavior of EV in charging. The proposed CA can be written as follows,

$$\vartheta_{n,t} = \begin{cases} 1 & M_{n,t} = 0 \\ \dfrac{C_n (SoC_n^d - SoC_{n,t})}{P_n^r (T_n^d - t)} & M_{n,t} = 1. \end{cases} \tag{9}$$

Where the binary parameter $M_{n,t}$ represents the social mode of EV_n at time t. When this parameter equals zero (i.e., RA has the highest degree in competing for charging), it means the corresponding EV has a pure selfish behavior and no ability to help other EVs. The social mode is assumed to have the zero value in the sufficient power cases since there is no need for help in charging during these cases. While, having a value of one (i.e., RA has a lower value than 1) means the corresponding EV has a social behavior to support other EVs in reducing their charging costs as will be seen later. This scenario may be met in the insufficient power cases e.g., overload. Here, the corresponding EV_n tries to decrease its

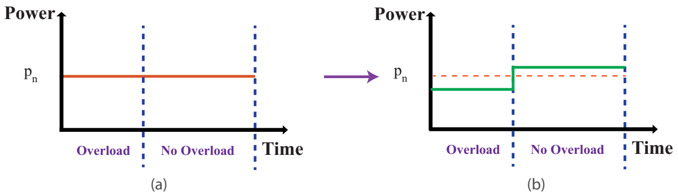

Fig. 2. An example of the charging power of EV_n when its social mode in the overload period equals (a) Zero. (b) One.

charging power during the overload period and to increase its charging power at other time slots under the same electricity tariff to give a chance for other EVs to charge as illustrated in Fig. 2. P_n^r is the charging rate of the charging infrastructure. Moreover, as shown in (9), the CA of EV increases meanwhile the time approaches the departure time of EV. However, the increase in the state-of-charge of EV will decrease its charging anxiety. This trend is believed to follow the practical behavior of EV in charging.

It is important to mention that (7) is the only common constraint that couples the charging schedules of EVs. This constraint makes the charging problem of EVs admits a generalized Nash equilibrium problem (GNEP). Moreover, this constraint reflects the insufficient power cases that can be met in the system. Note that in practice (7) is satisfied at the boundary to maintain the power balance in the system. It should be noted that in this paper the insufficient power cases and the overload cases are used interchangeably.

The lower bound P_n^{min} and the upper bound P_n^{max} of the charging power of EVs are defined by the instantaneous power constraint (8). Since this paper discusses a uni-directional charging of EVs, the lower bound is set to zero. However, it should be noted that the upper bound equals P_n^r in times when EV is plugged-in (i.e., $I_{n,t}=1$) and zero otherwise,

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

The proposed solution of this EV charging problem is based on a receding horizon optimization framework over horizon of T time steps rather than a single time step. However, only the first action of the optimal schedule will be applied at the current time step. This optimization will be carried out again in the following time step with a shifted horizon by one time step but with updated realizations based on the newly available information. It is worthy mentioning that the charging station has a wide range of uncertainties such as the weather conditions and the realization scenarios of the EVs. This makes the proposed optimization framework quite suitable here.

III. Distributed Charging Management of EVs

A. Optimality Conditions

Based on the Karush–Kuhn–Tucker (KKT) conditions of optimality, the Lagrangian function for the aforementioned optimization problem for each EV is given by

$$\begin{aligned}L=&\sum_{t\in\mathcal{T}}\frac{1}{\vartheta_{n,t}}\left(\frac{1}{2}S_n\Delta t^2p_{n,t}^2+pr_t\Delta tp_{n,t}\right)\\&-\sum_{t\in\mathcal{T}}\lambda_{n,t}\left(\sum_{n\in\mathcal{N}}p_{n,t}-p_{ava,t}\right)\\&+\sum_{t\in\mathcal{T}}\mu_{n,t}^{min}\left(P_n^{min}-p_{n,t}\right)+\sum_{t\in\mathcal{T}}\mu_{n,t}^{max}\left(p_{n,t}-P_n^{max}\right)\end{aligned} \tag{11}$$

with $\lambda_{n,t}$, $\mu_{n,t}^{min}$, and $\mu_{n,t}^{max}$ are the Lagrange multipliers of EV_n. Consequently, the first order optimality conditions are:

$$\frac{\partial L}{\partial p_{n,t}}=\frac{1}{\boldsymbol{\vartheta_n}}\left(S_n\Delta t^2\boldsymbol{p_n}+\boldsymbol{pr}\Delta t\right)-\boldsymbol{\lambda_n}+\boldsymbol{\mu_n^{min}}+\boldsymbol{\mu_n^{max}}=0, \tag{12}$$

$$\frac{\partial L_i}{\partial\lambda_{n,t}}=\boldsymbol{\lambda_n}\left(\textstyle\sum_{n\in\mathcal{N}}\boldsymbol{p_n}-\boldsymbol{p_{ava}}\right)=0, \tag{13}$$

$$\frac{\partial L_i}{\partial\mu_{n,t}^{min}}=P_n^{min}-\boldsymbol{p_n}\le 0, \tag{14}$$

$$\frac{\partial L_i}{\partial\mu_{n,t}^{max}}=\boldsymbol{p_n}-P_n^{max}\le 0. \tag{15}$$

Where the bold style for each symbol represents the vector values of this quantity over time $\mathcal{T}$. Due to the concavity of this problem i.e., concavity of the objective 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, the optimal solution i.e., the Nash equilibrium (NE), for each EV holds the following,

$$\frac{1}{\boldsymbol{\vartheta_n}}\left(S_n\Delta t^2\boldsymbol{p_n}+\boldsymbol{pr}\Delta t\right)\doteq\boldsymbol{\overline{\lambda}_n}, \tag{16}$$

with $\boldsymbol{p_n}$ has not violated its upper and lower bounds. Thus, the optimal solution can be uniquely represented in terms of $\boldsymbol{\overline{\lambda}_n}$ as follows

$$\begin{aligned}\boldsymbol{p_n}=&\ \mathcal{P}\left[\frac{\boldsymbol{\overline{\lambda}_n\vartheta_n}-\boldsymbol{pr}\Delta t}{S_n\Delta t^2}\right] && (17)\\=&\underset{P_n^{min}\le\boldsymbol{p_n}\le P_n^{max}}{\arg\min}\left|\left|\boldsymbol{p_n}-\frac{\boldsymbol{\overline{\lambda}_n\vartheta_n}-\boldsymbol{pr}\Delta t}{S_n\Delta t^2}\right|\right|^2. && (18)\end{aligned}$$

Note that $\mathcal{P}\,[.]$ is a projection operator of the argument into the feasible domain of EV_n. As it can be seen, each EV_n cares only about its local parameters and constraints. Thus, reaching the solution (i.e., $\boldsymbol{\overline{\lambda}_n}$) needs a collaboration between EVs through exchanging their public information which motivates the proposed distributed algorithm in this paper. From (17), it can be clearly shown that at the optimal solution the bigger the value of the charging anxiety of EV_n, the bigger the assigned charging power to it. This observation reflects the reason behind allocating the charging anxiety term in the objective function of EV.

B. Distributed Charging Management for Each EV

After assuming the privacy of each EV's local parameters, the centralized control methods are usually unavailable. Moreover, after considering a large number of EVs in the charging system network, the centralized approach is infeasible to gather all the information of EVs and to apply the solution in the specified interval. So, the distributed charging management is proposed. Here, the EVs in the system are called agents/nodes. These nodes are connected together by links to form a network system. Each node is assumed to have an individual local controller. Each local controller accesses only its local information, shares only its control variable ($\boldsymbol{\lambda}_n$), and interacts iteratively with other neighboring local controllers. By this interaction-based method, the uniform quantity $\overline{\boldsymbol{\lambda}_n}$ which represents the global decision-making value can be reached. To do so, the consensus network concept is utilized [15]. Algorithm 1 shows the proposed consensus-based distributed charging management (CDCM) for an EV in the current time step that contains the following phases:

1) Initialization phase: The EV aggregator predicts the value of $\boldsymbol{p_{ava}}$ over the horizon time $\mathcal{T}$. While, the agent EV_n calculate (initialize here) its optimal solutions ($\boldsymbol{p_n}$ and $\boldsymbol{\lambda_n}$). These results represent the ideal case i.e., no violation on the common constraint (7) has been met yet in any single time step over the horizon $\mathcal{T}$.
2) Checking phase: The validation of the common constraint will be checked for all time steps of the horizon $\mathcal{T}$. The algorithm terminates i.e., reaches the Nash equilibrium, if the available charging power $\boldsymbol{p_{ava}}$ is sufficient i.e., no overload is met, in any single time step. Otherwise, a compromised solution is expected to be reached between the agents i.e., EVs, through suppressing the charging powers of EVs currently demanded to meet the constraint as discussed in the next phase. It is worthy noting that the EV aggregator is responsible to check the violation of the common constraint.
3) Consensus phase: In each single time step, the followings will be met. First, violating the common constraint will be assigned to δp_t i.e., another consensus variable, that represents the power mismatch. This term is important to bring the power balance back into the system i.e., (7) is met at the boundary. Again, since the EV aggregator is the coordinator in the network system that can access all powers of EVs, it takes the task of this assignment and broadcasts its current value δp_t^i to all EVs. It should be noted that i is the iteration index in reaching the convergence. As known, the main purpose of this phase is to converge all values of $\lambda_{n,t}$'s of the nodes in the system to $\overline{\lambda_t}$. For that, each node updates its current $\lambda_{n,t}^i$ utilizing the sum of the weighted differences between this node's $\lambda_{n,t}^i$ and that of its neighbors' $\lambda_{j,t}^i$'s as in line 9. Moreover, the update of $\lambda_{n,t}^i$ will be affected also by the degree of violating the common constraint. Thus, the term $\eta \delta p_t^i$ is added, where, η is the step size. Note that N_n is the neighbor's set of node n, and $w_{n,j}$ is the connectivity strength between node n and j that have to be chosen in the range $[0 \ \frac{1}{N_n}]$ to ensure the intended convergence. When this stage of convergence is achieved, the charging power of EV with respecting to its local boundaries can be calculated [refer to line 11]. However, to check if this stage of convergence is the final desired one, a return [as in line 13] to check the common constraint is applied. The algorithm will iterate over the checking and the consensus phases repeatedly until the common constraint in line 3 is met.

Algorithm 1 CDCM

I. Initialization Phase

1: $Predict \ \boldsymbol{p_{ava}}$

2: $Initialize \ \boldsymbol{\lambda_n}, \ \boldsymbol{p_n}$

II. Checking Phase

3: **if** $\left|\sum_{n\in\mathcal{N}} \boldsymbol{p_n} - \boldsymbol{p_{ava}}\right| \leq \varepsilon_0$ **then**

4: Terminate

5: **end if**

III. Consensus Phase

6: **for** $\forall t \in \mathcal{T}$ **do**

7: $\delta p_t^i = \sum_{n\in\mathcal{N}} p_{n,t}^i - p_{ava,t}$

8: **while** $|\lambda_{n,t}^{i+1} - \lambda_{n,t}^i| > \varepsilon_1$ **do**

9: $\lambda_{n,t}^{i+1} = \lambda_{n,t}^i + \sum_{j\in\mathcal{N}_n} w_{n,j}(\lambda_{j,t}^i - \lambda_{n,t}^i) + \eta\delta p_t^i$

10: **end while**

11: $p_{n,t}^{i+1} = \mathcal{P}\left[\dfrac{\lambda_{n,t}^{i+1}\vartheta_{n,t} - pr_t\Delta t}{S_n \Delta t^2}\right]$

12: **end for**

13: Go back phase II

It should be noted that ε_0 and ε_1 are user defined values with better resolution and more iterations to reach the convergence at lower value.

IV. Simulation Results and Analysis

The focus of this paper is on the charging powers and costs of EVs with and without overload control and the system can be designed as in [16]. Due to the page limitation, a small case study is presented to show the effectiveness of the proposed algorithm while the large scale case study in one day is left for future extension. Thus, three EVs have been selected with arrival and departure times listed in Table I.

TABLE I
ARRIVAL AND DEPARTURE TIMES OF EVS

Target EV	EV_1	EV_2	EV_3
Arrival time (min.)	1	100	50
Departure time (min.)	400	460	500

The capacity of these EVs is 19 (kWh) while their initial and final SoCs are 0.2 and 0.9, respectively. The rated charging power is considered to be (3.3 kW). The total available power for charing (p_{ava}) is 2 (kW) in the period/slot (265-350 min) and 8 (kW) otherwise. Note that other values (random in general) will not change the effectiveness of the proposed method. The electricity tariff is illustrated in Fig. 3 (a) [10].

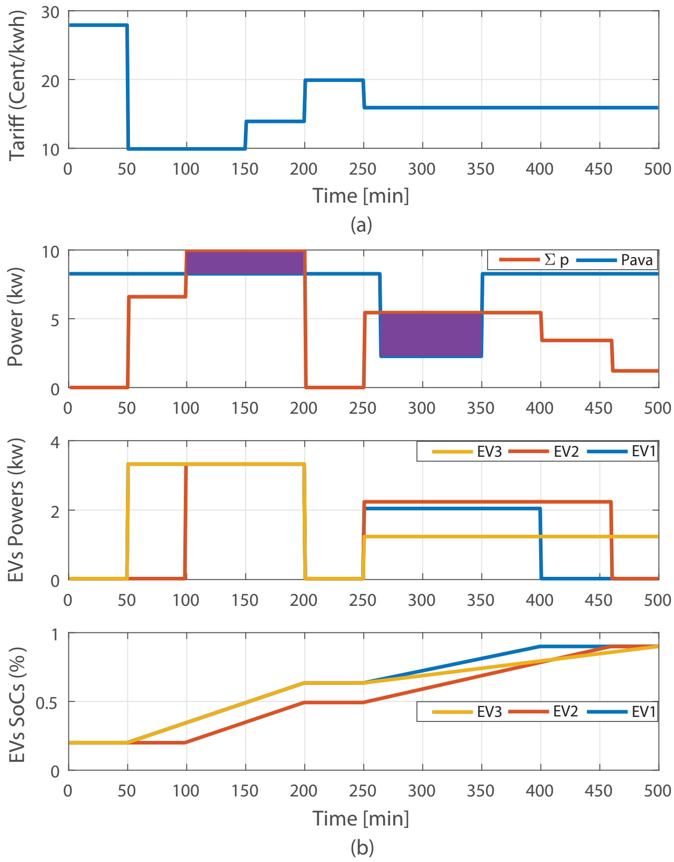

Fig. 3. (a) Electricity tariff (b) EVs' power and SoC responses without overload control.

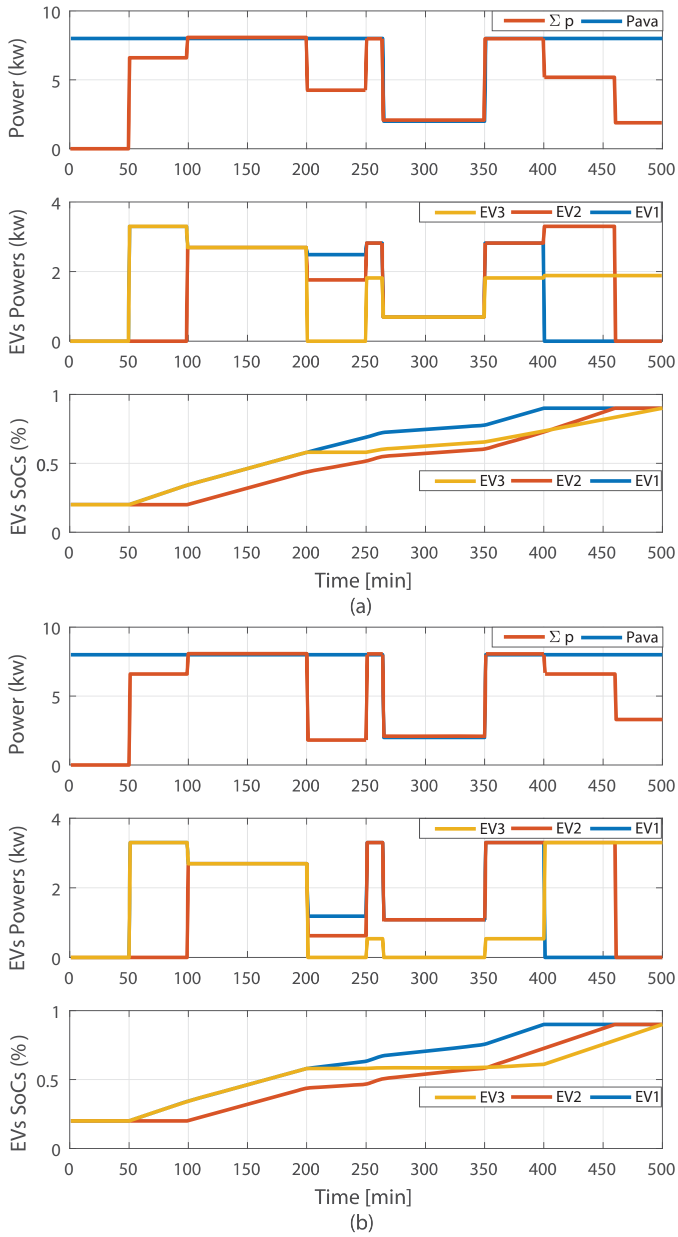

Fig. 4. EVs' power and SoC responses with overload control and (a) Without charging anxiety (b) With charging anxiety.

The simulation results have been divided into three parts. First, the EV charging problem is solved without considering constraint (7) i.e., without overload control and the results are shown in Fig. 3 (b). As it can be seen, all EVs have fully utilised the low price slots (50-150 min) and (150-200 min) and completed their charging requirements during the middle price slot (250-500 min). Note that no EV is charging during the high price periods (0-50 min) and (200-250 min). From the SoC response, it is clear that the EVs meet their charging requirements before their departure times. However, the total charging power of EVs ($\sum p$) is exceeded the limitation in two periods i.e., (100-200 min) and (265-350 min), which have been shaded in purple. The charging cost for each EV and the total charging cost for them (EV_{1-3}) under this case have been shown in Table II.

Second, the EV charging problem is solved with handling constraint (7) i.e., with overload control. However, here, the presented control did not consider the charging anxiety i.e., without charging anxiety (its value one all time) [6], [9]. The results are shown in Fig. 4 (a) which admit the same observations of that in Fig. 3 (b). Meanwhile, the total charging power of EVs ($\sum p$) always respects the total available power for charging and does not exceed it especially during (100-200 min) and (265-350 min). Note that during these two periods, the total available power for charging has been distributed evenly between the three EVs. This is because all EVs have the same parametric objective function and their preferred charging powers are bigger than the final evenly distributed ones. By comparing this case with the previous one, EVs lowered their charging powers during the constrained power periods. However, they increased their charging powers in other periods i.e., (200-250 min), (250-265 min), and (350-500 min), to fulfill their charging requirements. Since the increment in charging happened in higher price periods, it will lead to an increment in the charging costs as shown in Table II.

Third, the EV charging problem is solved with handling the constraint (7) and with considering the charging anxiety. Thus, here the total charging power of EVs also did not exceed

TABLE II
CHARGING COST OF EVS

Target EV	EV_1	EV_2	EV_3	EV_{1-3}
Without overload control ($)	1.743	1.904	1.743	5.390
Without charging anxiety ($)	1.867	2.004	1.784	5.655
With charging anxiety ($)	1.824	1.967	1.784	5.575
Social charging cost reduction($)	0.043	0.037	0	0.08

the total available power for charging as shown in Fig. 4 (b). However, the charging powers of EVs during the restricted power periods follow different strategies. In the period (100-200 min), a restricted power is met but all EVs have high charging anxiety (i.e., one) [refer to (9)]. Thus, similar to the pervious case i.e., without charging anxiety, the total available power for charging will be divided evenly between the three EVs. However, in the period (265-350 min) not all the charging anxieties of EVs have the value of one [again refer to (9)]. In this case, the charging anxiety of EV_3 is lower than one since it has a late departure time (i.e., capacity to help). Accordingly, EV_3 can stop charging and give a change to EV_1 and EV_2. Thus, this trend is called a social behavior of EV (i.e., EV_3). On the other hand, the charging anxieties of EV_1 and EV_2 are still one, thus, the power is distributed evenly between them in the period (265-350 min). Note that EV_3 compensates its charging requirement by increasing its charging power at different periods (250-265 min) and (350-500 min) but still at the same electricity tariff. This means EV_3 will not pay more charging price due to its social behavior. On the other hand, since both EV_1 and EV_2 have increased their charging power in the middle price period (265-350 min), they can decrease their charging power at the high price period (200-250) to full fill their charging requirements. This change in charging EVs will lower the charging cost of EV_1 and EV_2 as illustrated in Table II. Consequently, the proposed method has made a decrement in the charging cost (called social charging cost reduction) for EV_1 by 0.042 $ and for EV_2 by 0.037 $ and totally by 0.08 $ which listed also in Table II. It should be noted that the social charging cost reduction can be higher with longer times of the overload periods and different realizations of EVs.

V. CONCLUSION

By nature, all EVs follow a selfish behavior in charging to reduce their charging cost. However, it is still possible for EVs to contribute in reducing the charging cost for other EVs without deteriorating their own charging cost. Thus, in this paper, a distributed charging management with charging anxiety is proposed. This charging anxiety is included in the objective function of EV to tune its behavior to give an ability to EV to shift/reduce its charging demand to other time slots. This term is connected to the EV's physical parameters (capacity, state-of-charge and charging power rate) and demanded parameters (required energy and departure time). The charging problem then constructed as a generalized Nash equilibrium. The solution of this problem is based on a receding horizon optimization framework. This solution is then found in a distributed way utilising the concept of the consensus network. In simulation, three cases have been shown. The first did not consider the overload in the system. While the second took the overload into account but not the charging anxiety. The third, took the overload and the charging anxiety and showed an advantage in reducing the charging cost for EVs. An extension to this work will show the improvement in a large scale penetration of EVs and will investigate for possible different charging anxiety trends.

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