Distributed Coordination of Charging Stations Considering Aggregate EV Power Flexibility

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Abstract—In recent years, electric vehicle (EV) charging stations have witnessed rapid growth. However, effective management of charging stations is challenging due to individual EV owners’ privacy concerns, competing interests of different stations, and the coupling distribution network constraints. To cope with this challenge, this paper proposes a two-stage scheme. In the first stage, the aggregate EV power flexibility region is derived by solving an optimization problem. We prove that any trajectory within the obtained region corresponds to at least one feasible EV dispatch strategy. By submitting this flexibility region instead of the detailed EV data to the charging station operator, EV owners’ privacy can be preserved and the computational burden can be reduced. In the second stage, a distributed coordination mechanism with a clear physical interpretation is developed considering the AC power flow based network constraints. We prove that the proposed mechanism converges to the centralized optimum. Case studies validate the theoretical results. Comprehensive performance comparisons are carried out to demonstrate the advantages of the proposed scheme.

Index Terms—Charging station, aggregate flexibility, coordination mechanism, electric vehicle, AC power flow.

NOMENCLATURE

A. Acronyms

EV Electric vehicle.
CS Charging station.
PV Photovoltaic.
SOC State of charge.
CSO Charging station operator.
DSO Distribution system operator.
ADMM Alternating direction method of multipliers.

B. Symbols

$T$, $t$ Set of time slots and index.
$N$, $n/j$ Set of buses and index.
$E$ Set of lines.

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$r_{nj}, x_{nj}$  Resistance and reactance in line $(n, j)$. \\
$v_j$  Squared voltage magnitude at bus $j$ \\
$\ell_{nj}$  Squared current magnitude in line $(n, j)$. \\
$C_{bus}, C_{loss}$  Utility grid cost and power loss cost. \\
$\pi(t)$  Power loss price. \\
k  Index of iteration. \\
$\rho, \delta$  Penalty parameter, accuracy tolerance.

I. INTRODUCTION

The proliferation of electric vehicles (EVs) has spurred the rapid development of EV charging stations [1]. However, due to the random and relatively high EV charging power [2], the sudden pulse-like and high charging loads of the charging stations strain the distribution grid [3]. Meanwhile, various techniques, such as intermittent renewable generation and distributed energy storage, came into use in charging stations and distribution networks [4]. This further complicates the operation of charging stations and threatens the power system reliability. It is crucial to explore how to manage the growing number of charging stations and unlock the power flexibility hidden in EVs to jointly maintain system reliability.

Recently, there have been extensive literature on the optimal operation of multiple charging stations/microgrids to improve the system efficiency. For example, EV charging was proposed to align with the local wind power generation of charging stations [5]. It adopted the current practice of having EV charging stations curtail surplus energy or sell it back to the grid at a low and location-independent feed-in tariff. However, this results in low earnings of charging stations and ignores the power losses caused by energy transactions. To address this challenge, peer-to-peer (P2P) energy trading has emerged as a promising solution, in which participants can obtain higher revenues by exchanging energy with one another. A rule-based strategy to operate multiple charging stations was proposed in [6], where the charging stations with higher battery storage state of charge (SOC) are enforced to deliver energy to others. But how to design the incentives to engage charging stations was not addressed. A coordination mechanism with properly designed trading prices was desired [7]. Non-cooperative leader-follower game based P2P schemes were adopted for facility sharing [8] and sharing among multiple PV prosumers [9]. To better unlock prosumer’s flexibility, generalized Nash game based P2P schemes were developed [10]. However, the above non-cooperative game based schemes may lead to sub-optimal social welfare because of the conflicting interests between prosumers and the system operator. A cooperative game based scheme was proposed to form prosumer coalitions to meet their demands at the minimum total cost [11]. Distributed optimization is another way to design P2P energy trading schemes, which has been applied in the field of energy buildings [12], multi-energy systems [13], and charging stations [14]. A comprehensive review summarizing various P2P energy trading mechanisms can be found in [15]. However, the above studies mainly focused on the design of energy trading mechanisms without considering distribution network constraints.

Several studies began to integrate the distribution network model into energy trading to better match the reality. A practical distribution network model was incorporated in the energy sharing problem of microgrids [16]. A centralized energy trading framework of EV charging stations was proposed in [17] that integrated a power distribution network. The P2P energy trading problem of microgrids was formulated as a bi-level programming, which was then transformed into a single level optimization that can be solved centrally [18]. The above centralized schemes may jeopardise the privacy of charging stations by gathering their private data to make a central decision [19]. Therefore, distributed operation is preferred. To protect the privacy of microgrids, a distributed algorithm based on subgradient method was proposed in [20]. Compared with other distributed algorithms, the alternating direction method of multipliers (ADMM) based approach with good convergence properties and scalability [21] has attracted much attention. A distributed mechanism based on ADMM was proposed to determine the amount of energy traded among networked charging stations [22] and interconnected microgrids [23]. Reference [24] also adopted the ADMM method and considered a simplified LinDistFlow model. The distributed optimization based methods can achieve social optimality, but why participants should follow the decision rules derived from the Lagrangian function is not clear. In addition, the amount of sharing energy between a pair of charging stations was assumed to be equal. This ignores the power losses during transmission which the system operator has to compensate for.

Another important issue related to charging station management is how to take full advantage of the flexibility of EVs while protecting the privacy of vehicle owners. Reference [25] solved a centralized optimization problem to determine the EV charging schedules and to manage the power balance in the charging station. A centralized scheme based on improved particle swarm optimization was presented in [26] to schedule EV charging for cost reduction. However, the above methods require the charging station to know the data of all EVs, which may violate the privacy of EV owners. In addition, with an increasing number of EVs, solving an optimization problem with detailed EV data and constraints will be time-consuming [27]. An alternative approach is to first derive the aggregate flexibility of the large number of distributed energy resources, which is then taken as a whole to participate in the system operation. The aggregate flexibility of thermostatically controllable loads (TCLs) [28] and various distributed energy resources [29] has been studied. For example, a geometric approach was utilized to model the aggregate flexibility of TCLs [30]. An inner box approximation method was proposed to characterize the power flexibility region of various distributed energy resources [31]. The flexibility of virtual power plants was represented by a combination of a virtual battery and a virtual generator to make the high-dimensional problem tractable [32]. A learning-based method was proposed to provide real-time aggregate flexibility feedback of controllable loads [33]. Despite the above fruitful efforts, how to characterize the maximal potential power flexibility of EVs in a charging station remains to be investigated. In particular, EV charging stations has some constraints distinct
Our main contributions are three-fold:

1) We propose an optimization problem to characterize the aggregate power flexibility of all EVs inside a charging station. It generates the upper and lower power trajectories of the aggregate EV power flexibility region. We prove that any trajectory within this region corresponds to at least one feasible EV dispatch strategy. Thus, during operation, the charging station can adjust the actual aggregate power of EVs within this region without knowing the detailed information of each EV. This can protect individual EV owner’s privacy. Moreover, the challenging computational complexity of managing a large number of EVs can be resolved.

2) We propose a novel distributed coordination mechanism to reconcile the amount of energy that the charging stations want to trade with the distribution system operator’s schedule based on prices considering power losses. We prove that the proposed mechanism is guaranteed to converge to the centralized optimum.

3) Compared with the traditional method, the proposed method can achieve significant total cost savings, reduce power losses, and greatly improve the utilization of battery storage in charging stations.

The rest of this paper is organized as follows. Section II describes the overall system structure, challenges, and the proposed two-stage scheme. Sections III and IV introduce the aggregate EV power flexibility evaluation problem and the distributed coordination mechanism for charging stations, respectively. Simulation results are presented in Section V. Finally, Section VI concludes this paper.

II. OVERVIEW OF THE SYSTEM AND CHALLENGES

Fig. 1 shows the overall structure of the studied multi-charging station system. All charging stations are equipped with PV panels and battery storage, but they may have different capacities and EV charging patterns. We define $I$ as the set of charging stations in the system, each of which is indexed by $i \in I$. The charging stations are located at different buses of a radial distribution network. There is a distribution system operator (DSO) that monitors the power flow of the distribution network and the energy trading with the utility grid (connected to Bus 1). Let $T = \{1, \ldots, T\}$ denote the operation time horizon and $T = 24$. Each time slot, indexed by $t \in \{1, \ldots, T\}$, has an equal time interval $\Delta t$, i.e., 1 h.

To ensure the reliable and efficient operation of the multi-charging station system, it needs to coordinate well the numerous energy resources connected to the charging stations. This is complicated in three ways: 1) Agents with conflicting interests. For example, EV owners need to satisfy their charging needs, the charging station operator (CSO) aims to minimize its own operation cost, and the DSO has to ensure system security while minimizing total power loss. 2) Privacy protection and information asymmetry. The EV owners are not willing to reveal their private information (such as the charging needs) to the CSO; the distribution network constraints is only available to DSO; the DSO does not know the batteries and PV generations in the charging stations. 3) Computational complexity. It is time-consuming for the CSO to manage the numerous resources inside it (the large number of EVs, PV, battery storage, etc.) as well as deciding on the energy trading plan by solving a centralized optimization problem.

To address the above challenges, we propose a two-stage energy management scheme. In the first stage, the aggregate power flexibility region (will be explained in detail later) of all EVs inside each charging station is derived. This allows the CSO to know the adjustable capability of EVs while protecting the privacy of individual EV owners. This aggregate EV power flexibility region serves as a constraint of the charging station’s energy management problem in the second stage. In the second stage, a distributed coordination mechanism is proposed to facilitate energy trading among charging stations and with the utility grid, while ensuring the satisfaction of network constraints. The proposed mechanism is consistent with the asymmetric information structure that the network constraints are only available to the DSO while the charging station’s operational constraints are known solely to the CSO. Each stage will be discussed in detail in the following sections.

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TABLE I

| Ref. | Network constraints | Distributed | Clear physical interpretation | Aggregate EV power flexibility |
|------|---------------------|-------------|------------------------------|-----------------------------|
| [8], [9] | x | □ | □ | x |
| [13], [14] | □ | □ | □ | x |
| [16], [18], [23], [26] | □ | □ | □ | □ |
| [19], [20], [22], [24] | □ | □ | □ | □ |
| [33] | □ | □ | □ | □ |
| This paper | x | □ | □ | □ |

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Fig. 1. Structure of the EV charging station system in a distribution network.
III. AGGREGATE EV POWER FLEXIBILITY EVALUATION-THE 1ST STAGE

In this section, we first introduce the concept of aggregate EV power flexibility and then propose an optimization problem to approximate it. The obtained approximate aggregate power flexibility region will be used in the second-stage charging station coordination problem, when the actual EV dispatch strategies are determined.

A. Aggregate EV Power Flexibility

Let \( V_i \) denote the set of EVs that will arrive at and be charged in the charging station \( i \in \mathcal{I} \) in the next day. For each EV \( v \in V_i \), its charging need can be defined by four parameters: \((t_v^a, t_v^d, soc_v^{ini}, soc_v^{req})\), where \( t_v^a \) is its arrival time, \( t_v^d \) is the anticipated departure time which should meet \( t_v^a < t_v^d \), \( soc_v^{ini} \) is its initial battery SOC level, and \( soc_v^{req} \) represents the required least SOC when it leaves. In this paper, we assume that EV owners would like to reserve chargers one day in advance by submitting their parameters. Those parameters can either be estimated (e.g., \( soc_v^{ini} \)) or be set considering EV owners’ routines and future travel plans (e.g., \( t_v^a \)). For example, the initial SOC can be estimated by \( soc_v^{ini} = soc_v^{pre} - d_e/E_v \), where \( soc_v^{pre} \) is the current SOC, \( d_e \) is the distance between EV owner and the charging station, \( e_v \) is the average electricity consumption, and \( E_v \) is the EV battery capacity. This kind of web-based reservation system can be found in [34]. Making reservations can benefit both EV owners, charging stations, and the power grid. For the EV owners, they can book chargers in advance to avoid long-time searching for charging stations and to reduce queuing time. They can also obtain revenues by allowing flexible EV charging. For charging stations and the power grid, the power flexibility of EVs can be used to reshape the charging load and reduce the operation cost. The above-mentioned benefits encourage EVs to follow their submitted information. Considering that the proposed approach requires EVs’ submissions in advance, it would be more viable for EV owners with well-established routines. A possible application scenario is the charging stations in a university.

With the submitted information, the charging station operator has some flexibility in charging the EVs. For example, Fig. 2 gives two possible ways to meet the charging need of an EV. Let \( \{p_v(t), \forall t\} \) be the charging power of an EV \( v \) over time, then the range that the charging power can vary within is called the \( \text{EV’s power flexibility} \). If we sum up the power flexibility of all EVs in a charging station \( i \in \mathcal{I} \), then we can get the aggregate \( \text{EV power flexibility} \) of the charging station \( i \in \mathcal{I} \), denoted by \( \mathcal{F}_i \).

Unlike the controllable generators, whose flexibility can be described by their minimum and maximum power at each time slot, it is hard to characterize the power flexibility of an EV since its SOC is temporally coupled. The power flexibility in the current time slot can affect that in the next time slot. We want to describe EV power flexibility by a region that: 1) is time-decoupled so that it is easier to use; and 2) any trajectory within it corresponds to at least one feasible EV dispatch strategy. A simple example is given in Fig. 3. Suppose there are only one EV and two time slots. Two possible EV power flexibility regions are shown in the right-hand side of the figure. Case I has \( p_v^c(1) \in [0, 0.25E_{\max}] \) while Case II has \( p_v^c(1) \in [0.25E_{\max}, 0.3E_{\max}] \). We prefer Case II to Case I since it can provide flexibility in more time slots. Therefore, in addition to the above two requirements, we also hope that the region has more evenly distributed power flexibility across the declared charging time slots, rather than wide flexibility in some time slots but little or none in others.

B. Approximation of Aggregate EV Power Flexibility

For ease of use, we aim to approximate the aggregate power flexibility of EVs in a charging station \( i \in \mathcal{I} \) (denoted by \( \mathcal{F}_i \)) by a region \( \mathcal{F}_i \) consisting of a series of intervals \([\hat{p}_{d,i}(t), \hat{p}_{d,i}(t)]\) for each time slot \( t \in \mathcal{T} \). That is, \( \mathcal{F}_i \approx \mathcal{F}_i := [\hat{p}_{d,i}(1), \hat{p}_{d,i}(1)] \times \ldots \times [\hat{p}_{d,i}(T), \hat{p}_{d,i}(T)] \) so that the aggregate power flexibility can be specified by a lower power trajectory \( \{\hat{p}_{d,i}(t), \forall t\} \) and an upper power trajectory \( \{\tilde{p}_{d,i}(t), \forall t\} \). We formulate the following optimization problem to obtain the lower and upper power trajectories of the feasible region. We will prove later that for any \( \{\hat{p}_{d,i}(t), \forall t\} \in \mathcal{F}_i \), there always exists a feasible EV dispatch.

\[
\text{max } \sum_{t \in \mathcal{T}} \left( (\tilde{p}_{d,i}(t) - \hat{p}_{d,i}(t)) - w(\tilde{p}_{d,i}(t) - \hat{p}_{d,i}(t))^2 \right),
\]

\[
\text{s.t. } \hat{p}_{d,i}(t) = \sum_{v \in V_i} p_v^c(t), \forall t
\]
\begin{align}
- s_v^c(t)p_{\text{chg}}^c &\leq \bar{p}_v^c(t) \leq s_v^c(t)p_{\text{chg}}^c, \forall v, \forall t \\
0 \leq s_v^c(t) &\leq s_v^c_{\text{max}}, \forall v, \forall t \\
soc_v(t_v) = soc_v^{i\text{ini}}, soc_v(t_{v}) &\geq soc_v^{eq}, \forall v \\
soc_v(t + 1) = soc_v(t) + \frac{\bar{p}_v^c(t)\Delta t}{E_v}, \forall v, \forall t \neq T \\
soc_v^{\text{min}} \leq soc_v(t) &\leq soc_v^{\text{max}}, \forall v, \forall t \\
\sum_{v \in V} s_v^c(t) &\leq N_{\text{chg},i}, \forall t \\
\bar{p}_{d,i}(t) &= \sum_{v \in V} \bar{p}_v^c(t), \forall t \\
- s_v^c(t)p_{\text{chg}}^c &\leq \bar{p}_v^c(t) \leq s_v^c(t)p_{\text{chg}}^c, \forall v, \forall t \\
0 \leq s_v^c(t) &\leq s_v^c_{\text{max}}, \forall v, \forall t \\
soc_v(t_v) = soc_v^{i\text{ini}}, soc_v(t_{v}) &\geq soc_v^{eq}, \forall v \\
soc_v(t + 1) = soc_v(t) + \frac{\bar{p}_v^c(t)\Delta t}{E_v}, \forall v, \forall t \neq T \\
soc_v^{\text{min}} \leq soc_v(t) &\leq soc_v^{\text{max}}, \forall v, \forall t \\
\sum_{v \in V} s_v^c(t) &\leq N_{\text{chg},i}, \forall t, \forall t \\
\bar{p}_{d,i}(t) &\geq \dot{p}_{d,i}(t), \forall t; s_v^c(t) = s_v^c(t), \forall v, \forall t. 
\end{align}

where

\begin{equation}
s_v^p(t) = \begin{cases} 
1 & \text{if } t \in [t^c_v, t^d_v] \\
0 & \text{if } t < t^c_v \cup t > t^d_v 
\end{cases}, \forall v, \forall t. \tag{2}
\end{equation}

The objective function (1a) is to maximize the aggregate power flexibility of EVs while the quadratic term makes the flexibility be distributed more evenly across time (see Appendix A), and \(w\) is a weight parameter. Constraint (1b) defines the upper bound of the aggregate EV power flexibility. The charging power of an EV \(v\) is limited by (1c), where \(p^c_{\text{chg}}\) is the maximum charging/discharging power. \(s_v^c(t)\) indicates the charging status of an EV \(v\) at time slot \(t\). If the EV is being charged, \(s_v^c(t) = 1\); otherwise, \(s_v^c(t) = 0\). Constraints (1d) and (2) ensure that charging only happens during the EV’s declared parking time. If the EV is in the charging station, \(s_v^p(t) = 1\); otherwise, \(s_v^p(t) = 0\). (1e) gives the EV’s initial SOC and the charging requirement. (1f) and (1g) describe the EV’s SOC dynamics and SOC range. \(E_v\) is the battery capacity. Constraint (1h) ensures that the number of EVs being charged at any time slot cannot exceed the number of chargers \(N_{\text{chg},i}\) installed at the charging station \(i\). Similarly, (1i)-(1o) are the constraints related to the lower bound of the aggregate power flexibility. (1p) is the joint constraint to ensure that any aggregate power trajectory between \(\{\bar{p}_{d,i}(t), \forall t\}\) and \(\{\dot{p}_{d,i}(t), \forall t\}\) is achievable, which is formally stated in the proposition below.

**Proposition 1:** Let \(\{\bar{p}_{d,i}(t), \dot{p}_{d,i}(t), \forall t\}\) be the optimal solution of (1). For any aggregate power trajectory \(\{p_{d,i}(t), \forall t\}\) that satisfies \(p_{d,i}(t) \in [\bar{p}_{d,i}(t), \dot{p}_{d,i}(t)]\) for all time slots \(t \in T\), there exists a feasible EV dispatch strategy.

The proof of Proposition 1 can be found in Appendix B. In practice, the aggregate EV power flexibility \(\bar{F}_i\) can be generated by a smart EV management system using the above optimization problem (1) and submitted to the charging station operator for further use. The operator only knows the aggregate flexibility but not the detailed information of each EV, which can protect EV owner’s privacy to some extent.

**Remark:** The proposed model can also consider the EV’s willingness to be shed (not being charged at the maximum charging power) in the following way: If an EV owner is unwilling to be shed, then an earlier departure time \(t^d_v\) can be submitted to the smart EV management system. As a result, the EV will be scheduled to finish charging as soon as possible. On the contrary, a later departure time could be submitted when the EV owner is willing to participate in the flexible charging management. Moreover, to avoid not having enough chargers, when a new EV plans to arrive, the smart EV management system will check its submitted parameters \((t^i_v, t^c_v, soc_v^{i\text{ini}}, soc_v^{eq})\) first to determine if it can be served. A simplified method could be: If the number of EVs during its submitted period \([t^i_v, t^c_v]\) is fewer than the chargers, the EV can be served. Otherwise, the EV is informed to change its available time or to find another available charging station.

### IV. CHARGING STATION COORDINATION—THE 2ND STAGE

With the aggregate EV power flexibility of each charging station \(i \in I\), in this section, we formulate the charging stations’ coordination problem and propose a suitable distributed coordination mechanism to solve it.

#### A. Modelling of Charging Station

1) **EV Charging Demand:** The final dispatched aggregate charging demand in the charging station \(i \in I\), denoted by \(\bar{F}_i\), provided by the first stage:

\begin{equation}
\bar{p}_{d,i}(t) \leq p_{d,i}(t) \leq \dot{p}_{d,i}(t), \forall t. \tag{3}
\end{equation}

The charging power dispatched by the charging station may be less than the upper boundary, which may lead to dissatisfaction of EV owners with reduced utility [9]. We measure this incurred dissatisfaction cost as

\begin{equation}
C_{ev,i}(PD_{d,i}) = \sum_{t \in T} c_{sx,i}(p_{d,i}(t) - p_{d,i}(t)) \tag{4}
\end{equation}

where \(c_{sx,i}\) is the cost coefficient.

2) **Battery Operation:** We let \(p^c_{b,i}(t)\) and \(p^d_{b,i}(t)\) denote the discharging and charging power of the battery energy storage in charging station \(i \in I\) at time slot \(t\). The \(p^c_{b,i}(t)\) and \(p^d_{b,i}(t)\) should meet the following physical constraints:

\begin{align}
0 &\leq p^c_{b,i}(t) \leq p^c_{b,i}^{\text{max}}, \forall t, \tag{5} \\
0 &\leq p^d_{b,i}(t) \leq p^d_{b,i}^{\text{max}}, \forall t, \tag{6}
\end{align}

where \(p^c_{b,i}^{\text{max}}\) and \(p^d_{b,i}^{\text{max}}\) are the maximum discharging and charging power, respectively.
Along with battery discharging and charging, the battery storage SOC dynamics $soc_{b,i}$ can be expressed by:

$$soc_{b,i}(t + 1) = soc_{b,i}(t) - \frac{p^d_{b,i}(t)\Delta t}{\eta_d E_{b,i}} + \frac{p^c_{b,i}(t)\Delta t\eta_c}{E_{b,i}}, \forall t \neq T$$

where $E_{b,i}$ is the energy capacity of battery storage when it is fully charged; $\eta_d/\eta_c$ is the discharging/charging efficiency. The SOC should always be within its allowable range to guarantee no over-discharging or over-charging occurs:

$$soc_{b,i}^{min} \leq soc_{b,i}(t) \leq soc_{b,i}^{max}, \forall t,$$

where $soc_{b,i}^{min}$ and $soc_{b,i}^{max}$ are the minimal and maximal SOC levels, respectively. Besides, the battery SOC at the initial ($t = 1$) and final ($t = T$) time slots are restricted to be equal so that the battery operation decouples across different days

$$soc_{b,i}(1) = soc_{b,i}(T).$$

Both charging and discharging can cause battery degradation and the degradation cost is described by:

$$C_{b,i}(p^d_{b,i}, p^c_{b,i}) = c_{b,i} \sum_{t \in T} (p^d_{b,i}(t) + p^c_{b,i}(t)) \Delta t,$$

where $p^d_{b,i} = \{p^d_{b,i}(t), \forall t \in \mathcal{T}\}$, $p^c_{b,i} = \{p^c_{b,i}(t), \forall t \in \mathcal{T}\}$, and $c_{b,i}$ is the degradation cost coefficient.

### B. Energy Trading With Other Charging Stations/Utility Grid

In addition to using the local PV generation and battery storage, charging stations can also trade energy with other charging stations or the utility grid. In general, when the local PV generation exceeds the charging demand, the charging station can sell the surplus energy; otherwise, it can buy energy from other charging stations or the utility grid. These energy trades are performed on the distribution network.

1) **Conventional Method:** Conventionally, we let the charging station to buy/sell energy from/to the utility grid under a uniform price $\lambda^g_i(t)/\lambda^c_i(t)$. The cost for the charging station $i \in \mathcal{I}$ to trade energy at time slot $t$ is calculated as follows:

$$C_{g,i}(p^g_{g,i}, p^c_{g,i}) = \sum_{t \in \mathcal{T}} (p^g_{g,i}(t)\lambda^g_i(t) + p^c_{g,i}(t)\lambda^c_i(t)) \Delta t,$$

where $p^g_{g,i}(t)/p^c_{g,i}(t)$ is the power bought/sold from/to the utility grid.

However, since the charging stations are located at different buses and the power transmissions in distribution network result in power losses, giving them the same price is unfair. Also in that case, the DSO may need to pay for the power losses. To cope with these problems of the conventional method, we propose a new approach to better design the energy trading prices as follows.

2) **Proposed Method:** Due to the power loss of the network and the power flow limits, to be fair, the energy trading prices at different nodes should be different. To facilitate the energy trading, here we assume that the DSO will help to coordinate the trading by announcing an energy trading price $\lambda_{p,i}(t)$ to each charging station that takes into account multiple factors such as the grid buying/selling prices, the distance from the utility grid and other charging stations, etc. Upon receiving the price, the charging station will decide on how much energy it would like to trade. We let $p_{g,i}(t)$ represent the net exchange power imported by the charging station. It is the sum of power bought from all other charging stations and from the utility grid. $p_{g,i}(t)$ is negative when the charging station sells. The $p_{g,i}(t)$ should satisfy the following physical limits:

$$p_{g,i}^{min} \leq p_{g,i}(t) \leq p_{g,i}^{max}, \forall t,$$

where $p_{g,i}^{min}$ and $p_{g,i}^{max}$ are the minimum and maximum power imported by the charging station $i$. If $p_{g,i}(t) > 0$, it means that the charging station $i \in \mathcal{I}$ buys energy, and vice versa.

Given the locational energy trading price $\lambda_{p,i}(t)$, the cost for the charging station $i \in \mathcal{I}$ to trade energy at time slot $t$ is calculated as follows:

$$C_{g,i}(p_{g,i}) = \sum_{t \in \mathcal{T}} (p_{g,i}(t)\lambda_{p,i}(t)) \Delta t,$$

where the vector $p_{g,i} = \{p_{g,i}(t), \forall t \in \mathcal{T}\}$.

So far, we can formulate the total operation cost of charging station $i$, which consists of the above-mentioned terms

$$C_i(x_i) = C_{b,i} + C_{ev,i} + C_{g,i},$$

where vector $x_i = \{p_{d,i}, p_{g,i}, p^d_{b,i}, p^c_{b,i}\}$ summarizes the decision variables of charging station $i$.

In addition, each charging station is assumed to be equipped with renewables such as PV panels for reducing the energy bought from the grid. The PV power generation at time $t$ is represented by $p_{pv,i}(t), i \in \mathcal{I}$. The charging station should maintain its internal power balance at each time slot $t$:

$$p_{d,i}(t) = p_{g,i}(t) + p_{pv,i}(t) + p^d_{b,i}(t) - p^c_{b,i}(t), \forall t.$$

### C. Modelling of the Distribution Network

Considering that the charging stations are located at different buses of a radial distribution network, their energy trading cannot be achieved without the support of the power network. Thus, it is necessary to take into account the distribution network model. Typically, the distribution network can be modeled as a graph $G(N, \mathcal{E})$, where $N$ and $\mathcal{E}$ are the set of buses and lines, respectively. Then, we can index each bus in $N$ by $n = 1, 2, \ldots, N$, and a branch can be represented by $(n, j) \in \mathcal{E}$. A branch flow model is adopted [35]:

$$p_j(t) = P_{nj}(t) - r_{nj}\ell_{nj}(t) - \sum_{k:(j,k) \in \mathcal{E}} P_{jk}(t), \forall t,$$

$$q_j(t) = Q_{nj}(t) - x_{nj}\ell_{nj}(t) - \sum_{k:(j,k) \in \mathcal{E}} Q_{jk}(t), \forall t,$$

$$v_{ij}(t) = v_n(t) - 2(r_{nj}P_{nj}(t) + x_{nj}Q_{nj}(t))$$

$$+ (r_{nj}^2 + x_{nj}^2)\ell_{nj}(t), \forall t,$$

$$\ell_{nj}(t) = \frac{P_{nj}(t)^2 + Q_{nj}(t)^2}{v_n(t)}, \forall t,$$

$$\underline{p}_j \leq p_j(t) \leq \overline{p}_j, \quad \underline{q}_j \leq q_j(t) \leq \overline{q}_j, \forall t,$$
where $p_j$ and $q_j$ are the active and reactive power at bus $j \in \mathcal{N}$, $P_{nj}$ and $Q_{nj}$ are the active and reactive power flow in line $(n, j)$, $r_{nj}$ and $x_{nj}$ are the resistance and reactance in line $(n, j)$, $\ell_{nj}$ is the squared current $I_{nj}$ magnitude in line $(n, j)$, i.e., $\ell_{nj} = |I_{nj}|^2$, $v_j$ is the squared voltage $V_j$ magnitude at bus $j$, i.e., $v_j = |V_j|^2$, $\mathbf{c}$ and $\mathbf{s}$ represent the lower and upper bounds of the variable $\bullet$.

Let $n_i$ denote the bus that charging station $i$ is connected to. For the bus $n_i$, there is
\begin{equation}
      p_{n_i}(t) = p_{g,i}(t) + \lambda_{p,i}(t), \forall t,
\end{equation}
where $\lambda_{p,i}(t)$ is the dual variable of this equality, which is also the locational energy trading price. This equation builds the coupling connection between the charging station and the distribution network.

Bus 1, i.e., the slack bus in the distribution network, is responsible for buying/selling energy from/to the utility grid. We denote $p_{1}^b(t)/p_{1}^s(t)$ as the energy bought/sold by bus 1 at time slot $t$. Thus, the incurred cost is
\begin{equation}
      C_{bus1} = \sum_{i \in I} \left( p_{1}^b(t) \lambda_{p,i}^b(t) - p_{1}^s(t) \lambda_{p,i}^s(t) \right) \Delta t,
\end{equation}
where $\lambda_{p,i}^b(t)$ and $\lambda_{p,i}^s(t)$ are the utility electricity buy and sale prices, respectively. Further, they should meet the requirement $\lambda_{p,i}^b(t) < \lambda_{p,i}^s(t)$ to ensure that the distribution network won’t arbitrage by buying from and selling back to the utility at the same time.

Generally, the DSO is in charge of the distribution network management and will regulate the energy transactions among charging stations. Here, we use the minimization of utility grid cost plus power loss and minus the revenue of selling electricity to charging stations as the objective function of DSO,
\begin{equation}
      \min C_{dso}(\mathbf{x}_d) = C_{bus1} + C_{loss} - \sum_{i \in I} C_{g,i},
\end{equation}
where
\begin{equation}
      C_{loss} = \sum_{i \in I} \sum_{(i,j) \in \mathcal{E}} r_{ij} f_{ij}(t) \pi(t) \Delta t,
\end{equation}
\begin{equation}
      C_{g,i} = \sum_{i \in I} p_{g,i}(t) \lambda_{p,i}(t) \Delta t = \sum_{i \in I} p_{n_i}(t) \lambda_{p,i}(t) \Delta t,
\end{equation}
where $\pi(t)$ represents the price to turn the power loss into a monetary term. The DSO usually needs to buy electricity from the utility grid to maintain system power balance, and the electricity buying price is time-varying. Thus, the value of power loss at different time is also different, which is measured by a time-varying price $\pi(t)$. Vector $\mathbf{x}_d = \{ p, q, P, Q, \ell, v \}$ summarizes the decision variables, $p = \{ p_{n_i}(t), n \in \mathcal{N}, t \in \mathcal{T} \}$, $q = \{ q_{n_i}(t), n \in \mathcal{N}, t \in \mathcal{T} \}$, $P = \{ P_{nj}(t), (n, j) \in \mathcal{E}, t \in \mathcal{T} \}$, $Q = \{ Q_{nj}(t), (n, j) \in \mathcal{E}, t \in \mathcal{T} \}$, $\ell = \{ \ell_{nj}(t), (n, j) \in \mathcal{E}, t \in \mathcal{T} \}$, $v = \{ v_{n_i}(t), n \in \mathcal{N}, t \in \mathcal{T} \}$.

Note that if we adopt the conventional method (see (11)), the DSO manages the power flow of the distribution network by solving the following problem:
\begin{equation}
      \min C_{dso}^{base}(\mathbf{x}_d) = C_{bus1} + C_{loss} - \sum_{i \in I} C_{g,i},
\end{equation}
\begin{equation}
      \text{s.t. } p_{n_i}(t) = p_{g,i}(t) - p_{s,i}(t), \forall t, (16).
\end{equation}

### D. Distributed Coordination Mechanism

According to the above models, we can find that the charging stations and the distribution network interact with each other through equation (17), which acts as a bridge connecting the charging stations and the distributed network. In the following, we design a coordination mechanism by modifying the objective functions (14) and (19) to take into account the connecting equation (17). The coordination mechanism will run in an iterative process. In the $(k+1)$-th iteration:

The objective function of charging station $i$ is modified as
\begin{equation}
      C_i(\mathbf{x}_i) = C_{bi,i} + C_{ev,i} + C_{g,i} + \sum_{t \in \mathcal{T}} \frac{\rho}{2} (p_{g,i}(t) - p_{n_i}(t))^2,
\end{equation}
subject to
\begin{equation}
      p_{n_i}(t) = p_{g,i}(t) - p_{s,i}(t), \forall t, (18),
\end{equation}
where $\{ p_{g,i}(t), p_{n_i}(t), \forall t \}$ are the given desired energy trading profile $\{ p_{g,i}(t), \forall t \}$ and the DSO’s schedule. The charging station $i$ needs to meet DSO’s schedule as much as possible. Denote the charging station’s optimal energy trading profile as $\{ p_{g,i}^{k+1}(t), \forall t \}$.

Meanwhile, for DSO, its objective function is modified as
\begin{equation}
      C_{dso}(\mathbf{x}_d) = C_{bus1} + C_{loss} - \sum_{i \in I} C_{g,i},
\end{equation}
\begin{equation}
      + \sum_{i \in I} \sum_{t \in \mathcal{T}} \frac{\rho}{2} (p_{g,i}^{k+1}(t) - p_{n_i}(t))^2,
\end{equation}
subject to
\begin{equation}
      (3), (5)–(9), (12), (15), (16)–(17), (20),
\end{equation}
where $\{ p_{g,i}^{k+1}(t), \forall t \}$ are the desired energy trading profiles submitted by the charging stations. The DSO will decide on the energy trading schedule $\{ p_{n_i}(t), \forall i, \forall t \}$ to meet the needs of charging stations as much as possible, which is represented in the last quadratic term of the modified objective function (22a). After determining the energy trading schedule $\{ p_{n_i}^{k+1}(t), \forall i, \forall t \}$, the DSO will make the scheduling decisions for the charging stations based on this schedule. Thus, the coordination mechanism is complete.
Algorithm 1: Distributed Coordination Mechanism.

1: Set iteration index \( k = 0 \), convergence error tolerance \( \delta > 0 \), penalty parameter \( \rho > 0 \).
2: DSO initializes the trading price \( \lambda_{p,i}^k = 0 \), and desired traded energy \( p_{n,i}^k = 0 \) for all charging stations \( i \in I \).
3: \textbf{repeat}
4: \textbf{for} Each charging station \( i \in I \) \textbf{do}
5: \hspace{1em} CSO updates \( p_{g,i}^{k+1} \) according to the modified problem (21), and sends them to DSO.
6: \textbf{end for}
7: DSO then updates \( p_{n,i}^{k+1} \), \( \forall i \) according to the modified problem (22), and the trading prices \( \lambda_{p,i}^{k+1} \), \( \forall i \) via (23), and broadcasts them to each CSO.
8: Set \( k = k + 1 \)
9: \textbf{until} convergence stopping criterion (24) is satisfied.

Algorithm 1 outlines the proposed distributed coordination mechanism for charging stations to coordinate their energy trading. The mechanism iterates between the DSO and CSOs, updating the trading price and desired energy until a convergence criterion is met.

By solving the above optimization problem, the DSO will then update the energy trading prices \( \{\lambda_{p,i}^{k+1}(t), \forall i, \forall t\} \). Considering that the obtained \( p_{n,i}^{k+1}(t) \) may not equal to the charging station’s needs \( p_{g,i}^{k+1}(t) \), the DSO will adjust the prices to reduce this power imbalance by

\[
\lambda_{p,i}^{k+1}(t) = \lambda_{p,i}^k(t) + \rho \left( p_{g,i}^{k+1}(t) - p_{n,i}^{k+1}(t) \right), \forall t. \tag{23}
\]

When the power needed by the charging station \( p_{g,i}^{k+1}(t) \) is less than the DSO’s desired schedule \( p_{n,i}^{k+1}(t) \), i.e., \( p_{g,i}^{k+1}(t) - p_{n,i}^{k+1}(t) < 0 \), the DSO will lower the energy trading price \( \lambda_{p,i}^{k+1}(t) < \lambda_{p,i}^k(t) \) to incentivize the charging station to buy more electricity, and vice versa.

The interaction between the charging stations and the DSO happens iteratively, and the mechanism stops when the energy trading price becomes almost stable, i.e., the price difference between two successive iterations is less than the tolerance \( \delta \), i.e.,

\[
r = \|\lambda_{p}^{k+1} - \lambda_{p}^k\| \leq \delta. \tag{24}
\]

A completed description of the proposed coordination mechanism is shown in Algorithm 1. The data exchanged between the charging stations and the DSO consists solely of the energy trading schedule/profile and the trading prices. Therefore, the private data of individual charging stations and the network parameters owned by the DSO are well protected.

Still, we have three concerns about the above proposed coordination mechanism: 1) The quadratic equality constraint (16d) is nonconvex, making the DSO’s problem challenging to solve. 2) Is there any convergence guarantee for the proposed mechanism? 3) When it converges, will the equilibrium be close to or the same as the centralized optimum?

For the first issue, convex relaxation is performed to turn (16d) into a second-order conic inequality constraint, i.e.,

\[
\ell_{nj}(t) \geq \frac{P_{nj}(t)^2 + Q_{nj}(t)^2}{v_n(t)}, \forall t. \tag{25}
\]

The exactness of relaxation has been verified for the radial distribution network [35] when the power injection at each bus is not too large, and the bus voltage maintains around the nominal value.

For the rest two issues, we have

**Proposition 2:** The proposed distributed coordination mechanism is guaranteed to converge to the centralized optimum.

The proof of Proposition 2 is in Appendix C. Note that the proposed mechanism still works when the charging stations are in different feeders. For example, suppose the CS1 and CS4 are in feeder 1 while the CS2 and CS3 are in feeder 2, as shown in Fig. 4. In the proposed 2nd-stage coordination mechanism (Algorithm 1): (1) Each charging station only exchanges information with its corresponding DSO; and (2) Each DSO updates its strategy based only on the information about its own network and the utility buying/selling electricity prices, without needing to know the information of other DSOs/distribution networks. Hence, this distributed nature of the proposed mechanism allows it to work even when the charging stations are in different feeders. To be specific, CS1 and CS4 interacts with the DSO of feeder 1 iteratively until convergence; CS2 and CS3 interacts with the DSO of feeder 2 iteratively until convergence; these two iteration processes work independently.

**E. Practical Issues**

We further discuss some practical issues of the proposed mechanism below:

1) **Communication requirements:** This paper focuses on future power systems with more flexible loads and distributed energy resources (DERs) such as EVs in the distribution network. Under such circumstances, a more advanced communication system would be built to support the coordination between DERs, aggregators, and the DSO. There are some studies that mentioned such a two-way communication system. For example, Reference [34] introduced an internet-based system that establishes the communication between charging stations and DSO. Such a communication is also allowed in Reference [22]. Reference [23] proposed using IEC 61850 protocol to implement the communication between microgrids and DSO. Coordination approaches with less communication will be investigated in our future work.

2) **Uncertainties:** The proposed two-stage scheme gives the day-ahead EV charging and energy trading plans. In real-time, uncertainties caused by, e.g., deviations of EVs from their submitted information, may happen. To deal with such uncertainties, a real-time adjustment method as in Appendix D can be introduced.
3) Financial benefits to engage EVs: Normally, EV owners would prefer charging as soon as possible (CASAP). To promote their participation in the proposed management scheme, a financial benefit can be provided. Denote the total cost difference between the proposed and CASAP methods by $B^{tot}$, which is the benefit from EV flexible charging. Part of $B^{tot}$ could be allocated to EV owners as financial benefits to encourage them to join. Here, we propose a three-step benefit allocation scheme as follows:

**Step 1:** Benefits allocation between CSs. We first allocate the benefits between charging stations. $B_{cs}^{tot}$ is allocated to charging stations evenly, i.e., each charging station gets $B_i = B_{cs}^{tot}/I$, and each charging station’s cost becomes $C_i^{casap} = B_i$.

**Step 2:** Benefits allocation between CS and EVs. The benefit each charging station gets is allocated between the CS operator and the EV owners. To be fair, half of $B_i$ is given to CS operator while the other half is given to EV owners.

**Step 3:** Benefits allocation between EVs. The third step is the benefit allocation among EVs. Similarly, the benefit $B_{ev,i} = B_i/2$ is evenly allocated to all EVs.

V. SIMULATION RESULTS AND DISCUSSIONS

In this section, we evaluate the performance of the proposed two-stage scheme, including the aggregate EV power flexibility evaluation and the distributed coordination mechanism using an IEEE 33-bus test system [36] with four charging stations: CS1, CS2, CS3, and CS4, as shown in Fig. 5.

A. System Setup

We consider a system with four charging stations. They are all equipped with PV panels and batteries, but their capacities are different. The related batteries parameters are $E_{b,1}/E_{b,2} = E_{b,3}/E_{b,4} = 100/150/200/200$ kWh, $p_{b,1}^{c,max} = p_{b,4}^{d,max} = 30$ kW, $p_{b,2}^{c,max} = p_{b,3}^{d,max} = 45$ kW, $p_{b,3}^{c,max} = 60$ kW, $p_{b,4}^{c,max} = 60$ kW, $\eta_d = 0.95$, $c_{b,1}/c_{b,2}/c_{b,3}/c_{b,4} = 0.1$. The sale electricity price to the utility grid $\lambda_d$ is set to be a constant value 0.01 $$/kWh$. The maximum allowable traded power of the charging station is set as $p_{g,i}^{b,max} = p_{g,i}^{s,max} = 300$ kW, $\forall i$. In general, the number of EVs charging at a charging station reflects how busy the station is. If a charging station has more EV charging tasks, its charging pattern is more severe, and vice versa. We consider four charging stations with different busy levels: mild, moderate, and severe.

The number of chargers in each station $N_{chg,i}$ is 20. The daily number of EVs charging at station $i$ is $|V|_i$. A bigger ratio $|V|_i/N_{chg,i}$ means a severer charging pattern. For CS1, there are $|V|_1 = 30$ EVs during 6:00-22:00, i.e., $|V|_1/N_{chg,1} = 1.5$, representing a moderate charging pattern. The CS2 has a mild charging pattern, in which there are $|V|_2 = 20$ EVs during 6:00-22:00, i.e., $|V|_2/N_{chg,2} = 1$. The CS3 also has a moderate charging pattern with $|V|_3 = 30$ ($|V|_3/N_{chg,3} = 1.5$), but with 15 EVs during 4:00-14:00 and 15 EVs during 14:00-23:00. The CS4 has a severe charging pattern, $|V|_4 = 40$ ($|V|_4/N_{chg,4} = 2$), and there are 10 EVs during 2:00-8:00, 10 EVs during 8:00-14:00, 10 EVs during 14:00-20:00, and 10 EVs during 20:00-23:00. Other EV charging related parameters are $E_v = 40$ kWh, $soc^{min} = 0.1$, $soc^{max} = 0.9$, $soc^{int} = 0.2$, $soc^{eq} = 0.5$, $c_{es,i} = 0.1$. For the chargers, we have $p_{chg} = 6.6$ kW. We set the upper and lower limits of voltage magnitude in each bus as 1.06 p.u. and 0.94 p.u., respectively. The time-of-use electricity prices $\lambda_d(t)$ come from PJM [37] and the PV irradiation data comes from NREL [38]. As for PV power capacity and battery storage parameters, we refer to the similar typical parameters in [25]. For EV parameters, we refer to the Nissan Leaf EV model with battery pack 40 kWh and maximum charging power 6.6 kW [17].

B. Aggregate EV Power Flexibility

Fig. 6 shows the obtained aggregate EV power flexibility regions of the four charging stations based on the first stage problem. The area between the upper and lower power trajectories is the aggregate power flexibility that is available to dispatch by charging stations in the second stage. Within this area, any power trajectory is dispatchable and can satisfy the EVs’ charging requirements. Here, we randomly pick up one EV power trajectory in CS1 and recover its dispatch in Fig. 7. The charging power, charging status, and SOC all satisfy the constraints, which validates Proposition 1.

The aggregate EV power flexibility under different $w$ is shown in Fig. 8 (the grey area). When $w = 0$, the power flexibility
region is concentrated in periods 19, 20, and 22. With the help of the quadratic term parameterized by \( w \) in the objective function, the power flexibility region becomes more evenly distributed. This provides more available dispatchable opportunities for the charging station. But it is also worth noting that \( w \) should not be too large. As in Fig. 8, with the increase of \( w \), the power flexibility region gradually narrows. This is because that a larger \( w \) emphasizes more on the variance of power flexibility across different periods (as described in Appendix A), but less on maximizing the total power flexibility.

C. Exactness of the Second-Order Conic Relaxation and Convergence of the Proposed Coordination Mechanism

With the aggregate EV power flexibility obtained in the first stage, we then run the coordination mechanism proposed in the second stage to settle the energy transactions. At the equilibrium point, the voltages of buses with charging stations are shown in Fig. 9. We can see that all the voltages are within the allowable range. In addition, to check the exactness of the second-order conic relaxation, we also illustrate the difference between the left hand side \( P_{ij}(t)^2 + Q_{ij}(t)^2 \) and the right hand side of the inequality (25). As shown in Fig. 10, all gap values are less than \( 10^{-6} \), which is very small. That is, equality almost holds for the inequality constraint (25), so the second-order conic relaxation is exact.

Fig. 11 shows the convergence of the proposed distributed coordination mechanism. It can be found that the number of iterations to reach convergence is about 42, which indicates that the convergence speed is fast and acceptable.

D. Performance Evaluation

To demonstrate the advantages of the proposed mechanism, the conventional method (11) and (20) is used as a baseline. In the baseline, each charging station operates individually to calculate the input/output power from/to the grid.

1) Cost Comparison: TABLE II summarizes the costs under the two different mechanisms. The total cost of each charging station \( C_i \) comprises the energy trading cost \( C_{g,i} \), battery operation cost \( C_{b,i} \), and EV dissatisfaction cost \( C_{ev,i} \). The proposed mechanism (212 USD) performs better than the baseline (293.36 USD) with a significant total cost reduction (27.73%). In particular, under the proposed mechanism, the energy trading cost \( C_{g,i} \) for charging stations (CS2, CS3, and CS4) are negative, which means that they can earn revenue from selling energy to other charging stations or the utility grid instead of paying more on buying energy from the utility grid under the baseline. For the DSO, the proposed mechanism can also achieve a lower total cost (517.86 USD) than the baseline (547.89 USD). Specifically,
TABLE II  
COST COMPARISON BETWEEN BASELINE AND PROPOSED MECHANISM (UNIT: USD)

|                  | Charging station | Distribution network | Total cost | Reduction |
|------------------|------------------|----------------------|------------|-----------|
|                  | $C_{g,i}$   | $C_{b,i}$ | $C_{w,i}$ | $C_i$ | $\sum_{i\in\mathcal{G}} C_i$ | $C_{b,\text{loss}}$ | $C_{g,\text{loss}}$ | $C_{d,\text{so}}$ | |
| Baseline         | 71.71      | 12.65   | 21.99    | 106.35 | 293.36 | -71.71   | -27.78        | 547.89   | 841.24   | -        |
| Proposed         | 53.20      | 19.02   | 31.06    | 103.28 | 212.00 | -53.20   | -35.87        | 517.86   | 729.87   | 13.24%   |

Compared with the baseline, the proposed mechanism can reduce the amount of energy bought from the utility grid. In addition, the power loss cost of the proposed method is also lower than that of the baseline. This reduction in power loss benefits the transmission line. Finally, as seen in the table, the proposed mechanism (729.87 USD) outperforms the baseline (841.24 USD) in terms of the total cost of the overall system, with a great decrease (13.24%). In conclusion, the proposed mechanism can not only benefit the charging stations, but also the distribution network by reducing power losses and costs, resulting in a win-win situation.

2) Impact on Power Loss: To understand the impact of energy trading on the power flow of the distribution network, Fig. 12 visualizes the power loss on each line by using the line width to represent the amount of power loss. The thicker the line, the greater the power loss. In the circled area covering the charging stations and bus 1, the proposed method (Fig. 12(a)) generates much thinner lines than the baseline (Fig. 12(b)). This indicates less power loss in these lines, which is beneficial to prolong the service life of transmission lines. It can be concluded that the proposed coordination mechanism can promote local transactions and reduce the power loss of the distribution network.

3) Energy Trading Price: Since the energy trading cost accounts for the majority of the overall cost of the charging stations in both the proposed mechanism and the baseline, it would be interesting to analyze the energy trading prices underlying the outcomes. As mentioned before, under the proposed mechanism, the energy trading price is determined by the dual variable of (17), which well reflects the value of electricity at different buses, accounting for the load and generation levels, and the physical limits of the transmission lines, etc. Fig. 13(a) shows the energy trading price profiles of four charging stations. First, the trading prices of the four charging stations follow the same trend. This is because they are located close to each other. As a counter example, a case that the four charging stations are located far from each other (located at bus 7, 22, 25, and 33) is also simulated. Fig. 13(b) shows their trading prices. As seen, the trading prices are different and divergent.

4) Internal Power Distribution of Each Charging Station: Fig. 14 shows the charging station’s internal power distribution...
among the grid, battery energy storage, and PV, as well as
the SOC evolution of battery energy storage under the pro-
posed mechanism. For comparison, Fig. 15 shows the power
distribution under the baseline, which presents distinct features
from Fig. 14. A major difference is that: according to the SOC
level, the battery storage was not fully utilized in the baseline,
particularly for CS2-CS4; while under the proposed mechanism,
the battery SOCs of the four charging stations vary in the same
trend and experience a complete charging and discharging cycle.
Thus, it can be deduced that with the proposed properly designed
coordination mechanism and energy trading price, the utilization
of energy storage can be greatly promoted.

5) Scalability: To show the scalability of the proposed mech-
anism, we compare the computational time under different
number of charging stations: 4, 8, 12, 16, and 20. As seen in
Fig. 16, when the number of charging stations increases, the
total computational time of a CSO and DSO remains about
7 s and 150 s, respectively. This is because the calculations
of charging stations can be run in parallel. Therefore, the proposed
mechanism is not sensitive to the number of charging stations.

E. Real-Time Adjustment to Deal With Uncertainties

To demonstrate the effectiveness of the real-time adjustment
method in Appendix D, we conduct the following simulations.
We consider such a scenario: 5 EVs arrives at charging station
1 (CS1) 4 hours later than their submitted arrival times, 5 EVs
arrive at CS2 3 hours later, 4 EVs arrive at CS3 2 hours earlier,
and 3 EVs arrive at CS4 3 hours earlier. The actual PV power
deviations from the day-ahead predictions are also considered.
Take CS1 as an example, the simulation results are shown in
Fig. 17. Though there are uncertainties from EVs, the day-ahead
charging demand can still be well tracked in real-time through
the proposed method. The battery storage is adjusted to deal with
the deviations of PV generation and EV charging demands. As a
result, the real-time trading power with the distribution network
almost remains the same as the day-ahead scheduled value. This
validates the effectiveness of the real-time adjustment method
for addressing uncertainties.

F. Financial Benefit Allocation to Engage EVs

We compare the costs of charging stations under the pro-
posed method and the charging as soon as possible (CASAP)
method in TABLE III. The CASAP results in a higher total
cost (260.71 > 96.06) and the total cost difference between the
proposed and CASAP methods is $B^{\text{tot}}_{cs} = 260.71 - 96.06 = 164.65
USD. The benefit allocation method proposed in Section IV-E
is applied. The costs of each EV under the CASAP method
and the proposed method before and after benefit allocation are
shown as Fig. 18. It can be seen that the costs of each EV and
each charging station are no more than those under the CASAP
method, as shown in TABLE III and Fig. 18. Hence, all EVs are
willing to participate in the management scheme.
VI. CONCLUSION

This paper proposes a two-stage scheme to coordinate the EV charging stations. In the first stage, different from the existing approaches that assume the charging station has complete information about the EVs therein, we use an aggregate EV power flexibility region instead. This can protect EV owners’ privacy and be much easier for the charging station to dispatch. In the second stage, a novel distributed coordination mechanism is proposed. We prove that the proposed mechanism can converge to the centralized optimum. Simulations demonstrate the effectiveness of the proposed scheme and have the following findings:

1. Compared with the traditional method using a uniform price, the proposed coordination mechanism can achieve a significant total cost reduction of 13.24%.

2. The energy sharing between charging stations affects the local power flow of the distribution network, leading to a lower power loss.

3. Energy trading enhances the utilization rate of the battery storage deployed in the charging stations.

Future work includes: 1) a more elaborate day-ahead model to incorporate diverse types of uncertainties; 2) an improved approach with less dependence on the communication infrastructures; and 3) a fairer benefit allocation method for charging stations and EVs.

APPENDIX A

EXPLANATION FOR THE OBJECTIVE FUNCTION (1a)

Let \( x_{d,i}(t) = \hat{p}_{d,i}(t) - \hat{p}_{d,i}(t) \). Given the total flexibility across all periods \( \sum_{t \in T} x_{d,i}(t) \), we want to make the flexibility be distributed as evenly as possible by minimizing the following variance:

\[
\min \sum_{t \in T} \left( x_{d,i}(t) - \frac{1}{T} \sum_{t \in T} x_{d,i}(t) \right)^2 = \sum_{t \in T} x_{d,i}(t)^2 - \frac{1}{T} \sum_{t \in T} x_{d,i}(t)^2 \quad (\text{A.1})
\]

Since we assume that \( \sum_{t \in T} x_{d,i}(t)^2 \) is given, the second and third terms are constants that can be ignored. Hence, the above formula is equivalent to minimize the first term \( \sum_{t \in T} x_{d,i}(t)^2 \), which is just the quadratic term in objective function, i.e.,

\[
\max \sum_{t \in T} (\hat{p}_{d,i}(t) - \hat{p}_{d,i}(t)) - \omega(\hat{p}_{d,i}(t) - \hat{p}_{d,i}(t))^2.
\]

The first term in the objective function aims to maximize the total power flexibility. The parameter \( \omega \) acts as the weight to make a tradeoff between maximizing total power flexibility and minimize the variance.

APPENDIX B

PROOF OF PROPOSITION 1

For each time slot \( t \in T \), since \( p_{d,i}(t) \in \left[ \hat{p}_{d,i}(t), \hat{p}_{d,i}(t) \right] \), we can define an auxiliary coefficient:

\[
\alpha(t) := \frac{\hat{p}_{d,i}(t) - \hat{p}_{d,i}(t)}{\hat{p}_{d,i}(t) - \hat{p}_{d,i}(t)} \in [0, 1]
\]

so that \( p_{d,i}(t) = \alpha(t) \hat{p}_{d,i}(t) + (1 - \alpha(t)) \hat{p}_{d,i}(t) \). Then, we can construct a feasible EV dispatch strategy by letting

\[
\begin{align*}
\beta_c(t) & = (1 - \alpha(t)) \beta_{c_i}(t) \\
\delta_c(t) & = (1 - \alpha(t)) \delta_{c_i}(t) \end{align*}
\]

for all time slots \( t \in T \).

We prove that it is a feasible EV dispatch strategy as follows. First, due to (1p) we have \( s_i^c = s_i^c = s_i^c \), thus, constraints (1d) and (1h) hold for \( s_i^c(t) \). Furthermore,

\[
\begin{align*}
q_{d,i}(t) & = \alpha(t) \hat{q}_{d,i}(t) + (1 - \alpha(t)) \hat{q}_{d,i}(t) \\
& = \alpha(t) \sum_{v \in V_i} \beta_{c_i}(t) + (1 - \alpha(t)) \sum_{v \in V_i} \beta_{c_i}(t) \\
& = \sum_{v \in V_i} [\alpha(t) \beta_{c_i}(t) + (1 - \alpha(t)) \beta_{c_i}(t)] \\
& = \sum_{v \in V_i} p_{c_i}(t) \quad (B.3)
\end{align*}
\]

Hence, constraint (1b) holds for \( p_{d,i}(t) \) and \( p_{c_i}(t) \), \( \forall v \). Similarly, we can prove that constraints (1c), (1e)-(1g) are met. Therefore, we have constructed a feasible EV dispatch strategy, which completes the proof.

APPENDIX C

PROOF OF PROPOSITION 2

For objective function (21a), if we add a constant term \( -\beta_{k_{p,i}}(t) k_{p,i}(t) \Delta t \) to it, this won’t affect the optimal solution of the problem. Then we can reorganize the objective function as follows

\[
C_t(x_k) = C_{b,i} + C_{e,i} + \sum_{t \in T} [p_{g,i}(t) - \beta_{k_{n_i}}(t)] \Delta t
\]

\[
+ \sum_{t \in T} \frac{\rho}{2} (p_{g,i}(t) - \beta_{k_{n_i}}(t))^2.
\]
Similarly, we add a constant term \( p_{g,i}^{k+1}(t) \lambda p_{i}^{k}(t) \Delta t \) to the objective function (22a), and reorganize it into:

\[
C_{dso}(x_d) = C_{bus1} + C_{loss} + \sum_{t \in T} \left[ p_{g,i}^{k+1}(t) - p_{n}(t) \right] \lambda p_{i}^{k}(t) \Delta t + \sum_{t \in T} \frac{p_{g,i}^{k+1}(t) - p_{n}(t))^2}{2}.
\]  
(C.2)

After the equivalent transformations, we can find that our proposed mechanism turns into the classical ADMM framework. It has been proven that the distributed ADMM framework has good convergence performance and can converge to a centralized optimum if the problem is convex. Recall that we have carried out convex relaxation (25) in dealing with the first issue. Therefore, we can easily prove Proposition 2 following a similar procedure as the ADMM framework.

**APPENDIX D**

**REAL-TIME ADJUSTMENT METHOD**

To differentiate, denote the aggregate EV charging power strategy and the scheduled energy trading power with the distribution system returned by the proposed two-stage coordination scheme by \( p_{da}^{t}(t) \), \( \forall t \) and \( p_{rt}^{t}(t) \), \( \forall t \), respectively.

**At time slot \( t = 1 \):**

**Step 1:** First, for charging station \( i \), the day-ahead determined strategy \( p_{da}^{t}(t) \), \( \forall t \) is used as a reference to be tracked in real-time. The smart EV management system will use the realized EV information at \( t = 1 \) and the predicted future information for \( t = 2, \ldots, T \) to update the real-time EV aggregate power strategy \( p_{da}^{t}(t) \), \( \forall t \) by solving:

\[
\begin{align*}
\min & \quad \sum_{t \in T} \left( p_{da}^{t}(t) - p_{rt}^{t}(t) \right)^2, \\
\text{s.t.} & \quad p_{da}^{t}(t) = \sum_{v \in V} p_{v}^{t}(t), \quad \forall t \\
 & \quad -s_{v}^{t}(t) p_{chg} \leq p_{v}^{c}(t) \leq s_{v}^{c}(t) p_{chg}, \quad \forall v, \forall t \\
 & \quad 0 \leq p_{v}^{c}(t) \leq s_{v}^{c}(t), \quad \forall v, \forall t \\
 & \quad soc_{v}^{t}(t) = soc_{v}^{mi} + soc_{v}^{d}(t) \geq soc_{v}^{eq}, \quad \forall v \\
 & \quad soc_{v}^{t}(t + 1) = soc_{v}^{t}(t) + \frac{p_{v}^{c}(t) \Delta t}{E_{v}}, \quad \forall v, \forall t \neq T \\
 & \quad soc_{v}^{min} \leq soc_{v}^{t}(t) \leq soc_{v}^{max}, \quad \forall v, \forall t \\
 & \quad \sum_{v \in V} p_{v}^{c}(t) \leq N_{chg,i}, \quad \forall t \\
 & \quad \begin{cases} 1 & \text{if } t \in \left[ t_{d}, t_{d}^{1/2} \right], \\
 0 & \text{if } t < t_{d}, \quad \forall v, \forall t. \end{cases}
\end{align*}
\]  
(D.1a)–(D.1i)

where \( T = \{ 1, \ldots, T \} \).

**Step 2:** With the \( p_{da}^{t}(t) \), \( t \in T \) output by (D.1), the realized PV power \( p_{pr}^{t}(1) \) at \( t = 1 \), and its predictions for \( t = 2, \ldots, T \), the charging station \( i \) solves (D.1) to track the day-ahead scheduled energy trading power with the distribution system 

\[
\begin{align*}
\min & \quad \sum_{t \in T} \left( p_{da}^{t}(t) - p_{rt}^{t}(t) \right)^2 + c_{b,i} \left( p_{b,i}^{t}(t) - p_{crt}^{t}(t) \right) \Delta t, \\
\text{s.t.} & \quad p_{da}^{t}(t) = p_{da}^{t}(t), \quad \forall t \\
 & \quad p_{b,i}^{t}(t) = p_{da}^{t}(t) + p_{rt}^{t}(t) + p_{b,i}^{d}(t) - p_{crt}^{t}(t), \quad \forall t \\
 &\text{where the first term in the objective function is the gap between actual and day-ahead scheduled power, and the second term is the battery operation cost. (D.2b) represents the new power balance.}
\end{align*}
\]  
(D.2a)–(D.2c)

The above obtained real-time strategies at \( t = 1 \) will be implemented, such as \( p_{da}^{t}(1) \) and \( p_{rt}^{t}(1) \).

**At time slot \( t = 2 \),** the above similar procedure will be performed with the updated information of EVs, PV power generation, and the time horizon changes to \( \mathcal{T} = \{ 2, \ldots, T \} \).

... Until \( t = T \).

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