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Electric Vehicle Charging Scheduling Strategy for Supporting Load Flattening Under Uncertain Electric Vehicle Departures

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***Abstract*—The scheduled electric vehicle (EV) charging flexibility has great potential in supporting the operation of power systems, yet achieving such benefits is challenged by the uncertain and user-dependent nature of EV charging behavior. Existing research primarily focuses on modeling the uncertain EV arrival and battery status yet rarely discusses the uncertainty in EV departure. In this paper, we investigate the EV charging scheduling strategy to support load flattening at the distribution level of the utility grid under uncertain EV departures. A holistic methodology is proposed to formulate the unexpected trip uncertainty and mitigate its negative impacts. To ensure computational efficiency when large EV fleets are involved, a distributed solution framework is developed based on the alternating direction method of multipliers (ADMM) algorithm. The numerical results reveal that unexpected trips can severely damage user convenience in terms of EV energy content. It is further confirmed that by applying the proposed methodology, the resultant critical and sub-critical user convenience losses due to scheduled charging are reduced significantly by 83.5% and 70.5%, respectively, whereas the load flattening performance has merely been sacrificed by 17%.**

***Index Terms*—Electric vehicle (EV), EV fleets, uncertain departure, user convenience, distributed solution.**

I. Introduction

THE climate change due to greenhouse gas emissions from substantive consumption of fossil fuels is threatening human societies worldwide [1]. As a countermeasure, reducing carbon emissions from burning fossil fuels is attracting much attention [2], [3]. Since the transportation sector is accountable for a significant proportion of carbon emissions [4], internal combustion engine vehicles are being gradually replaced by electric vehicles (EVs) along with the global transportation decarbonization trend [5]. As the number of EVs increases, EV charging demand is also growing rapidly [6]. The ever-increasing stock of EVs with the uncontrolled charging mode can yield undesirable impacts on the distribution networks, such as exacerbated load fluctuations, elevated load peaks [7], and transformer overloading [8]. Meanwhile, studies have shown that the connecting time of EVs usually exceeds the time that is required for charging [9], [10]. Thus, EVs can offer opportunities for effective demand-side management regarding their charging power and time through smart charging [11]. Smart charging can add flexibility in the operation of power system by providing control to EV users and the power system operator. To implement smart charging, enablers including technology and EV user cooperation are required. The technology enablers should provide functionalities that can make the system intelligent in operation, such as artificial intelligence and data-driven techniques. Besides, the EV user cooperation should allow the charging operator to affect the user charging behavior to a certain extent. Such cooperation can be achieved by active interactions between charging operators and EV users through real-time communication.

Given the great potential of EV charging in improving the operational performance of the power grid, various technologies and mechanisms have been proposed in the literature. To improve reliability, durability, and user-friendliness, wireless charging systems have been investigated to charge the EVs inductively [12], [13]. Besides, with the increased charging speed demand, the charging power of EVs has been improved from level 1 AC charging (typical charging power up to 2 kW) to level 2 AC charging (typical power up to 20 kW) and level 3 DC charging (typical power up to 130 kW) [14], [15]. Meanwhile, to improve the flexibility of the EV charging process, instead of simply considering the unidirectional grid-to-vehicle (G2V) mode, bidirectional vehicle-to-grid (V2G) technology has been intensively studied [16] -

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[18]. Except for developing smart charging technologies, a lot of smart charging strategies have also been proposed in the literature to enhance the performance of the power grid from various aspects. Under the electricity market environment, the EV charging flexibility can be utilized for minimizing both the energy generation cost [19] and EV charging cost [20], reducing the parking fees [21], and maximizing the total profit of an EV aggregator [22]. From the system operator's point of view, EV charging scheduling can be used to mitigate the pressure of networks on requiring intervention [23], provide secondary frequency regulation [24], stabilize the grid operation to avoid or delay heavy investment costs for strengthening the grid [14], [25], [26], and reduce voltage deviations of the electricity distribution network [27].

As a promising EV charging flexibility application scenario, load flattening-oriented charging scheduling at the distribution level of the utility grid can not only improve the economic performance of the system by reducing the start-up and operating costs of the generators [28], but also enhance the network security by avoiding the substation transformer overloading [29] and stabilizing the grid. Hence, the optimal charging resource management problem for supporting load flattening operation is investigated in this paper.

To achieve the load flattening target using the EV charging flexibility, challenges induced by the uncertain and user-dependent nature of EV charging behavior [30] should be first addressed. To cope with this challenge, different approaches have been proposed in the literature to describe the uncertainties in EV charging behavior. In [31], the uncertain EV arrival time is formulated as a Markov chain decision process. In [32], a stochastic simulation method is presented to generate EV charging profiles including the battery status and charging point selection. In [33], the charging start time and battery type are modeled using scenarios generated from a stochastic framework using the Monte Carlo simulation method. In [34], the uncertain EV charging demand and the number of connected EVs are modeled using stochastically generated scenarios based on past data. In [35], the uncertain EV arrival time is modeled by scenarios complying with the Poisson distribution. In [36], the EV arrival and charging demand are simulated using a stochastic process. In [37], the uncertainty in EV energy requirement is captured by a scenario-wise ambiguity set with a family of distributions.

Though previous works have made fruitful achievements in handling uncertain EV charging behavior, the departure time of EVs is assumed to be a known parameter provided by EV users upon arrival [38], [39]. However, this assumption may be too optimistic since unexpected trips may occur in real life when EV users need to leave earlier for unexpected events. Considering that unexpected trips are inevitable, this paper intends to develop an optimal EV charging scheduling strategy for supporting load flattening under the condition that some EVs may experience unexpected trips.

To this end, understanding the impact of and preparing for unexpected trips are vital for designing and assessing the EV charging scheduling strategies. When unexpected trips occur, on the one hand, the shorter charging time may result in energy deficiency of EVs and range anxiety of EV users, on the other hand, the scheduled charging can worsen the energy-deficient issue by reducing the power of charging or postponing the time of charging. Hence, only charging the EVs to the required energy level before their scheduled time of departure (e.g., [19], [29], [40]) is not enough, the energy deficiency induced by unexpected trips must also be handled in the charging scheduling problems. To address this challenge, this paper is dedicated to developing a methodology such that the impact of energy deficiency on EV users is controlled below acceptable degrees in the charging scheduling process.

Since a large number of EVs are connected at the distribution level, the dimensional disaster [41] that challenges the solution process needs to be addressed. To handle the dimensional problem, a distributed solution framework that includes a hierarchical reformulation and an alternating direction method of multipliers (ADMM) based solution method is proposed.

The contributions of this paper are summarized as follows.

1) An optimal EV charging scheduling strategy is proposed for supporting the load-flattening operation at the distribution level of the utility grid, in which the uncertainties especially the unexpected trips in EV charging are explicitly considered.

2) A holistic methodology for describing uncertain unexpected trips and restricting their negative impacts is developed.

3) A distributed solution framework including a hierarchical reformulation and an ADMM-based solution method is proposed to ensure computational efficiency for large EV fleets.

4) The effectiveness of the proposed methodology is comprehensively analyzed from multiple aspects under different uncertainty levels.

The remainder of this paper is organized as follows: Section II describes the load flattening-oriented EV charging scheduling problem of the distribution network operators (DNOs). In Section III, the proposed methodology for handling unexpected EV trips is provided and applied to the load flattening problem. In Section IV, a distributed solution framework is provided. The simulation results and discussions are presented in Section V. Section VI concludes this paper

II. Description of Load Flattening-oriented EV Charging Scheduling Problem of DNOs

A. System Description

The structure of the studied distribution system is shown in Fig. 1. In this system, we consider two different types of loads. The first type of load is from residential appliances that cannot be interrupted so as not to disturb people's daily lives [42], [43], and the second type of load is flexible EV charging load with continuously controllable charging rates [44]. The V2G operation is not considered in this paper because the V2G infrastructure is still underdeveloped, and frequent discharging can accelerate battery degradation.

The DNO aims to utilize the flexible EV charging demand to smooth the load profile of the distribution system. For the residential load, only the forecast information is available to the DNO. For the flexible EV charging load, information about the initial state-of-charge (iSOC), EV battery capacity, maximum charging power, and planned time of departure is obtained from each EV upon arrival. In this context, the DNO directly receives the charging information from EVs and sends charging control signals to them, forming a centralized control structure between the DNO and EVs.

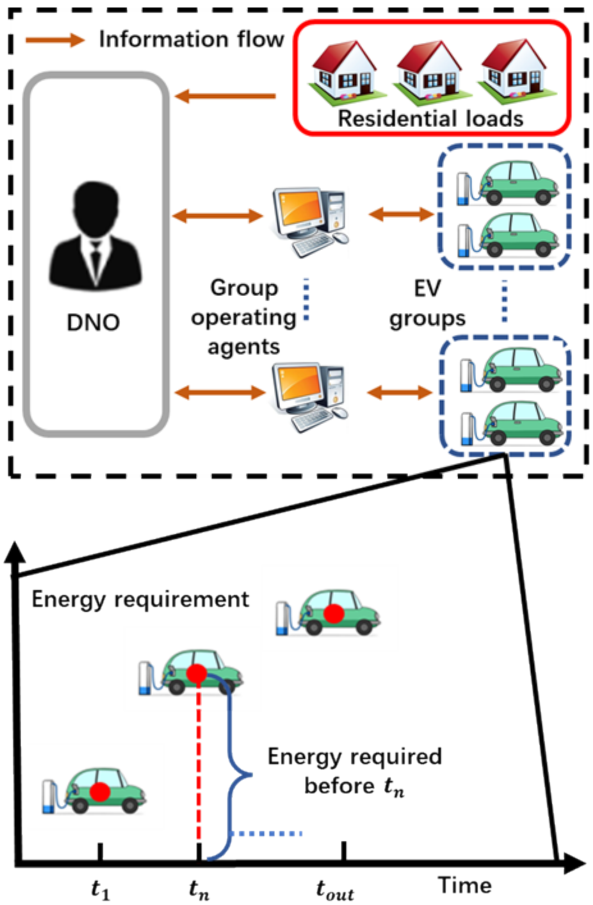

Fig.1. Structure of studied distribution system.

The centralized control is feasible for scheduling a small number of EVs. However, when large EV fleets are involved, solving such a centralized optimization problem is challenged by the complexity of the problem. Thus, this paper proposes a two-layer control framework by clustering the EVs into different groups and introducing group operating agents. The group operating agents act as intermediary control systems, which can be considered as distributed computation nodes that work cooperatively to share the computational burden of the DNO. This two-layer control framework can bring two benefits, which are improving the computational efficiency of the DNO and reducing the communication burden between the DNO and the EVs.

After clustering the EVs, the DNO makes charging scheduling decisions for each group in the upper layer based on the group parameters to reduce the total load fluctuation. In the lower layer, the group operating agents dispatch the charging power of the EVs to meet the load requirements of the DNO. In each group, the individual EV charging constraints such as power limits and energy requirements will be explicitly involved.

For such a smart charging control system, information exchanged between EV users and the DNO is a critical problem. Hence, some communication protocols such as the open charging point interface protocol are key enablers to achieving efficient information exchange. Besides, to achieve real-time control of EV charging rates, technologies like charging service provider apps need to be adopted. In this paper, only the level 2 charging rates are considered because the level 1 charging rate is too slow and the level 3 charging infrastructure is not widely deployed. In the early stages of developing such a smart charging system, incentives may be needed to encourage EV users to adopt the habit of declaring their charging information

B. Rolling Horizon Scheduling

Rolling horizon technique is used to indicate that a time-dependent model is solved repeatedly, and in which the scheduling interval is moved forward in time during each solution step. In the studied distribution system, the DNO needs to determine the EV charging rate under the uncertainties in EV charging information and residential loads. Besides, the charging decisions need to be made in a period-by-period manner to keep pace with the updated EV charging information. Hence, a rolling horizon charging scheduling model is adopted to solve the charging scheduling problem [45]. In the rolling horizon charging scheduling model, data are divided into three categories, i.e., past knowledge, solution data, and future forecast. The past knowledge includes the completed EV charging scheduling operation. The solution data are the charging decisions obtained by solving the current rolling horizon optimization models. The future forecast is the residential load forecast information. In this paper, the residential load forecast horizon of the DNO is set to be 8 hours. Besides, under the level 2 charging rate, 8 hours are enough to allow most EVs to be fully charged. Hence, for each repetition of the rolling horizon charging scheduling model, the scheduling horizon of the DNO is set to be 8 hours. As in [45], the optimization resolution is set to be 15 min. Under this parameter setting, the scheduling horizon of the optimization problem is 8 hours, and the problem will be solved every 15 min. Meanwhile, to update the continuously changing EV information at the same pace as the rolling horizon charging scheduling model, only the first step of the scheduling solution is implemented.

C. Centralized Problem Formulation

In the centralized charging scheduling optimization model, the charging information of each EV is explicitly incorporated. The DNO optimizes the scheduling problem to determine the EV charging power based on the residential load forecast.

$$\min_{P_{k,t}} \sum_{t\in T}\left(\sum_{k} P_{k,t} + P_{res,t} - P_{ave}\right)^2 \tag{1}$$

s.t.

$$\begin{cases} 0 \le P_{k,t} \le \overline{P}_{k,t} & t_{k,in} \le t \le t_{k,d} \\ P_{k,t} = 0 & \text{otherwise} \end{cases} \tag{2}$$

$$P_{ave} = \sum_{t \in T} \frac{\sum_k P_{k,t} + P_{res,t}}{T} \tag{3}$$

$$SOC_{k,t+1} = SOC_{k,t} + \frac{\eta}{E_k} P_{k,t} \tag{4}$$

$$\underline{SOC} \le SOC_{k,t} \le \overline{SOC} \tag{5}$$

$$iSOC_k + \frac{\eta}{E_k} \sum_{t=t_{k,in}}^{t_{k,d}} P_{k,t} = \overline{SOC} \tag{6}$$

where $P_{k,t}$ and $P_{res,t}$ are the charging power of EV k and the residential load at time t, respectively; P_{ave} is the average total load across the scheduling horizon; T is the total scheduling horizon; $t_{k,in}$ and $t_{k,d}$ are the arrival time and departure time of EV k, respectively; $SOC_{k,t}$ is the state-of-charge (SOC) level of EV k at time t, which is bounded by its lower and upper limits $\left[\underline{SOC}, \overline{SOC}\right]$; $iSOC_k$ is the initial SOC when EV k arrives. E_k is the energy capacity of EV k; and η is the charging efficiency.

In the objective function, the total load variation across the rolling horizon is minimized. The EV charging power is limited by (2). The average load is calculated by (3). Constraints (4)-(6) are SOC constraints of EVs.

Since EVs may experience unexpected trips, the departure time of the EVs becomes uncertain parameters. The range of the EV departure time is given by:

$$t_{k,in} \le t_{k,d} \le t_{k,out} \tag{7}$$

where $t_{k,out}$ is the user-provided departure time of EV k. When the EV departure time is uncertain, postponing the time of charging or decreasing the power of charging can cause energy deficiency of EVs. Hence, the DNO needs to charge the EVs as fast as possible to reduce the range anxiety of EV users, making the EV charging load uncontrollable. To cope with this problem, a holistic methodology is proposed in the next section to find a compromise solution that balances the load flattening target of the DNO and EV user conveniences. In the developed methodology, part of the charging flexibility is sacrificed to ensure that the energy deficiency is controlled below acceptable degrees, whereas most of the flexibility can still be utilized to support the load-flattening operation.

III. Proposed Methodology

In this section, an estimation model for occurrence probability of unexpected trips (PUT) is firstly proposed to describe the uncertainty in unexpected EV trips. Then, a multi-level user convenience model is presented. Based on the uncertainty and user convenience models, a novel risk-constrained segmental charging strategy is proposed. The new formulation of the load flattening problem using the proposed methodology is presented at the end of this section.

A. Estimation Model for PUT

EV user charging behavior is affected by many factors such as the age of users, EV type, iSOC, and dwelling period [46]-[49]. Among these factors, some information such as EV type, EV initial SOC, and EV dwelling period can be acquired easily. Some information such as EV user characteristics is hard to access due to privacy concerns. Hence, the estimation model in this paper selects the EV type, iSOC, and dwelling period as explicit factors and treats other factors by using an aggregated factor. Notably, to estimate the contributions of each factor to the PUT of EV users, real-world EV charging data are required. The data that need to be collected should at least include EV type, EV dwelling time, iSOC, and historical data of having unexpected trips. After acquiring the real-world charging data, the contributions of each factor to the PUT of EV users can be estimated by using regression models. At this moment, it is not possible to collect detailed EV charging data. Hence, it is assumed that the contributions of each factor to the final PUT of EV users are known and are uniformly distributed to each considered factor, as shown in Fig. 2.

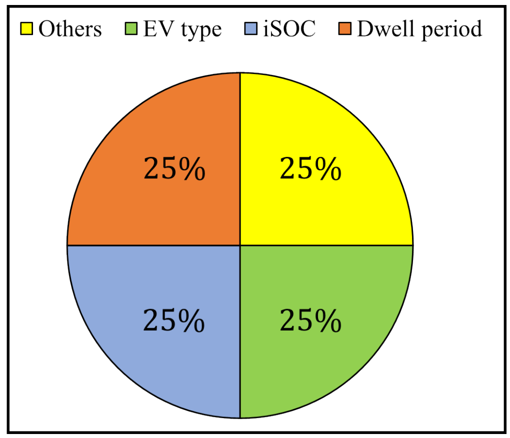

Fig. 2. Contribution of each factor to final PUTs of EV users.

Three types of EVs are considered in this paper, including public buses, commercial EVs, and private EVs. Among the three types of EVs, public buses are considered the least likely to have unexpected trips since they have a stable routine. Because of the highly uncertain personal behaviors [46], private EVs are assumed most probable to experience unexpected trips. Finally, the likelihood of commercial EVs having unexpected trips lies between the public buses and the private EVs. The iSOC can affect the charging behavior of EV users [50], and it is assumed that a linear relationship exists between the PUT and the iSOC in this model. That is, when other factors are fixed, EV users with lower iSOC will have smaller PUTs. For the dwelling period, each day is divided into three sets of periods, including the resting period T_r (hours 1-8), the working period T_w (hours 9-17), and the after-work period T_{aw} (hours 18-24). Among the three periods, unexpected trips are most unlikely to occur during the resting period with low human activity. Since people have a relatively fixed routine during the working period, the unexpected trip is an event with medium probability during this period. The unexpected trips are most likely to occur during the after-work period since human activities become highly unpredictable in this period. For other factors, a random value is generated to represent their contributions in the estimation model. The above statements can be summarized as:

$$\pi_{UT}=\alpha+\beta\cdot iSOC+(aL_r+bL_w+cL_{aw})+\gamma \tag{8}$$

where π_{UT} is the PUT; α and β are the estimation parameters of PUT for EV types and iSOC, respectively; $iSOC$ is the iSOC of EV; a, b, and c are PUT parameters for resting, working, and after-work periods, respectively; and L_r, L_w, and L_{aw} are the numbers of dwelling intervals in resting, working, and after-work periods, respectively. Based on previous discussions, it is assumed that relationships of the estimation parameters of the PUT for public buses α_{bus}, commercial EVs α_{com}, and private EVs α_{pri} are $\alpha_{pri}=2\alpha_{com}$ and $\alpha_{com}=2\alpha_{bus}$. Meanwhile, the relationships of the estimation parameters of the PUT for different dwelling periods are assumed to be $2a=b$ and $2b=c$.

The PUT indicates how likely an EV user will leave earlier than the planned time. In this paper, it is assumed that all unexpected trips are induced by unexpected events featured with nonanticipativity. Besides, it is assumed that the probabilities of EVs having unexpected trips in different periods are consistent with the parameter settings in the estimation model. Therefore, for a connected EV, its probability of having an unexpected trip in each single interval π_{UT}^{si} can be expressed by:

$$\pi_{UT}^{si}=\begin{cases} a\dfrac{\pi_{UT}}{aL_r+bL_w+cL_{aw}} & t\in T_r \\ b\dfrac{\pi_{UT}}{aL_r+bL_w+cL_{aw}} & t\in T_w \\ c\dfrac{\pi_{UT}}{aL_r+bL_w+cL_{aw}} & t\in T_{aw} \end{cases} \tag{9}$$

B. Multi-level User Convenience Model

When unexpected trips occur, EVs may experience energy deficiency due to shorter charging time and charging scheduling. Such energy deficiency can increase the range anxiety of EV users and reduce EV user convenience. In existing works, user conveniences are normally considered from the perspective an individual EV user, e. g., the time sensitivity of EV user in [21] and the energy sensitivity of EV user in [51]. However, this paper investigates the charging scheduling problem from the perspective of the DNO, which is more concerned about the overall user satisfaction level instead of individual user convenience levels. Hence, the user convenience in this paper is defined as the proportions of EVs with energy content above the predefined levels by the time they are unplugged:

$$u_l=\frac{n_l}{N}\times 100\% \tag{10}$$

where u_l is the l^{th} user convenience level; n_l is the number of EVs with energy content above the l^{th} required level; and N is the total number of EVs. Under this model, multiple levels can be defined regarding different critical impact levels on user convenience. In this paper, the critical one-trip and sub-critical two-trip SOC levels are used as the criteria for evaluating user convenience, as shown in Fig. 3. According to the data reported in [9], each trip approximately consumes 28% of the battery capacity and the lowest allowed SOC level is 0.10. Therefore, it can be inferred that the minimum one-trip SOC level is $SOC_1=0.38$ and the two-trip SOC level is $SOC_2=0.66$. In this paper, the one-trip SOC is defined as the critical SOC level (level-1 SOC) and the two-trip SOC is defined as the sub-critical SOC level (level-2 SOC).

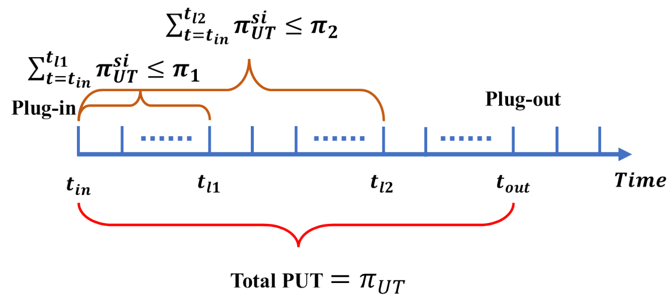

Fig. 3. Illustration of segmental charging strategy.

C. Risk-constrained Segmental Charging Scheduling Strategy

To respect the user convenience defined in (10), a risk-constrained segmental charging strategy is proposed to make customized charging plans for EV users based on the estimated PUTs. First, for EV k with scheduled energy content less than a predefined energy level SOC_l at time t_l, its risk of leaving with an energy content less than SOC_l at time t_l is determined by its cumulative PUT until t_l. Based on this, the risk limit π_l is defined as the cumulative PUT limit for charging EVs to reach predefined critical energy level SOC_l. In the proposed strategy, it is ensured that by the time the cumulative PUT of EV k reaches the risk limit π_l, the energy content of EV k is above the predefined critical energy level SOC_l. To achieve this target, the scheduling results need to guarantee that each EV is charged to the desired energy level SOC_l before its cumulative PUT exceeds the risk limit π_l, as described in (11) and (12).

$$SOC_{t_l}\ge SOC_l \tag{11}$$

$$\sum_{t=t_{in}}^{t_l}\pi_{UT}^{si}\le\pi_l\le\sum_{t=t_{in}}^{t_l+1}\pi_{UT}^{si} \tag{12}$$

where t_l is the time slot after which the cumulative PUT of the EV just exceeds the l^{th} risk level, and the SOC level at t_l is denoted by SOC_{t_l}.

Constraint (11) ensures that at the time slot t_l, the scheduled EV energy content SOC_{t_l} is above the desired energy level SOC_l. Constraint (12) calculates the time slot t_l for each EV based on their estimated PUTs.

In the proposed strategy, part of the EV charging flexibility is sacrificed, as illustrated in Fig. 4. The outer parallelogram represents the full EV charging flexibility [52]. Under the proposed strategy, part of the EV charging flexibility is lost due to the restrictions on energy levels at certain scheduling time slots. The lost flexibility is plotted as the shaded area in Fig. 4.

D. Segmental Charging-based Load Flattening

By applying the proposed methodology to the load flattening problem, the user convenience-oriented problem becomes:

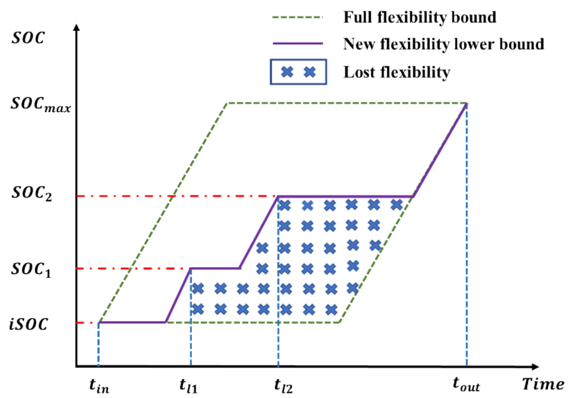

Fig. 4. EV charging flexibility under proposed strategy.

$$\min_{P_{k,t}} \sum_{t\in T}\left(\sum_{k} P_{k,t}+P_{res,t}-P_{ave}\right)^2 \tag{13}$$

s.t.

$$(2)\text{-}(7) \tag{14}$$

$$(9),(11),(12) \tag{15}$$

$$iSOC_k+\frac{\eta}{E_k}\sum_{t=t_{k,in}}^{t_{k,l}} P_{k,t}\geq SOC_l \tag{16}$$

The segmental charging requirements are stated in constraints (15) and (16). Constraint (16) ensures that the energy content of EV k at $t_{k,l}$ is no less than the predefined energy level SOC_l. In the centralized model, the DNO needs to consider all the EV charging information to make customized charging scheduling decisions. Solving such a problem for large EV fleets is computationally challenging. In the next section, a hierarchical framework of the problem (13)-(16) is developed.

IV. Proposed Distributed Solution Framework

In this section, a clustering method is proposed to divide EVs into different groups. The EV groups and DNO form a hierarchical model as shown in Fig. 1. An ADMM-based solution method is then developed to obtain the charging scheduling solution in a distributed way.

A. EV Clustering Method

The charging scheduling decisions are made in a rolling horizon fashion with 32 scheduling intervals. Since all EVs should be fully charged by the time they plan to be unplugged, EVs with the same remaining planned dwelling time are clustered as a group considering they have the same scheduling length. The group parameters to be identified when clustering the EVs include the power range, the total energy demand, and the aggregated segmental energy requirement imposed by the proposed strategy. The power range of group g can be acquired by summing up the power of all the EVs belonging to that group:

$$0\leq P_{g,t}\leq \bar{P}_{g,t}=\sum_{k\in g}\bar{P}_k \tag{17}$$

where $P_{g,t}$ is the aggregated charging power of group g, which is bounded by its upper limit $\bar{P}_{g,t}$; and $\bar{P}_k$ is the maximum charging power of EV k.

The energy demand E_k^d for EV k is the energy needed to fully charge that EV. The energy demand E_g^d for each group g is the summation of individual EV energy demand E_k^d in that group, as shown in (18).

$$E_g^d=\sum_{k\in g}E_k^d \tag{18}$$

The minimum required energy before a specific time interval for a group can be obtained by summing up all the segmental energy requirements of EVs before that time, as illustrated in Fig. 1. For individual EVs, the l^{th} level of energy requirement $E_{k,l}^r$ for EV k can be calculated as:

$$E_{k,l}^r=(SOC_l-iSOC_k)E_k \tag{19}$$

After obtaining $E_{k,l}^r$ for every EV in group g, the aggregated segmental energy requirement E_{g,t_n}^r of group g before the n^{th} time interval t_n can be obtained by:

$$E_{g,t_n}^r=\sum_{k\in g}E_{k,l}^r \quad t_l\leq t_n \tag{20}$$

B. ADMM-based Solution Method

The ADMM algorithm can solve optimization problems in the following separable form:

$$\min_{\boldsymbol{x}\in \boldsymbol{X},\boldsymbol{z}\in \boldsymbol{Z}}(f(\boldsymbol{x})+g(\boldsymbol{z})) \tag{21}$$

s.t.

$$\boldsymbol{Ax}+\boldsymbol{Bz}=\boldsymbol{d} \tag{22}$$

where $\boldsymbol{x}$ and $\boldsymbol{z}$ are the decision variables that can be optimized separately. The augmented Lagrangian optimization problem can be written as:

$$\begin{aligned}\min_{\boldsymbol{x}\in \boldsymbol{X},\boldsymbol{z}\in \boldsymbol{Z}} L_\rho(\boldsymbol{x},\boldsymbol{z},\boldsymbol{\lambda})=f(\boldsymbol{x})+g(\boldsymbol{z})-\\ \boldsymbol{\lambda}^{\mathrm{T}}(\boldsymbol{Ax}+\boldsymbol{Bz}-\boldsymbol{d})+\frac{\rho}{2}\|\boldsymbol{Ax}+\boldsymbol{Bz}-\boldsymbol{d}\|_2^2\end{aligned} \tag{23}$$

where $\boldsymbol{\lambda}$ is the Lagrangian multiplier vector; ρ is the penalty factor; and $\|\cdot\|_2^2$ is the l_2 norm of vectors. By introducing the scaled dual variable ξ, (23) can be rewritten in its scaled form:

$$\min_{\boldsymbol{x}\in \boldsymbol{X},\boldsymbol{z}\in \boldsymbol{Z}} L_\rho(\boldsymbol{x},\boldsymbol{z},\xi)=f(\boldsymbol{x})+g(\boldsymbol{z})+\frac{\rho}{2}\|\boldsymbol{Ax}+\boldsymbol{Bz}-\boldsymbol{d}-\xi\|_2^2+C \tag{24}$$

$$\xi=\frac{\boldsymbol{\lambda}}{\rho} \tag{25}$$

where C is a constant. Problem (24) and (25) can be solved in a distributed way using the ADMM algorithm through an iterative process:

$$\boldsymbol{x}_{v+1}=\arg\min_{\boldsymbol{x}\in \boldsymbol{X}} L_\rho(\boldsymbol{x},\boldsymbol{z}_v,\xi_v) \tag{26}$$

$$\boldsymbol{z}_{v+1}=\arg\min_{\boldsymbol{z}\in \boldsymbol{Z}} L_\rho(\boldsymbol{x}_{v+1},\boldsymbol{z},\xi_v) \tag{27}$$

$$\xi_{v+1}=\xi_v+(\boldsymbol{Ax}_{v+1}+\boldsymbol{Bz}_{v+1}-\boldsymbol{d}) \tag{28}$$

where v is the iteration number. As can be observed, variables $\boldsymbol{x}$ and $\boldsymbol{z}$ are optimized in separated steps, which enables distributed optimization of the original problem. At the end of each iteration, the convergence is checked by examining (29).

$$\sqrt{\left\| \xi_{v+1} - \xi_v \right\|^2} \le \varepsilon \tag{29}$$

Based on the ADMM algorithm, a distributed reformulation of the charging scheduling problem is proposed. In the reformulated problem, the primary optimization problem for the DNO only considering the EV group parameters is given as:

$$\min_{P_{g,t,v+1}} \left\{ \sum_{t\in T}\left(\sum_g P_{g,t,v+1} + P_{res,t} - P_{ave}\right)^2 + \frac{\rho}{2}\sum_{t\in T}\sum_g\left(P_{g,t,v+1} - \sum_{k\in g} P_{k,t,v} + \xi_v\right)^2 \right\} \tag{30}$$

s.t.

$$\begin{cases} 0 \le P_{g,t,v+1} \le \overline{P}_{g,t} & t \le t_{g,d} \\ P_{g,t,v+1} = 0 & \text{otherwise} \end{cases} \tag{31}$$

$$\sum_{t=1}^{t_n} P_{g,t,v+1} \ge E^r_{g,t_n} \quad \forall t_n \le t_{g,d} \tag{32}$$

$$\eta \sum_t P_{g,t,v+1} = E^d_g \tag{33}$$

$$P_{ave} = \frac{\sum_{t\in T}\left(\sum_g P_{g,t,v+1} + P_{res,t}\right)}{T} \tag{34}$$

where $P_{g,t,v+1}$ is the scheduled group power in the primary problem at the current iteration; and $P_{k,t,v}$ is the scheduled EV charging power from the secondary problem in the last iteration. In this formulation, the power of each group is constrained by (31). The aggregated segmental energy requirement for each group is fulfilled through (32). The total energy demand of each group is satisfied by (33), and the average power of the total scheduling horizon is given by (34).

For each EV group, the group scheduling information $P_{g,t,v+1}$ is received from the DNO and the charging power of individual EVs is dispatched to meet the demand of the DNO. Thus, the secondary problem for each EV group can be formulated as:

$$\begin{cases} \min_{P_{k,t,v+1}} \left\{ \sum_{t\in T}\left(P_{g,t,v+1} - \sum_{k\in g} P_{k,t,v+1}\right) + \sum_{t\in T}\left[\frac{\rho}{2}\left(P_{g,t,v+1} - \sum_{k\in g} P_{k,t,v+1} + \xi_v\right)^2\right] \right\} \\ \text{s.t. } (2),(4)\text{-}(7),(15),(16) \end{cases} \tag{35}$$

In this problem, the scaled dual variable is updated according to the differences between the scheduling results of the DNO and group operating agents:

$$\xi_{v+1} = \xi_v + \left(\sum_{k\in g} P_{k,t,v+1} - P_{g,t,v+1}\right) \tag{36}$$

The charging scheduling problem can be solved using the ADMM algorithm, in which the DNO and the EV groups optimize their problems separately. The procedure of the distributed solution framework is summarized as follows.

Algorithm 1

1. Initialize $v=0$, $\xi_0=0$, $\rho=100$, $\varepsilon=0.01$, $P_{k,t,0}=0, \forall k,t$
2. **while** (29) is false, $v \leftarrow v+1$ **do**
3. Solve (30)-(34) with $(P_{k,t,v}, \xi_v)$ to obtain $P_{g,t,v+1}$
4. Solve (35) for each EV group parallelly with $(P_{g,t,v+1}, \xi_v)$to obtain $P_{k,t,v+1}$
5. Update $\xi_{v+1} = \xi_v + \left(\sum_{k\in g} P_{k,t,v+1} - P_{g,t,v+1}\right)$
6. **end while**
7. Return $P_{k,t,v+1}$

V. Simulation Results and Discussions

In this section, the performance of the proposed strategy is evaluated by comparing it with the uncontrolled charging strategy and conventional load flattening charging strategy without considering unexpected trips [29].

A. Basic Data

The scaled real-world demand data [53] are used as the forecast and actual residential load profiles, as shown in Fig. 5.

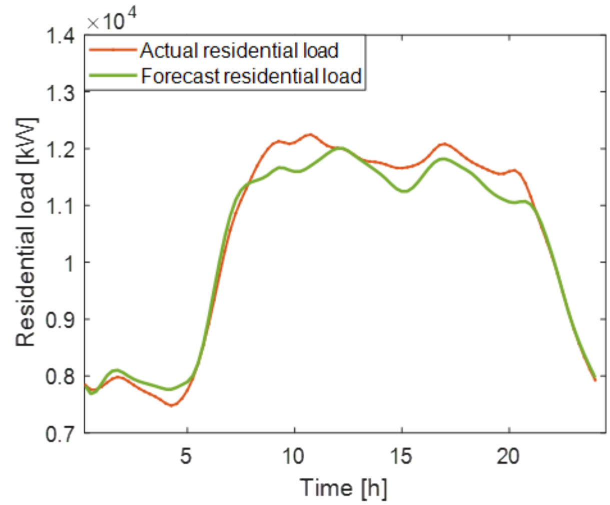

Fig. 5. Residential load information.

The demand data feature high demand in working and after-work periods, and low demand in resting periods. Hence, the selected demand data can well reflect general daily electricity consumption patterns. Besides, the EV charging data are hard to be acquired in the real world. Hence, EV charging scenarios are generated by using the typical EV models and charging behavior probability distributions in [47]. The highest PUT is set to be 40%. By using the Monte-Carlo simulation approach [47], a total of 1000 EV scenarios are generated, and 238 of them leave before their planned departure time. The charging efficiency for all the EVs is set to be $\eta=0.95$ [40]. In the ADMM algorithm, the convergence threshold is set to be $\varepsilon=0.01$ and the penalty factor is $\rho=100$. Because some EVs have a high PUT and a low iSOC, small risk limits are not feasible for them to reach the predefined energy levels. To make the segmental charging strategy feasible for all EVs, the minimum risk limits that enable all the EVs to reach the predefined energy levels are selected. Based on this criterion, the risk limits for the critical and sub-critical levels of user convenience are set to be $\pi_1 = 3\%$ and $\pi_2 = 7\%$, respectively.

B. Results and Discussions

The total loads of the studied charging strategies are presented in Fig. 6. In the uncontrolled charging strategy, the peak demand is observed during hours 16 to 22, which corresponds to the period when most EVs are plugged to charge. The period between midnight and morning (hours 1 to 7) has the lowest load demand throughout the day. For the conventional load flattening charging strategy, the load difference between the peak demand hours and other periods is minimized and no obvious peak is observed. But a valley still exists between hours 2 to 6, which is induced by the insufficient regulating capability of EVs. For the proposed strategy, part of the charging load between peak demand hours is shifted to valley demand hours compared with the uncontrolled charging strategy. However, a lower peak still exists in the load profile of the proposed strategy. The unshaved load is necessary for satisfying the segmental energy requirement of EVs and thus cannot be shifted to valley demand hours.

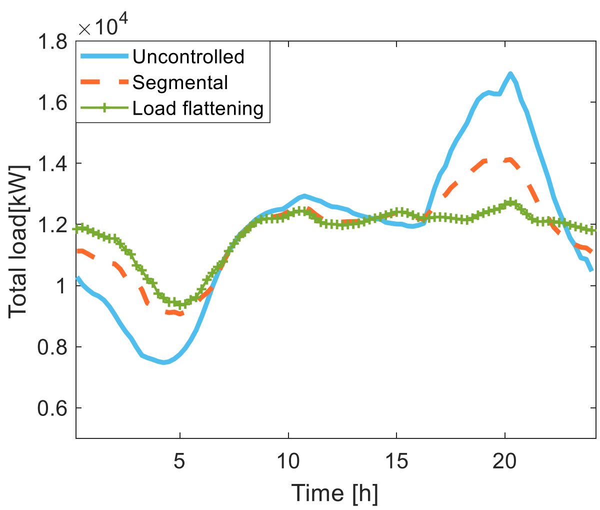

Fig. 6. Total loads of studied charging strategies..

Figure 7 presents the SOC levels of EVs that leave earlier than planned departure time. The conventional load flattening charging strategy gives most violations against the required energy levels. Under this strategy, a total of 94 EVs fail to satisfy the critical one-trip SOC level and 183 EVs fail to meet the sub-critical two-trip SOC level, which consist of 9.4% and 18.3% of the total EV fleet, respectively. Compared with the conventional load flattening charging strategy, the proposed strategy substantially reduces the number of violations against the predefined SOC levels (with only 18 violations for level 1 and 78 violations for level 2). In Fig. 7, a long flat segment can be observed for the proposed strategy, which corresponds to the sub-critical SOC level of 0.66. Although the uncontrolled charging strategy can minimize the energy-deficient problem of EVs compared with other charging strategies, it is still inevitable that some EVs would experience critical or sub-critical energy deficiency.

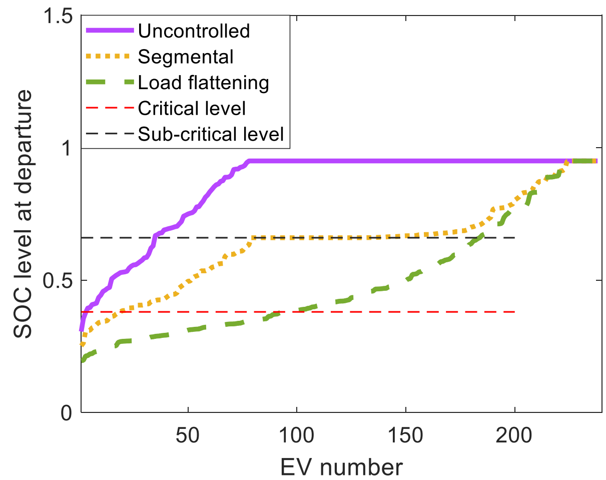

Fig. 7. SOC levels of EVs leaving earlier than planned departure time.

The scheduling results of the studied charing strategies are displayed in Table I and summarized in Fig. 8.

TABLE I
SCHEDULING RESULTS OF STUDIED CHARING STRATEGIES

Strategy	Peak load (kW)	Peak-to-valley ratio	Normalized load variation	Level 1 user convenience (%)	Level 2 user convenience (%)
Uncontrolled	16933	2.2638	1.00	99.7	96.6
Proposed	14222	1.5684	0.30	98.2	92.2
Load flattening	12738	1.3609	0.13	90.6	81.7

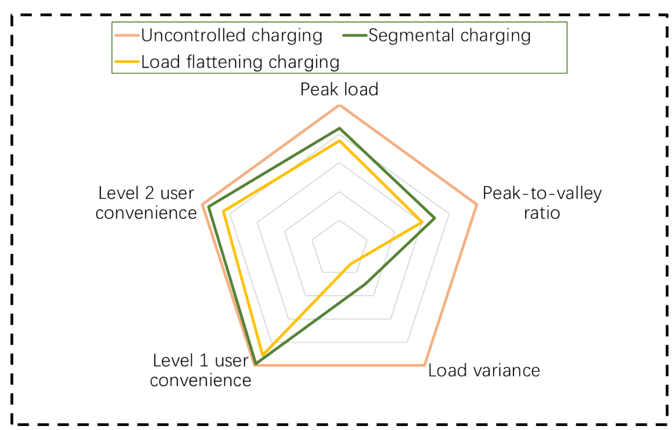

Fig. 8. Comparison of scheduling results of studied charing strategies.

Compared with the conventional load flattening charging strategy, the load flattening performance of the proposed strategy is reduced by 17% (from reducing 87% of the load variance to reducing 70% of the load variance). Though the conventional load flattening charging strategy performs better than the proposed strategy in reducing the load fluctuations, it has severely damaged user convenience by causing 91 critical energy-deficient users and 149 sub-critical energy-deficient users, respectively. Whereas the proposed strategy only results in 15 critical and 44 sub-critical energy-deficient users, respectively. Compared with the conventional load flattening charging strategy, the proposed strategy reduces the charging scheduling-resulted energy-deficient users by 83.5% (from 91 to 15) for the critical user convenience level, and 70.5% (from 149 to 44) for the sub-critical user convenience level, respectively.

The convergence rate of the developed distributed solution framework is illustrated in Fig. 9 for six consecutive time intervals (intervals 41-46), which confirms that the problem converges quickly with the proposed distributed solution framework.

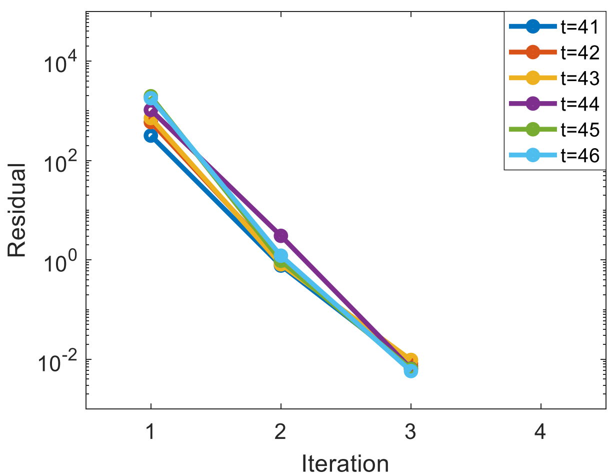

Fig. 9. Convergence rate of proposed distributed solution framework.

C. Impact of Customization

This paper utilizes individual PUT information to make customized charging plans for each EV user, which complicates the scheduling problem and increases the workload. To validate the necessity of customization, a non-customized segmental charging strategy is applied. In this strategy, the PUT for all EVs is considered identical and is equal to the proportion of EVs having unexpected trips. For this strategy, the critical and sub-critical user convenience levels are 97.5% and 91.6%, respectively. Compared with the customized strategy, we can find that the non-customized segmental charging strategy can increase the number of scheduling-resulted critical (from 18 to 22) and sub-critical (from 44 to 50) energy-deficient users. By using the non-customized segmental charging strategy, the peak load, peak-to-valley ratio, and normalized load variance are 14355 kW, 1.6391, and 0.36, respectively. Compared with the uncontrolled charging strategy, the non-customized segmental charging strategy can achieve 15.2% of peak load reduction, 27.6% of peak-to-valley ratio reduction, and 63.9% of load variance reduction, respectively. However, compared with the customized segmental charging strategy, the non-customized strategy increases the peak load, peak-to-valley ratio, and normalized load variance by 0.9% (14222 kW to 14355 kW), 4.3% (1.5684 to 1.6391), and 6.1% (0.30 to 0.36), respectively. Hence, it can be concluded that customization is an important measure to further enhance both the user convenience and load-flattening performances of the proposed strategy.

D. Sensitivity Analysis of PUT Levels

The PUT level is an indication of EV user credibilities, namely, to which extent can the information provided by EV users be trusted. In this subsection, the impacts of the PUT levels on the scheduling results are analyzed for different PUT levels ranging from 10% to 50%.

Figure 10 gives the evolution results of peak loads and the peak-to-valley ratios for the studied strategies under different PUT levels. It can be observed that changing the PUT level has limited impacts on the load profiles of both the uncontrolled charging and the conventional load flattening charging strategies. On the contrary, the performance of the proposed strategy is significantly affected by the PUT level. As the PUT level increases from 10% to 50%, the peak loads and the peak-to-valley ratios of the uncontrolled charging and the conventional load-flattening charging strategies remain almost unchanged. In contrast, for the proposed strategy, the peak load increases from 12956 kW to 14803 kW, and the peak-to-valley ratio increases from 1.3344 to 1.6183. The same result is also observed for the normalized load variances presented in Fig. 11. The normalized load variance of the conventional load flattening charging strategy only ranges between 0.09 and 0.15 with increasing PUT level, whilst that of the proposed strategy increases from 0.11 to 0.38. This evolution trend suggests that when EV users become less trustworthy, more charging flexibility will be sacrificed to guarantee user convenience. As a result, the load-flattening performance of the proposed strategy is undermined.

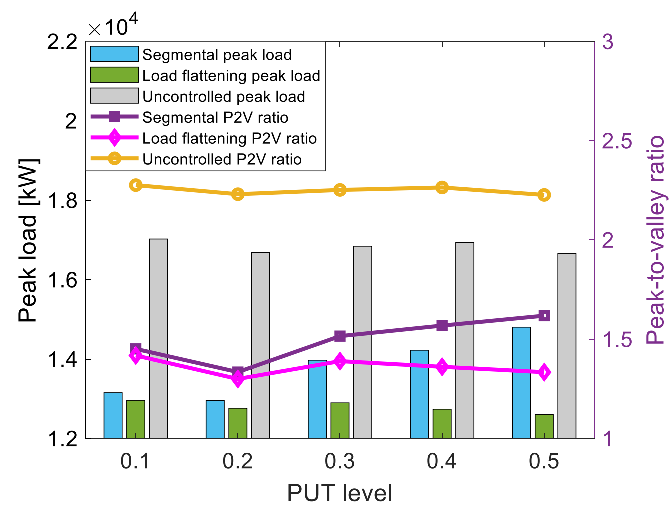

Fig. 10. Evolution results of peak loads and peak-to-valley ratios with different PUT levels.

Figure 12 gives the analysis results of user convenience under different PUT levels. It can be observed that the uncontrolled charging strategy performs the best and the conventional load flattening charging strategy performs the worst. For these two strategies, their user convenience levels will decrease as the PUT level increases. This is because EV users are more likely to experience unexpected trips under higher PUT levels. However, for the proposed strategy, we can find that user convenience levels are constrained in a certain range instead of simply decreasing with increased PUT levels. The constraining ranges are defined by the risk parameters π_l and affected by the actual EV charging scenarios.

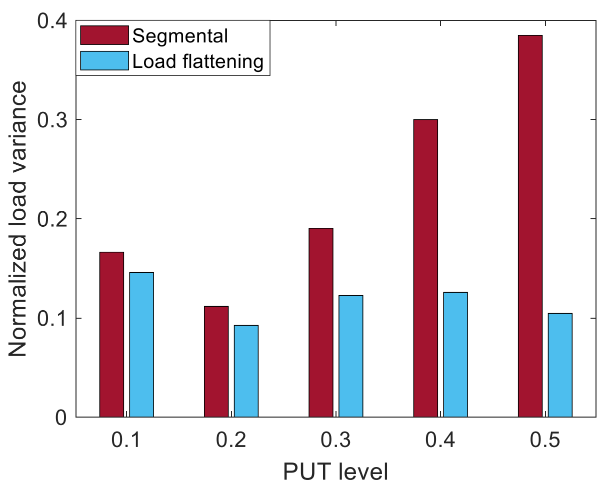

Fig. 11. Normalized load variances under different PUT levels.

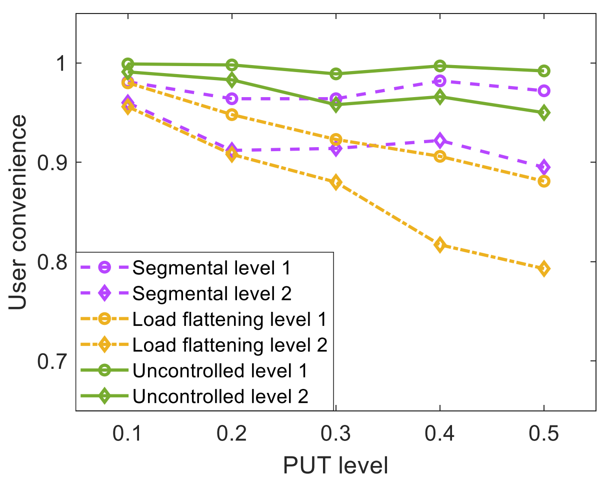

Fig. 12. Analysis results of user convenience under different PUT levels.

From the sensitivity analysis of PUT levels, it may be noticed that as the PUT level moves closer to 0, the proposed strategy degrades to the conventional load-flattening charging strategy. This is because the segmental restrictions induced from unexpected trips are relaxed and the flexibility loss approaches 0. Therefore, it may be concluded that the conventional load flattening charging strategy is an ideal form of the proposed strategy where the planned trips of all EV users are uninterrupted.

VI. Conclusion

This paper studies the load flattening-oriented charging scheduling strategy for EVs under the assumption that some EV users may leave earlier than planned. Compared with the existing literature, this assumption is more realistic since randomness in human activity is inevitable. In the proposed methodology, the DNO first estimates the PUT of EV users based on the information provided by EV users, then schedules the charging rates of EVs to flatten the load profile while ensuring EV user convenience.

The numerical results suggest that completely ignoring unexpected trips of EV users can severely affect their user convenience, and the proposed methodology is proven efficient in enhancing user convenience by reducing 83.5% of critical and 70.5% of sub-critical user convenience loss, respectively. From the perspective of the DNO, the proposed segmental charging strategy can achieve 16.0 % of peak load reduction, 30.7% of peak-to-valley ratio reduction, and 70.0% of load variance reduction, respectively. Besides, customization is an important measure to enhance the performance of the proposed methodology. By making customized charging plans for different EVs, the load variance is further reduced by 6.1%, and the user convenience levels are also improved. Though customization can worsen the dimensional disaster for large-scale EV fleets, the proposed distributed solution framework can solve the optimization problems effectively. The sensitivity analysis against the PUT level shows that as trip plans of EV users become more reliable, more charging flexibility can be preserved for reducing system load fluctuations without undermining user convenience levels.

Finally, the proposed methodology is used to restrict the impacts of unexpected trips on EV user convenience while ensuring smart charging performances. Hence, for smart charging strategies in which energy deficiency caused by unexpected trips cannot be ignored, the proposed methodology can be included to improve the applicability of these smart charging strategies.

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