Distributed Electric Vehicles Charging Management Considering Time Anxiety and Customer Behaviors

Amro Alsabbagh, *Member, IEEE*, Brian Wu, Chengbin Ma, *Senior Member, IEEE*

***Abstract*—This paper proposes a charging management of electric vehicles (EVs) that considers time anxieties and different behaviors of EV customers. The time anxiety concept is newly presented to address some uncertain events that may happen meanwhile charging of EVs, affect their charging patterns, and prevent them from meeting their energy demands. The working principle of the concept relies on prioritizing the charging before the event occurrences, and thus changing the EV charging patterns. Based on this concept, four different EV customer behaviors are proposed and their influences are investigated. The EV charging problem is formulated as a generalized Nash equilibrium game, in which each EV minimizes its charging cost given its charging requirements and the charging facility constraints. The solution is developed on the basis of receding horizon optimization and reached iteratively in a distributed manner. Detailed simulation and comparison results are introduced to verify the effectiveness of the proposed charging management with the different time-anxiety-based EV customer behaviors.**

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

NOMENCLATURE

$\mathcal{N}$	Number of EVs
$\mathcal{T}$	Time interval of EV charging
T	Number of time steps in EV charging interval
t	Specific time
$p_{g,t}$	Power of GS at time t
$p_{pv,t}$	Power of PVS at time t
$p_{b,t}$	Power of BESS at time t
$p_{l,t}$	Power of BLS at time t
$p_{n,t}$	Charging power of EV$_n$ at time t
p^c_t	Charging power capacity of EVCS at time t
P^{max}_g	Maximum power capacity of EVCS feeder
η_t	Overload safety factor at time t
$P^{min}_{n,t}$	Lower bound of EV$_n$ charging power at time t
$P^{max}_{n,t}$	Upper bound of EV$_n$ charging power at time t
P^r_n	Charger power rate of EV$_n$
t^a_n	Arrival time of EV$_n$ to EVCS
t^d_n	Departure time of EV$_n$ from EVCS
$\mathcal{T}^c_n$	Charging duration of EV$_n$
E^a_n	Energy of EV$_n$ when it arrives at EVCS
E^d_n	Energy of EV$_n$ when it departs from EVCS
E^r_n	Charging energy demand of EV$_n$
$SoC_{n,t}$	State of charge of EV$_n$ at time t
SoC^a_n	State of charge of EV$_n$ at the arrival time
SoC^d_n	State of charge of EV$_n$ at the departure time
C_n	Battery capacity of EV$_n$
η_c	Charging efficiency
Δt	Time step
$t^{d\prime}_n$	Starting time of EV$_n$ driver anxiety
E^x_n	Anxious energy of EV$_n$ driver
ρ^s_n	Electricity price sensitivity of EV$_n$ driver
ρ_t	Electricity price
$A'_{n,t}$	Influence of time anxiety of EV$_n$ driver
$A_{n,t}$	Normalized influence of EV$_n$ driver time anxiety
$B_{n,t}$	Basic influence of time anxiety of EV$_n$ driver
A^{min}_n	Lower bound of anxiety influence of EV$_n$ driver
A^{max}_n	Upper bound of anxiety influence of EV$_n$ driver
$\Delta A^i_{n,t}$	Impact difference resulted by the ith behavior
$\lambda_{n,t}$	Lagrange multiplier of common constraint
$\mu^{min}_{n,t}$	Lagrange multiplier of EV$_n$ lower bound power
$\mu^{max}_{n,t}$	Lagrange multiplier of EV$_n$ upper bound power
L_n	Lagrangian function of EV$_n$ charging problem
$\overline{\lambda_t}$	Uniform Lagrange multiplier of common constraint
$\mathcal{P}[.]$	Projection operator of an argument into a domain
$E^{x,th}_n$	Threshold of anxious energy of EV$_n$ driver

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A. Alsabbagh is going to be a postdoctoral fellow with the Department of Electrical Engineering, Polytechnique Montreal, Montreal QC H3T 1J4, Canada (e-mail: amro.alsabbagh@hotmail.com).

C. Ma is with the University of Michigan-Shanghai Jiao Tong University Joint Institute, Shanghai Jiao Tong University, Shanghai 200240, China (e-mail: chbma@sjtu.edu.cn).

B. Wu is with the Stephen M. Ross School of Business at the University of Michigan, Ann Arbor MI 48109-1234, USA (e-mail: wux@umich.edu).

I. INTRODUCTION

DUE to the energy demand growth and environmental concerns, renewable energy sources and electric vehicles (EVs) have received a prominent interest. This has increased the total charging load of EVs into the electric grid as EVs need to be charged frequently [1]. It is known that this total load should always respect the charging power capacity of the facility, e.g., charging station, to avoid creating overload cases that could affect its stability and efficiency [2]. Since the charging requirements of EVs are different due to the various demands of their customers, i.e., drivers, it is important to develop a charging management, i.e., control, that considers all the above issues properly in a dynamic charging environment.

The charging management of EVs was addressed in the literature for several aspects including the reduction of EV charging costs by controlling their charging schedules, i.e., power distribution, constrained to specific charging requirements. In this management, two control architectures can be mainly found, namely centralized and distributed approaches.

Ref. [3] centrally optimized the EV charging schedules with consideration of utility demand curtailment request. Ref. [4] presented a centralized scheme on the basis of learning particle swarm optimization for optimal EV charging schedules and economic benefits. Ref. [5] proposed a four-stage optimization control approach into EV charging station for operational cost reduction as well as supply and demanded power balance. On the other hand, the distributed control has also drawn a prominent concern because of its unique features. These features include communication burden reduction and customer privacy protection as it secures their private information. Ref. [6] implemented a game-theory-based approach for trade-off optimization between EV reserves provision and charging benefits. Ref. [7] proposed a fuzzy-logic-based approach for maintaining a power balance among the components of charging station. Ref. [8] applied a noncooperative game theory for EV charging cost minimization. The above existing control methods lacked detailed investigations on the power distribution among individual EVs, particularly under limited charging power capacity. Also, they did not represent the influences of uncertain events that may lead to rescheduling of charging power patterns. A further point is that the EV charging management should incorporate EV driver behaviors. These individual behaviors are usually very different, in terms of charging quantities and events. Modeling these behaviors in a systematic way is still ongoing research [9]–[15].

Ref. [11] investigated in the behavioral subscription of customers to a particular plan in the demand response management program. The development of the customer behavior was designed on the basis of logistic regression model and assumed attributes. Ref. [12] proposed a robust optimization method to address the customer behavior uncertainties in order to minimize comfort violation in household load scheduling. This method was simple in modelling and represented the behavior as additional constraints in the scheduling problem. Ref. [13] introduced a multi-objective optimization framework in EV charging stations that considered profitability improvement and customer satisfaction enhancement. The satisfaction of EV customers could be tuned by the shape parameters of the customer satisfaction model. Ref. [14] studied a competition-based method to determine the electricity price in electric vehicle charging stations. The EV customer behavior of selecting the charging station was formulated on the basis of electricity price, distance to charging station, and number of charging poles in charging station. Ref. [15] considered a customer behavior uncertainty in the household energy scheduling problem. The proposed model of customer satisfaction level was included as a set of constraints in this problem to reflect the comfort violation caused by customer behavior. In the aforementioned approaches, the customer behavior was modeled by a single mathematical formula, and then different customer behaviors could be represented by tuning parameters in this formula. In addition, some of these customer behavior models used their own proposed formulations but lacking theoretical justification. In order to provide more accurate descriptions, it is of interest to differentiate between customer behaviors by different unique mathematical formulas and include them into the EV charging management problem.

Unlike the above literature, this paper introduces an EV charging management which addresses the aforementioned shortcomings. It formulates the EV charging problem on the basis of game theory with a charging cost minimization preference for each individual EV. It comprehensively studies the EV charging power distribution, i.e., EV charging patterns. Moreover, it proposes different EV customer behaviors and time anxiety concept that prioritizes the charging power of EVs before the occurrences of some uncertain events. Note that here EV customer, driver, and EV are all used as alternatives. The major work of this paper is summarized as follows:

1) A time anxiety concept of EV is newly proposed to mitigate the influence of uncertain events that may happen in the EV charging time durations and prevent EVs from meeting their energy demands.
2) Four different behaviors of EV customers are proposed and integrated into the EV charging management on the basis of the time anxiety concept and standard theoretical knowledge from social sciences and economics.
3) The dynamics of the time anxiety is systematically formulated and mapped to the proposed anxious energy, which is considered as the effect of the uncertain events on the EV customer charging requirements. Several case studies are presented to show the influences on the EV charging patterns including limited charging power capacity.

The rest of this paper is organized as follows. Section II models the system and the charging domain. Section III formulates the EV charging problem with the time anxiety and EV customer behaviors and develops the solution. Detailed simulation and comparison analyses are discussed in section IV. Finally, the conclusion is presented in section VI.

II. System Model and Charging Domain

As this paper focuses on charging EVs, the studied system is named as EV charging station (EVCS) which is considered as a distribution power network, part of the electric grid. This EVCS consists of several nodes (i.e., systems) which are connected together by power and communication lines as illustrated in Fig. 1. The first system is the grid system (GS) which represents the electric grid supply point. The other systems are a photovoltaic system (PVS), a battery energy storage system (BESS), and a base load system (BLS), in which each system could represent a group of systems of the same kind. The models of the PVS and the battery of BESS and EV are derived as in [16]–[18], and the BLS is considered as a building load demand, i.e., non-EV demand [19]. Moreover, there are a number of EVs ($\mathcal{N} := \{1, 2, \ldots, N\}$) which need to be charged and an EVCS operator whom addresses the following organizing missions:

1) Controls the power flow among GS, PVS, BESS, and BLS. Since the focus of this paper is on charging EVs, this power flow is controlled in a similar way of [5].
2) Broadcasts the charging power capacity, which indicates to the total available power for charging EVs, and checks its violation.

3) Helps in exchanging the public (i.e., shared) information between the aforementioned systems.

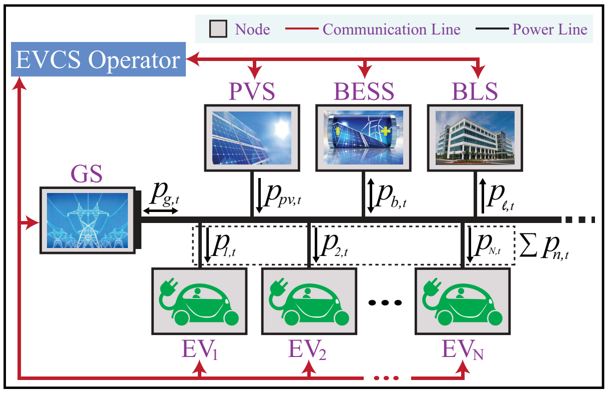

Fig. 1. Structure of the test system.

As shown in Fig. 1, $p_{g,t}$, $p_{pv,t}$, $p_{b,t}$, and $p_{l,t}$ are the power flows of GS, PVS, BESS, and BLS, respectively at time t. Moreover, $\sum_{n\in\mathcal{N}} p_{n,t}$ is the total charging power demand of EVs given that $p_{n,t}$ is the charging power of EV$_n$ at time t. After supporting the power demand of BLS, the total demand of EVs has to respect the charging power capacity of EVCS (i.e., charging domain) p^c_t as written in (1). This represents the common constraint that couples the charging schedules of EVs. If P^{max}_g is the maximum loading power capacity of EVCS feeder, which is related to the EVCS infrastructure, and $\eta_t(\leq 1)$ is its overload safety factor [8], the charging power capacity of EVCS can be defined by (2). Thus, if (1) is violated, an overload case is occurred in the EVCS.

$$\sum_{n\in\mathcal{N}} p_{n,t} \leq p^c_t, \quad \forall t\in\mathcal{T}, \tag{1}$$

$$p^c_t = \eta_t(P^{max}_g + p_{pv,t} + p_{b,t} - p_{l,t}), \quad \forall t\in\mathcal{T}. \tag{2}$$

Moreover, if the lower and upper bounds of the EV$_n$ charging power are $P^{min}_{n,t}$ and $P^{max}_{n,t}$, respectively, then $P^{min}_{n,t} \leq p_{n,t} \leq P^{max}_{n,t}$ has to be held, namely the instantaneous power constraint. As this paper addresses the charging problem of EVs, $P^{min}_{n,t} = 0$ here. While, the upper bound equals the EV$_n$ charger power rate P^r_n within the charging time duration and zero otherwise. This can be defined by (3) after considering t^a_n as the arrival time of EV$_n$ to EVCS, t^d_n as its departure time from it, and $\mathcal{T}^c_n$ as its charging duration, i.e., $t\in\mathcal{T}\cap[t^a_n, t^d_n]$.

$$P^{max}_{n,t} = \begin{cases} P^r_n & t\in\mathcal{T}^c_n, \\ 0 & t\in\mathcal{T}\backslash\mathcal{T}^c_n. \end{cases} \tag{3}$$

If $SoC_{n,t}$ is the state of charge (SoC) of EV$_n$ at time t, SoC^a_n is its SoC at the arrival time, and SoC^d_n is its SoC at the departure time, then (4) has to be held during charging. Given that C_n is the battery capacity (kWh) of EV$_n$, $\eta_c \in (0,1]$ is its charging efficiency, and Δt is the time step, the dynamic model of charging the EV on-board battery can be described by the linear model in (5).

$$SoC^a_n \leq SoC_{n,t} \leq SoC^d_n, \tag{4}$$

$$SoC_{n,t+1} = SoC_{n,t} + \frac{\eta_c p_{n,t}\Delta t}{C_n}. \tag{5}$$

It has to be noted that each EV$_n$ has an energy request, i.e., demand, E^r_n. This energy can be written as in (6) given that E^a_n is EV$_n$ energy when it arrives at EVCS and E^d_n is the energy that needs to be met before its departure time.

$$E^r_n = E^d_n - E^a_n = C_n\left(SoC^d_n - SoC^a_n\right) = T\sum_{t\in\mathcal{T}} p_{n,t}. \tag{6}$$

III. EV Charging Problem

The charging problem of each EV$_n$ is defined to minimize its charging cost with consideration of the aforementioned charging domain. Since each EV$_n$ has its own charging time duration, it has to be included in the charging problem. Moreover, in realistic scenarios, EV drivers may have different preferences (i.e., willing) to charge their EVs within these charging time durations. For example, some EV drivers are more anxious to charge their EVs at the early arrival periods to EVCS than others as they are afraid of meeting uncertain s-cenarios, i.e., events, that can happen in the later charging time periods. Such these events are the overload cases that constrain the EV charging power and the earlier departure times of EVs than scheduled from EVCS. These events may cause EVs to depart from EVCS without fulfilling their charging demands, and thus create worries (anxieties) to EV drivers meanwhile charging. Due to the human being nature, the degrees of these anxieties could be different among EV drivers, and thus their responses during charging will be different in order to relax their anxieties. Hence to make the charging problem more realistic, this anxiety and the resulted EV driver response (i.e., behavior) have to be included in the charging problem and to be addressed. This paper is dedicated to tackle this issue by proposing a time anxiety of EV driver that reflects the timely weighted concern to charge his/her EV within the charging duration $\mathcal{T}^c_n$. This anxiety leads the driver to secure more charging power in advance before possibly meeting the uncertain events. For clarity purposes, the influence of the proposed time anxiety is illustrated in Fig. 2. Here, Fig. 2(a) shows the original demanded charging power of EV$_n$ in the charging duration without acknowledging the EV$_n$ driver's anxiety; while Fig. 2(b) illustrates the modification in the demanded charging power when the EV$_n$ driver responds to the anxiety. In the figure, it is assumed that the EV$_n$ driver has anxiety about the occurrence of an event starting from $t^{d\prime}_n$, and $[t^{d\prime}_n, t^d_n]$ is the anxious time interval. Thus, the charging energy during this interval is defined as an anxious energy E^x_n. Note that Δt is the time step, and t ranges here within the anxious time interval.

$$E^x_n = \Delta t \sum_{t\in[t^{d\prime}_n, t^d_n]} p_{n,t}. \tag{7}$$

This energy represents the charging amount that the EV driver is anxious to possibly miss due to the event occurrence. As a result, EV$_n$ will try to shift part or all of the charging energy demand (i.e., shifted energy) from the anxious time interval to earlier time periods, as seen in Fig. 2(b). This will mitigate or cancel the anxiety of EV$_n$ driver if the remaining anxious energy, E^x_n, is close to or lower than its threshold.

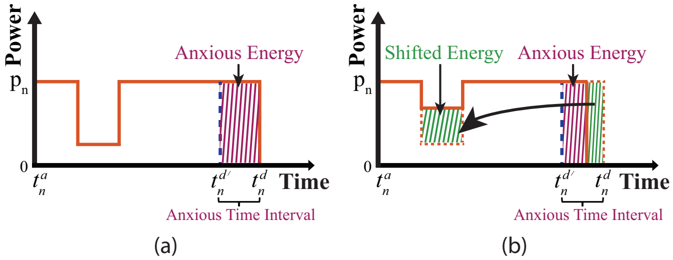

Fig. 2. Concept of the charging power of EVn. (a) Without time anxiety. (b) With time anxiety.

A. Problem Formulation

As each EV$_n$ seeks to reserve its own preference, i.e., minimizes its charging cost (\$), the charging problem is formulated as a noncooperative game-theoretic problem. Given that ρ_n^s is the electricity price sensitivity ($\$/(kWh)^2$) of EV$_n$, Δt is the time step (h), $p_{n,t}$ is the charging power (kW) of EV$_n$, ρ_t is the electricity price ($\$/kWh$), and $A_{n,t}$ is the influence of the time anxiety (dimensionless as seen in (11)-(13)), the charging problem of each EV$_n$ is defined as follows,

$$\min_{p_{n,t}} \sum_{t\in\mathcal{T}} A_{n,t}\left(\frac{1}{2}\rho_n^s \Delta t^2 p_{n,t}^2 + \rho_t \Delta t p_{n,t}\right), \tag{8}$$

$$\text{s.t.} \sum_{n\in\mathcal{N}} p_{n,t} \leq p_t^c, \qquad \forall t \in \mathcal{T}, \tag{9}$$

$$P_{n,t}^{min} \leq p_{n,t} \leq P_{n,t}^{max}, \qquad \forall t \in \mathcal{T}. \tag{10}$$

Since the EV charging problem is formulated on the basis of game theory and given that the constraint (9) couples all the charging power demands of EVs, this problem is actually a generalized Nash equilibrium (GNE) problem [20]. As designed by the cost function (8), a larger electricity price will lead to a lower charging power. Moreover, from a mathematical perspective if the driver has a big anxiety to charge his/her EV, i.e., needs to have a high charging power, then $A_{n,t}$ has to be small. Given the discussion early this section, the anxiety at the early charging time duration is expected to be higher than at the late duration to prioritize the charging before the event occurrence. Then, the value of $A_{n,t}$ increases gradually over the charging time duration as basically defined by (11) and shown in Fig. 3(a). As this paper investigates in the EV driver behavior, it further proposes four different behaviors on the basis of (11), namely non time anxious driver (NTAD), less time anxious driver (LTAD), mid time anxious driver (MTAD), and high time anxious driver (HTAD) as defined by (12) and illustrated in Fig. 3(b)-(c). The function formulation of each behavior type is selected on the basis of insights from social sciences and economics [21]. It has to be noted that NTAD represents the careless behavior of EV driver to the anxious energy, which is the common model in the EV charging problem literature.

$$B_{n,t} = min\left(\frac{max(t - t_n^a,\ 0)}{t_n^d - t_n^a},\ 1\right). \tag{11}$$

$$A'_{n,t} = \begin{cases} A_n^{max} \times 1 & \text{for NTAD,} \\ A_n^{max} \times ln[B_{n,t}(e-1)+1] & \text{for LTAD,} \\ A_n^{max} \times B_{n,t} & \text{for MTAD,} \\ A_n^{max} \times \dfrac{e^{B_{n,t}}-1}{e-1} & \text{for HTAD.} \end{cases} \tag{12}$$

Note that A_n^{max} is the upper bound of the anxiety influence which is assumed to be one for normalization purposes. In general cases, the lower bound A_n^{min} may have any value in the range $[0, A_n^{max}]$, thus a transformation is applied on (12) as defined by (13) and shown in Fig. 3(d).

$$A_{n,t} = \left(\frac{A_n^{max} - A_n^{min}}{A_n^{max}}\right) \times A'_{n,t} + A_n^{min}. \tag{13}$$

It is clear from Fig. 3 that the anxiety influence of LTAD (i.e., $A_{n,t}^{LTAD}$) is bigger than that of MTAD (i.e., $A_{n,t}^{MTAD}$) in which is bigger than that of HTAD (i.e., $A_{n,t}^{HTAD}$), and all are smaller than that of NTAD (i.e., $A_{n,t}^{NTAD}$). It is worthy to note that the value of $(A_n^{max} - A_n^{min})$ is actually the EV driver time anxiety, i.e., time anxiety depth. This explains the relationship of the smaller (i.e., closer to zero) value of A_n^{min} is, the bigger time anxiety of EV driver is. Also, a smaller A_n^{min} leads obviously to a smaller $A_{n,t}$. Again, the bigger anxiety leads to larger willing of EV driver to fulfill his/her charging demand as early before approaching the departure time, and thus to lower the amount of the anxious energy.

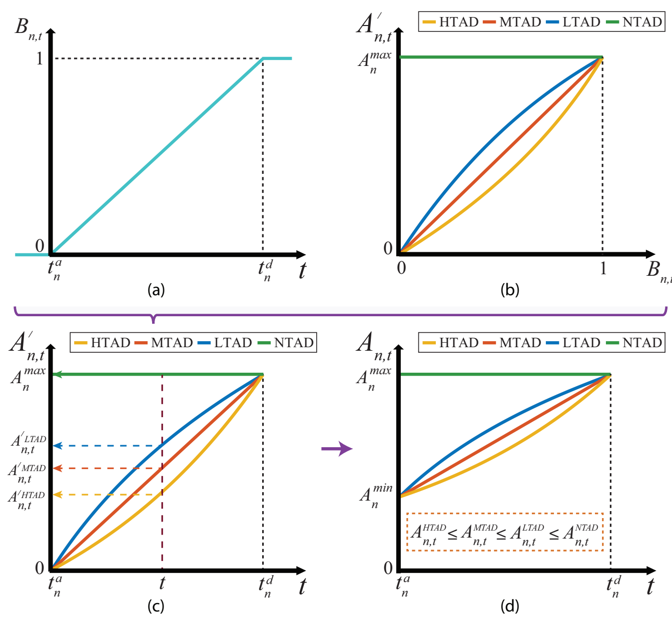

Fig. 3. (a) Dynamics of the basic anxiety influence over time. (b) Anxiety influence vs. its basic value under different behaviors of EV drivers. (c) Anxiety influence vs. time. (d) Modified scale of anxiety influence vs. time.

Based on the aforementioned discussions, the time-anxiety-based behavior of EV driver is determined by two factors. The first is the time anxiety depth and the second is the curve shape, i.e., behavior type. For clarity of the latter point along with the indicative meanings of the selected behavior names, their influences are illustrated in Fig. 4 given the same time anxiety depth. Here, the fixed anxiety influence of NTAD, i.e., A_n^{max}, is chosen as a reference value as shown in Fig. 4(a).

The difference between it and the anxiety influence which is resulted by the proposed behavior is considered as the impact difference. For example, $\Delta A_{n,t}^{LTAD} = A_n^{max} - A_{n,t}^{LTAD}$ is the impact difference (i.e. modification) resulted by the LTAD behavior. As seen in Fig. 4(b), the LTAD behavior scales down the reference anxiety influence during the charging time duration by different weighted values that reflect the anxiety dynamics of EV driver within this duration. Meanwhile, and as indicated by the name, the MTAD behavior scales down more the reference anxiety influence as he/she has a bigger anxiety for charging as depicted in Fig. 4(c). Comparing with LTAD and MTAD and as seen in Fig. 4(d), HTAD has the largest impact in lowering the reference anxiety influence. Thus, this driver is most willing driver, i.e., competitor, among others to charge his/her EV during the charging duration to reduce the amount of his/her anxious energy, and accordingly (14) holds.

$$\Delta A_{n,t}^{NTAD} \leq \Delta A_{n,t}^{LTAD} \leq \Delta A_{n,t}^{MTAD} \leq \Delta A_{n,t}^{HTAD}. \quad (14)$$

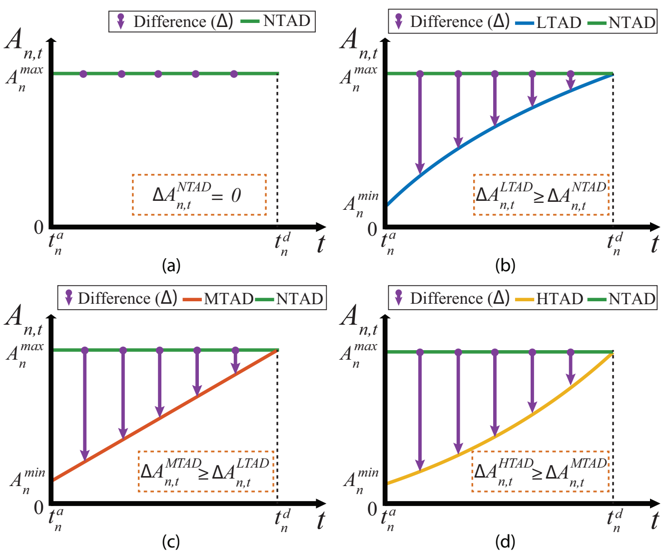

Fig. 4. (a) Reference anxiety influence of NTAD. (b) Modified anxiety influence of LTAD. (c) Modified anxiety influence of MTAD. (d) Modified anxiety influence of HTAD.

B. Problem Solution

As known, the charging environment is dynamic in which some uncertain events could happen meanwhile charging. Thus, addressing the charging problem over T time steps rather than a single one is valuable to determine the amount of anxious energy and to take the actions of changing the EV charging patterns in advance. Hence the solution of the EV charging problem in this paper is formulated on the basis of receding horizon optimization [22]. In this framework, the optimization process is calculated over the T time steps, however, only the first optimal action is applied at the current time step. In the next time step the optimization process will be implemented again with one-time-step shifted horizon and with newly updated and available information. The optimization process is formulated on the basis of Karush–Kuhn–Tucker (KKT) conditions of optimality. Thus, given that $\lambda_{n,t}$, $\mu_{n,t}^{min}$, and $\mu_{n,t}^{max}$ are the Lagrange multipliers, the Lagrangian function of the EV charging problem, i.e., (8), (9), and (10), for each EV$_n$ can be introduced by (15). If a bold style of a symbol is introduced to refer to its values over T time steps, i.e., $T \times 1$ vector, the gradient condition of KKT necessary optimality conditions can be then given by (16).

$$\begin{aligned} L_n = &\sum_{t\in\mathcal{T}} A_{n,t}\left(\frac{1}{2}\rho_n^s \Delta t^2 p_{n,t}^2 + \rho_t \Delta t p_{n,t}\right) \\ &- \sum_{t\in\mathcal{T}} \lambda_{n,t}\left(\sum_{n\in\mathcal{N}} p_{n,t} - p_t^c\right) \\ &+ \sum_{t\in\mathcal{T}} \mu_{n,t}^{min}\left(P_{n,t}^{min} - p_{n,t}\right) + \sum_{t\in\mathcal{T}} \mu_{n,t}^{max}\left(p_{n,t} - P_{n,t}^{max}\right), \end{aligned} \quad (15)$$

$$\begin{aligned} \frac{\partial L_n}{\partial \boldsymbol{p_n}} = &\boldsymbol{A_n}\left(\rho_n^s \Delta t^2 \boldsymbol{p_n} + \boldsymbol{\rho}\Delta t\right) - \boldsymbol{\lambda_n} + \boldsymbol{\mu_n^{min}} + \boldsymbol{\mu_n^{max}} \\ = &\mathbf{0}. \end{aligned} \quad (16)$$

It has to be noted that the KKT necessary conditions of this problem are sufficient as the problem is convex due to convexity of the cost function and the linear constraints. Thus, since the charging problem is GNE problem, the existence and uniqueness of its Nash equilibrium (NE) can be then proofed. As the most socially stable equilibrium is of interest here, the Lagrange multipliers of the common constraint (9) of all EVs have to share the same value, i.e., $\overline{\boldsymbol{\lambda}}$ [23]. This NE can be expressed by (17) in which $\boldsymbol{p_n}$ is between $\boldsymbol{P_n^{min}}$ and $\boldsymbol{P_n^{max}}$. Hence the $\overline{\boldsymbol{\lambda}}$-based solution can be uniquely presented by (18) given that $\mathcal{P}[.]$ is a projection operator of the argument into the EV$_n$ feasible charging domain, i.e., respecting its local constraint (10).

$$\boldsymbol{A_n}\left(\rho_n^s \Delta t^2 \boldsymbol{p_n} + \boldsymbol{\rho}\Delta t\right) \doteq \overline{\boldsymbol{\lambda}}, \quad (17)$$

$$\boldsymbol{p_n} = \mathcal{P}\left[\frac{\frac{\overline{\boldsymbol{\lambda}}}{\boldsymbol{A_n}} - \boldsymbol{\rho}\Delta t}{\rho_n^s \Delta t^2}\right]. \quad (18)$$

To reach this solution, all the information in (18) including $\overline{\boldsymbol{\lambda}}$ and $\boldsymbol{A_n}$ have to be known. If a centralized control method is the case here, all these information have to be revealed to its global controller to allow it assigning the charging power of each EV. However, since securing the privacy is of concern here, this centralized method turns out to be invalid. This issue becomes more critical in practice after including the EV driver behavior which is a unique private information. As a result, a distributed charging management is proposed here in which the charging decisions of EVs are made by themselves through their local controllers. Each local controller needs to reach the solution of (18) on the basis of its local information, i.e., $\boldsymbol{A_n}$, ρ_n^s, and $\boldsymbol{\lambda_n}$, as well as the global shared ones of $\boldsymbol{\rho}$ and other neighboring EVs' $\boldsymbol{\lambda}$'s (i.e., $\mathcal{N}_n$). As mentioned early section II, each EV$_n$ in the EVCS is considered as a node in which all the nodes including that of EVCS operator are connected by communication links and the resulting network can be illustrated in Fig. 5. The shared (i.e., public) information between the nodes are shown here and the organizing missions of EVCS operator are the three ones discussed in section II. Moreover, each EV$_n$ executes algorithm 1, which is the proposed distributed charging management with the time anxiety concept (DCMTA). For clarity in the description, this algorithm is divided into four tasks with meaningful names that indicate to their functions, namely initialization, optimization, modification, and communication tasks.

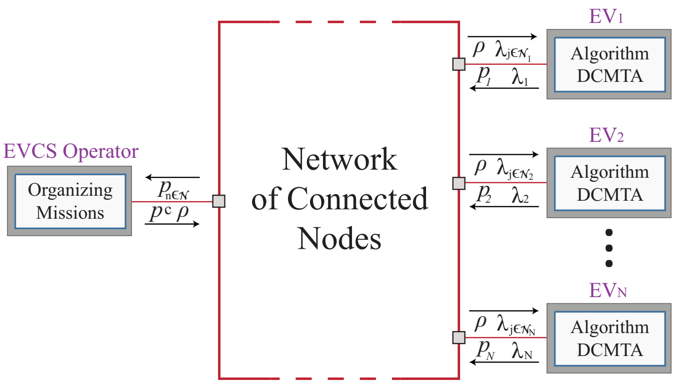

Fig. 5. The interactive communications within the network of connected nodes.

In the first task of the algorithm, initialization is performed by assigning both A_n^{max} and A_n^{min} to one for normalization and modification purposes. Afterwards, the optimization task is applied in which the EV$_n$ finds its optimal charging pattern, i.e., schedule, individually over the the horizon time. This is achieved by solving the charging problem of EV$_n$ respecting its own local current constraint only [as in line 3], and the findings are $\boldsymbol{p_n}$ and $\boldsymbol{\lambda_n}$. The current constraint here refers to the upper limit of charging power $\boldsymbol{P_n^{max}}$ which may be updated [as in line 19]. Note that at this point of the first round execution of this task, the EV$_n$ has not addressed its anxious energy nor overload cases if they occurred in EVCS, however, they will be tackled in the following two tasks.

In the modification task, the anxious energy of EV driver E_n^x is calculated on the basis of the results of the previous task, i.e., $\boldsymbol{p_n}$. Then, E_n^x is checked if it exceeds its threshold $E_n^{x,th}$, which is a predefined value and is determined by the EV driver. Note that the more the EV driver wants to be robust against an uncertain event, the lower the $E_n^{x,th}$ is. If the current anxious energy is larger than the threshold, it means that the EV driver is not satisfied with the current $\boldsymbol{p_n}$ because this $\boldsymbol{p_n}$ is not suitable to meet his/her charging demand E_n^r given the potential occurrence of an uncertain event. Therefore, the EV driver modifies his/her time anxiety influence, as it has a direct influence on $\boldsymbol{p_n}$ and thus on E_n^x, by increasing its depth, i.e., reduces the lower limit A_n^{min} by a fixed amount ε_1. This modification is implemented in an iterative way until the EV driver succeeds in making his/her anxious energy below its threshold. In other words, the EV driver becomes satisfied with the current $\boldsymbol{p_n}$ as it is considered to be robust to meet his/her E_n^r given the potential occurrence of an uncertain event. Each iteration involves the process of re-optimization of the charging pattern, re-calculation of the current anxious energy, and re-reduction of the lower limit if the anxious energy. Once this task is completed, the resulting charging pattern of EV$_n$ is considered to be optimal with an acceptable remaining anxious energy.

Then, the communication task is processed in which the EV$_n$ node communicates with others to handle the overload cases in EVCS if they occurred. To do so, the common constraint (9) is first checked over the time horizon [refer to line 10]. The algorithm terminates with the optimal solution if the constraint is not violated, i.e., no overload cases are occurred. On the other hand, if the current total power demand of EVs is bigger than the charging power capacity at any time step, the total demand will be pulled down to meet the capacity by a compromised procedure among EVs through restraining their current power demands. As explained before, this solution can be reached by requiring all $\lambda_{n,t}$'s of EVs to share the same global decision-making value $\overline{\lambda_t}$, an element of $\overline{\boldsymbol{\lambda}}$. The procedure to do that is achieved by an interaction-based method which utilizes the consensus network concept [23], [24]. First, the surplus power demand of EVs above the power capacity, which is needed to be cut, is calculated and assigned to Δp_t [refer to line 15]. Then, an update on the $\lambda_{n,t}$ of EV$_n$ is applied by exploiting the sum of the weighted discrepancies between it and its neighbors, i.e., $\lambda_{j,t}$'s, as well as the weighted surplus power Δp_t [as in line 17]. Note that the two weight parameters β_n and α_n as well as ε_1, ε_2, and ε_3 are all user defined values. Once the converged value $\overline{\lambda_t}$ is reached, the upper limit of the charging power of EV$_n$ is updated in a similar way to (18) [refer to line 19]. After tackling the overload cases in all time steps of the time horizon, EV$_n$ has to re-optimize its charging pattern with the updated local current constraint. The iteration process through the optimization, modification, and communication tasks remains until both the anxious energy and overload cases are completely addressed, then algorithm 1 terminates at line 11.

IV. Simulation Analysis

The performance of the proposed algorithm with the time anxiety concept and the different EV driver behaviors is evaluated by two aspects. The first aims to investigate in the charging patterns of EVs, i.e., EV charging power distribution. Thus, a small scale of EVs with different case studies are introduced to clearly show the charging dynamics in an example time interval of the day. The second aspect, on the other hand, is presented to proof the influences of the proposed issues in conserving the profit of EVCS operator and the satisfactions of EVs in a large scale penetration of EVs throughout one day. The simulation configuration, which is adopted in both aspects, is set up as follows.

The capacity of the on-board battery of EVs and their charger power rates are randomly selected in the ranges 7.6–85 (kWh) and 3.3–10 (kW), respectively [19], [25]. The SoCs of these EVs at the arrival and departure times are randomly generated following a normal distribution in the ranges 0.2–0.6 (%) and 0.7–0.9 (%), respectively [26], [27]. As known, EVs can arrive to EVCS at any time and particularly during the potential peak arrival times [8]. Meanwhile, the charging time durations of EVs in EVCS are determined on the basis

Algorithm 1 Distributed Charging Management with Time Anxiety (DCMTA)

I. Initialization Task

$A_n^{max} = 1$

$A_n^{min} = 1$

II. Optimization Task

$Solve\ (8)\ subject\ to\ (10)$

III. Modification Task

Calculate E_n^x by (7)

if $E_n^x \geq E_n^{x,th}$ **then**

  $A_n^{min} \leftarrow A_n^{min} - \varepsilon_1$

  Calculate $\boldsymbol{A_n}$ by (13)

  Go back phase II

end if

IV. Communication Task

if $(\left|\sum_{n\in\mathcal{N}} \boldsymbol{p_n} - \boldsymbol{p^c}\right| \leq \boldsymbol{\varepsilon_2})$ **then**

  Terminate

end if

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

  while $\sum_{n\in\mathcal{N}} p_{n,t} > p_t^c + \varepsilon_2$ **do**

    $\Delta p_t = \sum_{n\in\mathcal{N}} p_{n,t} - p_t^c$

    while $max(|\lambda_{n,t} - \lambda_{j,t}|) > \varepsilon_3$ **do** $\quad \forall j \in \mathcal{N}_n$

      $\lambda_{n,t} \leftarrow \lambda_{n,t} + \sum_{j\in\mathcal{N}_n} \alpha_n(\lambda_{j,t} - \lambda_{n,t}) + \beta_n \Delta p_t$

    end while

    $$P_{n,t}^{max} = \mathcal{P}\left[\frac{\frac{\lambda_{n,t}}{A_{n,t}} - \rho_t \Delta t}{\rho_n^s \Delta t^2}\right]$$

  end while

end for

Go back phase II

of some issues including the predicted next travel schedules and charging demands, i.e., requirements. Hence the departure times of EVs from EVCS are randomly set with realistic consideration of these issues. The electricity price sensitivity is assumed to be 0.001 ($\$/(kWh)^2$) to make a suitable response to the low electricity prices, and the data profiles of temperature and solar irradiance for solar power generation, BLS load, and electricity price are adopted as in [28]–[30], respectively.

A. Small Scale of EV Penetration

Following the above explanation and simulation configuration, three EVs are selected here and their specifications are reported in Table I. As seen, each EV driver is assumed to have a different behavior (BEHR.) from others. The anxious time interval of each EV_n is considered to be the last hour of the charging duration, i.e., $t_n^{d\prime} = t_n^d - 1$ (h). As shown, these EVs are scheduled to be charged during the time interval 8:00–14:00 in which the electricity price is illustrated in Fig. 6(a). In this section, three case studies are introduced that focus on different points and their results are illustrated in Fig. 6(b)-(d).

The first case study discusses the influence of the anxious energy threshold (Anx. Eng. THLD) on the EV anxiety depth and charging cost. In this regard, EV_3 is selected as an example with five scenarios. Each scenario (S) has a specific demand

TABLE I
SPECIFICATIONS OF THE EXAMPLE THREE EVS

SPEC	C_n (kWh)	P_n^r (kW)	t_n^a (h)	t_n^d (h)	SoC_n^a (%)	SoC_n^d (%)	BEHR.
EV_1	17	3.3	8:30	13:10	0.21	0.90	HTAD
EV_2	18	3.3	8:35	13:20	0.23	0.89	LTAD
EV_3	19	3.3	8:40	14:00	0.32	0.85	MTAD

of the anxious energy threshold as listed in Table II. Since the anxious energy threshold of S_1 is large enough 3.3 (kWh), it indicates for a loose charging demand of the driver and thus he/she has no anxiety depth here, i.e., 0.00 (%). Consequently, the charging pattern of EV_3 results only from the electricity price and the charging requirements. In other words, EV_3 is charged with its upper limit of charging power, P_3^r, 3.3 (kW) at electricity price 0.150 ($\$/kWh$) and fulfilled its charging demand at price 0.160 ($\$/kWh$) with no further need to be charged at 0.180 ($\$/kWh$).

For other scenarios, i.e., S_2-S_5, their charging patterns follow similar trend to that one of S_1. However, as designed in the modification task of algorithm 1, the smaller anxious energy threshold leads to a smaller value of A_n^{min}, and thus a bigger anxiety depth. In other words, the EV driver will reasonably be more anxious to reduce his/her current anxious energy to meet the demanded anxious energy threshold. Consequently, EV_3 tries to shift, i.e., reschedule, more charging energy from the anxious time interval to earlier times if possible as depicted in Fig. 6(b). If the shifted energy is moved to a time interval with higher electricity price rate, an increase in the charging cost will be occurred. Thus, the charging cost of S_2 is the same of S_1 while the charging cost of S_5 is the highest among others as the amount of its shifted energy is the highest from the electricity price 0.160 ($\$/kWh$) to 0.180 ($\$/kWh$). Note that if a charging cost increase is happened, it is still small and EV_3 sacrifices it in order to meet its charging energy demand rather than mismatching it due to some unpredicted events when it leaves the EVCS.

TABLE II
ANXIETY DEPTHS AND CHARGING COSTS OF EV_3 UNDER DIFFERENT ANXIOUS ENERGY THRESHOLDS.

Scenario	S_1	S_2	S_3	S_4	S_5
Anx. Eng. THLD (kWh)	3.300	2.640	1.650	0.660	0.000
Anxiety Depth (%)	0.00	0.02	0.14	0.20	0.25
Charging cost ($)	1.599	1.599	1.616	1.634	1.649

In the second case study, the effect of the EV driver behavior is discussed. The EV_2 is selected here as an example and its driver behavior is changed among the NTAD, LTAD, MTAD, and HTAD for investigation purposes. The anxiety depth of EV_2 driver is assumed to be 0.26 (%) and the results are shown in Table III and Fig. 6. As seen, different behaviors lead to different anxious energies and charging costs. As illustrated in the anxiety influence map of Fig. 6(c), the impact difference of HTAD is the highest, then orderly those ones of MTAD, LTAD, and NTAD, which match the discussion in section III-A. This issue results in making the anxious energy of HTAD to be the lowest, then that ones of MTAD, LTAD, and NTAD, respectively. Note that the anxious energy of NTAD is the biggest among others because the driver is careless about this quantity. It is observed that the more anxious driver tries to shift more energy from the anxious time interval to earlier intervals to reduce his/her anxious energy. Under the example electricity profile, these earlier time intervals have electricity price 0.180 ($\$/kWh$) comparing with 0.160 ($\$/kWh$) of the original intervals. Thus, a small increase in the charging cost is occurred by the more anxious driver, in which it is accepted by him/her in order to secure his/her charging demand to be reached if some unpredicted circumstances are occurred near or in the anxious time interval.

TABLE III
ANXIOUS ENERGIES AND CHARGING COSTS OF EV_2 UNDER DIFFERENT DRIVER BEHAVIORS.

EV Driver Behavior	NTAD	LTAD	MTAD	HTAD
Anxious Energy (kWh)	3.300	1.650	0.715	0.330
Charging cost (\$)	1.940	1.977	1.992	1.999

The third case study investigates in the charging patterns of EVs under different charging requirements, behaviors, and charging power capacities of EVCS. Here, besides of the EV specifications in Table I, their demanded anxious energy thresholds are listed in Table IV. The charging capacity of EVCS is considered here, as an example, to be 12 (kWh) except during the time interval 9:00-9:30, in which it is set as 5.5 (kWh). As seen from the results in Fig. 6(d), all EVs try to fulfil their charging requirements including the anxious energy thresholds at the lowest charging costs. The dynamics of the anxiety influences including the anxiety depths reflect the way of how these EVs are responding to meet their charging requirements under the charging conditions of EVCS, i.e., electricity price and charging capacity.

Since EV_1 driver is HTAD and has a small, i.e, tough in demand, anxious energy threshold 0.825 (kWh), it has a large impact difference and a wide energy depth 0.26 (%). Thus, EV_1 competes more than others to make its charging power the highest during the limited charging capacity 9:00-9:30. Although EV_2 has a bigger, i.e., looser to be met, anxious energy threshold than EV_1, its driver is LTAD and it has a stricter charging demand to be met, i.e., big energy demand and short charging duration. Thus, its anxiety depth is also wide 0.28 (%) and its charging power during 9:00-9:30 is between EV_1 and EV_3. Finally, EV_3 has loose charging requirements, i.e., small energy demand and long charging duration, as well as a moderate anxious energy threshold 1.100 (kWh). Thus, it competes less during 9:00-9:30, and its charging power is the lowest here.

The charging cost of EV_3 is the lowest due to its charging requirement and the less charging amount during the interval of high electricity price 0.180 ($\$/kWh$). Although the charging cost of EV_1 is similar to EV_2 as they have similar charging requirements, it is a bit lower as it has more chance to be charged during the interval of low electricity price 0.150 ($\$/kWh$). Note that the SoCs of EVs start from their arrival values and end up with the departure values which are listed in Table I and their increase dynamics are proportional to their charging power amounts.

TABLE IV
CHARGING RESPONSES OF EVS UNDER A SPECIFIC CHARGING CAPACITY.

Target EV	EV_1	EV_2	EV_3
Anx. Eng. THLD (kWh)	0.825	1.650	1.100
Anxiety Depth (%)	0.26	0.28	0.18
Charging cost (\$)	1.968	1.975	1.635

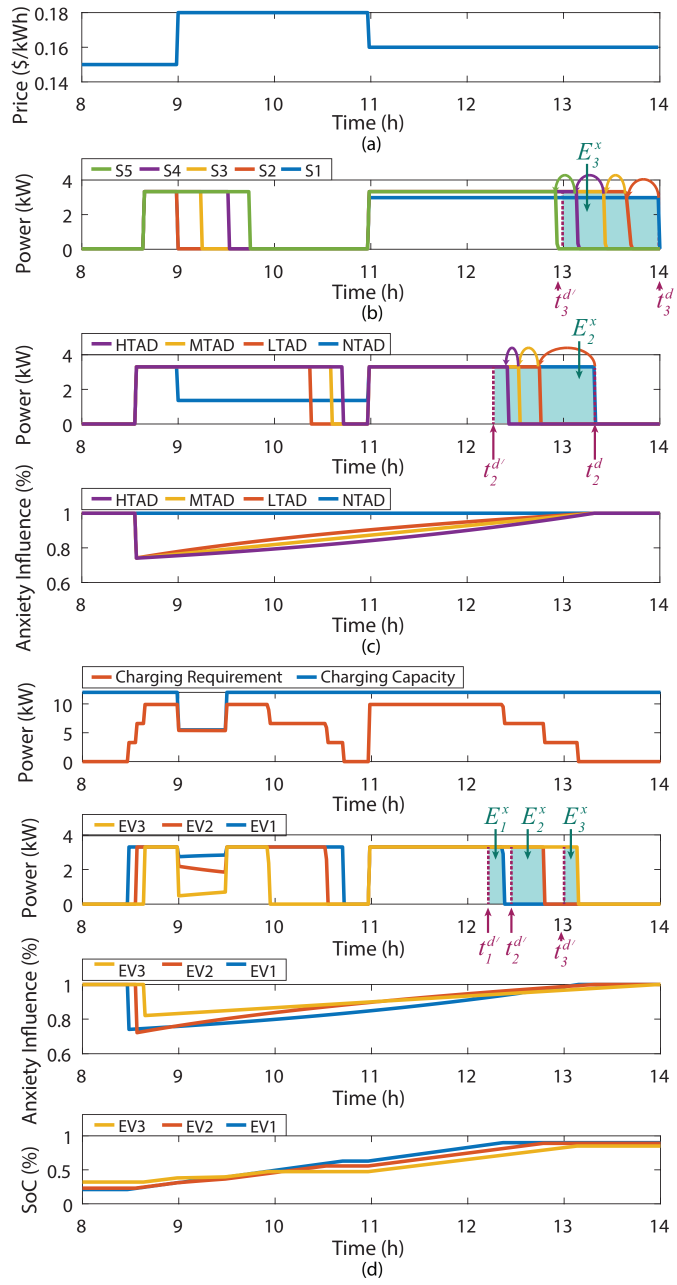

Fig. 6. (a) Electricity price profile. (b) Charging power of EV_2 under different anxious energy thresholds. (c) Charging power and anxiety influence of EV_2 under different driver behaviors. (d) Charging capacity, charging requirement, and EVs' responses of power, anxiety influence, and SoC.

B. Large Scale of EV Penetration

The influences of uncertain events at different penetration numbers of EVs are discussed and evaluated. Such these events are the overloads and earlier (i.e., actual) departure times of EVs than scheduled ones which may occur near or in the anxious time intervals of EVs. The second type of events is selected here as an example in the discussion and the difference between the actual and scheduled departure times is symbolized Δt^d which is assumed to vary in the range $[0, 1(h)]$. The chosen literature method for comparison defines the EV departure time as an accurate information and does not consider a potential discrepancy that may happen on it nor its consequences [8]. In other words, this method considers the behavior of all EV drivers to be NTAD, and thus it is named as non-anxiety method (NA-M) while the proposed method is called time-anxiety method (TA-M). Moreover, two criteria are considered here for evaluation. The first is the profit of EVCS by selling charging energy to EVs. The second criterion is the satisfaction of EV driver on the charging cost and energy demand, i.e., the increase in the charging cost and the charging energy mismatch between the demanded and actual received ones [13]. A 100-run Monte Carlo simulation with different EV specifications and charging requirements at each run is adopted to give an average evaluation between the two methods.

As seen in section IV-A, EVs in TA-M are more able to fully meet their energy demands in shorter charging durations since their EV charging decisions are more robust against the departure time uncertainties. This actually has two influences. First, since the actual charging durations of EVs in TA-M are shorter than in NA-M, its service rate of EVs in one day is higher than in NA-M. The second influence is that the amount of sold energy by EVCS to EVs is higher in TA-M since its charging energy mismatches of EVs are lower than in NA-M. Thus, TA-M guarantees higher profit to EVCS than NA-M as seen in Fig. 7(a). Moreover and as seen in Fig. 7(b), TA-M conserves higher satisfactions for EVs than NA-M since EVs here are more able to meet their energy demands with no/small increase in the charging cost, as discussed in the first case study of section IV-A.

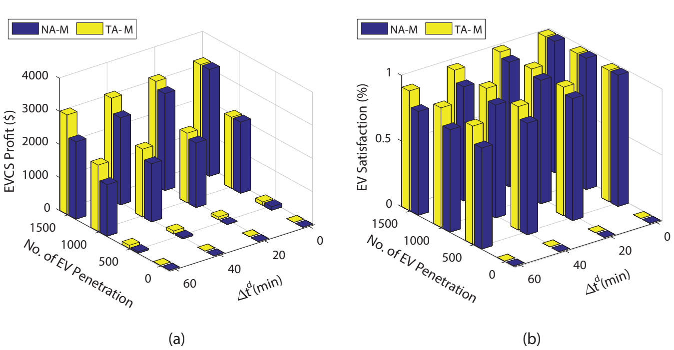

Fig. 7. Influences of departure time uncertainty and No. of EV penetration on (a) EVCS profit. (b) EV satisfaction.

V. Conclusion

The behavior of EV customer plays an important role in making the charging decisions in the EV charging problem. Thus, an improved model to this behavior is significant to have more realistic and effective charging decisions. To this end, this paper proposed a time anxiety concept to mitigate the influences of some uncertain events that could happen meanwhile charging. Based on this concept, it formulated different EV customer behaviors and included them into the EV charging problem. This problem was designed as a nooncooperative game and the solution was developed in a distributed way. Detailed case studies were introduced to show the influences on small and large scales. Moreover, the proposed algorithm was benchmarked against another one to further proof its performance and efficacy in securing the profit of charging facility and the satisfactions of EV customers. Consequently, the proposed charging management is worthy to be integrated in EVCS when there is a large number of EVs with different charging behaviors that usually change dynamically. Thus, the EVCS operator will be released from difficulties in collecting all the individual EV information and in applying the solution centrally in a specified interval. Furthermore, this charging management could be integrated to increase the satisfactions of the target EV customers in terms of privacy protection. This issue is important when these customers have high concerns about securing their information and behaviors.

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Amro Alsabbagh (S'16-M'20) received the B.S. and M.S. degrees both in the automatic control and computers engineering from Al-Baath University, Homs, Syria, in 2010 and 2015, respectively, and the Ph.D. degree in control science and engineering from the University of Michigan-Shanghai Jiao Tong University Joint Institute, Shanghai Jiao Tong University, Shanghai, China, in 2020. He is going to be a postdoctoral fellow with the Department of Electrical Engineering, Polytechnique Montreal, Montreal, Canada. His research interests include modeling and control of micro/smart grid and distribution network, especially with integration of electrical vehicles.

Dr. Amro is a technical paper reviewer in many journals including IEEE Transactions on Industrial Informatics and IEEE Transactions on Industrial Electronics. He won the IEEE-IES student paper travel assistance award in 2018 and the Shanghai Jiao Tong University Excellent International Post-Graduate Students in 2020.

Brian Wu received his B.S. from Tsinghua University in China, M.Sc. from National University of Singapore, and Ph.D. from the Wharton School at the University of Pennsylvania prior to joining the Ross School of Business in 2007. He serves as the faculty director of China Initiatives. His research examines the role of firm capabilities in influencing the dynamics of corporate scope and the evolution of industries.

Dr. Brian served on the Research Committee (2010-12) and the Executive Committee (2013-15) of the Academy of Management (AOM) Business Policy and Strategy Division. He was elected as Representative at Large for the Corporate Strategy Interest Group and the Behavioral Strategy Interest Group of the Strategic Management Society (2014-16). He serves as an Associate Editor for Strategic Management Journal, the strategy fields flagship journal. He serves on the Academic Committee of Alibaba Group Research Institute. He has been recognized with the US Small Business Administration Best Student Paper Award, AOM Technology and Innovation Management Division Stephan Schrader Best Conference Paper Award, INFORMS Organization Science Dissertation Proposal Competition Award (finalist), AOM Technology and Innovation Management Division Past Chairs Emerging Scholar Award (runner-up), Academy of Management BPS Division Distinguished Paper Award, Neary PhD Teaching Excellence Award, 3M Nontenured Faculty Award, Sanford R. Robertson Professorship (school-wide junior faculty award that recognizes career achievement and outstanding performance in research and teaching), and Michael R. and Mary Kay Hallman Fellowship. He was named one of Poets & Quants' best 40 business school professors under 40 in 2016.

Chengbin Ma (M'05-SM'18) received the B.S. degree in industrial automation from East China University of Science and Technology, Shanghai, China, in 1997, and the M.S. and Ph.D. degrees in electrical engineering from The University of Tokyo, Tokyo, Japan, in 2001 and 2004, respectively. From 2004 to 2006, he was an R&D Researcher with the Servo Motor Laboratory, FANUC Limited, Japan. Between 2006 and 2008, he was a Postdoctoral Researcher with the Department of Mechanical and Aeronautical Engineering, University of California, Davis, USA. He joined the University of Michigan-Shanghai Jiao Tong University Joint Institute, Shanghai Jiao Tong University, Shanghai, China, in 2008, and currently an Associate Professor of electrical and computer engineering. His research interests include energy management, megahertz wireless power transfer, dynamics and motion control, and wide applications in electronic devices, electric vehicles, microgrids, smart grids, etc.

Dr. Ma is an IEEE senior member. He serves as Delegate of Energy Cluster, Chair of Energy Storage Technical Committee and Chair of Shanghai Chapter, IEEE Industrial Electronics Society. He is an Associated Editor for the IEEE Transactions on Industrial Informatics and IEEE Journal of Emerging and Selected Topics in Industrial Electronics. He won many teaching and research awards at Shanghai Jiao Tong University, such as Koguan Top Ten Best Teacher Award in 2017 and Koguan Top Ten Research Group Award in 2014. He also received Research Excellence Award from AirFuel Alliance, USA, in 2019.