A Distributed Electric Vehicle Charging Scheduling Platform Considering Aggregators Coordination

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ABSTRACT

In this paper, a two-layer distributed optimization platform employing the alternating direction method of multipliers (ADMM) method is developed as an exchange problem to solve the electric vehicle charging management problem (EVCMP). The proposed model establishes a coordination layer between the EV aggregators, which increases the optimization’s overall efficiency while preserving aggregators’ independence. Numerical tests validate that the proposed coordinated distributed platform (CDP) enhances the load profile’s smoothness compared to the locally coordinated and uncoordinated charging platforms. Moreover, CDP also decreases the total EV charging costs by 35%, compared to the uncoordinated charging approach.

INDEX TERMS

Alternative direction method of multipliers, battery degradation, distributed optimization, electric vehicle aggregation, mixed integer programming.

I. INTRODUCTION

A. AIMS AND MOTIVATION

The global EV industry continues to expand rapidly. It is expected that the number of public and private chargers for EVs (excluding two/three-wheelers) grows from 870 thousand and 6.4 million today to almost 11 and 135 million in 2030, respectively [1]. These chargers provide around 470 TWh of energy, which will account for 1%, 3%, and 4% percent of electricity consumption in the US, Europe, and China, respectively [1]. This massive energy could overburden the power grid at certain times of day if appropriate control actions on charging processes are not taken [2]. Considering the current structure of the EV charging market in which different entities such as nonprofits and profit aimed charging companies, automakers, and utilities are the owners of charging equipment and responsible for controlling the charging and discharging processes [3], the role of EV aggregator (EVA) in EV charging management problem (EVCMP) is undeniable.

The coordination of EVs operation can form a sizeable virtual storage capacity capable of offering ancillary services to the grid [4]. Besides, considering the EVA’s collaboration can further enhance the EV potential to reshape the electricity load curve while preserving the EVs and EVAs’ objectives and constraints.

The coordination methods used to solve EVCMP are classified in centralized and distributed approaches [5]. Centralized control schemes provide an optimal solution for EVCMP, but they require a complex communication network and sensitive information communication. In a centralized approach, EV users first admit to sharing their private information with an EVA. Then the EVA solves the optimization problem for all EVs and itself [6]. On the other hand, EVAs have a more passive role in distributed approaches compared to the centralized methods [5]. Distributed optimization methods have the advantages of distributing the computational tasks among many entities to provide each entity with a manageable problem size [7, 8]. Therefore, EVs and EVAs are both responsible for solving their optimization problem according to the global optimization constraints. Distributed optimization not only mitigates the users’ privacy preservation concerns but also minimizes the significant communication overhead and computational burden in centralized model [8, 9].

The distributed charging management literature can be classified based on the number of coordination layers. A single coordination layer scheme only includes the coordination between EV and EVA, but a two-layer coordination scheme considers the coordination among EVAs as well. Given different types of EVAs with a wide variety of objectives and constraints, it is required to consider a communication layer among EVAs to increase the system’s overall efficiency.
while fulfilling the individual EVA constraints in a distributed optimization platform.

B. RELEVANT LITERATURE

The problem of defining distributed schemes for EVs’ charging control has been investigated in several studies [9, 10]. Distributed algorithms can be classified into (sub)gradient method and consensus theory. Gradient-based methods are well-established distributed/decentralized algorithms [9, 11]. As a cooperative charging management problem for plug-in EVs, authors in [5] use a gradient descent method for constrained optimization called “Consensus and Innovation.” Reference [12] deploys a projected gradient descent approach, and [13] implements a shrunken primal-dual sub-gradient algorithm to control EVs charging and solve the load variance minimization problem.

The ADMM approach [14] is more implemented among the decentralized methods in the literature because of its capability to support non-strictly convex cost functions and to handle large-scale problems [7, 14]. ADMM is used in [15–18] to solve the EVCMP. However, most of these papers consider a single coordination layer between EVs and EVA to solve EVCMP [15, 16] or neglect the coordination among them [17, 18].

Although [17, 18] study several aggregators, their proposed model does not analyze the collaboration between EVAs and its benefits over a system without this collaboration. Reference [19], compares three algorithms based on the method of multipliers and projected gradient descent where EVAs communicate with other EVAs, but the EVs goals are not investigated. A Sparsity-promoting distributed charging control between EVAs is employed in [20]. However, the EVs charging objective functions and constraints are simplified.

Reference [21] develops a non-cooperative platform based on game theory among the EVAs. Although in [21] the distributed platform, each EVA considers the actions of the neighboring aggregator, the EV charging management is controlled directly by EVAs within a centralized platform, where EV charging start time and energy profiles are determined by the EVA.

Although [22] proposes a distributed model to solve EVCMP that considers the collaboration among EVA, it uses the distribution system operator as the central coordinator. Moreover, it considers a centralized platform between EVAs and EVs in which EVAs determine the charging and discharging programs of EV. Reference [21] devises a competitive-non-cooperative game that considers the actions of the neighboring aggregators. But the model in the first layer (EV-EVA coordination layer) is centralized in which EVAs determine EVs charging energy profiles and charging start time [21]. Furthermore, it should be pointed out that features such as the ownership, geographical location and load type provide us with different kinds of EVAs with a wide variety of objectives and constraints [1]. For example, considering charging ownership, aggregation of private EV charging events (e.g., Home charging) and public EV charging events (e.g., street charging) are usually performed by different EVAs which have distinct objectives [23]. However, the EVCMP literature mostly considers one kind of aggregator, and ignore the others [15], [18].

Advance charging management algorithms and the proliferation of bidirectional chargers provide the opportunity to modify the agents’ objective functions and constraints to illustrate the effect of the vehicle to grid (V2G) technology. To accomplish this goal employing mixed-integer quadratic programming (MIQP) ADMM-based optimization platform is a popular solution [24]. In the case of application, [25] introduces the application of integer programming in a decentralized unit commitment problem, and [22] uses the same concept in distributed EV optimization. Reference [26] develops [15] by establishing a single layer MIQP ADMM-based platform to solve EVCMP and reformulate the problem constraints by considering individual positive and negative power exchange tariffs and individual EV and EVA charging/discharging constraints.

In terms of the objective function, since a distributed framework lets each agent have its objective, the distributed EVCMP literature includes different EVs’ goals [27]. Minimizing the battery degradation cost is one of these objectives, which inspires the investigation of the batteries’ optimal operation. Considering EVs discharging capability and its importance in load management of future power systems, the effect of EVs discharging and charging should be viewed individually in battery degradation optimization. Nevertheless, considering the battery degradation cost models in distributed EV charging platforms is notably challenging due to the convexity problems. Hence, distributed EV charge management schemes involving accurate and realistic battery models are required [9]. References [15, 22] deal with the optimal trade-off between the accumulated battery degradation cost of EVs and the total generation cost in a distributed charging management scheme, but the proposed battery degradation cost (BDC) models are simplified. The BDC model presented in [20] also does not consider the individual effects of V2G in battery degradation. Reference [18, 28] present a more detailed BDC model by considering the cell units’ number in EVs’ batteries, cell units’ energy capacity, and the nominal voltage. However, using non-integer programming is not suitable to assess the effects of the discharging capability in their model.

The results and analysis in this work differ from the related papers in the literature in several aspects. Unlike [15–19, 22] which do not consider the EVA collaboration, a two-layer coordinated distributed EV charging platform is established in this paper. Two types of aggregators, which aggregates different types of EV loads in private and public charging events, are considered in this work. The presented model not only considers the data exchange between EVA and their corresponding EVs via a distributed platform but also, as opposed to [21] provides the opportunity for collaboration among different types of aggregators. In addition, there is no need to share EVs’ sensitive information, such as driving
patterns and individual user energy requirements, among aggregators. Furthermore, while the proposed distributed optimization problem considers battery degradation model effects on EVCMP, it is not only focused on the EV charging process as in [15, 20, 22, 24, 25]. Instead, we reformulate the optimization problem as a MIQP problem and develop the battery degradation cost proposed in [18, 26, 28] to analyze the significant effect of EV discharging capability on meeting the EVAs and EVs goals and capacity constraints. Furthermore, CDP provides the opportunity to consider different tariffs for negative and positive power exchange with the grid and individual charging and discharging constraints using a MIQP model.

In this paper, individual EVA’s aim is load variance minimization. Besides, the EVs have two goals: minimizing the charging cost and the battery degradation cost.

C. CONTRIBUTIONS AND ORGANIZATION

In this paper, a two-layer distributed EV charging management platform is developed considering the EVA collaboration. The main contributions of this paper are summarized as follows:

- **Novel Distributed Platform:** A two-layer distributed EV charging management platform is established, which is responsible for EVs and EVA coordination in the first layer and the EVAs collaboration in the second layer. The performance of the developed EVAs collaboration layer is then assessed, and its impact on the overall efficiency of EVs and EVAs’ objectives is analyzed. The second layer updates each aggregator information about the load profile of other EVAs.

- **Comprehensive Battery and Energy Exchange Models:** The BDC model proposed in [28] is expanded to demonstrate the effects of EVs’ discharging capability. In this regard, the CDP is reformulated as a MIQP optimization to assess the impacts of EVs’ discharging capability. The proposed model is also capable of considering asymmetric tariffs for negative and positive power exchange of EVs with the grid. Moreover, the expanded CDP also considers EV battery in both charging and discharging processes individual charging and discharging constraints.

This paper extends the scope of the authors’ previous work [29] in three fronts: (i) it explains the proposed platform’s theory and mathematical background in more detail; (ii) it conducts a comprehensive evaluation focusing on analyzing the effects of the V2G and energy constraints on EV and EVAs’ metrics in CDP; (iii) it demonstrates the convergence rate of primal and dual residuals of the CDP.

The paper is organized as follows. Section II elaborates the mathematical formulation of the objective function and constraints. Section III initially explains the problem decomposition model, then reformulates the optimization problem based on CDP. Simulations’ data, metrics, and numerical results are presented in Section IV. This paper concludes and envisions future works in Section V.

II. MATHEMATICAL MODEL OF EV AGGREGATION

This paper establishes an EVCMP for a finite time horizon \( t \in T = \{1, \ldots, T\} \). Assuming that each EVA involved aggregates \( N_i \) EVs, where \( i \in \{1, \ldots, M\} \) and \( j \in \{1, \ldots, N_i\} \) denote the set of EVA and EVs, respectively. The EVCMP can be expressed as

\[
\begin{align*}
\text{minimize} & \quad \sum_{i=1}^{M} \left\{ F^a_i(x^a_i, \hat{x}^a_i) + \gamma_i \sum_{j=1}^{N_i} F_{i,j}(x_{i,j}) \right\} \\
\text{subject to} & \quad x^a_i = \sum_{j=1}^{N_i} x_{i,j} \quad \forall i \\
& \quad x_{i,j} \in \mathbb{X}_{i,j} \quad \forall i \\
& \quad x_{i,j} \in \mathbb{X}_{i,j} \quad j = 1, \ldots, N_i \quad \forall i
\end{align*}
\]

where \( F^a_i(x^a_i, \hat{x}^a_i) \) and \( F_{i,j}(x_{i,j}) \) are the objective functions associated to EVA \( i \) and EV \( j \), respectively; \( x^a_i \) denotes the power aggregated by EVA \( i \), \( \hat{x}^a_i = \sum_{z \neq i} x^a_z \) stands for the sum of the other aggregators’ power exchange with the grid at each time step, and \( x_{i,j} \) denotes the charging power of EV \( j \) with \( x_{i,j} < 0 \) for discharging; \( \gamma_i \geq 0 \) represents the trade-off between these objective functions; \( \mathbb{X}^a_i \) and \( \mathbb{X}_{i,j} \) denote the feasible sets of EVA \( i \) and EV \( j \) decision variables, respectively. The objective functions and constraints of Eq. (1) explained in the following sections. The optimal value of \( \gamma \) is chosen based on the study conducted in [15, 26].

A. INDIVIDUAL EV OBJECTIVE FUNCTIONS

In the proposed model, every EV optimizes its preferred (local) objective function and sends its charging profile to the corresponding EVA. To consider the effects of battery degradation cost and electricity bill cost (EBC) on the final EVs’ charging profile, we consider the minimization of these two terms as the objective function of EVs. The objective function of any EV \( i,j \), aggregated by any EVA, thus, can be mathematically written as follows:

\[
F_{i,j}(x_{i,j}) = \beta_{1i} \sum_{t=1}^{T} \left( \pi_{i,t}^\text{ch} x_{i,j,t} - \pi_{i,t}^\text{dis} x_{i,j,t} \right) + \beta_{2i} \sum_{t=1}^{T} \left( \alpha_{1i} (p_{i,j,t}^\text{ch} x_{i,j,t})^2 + \alpha_{2i} p_{i,j,t}^\text{dis} x_{i,j,t} \right) + \alpha_{3i}
\]

where electricity bill cost (first term) and BDC (second term) are weighted by \( \beta_{1i} \) and \( \beta_{2i} \in [0, 1] \), respectively, to form the weighted sum objective function. \( p_{i,j,t}^\text{ch} \) and \( p_{i,j,t}^\text{dis} \) denote charging and discharging variables, respectively, where \( x_{i,j,t}=p_{i,j,t}^\text{ch} \). Charging and discharging fee are represented by \( \pi_{i,t}^\text{ch} \) and \( \pi_{i,t}^\text{dis} \), \( \alpha_{1i} \), \( \alpha_{2i} \), and \( \alpha_{3i} \) represent constant battery degradation cost coefficients.

In [18, 28], the battery degradation cost is developed as a quadratic function. It is essential to know that the charging process to satisfy the EV users’ requested energy has much less impact on the final degradation cost than when EV users use their discharging capability. Therefore, to show the
considerable effects of discharging on the battery degradation cost in the objective function, the battery model presented in [28] is modified to calculate battery charging and discharging degradation costs separately. It should be noted that \(\alpha_{ij}, \alpha_{ij}^{\text{dis}}\), and \(\alpha_{ij}^{\text{ch}}\) are determined based on the number, energy capacity, nominal voltage, and price of energy units of each battery cell [28]. The impacts of EV charging and discharging on EBC are also considered in the second term of Eq. (2). Considering the EVs’ discharging capability, different negative and power exchange tariffs are used in this equation. In addition, each EVA can define its discharging price.

### B. INDIVIDUAL EV CONSTRAINTS

The constraints of EV\(_{i,j}\), aggregated by any EVA\(_i\), are developed as follows:

\[
ED_{i,j} = \sum_{t=1}^{T} \left( p_{i,j}^{\text{ch}} - p_{i,j}^{\text{dis}} / \eta_{i,j}^{\text{dis}} \right) / m \tag{3a}
\]

\[
x_{i,j,t} = u_{i,j}^{\text{ch},t} - u_{i,j}^{\text{dis},t} \tag{3b}
\]

\[
u_{i,j}^{\text{ch},t} + u_{i,j}^{\text{dis},t} \leq A_{i,j,t} \tag{3c}
\]

\[
0 \leq p_{i,j}^{\text{dis},t} \leq p_{i,j}^{\text{max},t} u_{i,j}^{\text{dis},t} \tag{3d}
\]

\[
0 \leq p_{i,j}^{\text{ch},t} \leq p_{i,j}^{\text{max},t} u_{i,j}^{\text{ch},t} \tag{3e}
\]

\[
E_{i,j,t+1} = E_{i,j,t} + \frac{1}{m} \sum_{t=1}^{T} \left( \eta_{i,j}^{\text{ch},t} x_{i,j,t} - p_{i,j}^{\text{dis},t} / \eta_{i,j}^{\text{dis}} \right) \tag{3f}
\]

\[
E_{i,j,t} \leq E_{i,j,t} \tag{3g}
\]

where \(ED_{i,j}\) stands for the EV\(_{i,j}\) energy demand; \(\eta_{i,j}^{\text{ch}}\) and \(\eta_{i,j}^{\text{dis}}\) denote EVs’ charging and discharging efficiency, respectively; \(m\) represents the number of time steps in an hour. Energy balance equation is shown in Eq. (3a), and Eq. (3b) decomposes the \(x_{i,j,t}\) to charging and discharging variables. Eq. (3c) prevents simultaneous charging and discharging where \(A_{i,j,t} \in \{0,1\}\) stands for EV\(_{i,j}\) connection status and charging and discharging binary status are represented by \(u_{i,j}^{\text{ch},t}\) and \(u_{i,j}^{\text{dis},t}\), respectively. It should be noted that adding these binary variables turn the problem to an MIQP problem [25]. Eq. (3e) and Eq. (3d) present the maximal discharging and charging constraints. Note that the overlined and underlined letters represent the upper and lower limits variables, respectively. To consider the technical limits of EVs’ batteries and their impacts on the aggregated EVs load profile, energy constraints are considered in Eq. (3f) and Eq. (3g). The equality constraint represents the energy balance of EVs’ batteries at each time step, and the inequality constraint shows the maximal and minimal battery capacity. It is worth noting that the proposed model is integer programming because of the binary variables. However, the ADMM-based approach has been confirmed valid to converge in a finite number of iterations [24, 25]. Note that regardless of the EV and EVA set of objectives, the problem is always quadratic because of the augmented Lagrangian portion of ADMM formulation.

### C. EV AGGREGATOR OBJECTIVE FUNCTION

While each EV controls EBC and BDC, EVAs carry out the valley filling in off-peak hours and peak shaving in peak hours, which helps the power grid operator to manage the demand more efficiently. In this work, private EVAs (Pr) and public EVAs (Pu) aggregate private and public EV charging events, respectively. It is essential to know that based on the proposed CDP, each aggregator should have access to the aggregated demand profile of other aggregators to achieve the load variance minimization goal. That is why we update the EVAs’ objective function in (1) considering the EVAs’ collaboration. The load variance minimization problem is developed as follows:

\[
F_1(x_{i}^{a}, \hat{x}_{-i}^{a}) = \delta(|D_{i} + x_{i}^{a} - \hat{x}_{-i}^{a}|^2 / 2) \tag{4}
\]

where \(\delta\) is a scaling empirical parameter that changes the EVAs’ objective function unit. The non-EV demand profile \(D_{i} \in \mathbb{R}^T\) is assumed to be known.

### D. EV AGGREGATOR CONSTRAINTS

EVAs constraints are presented as follows:

\[
u_{i,t}^{a,\text{ch}} + u_{i,t}^{a,\text{dis}} \leq 1 \tag{5a}
\]

\[
x_{i,t}^{a} = p_{i,t}^{a,\text{ch}} - p_{i,t}^{a,\text{dis}} \tag{5b}
\]

\[
0 \leq p_{i,t}^{a,\text{dis}} \leq p_{i,t}^{a,\text{max},t} u_{i,t}^{a,\text{dis}} \tag{5c}
\]

\[
0 \leq p_{i,t}^{a,\text{ch}} \leq p_{i,t}^{a,\text{max},t} u_{i,t}^{a,\text{ch}} \tag{5d}
\]

where the aggregated discharging and charging variables for each EVA are represented by \(p_{i,t}^{a,\text{dis}}\) and \(p_{i,t}^{a,\text{ch}}\). In Eq. (5a), \(u_{i,t}^{a,\text{dis}}\) and \(u_{i,t}^{a,\text{ch}}\) are discharging and charging binary variables at any time, used to decompose \(x_{i,t}^{a}\) to discharging and charging variables in Eq. (5b). Eq. (5c) and (5d) present the grid exchange power limits for discharging and charging processes accordingly. In other words, EVAs’ capacity constraints for discharging and charging are reflected in these two equations, separately.

### III. DISTRIBUTED EV AGGREGATION MODELS

In a centralized optimization, each EVA solves the optimization sub-problems of all corresponding EVs and determines its charging profile \(x_{i,j} = [x_{i,j}(1), \ldots, x_{i,j}(T)]^\top\), which increases the computational overhead and decrease the scalability of the control platform. To address this concern, a distributed platform based on ADMM is employed in this work to decompose the optimization problem into smaller sub-problems between EVAs and EVs.

The overall architecture of the proposed model is displayed in Fig. 1. In CDP, the DN operator sends the electricity price to the aggregators. Then each EVA updates the price based on its policies and sends the price along with the aggregated charging profile to each EV via its ADMM-based platform. In each time step \(k\), the EVA and the EVs solve their optimization subproblems independently. The continuous update of the incentive signal (the scaled price signal \(\tilde{x}_i\) and the updated average profile of all subproblem solutions \(\hat{x}_i\)) drives the solution to the EVA optimum solution. In response to the EVAs, EVs send their charging profile to
their corresponding EVAs. Meanwhile, the EVAs exchange their load profiles for modifying the distribution system’s aggregated demand profile.

A. PROBLEM DECOMPOSITION

The objective function and constraints (except Eq. (1b)) developed in Eq. (1), can be directly decomposed among EVs and their corresponding ESA. If Eq. (1b) is ignored, each EV can locally define its optimal charging profile \( F_{i,j}(x_{i,j}) \) from its feasible set \( X_{i,j} \). Each ESA also calculates the optimal discharging profile \( x_i = [x_i^a(1), \ldots, x_i^a(T)]^\top \) within its feasible set \( X_i^a \) to minimize \( F_i^a(x_i^a, \hat{\omega}_i^a) \). The problems should be coupled through the equilibrium constraint where \( x_i^a = \sum_{j=1}^N x_{i,j} \).

Then the problem can be reformulated as an exchange optimization problem [14, 30]. Since EVs and ESAs have separate sub-problems, we assumed that \( x_{i,0} = -x_i^a \), which redefines the ESA as sub-problem 0. Moreover, the EVs are represented by sub-problems \( j = 1, \ldots, N_i \). Therefore the number of subproblem for each cluster of agents including an EV and its corresponding ESA is \( N_i + 1 \). To simplify notation, the sub-problems’ optimization variables in each cluster are defined in \( x_i = [x_i^a(0), x_i^a(1), \ldots, x_i^a(N_i)]^\top \). Appendix A provide more information about the exchange problem and reformulating the optimization problem to ADMM.

B. OPTIMIZATION MODEL

The exchange problem can be solved using an ADMM-based method where any ESA aggregate the objective function of all corresponding EVs. Eq. (6) and Eq. (7) show EVs and EVAs solve their objective functions using the ADMM-based platform. At each iteration \( k \), the following update processes lead to the optimal solution:

\[
\begin{align*}
    x_{i,j}^{k+1} &= \arg\min \left\{ \frac{\gamma_i}{2} F_{i,j}(x_{i,j}) + \frac{\rho}{2} \left\| x_{i,j} - x_{i,j}^k + \hat{x}_i^k + \frac{y_{i,j}^k}{\rho} \right\|_2^2 \right\} \\
    \text{subject to} \quad &x_{i,j} \in X_{i,j}
\end{align*}
\]

\[
\begin{align*}
    x_i^{k+1} &= \arg\min \left\{ \frac{\rho}{2} \left\| x_i - x_i^k + \hat{x}_i^k + \frac{y_{i,0}^k}{\rho} \right\|_2^2 \right\} \\
    \text{subject to} \quad &-x_{i,0} \in X_i^a
\end{align*}
\]

where \( y_{i,j}^k \) stands for the Lagrange multiplier associated with Eq. (1b) (the power balance constraint) at iteration \( k \), which one can interpret as price vector; \( \rho \) represents the penalty parameter of the augmented Lagrange function; and \( \hat{x}_i^k \) denotes the average power mismatch of the each cluster of agents at iteration \( k \) calculated as

\[
\hat{x}_i^{k+1} = \frac{1}{N_i+1} (x_{i,0}^{k+1} + \sum_{j=1}^N x_{i,j}^{k+1})
\]

Exchange ADMM can be observed as a general equilibrium form of the price adjustment process presented in [31]. In other words, it represents a competitive market running towards a market equilibrium where each agent adjusts its consumption \( x_{i,j} \) to minimize its individual cost \( f_{i,j}(x_{i,j}) \) adjusted by the cost \( y_{i,j}^k \) to \( x_{i,j} \). As \( y_i \) converges to an optimal price vector for each ESA, the effect of the proximal regularization term declines. The proximal regularization term can be defined as each agent’s commitment to helping clear the market.

C. CONVERGENCE CRITERIA

In order to stop the back and force procedure between EVs and their corresponding ESAs, appropriate convergence criteria are required. That is why the primal residual \( r_i^k \in \mathbb{R}^T \) and dual residual \( s_{i,j}^k \in \mathbb{R}^T \) are specified as the convergence criteria [14].

\[
\begin{align*}
    r_i^k &= -x_i^k \\
    s_{i,j}^k &= -\rho(N + 1) (x_{i,j}^k - x_{i,j}^{k-1} + (x_i^{k-1} - x_i^k))
\end{align*}
\]

\[
\begin{align*}
    ||r_i^k||_2 &\leq \epsilon_i^p \quad \text{(10a)} \\
    ||s_{i,j}^k||_2 &\leq \epsilon_i^d \quad \text{(10b)}
\end{align*}
\]

Eq. (10) and (11) show the primal and dual convergence criteria, respectively. While \( s_{i,j}^k = [s_{i,1,j}^k, \ldots, s_{i,N_i,j}^k]^\top \), stopping criteria can be defined, considering \( \epsilon_i^p \) and \( \epsilon_i^d \) in (12).

D. ALGORITHM

The optimization procedure for any ESA is summarized in Algorithm 1. Note that \( \rho \) determines the stability status and the speed of convergence of the CDP. Here, the value of \( \rho \) is selected within the stable region to ensure convergence. See [13] for more details on the selection of \( \rho \).

Algorithm 1: CDP Algorithm

\[
\begin{align*}
    \text{Initialization:} \quad &\rho, y_i^0, \hat{x}_i^0, x_{i,0}, \hat{\omega}_i^0, \epsilon_i^p, \epsilon_i^d \\
    k &= 0 \\
    \text{for } i = 1 : M \text{ do} \\
    \text{while Eq. (12) is not true do} \\
    \text{for } j = 1 : N_i \text{ do} \\
    \text{Solve the EVs’ optimization problems (Eq. (6))} \\
    \text{end for} \\
    \text{Solve the EVAs’ optimization problem (Eq. (7))} \\
    \text{Update } y_i^{k+1} \text{ by Eq. (8)} \\
    \text{Update } \hat{x}_i^{k+1} \text{ by (9)} \\
    \text{Calculate } r_i^k \text{ and } s_{i,j}^k \text{ by Eq. (10) and (11)} \\
    \text{Break the loop if Eq. (12) is true} \\
    \text{Send } \hat{x}_i^{k+1} \text{ and } y_i^{k+1} \text{ to EVs} \\
    \text{end while} \\
    k &= k + 1 \\
    \text{end for}
\end{align*}
\]
IV. SIMULATION, DATA, METRICS, AND ANALYSIS
A. SIMULATION DATA AND CASE STUDY

It is assumed that the aggregators have access to the hourly electricity price and aggregated demand profile of non-EV loads. The demand profile is available for 15 minutes time intervals (m=4) in a sample day [32]. Various aggregators for private and public charging events with different load profiles are studied in this paper. For public charging events, we considered Chattanooga Area Regional Transportation Authority (CARTA) as the aggregator. The EV charging behavior data, such as connection time and the energy requirement, are obtained from the historical EV database CARTA for a sample weekday in March 2020, which has thirty-two charging events [33]. We also consider a private EVA with forty charging events where EVs’ battery capacity and $E_{i,j}^0$ are normally distributed over [30, 50] kWh and [6, 24] kWh, respectively. Moreover, the connection time for the private charging events is between 6 pm and 6 am. The maximum required energy for these events is 80% of the EV battery capacity. Another assumption is that EVs are only charged once a day, and their requested energy must be supplied when they are disconnected from the grid. Besides, based on the case study data, $E_{i,j}^0$ is less than $E D_{i,j}$ for all $E V_{i,j}$. The simulation parameters of EVAs and EVs are summarized in Table 1.

Electricity wholesale price, which is determined based on time of use pricing approach, is extracted from the southern California rate plan [34], where the electricity (EV charging) price is 14 cent/kWh and 38 cent/kWh in off-peak and peak-hours, respectively. The developed distributed EV coordination method gives the opportunity to different EVAs to modify their final price profile based on their policies. To observe the charging services fee in public charging events, $\pi_{i,t}^{ch}$ is 10% more than private charging events’ price. Furthermore, to apply different tariffs for discharging and charging price, $\pi_{i,t}^{dis}$ is considered as 95% of charging price.

The type of battery considered for the simulation is a lithium battery widely applied in EVs. The battery package in an EV is composed of a set of identical lithium-battery cells and $\alpha_{1j}$, $\alpha_{2j}$, and $\alpha_{3j}$ are selected based on the assumption that the nominal energy capacity and voltage of this type of cell units are 2.5 Ah (Amp × Hour) and 3.3 V, respectively [28]. Besides, $\$15$ is the price on each cell unit [28]. It is assumed that all of the cell units in an EV experience the same (dis)charging condition at all times. Furthermore, the battery coefficients’ values depend on the battery cells nominal voltage value and their number and energy price, which are similar for charging and discharging [28]. It should be noted that the EV input data (i.e., arrival time and amount of energy request) have dependencies, which should be considered. See [35, 36] for more details on modeling the EV input data considering input data dependencies.

It is almost impossible to select a single $\rho$ that would work the best for all objectives [22]. The value of ADMM parameters used in the simulation are listed in Table 2. The implementations of CDP are done on a desktop computer with Intel®CoreTM i7 7700 3.60 GHz processor, eight cores, and 64 GB RAM, by MATLAB CVX [37] using GUROBI as the solver [38].

| Symbol | Parameter | Value |
|--------|-----------|-------|
| $\pi_{i,t}^{ch}$ | Maximal discharging rate | 8kW |
| $\pi_{i,t}^{ch}$ | Maximal charging rate | 8kW |
| $E_{i,t}^{ch}$ | Maximal energy | 50 kWh |
| $E_{i,t}^{ch}$ | Initial energy | 2.5 kWh |
| $\eta_{i,t}^{ch}$ | Discharging efficiency | 90% |
| $\eta_{i,t}^{ch}$ | Charging efficiency | 90% |
| $\alpha_{1j}$ | Battery degradation parameter 1 | 0.004 $\$/kWh |
| $\alpha_{2j}$ | Battery degradation parameter 2 | 0.075 $ |
| $\alpha_{3j}$ | Battery degradation parameter 3 | 0.003 |
| $\pi_{i,t}^{dis}$ | Aggregated maximal discharging rate | 136kW |
| $\pi_{i,t}^{ch}$ | Aggregated maximal charging rate | 136kW |

B. SIMULATION METRICS

To evaluate different scenarios from the EVs users’ perspective, the total amount of charging costs is considered in each scenario as an indicator. Furthermore, two evaluation metrics to assess EVAs’ objectives are defined as follows:

| Symbol | Parameter | Value |
|--------|-----------|-------|
| $\rho$ | Penalty factor | $10^{-4}$ |
| $\sigma_{1,2}^p$ | Primal feasibility threshold | 0.1 |
| $\sigma_{1,2}^d$ | Dual feasibility threshold | 0.01 |
1) Peak-to-peak (P2P)

P2P is the first performance index [18]. This metric indicates a sudden decrease or increase in the total demand, formulated as follows:

\[
P2P = \max (TD_t) - \min (TD_t)
\]

where the aggregated net-load demand of grid including the EVA loads is represented by \(TD_t\), which equals to \(TD_t = D_t + \sum_{i=1}^{M} x_t\).

2) Standard deviation (SD)

The second EVA’s metric is the standard deviation from the average \(TD_t\), which is formulated as:

\[
SD = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (TD_t - \overline{TD})^2}
\]

where \(\overline{TD}\) is the aggregated total demand average over the time horizon, seen by the DN operator.

C. SIMULATION ANALYSIS

To assess the effectiveness of the proposed distributed charging coordination method, three scenarios are considered in this paper. In Scenario 1, CDP is compared with various types of EV charging management structures. In Scenario 2, the effects of EVs’ objective functions on simulation results are analyzed. To assess the impacts of EVs discharging constraints and asymmetric negative and positive energy tariffs on the aggregators and EV indices, the proposed MIQP model is compared to the quadratic programming (QP) model in Scenario 3.

**Scenario 1:** Scenario 1 analyzes the various coordinated and uncoordinated charging structures’ effects on EVs’ and EVAs’ metrics. This scenario includes 5 cases. To study the simulation results of this scenario on aggregators’ objective functions, it is assumed that \(\gamma_i = 0 \forall i\). Case 1 demonstrates the uncoordinated EV charging framework in which the EVs start the charging process as soon as they are connected to the EVSEs. Case 2 represents the locally coordinated charging platform, where each EVA solves its objective function without any coordination with other EVAs. Case 3 shows the coordinated public-uncoordinated private platform, and Case 4 represents the coordinated private-uncoordinated public platform. Finally, Case 5 is used to show CDP or the fully-coordinated public charging structure. Fig.2 shows the charging structure in the first four cases. Case 5 is displayed in Fig.1.

Fig.3 demonstrates the impacts of each charging platform on the network’s load profile. To illustrate the importance of EVs’ batteries as a potential energy storage method, Scenario 1 studied both V2G and No-V2G modes. As we expected, Case 5 (fully coordinated charging structure) has the best performance in peak shaving and valley filling compared to all other charging structures. On the other hand, Case 1 (fully uncoordinated charging structure) demonstrates the worse results. Furthermore, the final load profile in all cases (except Case 1) improves when V2G is considered. Comparing Case 2 and Case 5 confirms that by implementing optimal local charging, there is a chance to improve the smoothness of the final load profile when private and public discharging events do not coincide. Conversely, when there is no coordination, each EVA tries to improve the load profile individually that causes over (dis)charging. Looking at the time interval between 6 pm and 9 pm in Fig.3b, a sudden drop can be seen in the aggregated load profile graph due to simultaneous discharging of both EVAs.

The private charging events are uncoordinated in Case 3, where EVs start to charge as soon as they are connected to the grid. Since this time coincides with the network’s evening peak electricity consumption, the peak hours consumption increases even more. On the other hand, coordinated public charging tries to compensate for this increase by discharging. Besides, a comparison between Case 3 in Fig.3a and Fig.3b reveals that public charging performance efficiency enhances when EVs have the discharging ability. In public charging events, EVs are normally start the connection to the EVSEs in the network’s off-peak hours (based on a sample day in CARTA data) [33]. Consequently, in Case 4, which demonstrates the uncoordinated public charging, the overall load profile is close to Case 5. However, load variance is still higher in Case 4 compared to Case 5. Fig.4 demonstrates the total EVs’ cost in all cases. The locally coordinated (Case 2) and fully coordinated (Case 5) cases have the best situation in terms of the total costs. Furthermore, comparing Case 1 and Case 3 shows the considerable negative effects of uncoordinated private charging on the total cost. Note that since BDC is a long-term cost, its value is negligible compared to EBC.

The simulation metrics for Scenario 1 can also be seen in Table 3. This table illustrates that in Case 2 and Case 5, the EV and EVAs’ metrics improve when we use coordinated optimal charging. For example, the total cost in Case 1 is about 40% and 55% more than Case 5 in No-V2G and V2G-capable charging types, respectively. In addition, compared to Case 1, in Case 5 (No-V2G), SD and P2P values decrease by 26% and 133 kW, respectively. Due to the uncoordinated private charging during peak hours, total cost remarkably rose in Case 3. Although an increase in the total cost is observed in Case 4, it is not as large as in Case 3. The reason is that the connection time window of the private charging events is different from public charging events.

As is expected, Case 5 has the best situation in terms of load variance minimization. However, the results show that the total cost in Case 2 is slightly lower than in Case 5 because of the extra discharging of EVAs during peak hours. Despite that, we can increase the weight of the cost minimization objective function for the EVs in CDP (Case 5). Table 3 also illustrates that due to the importance of discharging capability in the optimization, in all cases except Case 1, in V2G mode, the EVAs’ and EVs’ metrics improve significantly. For example, in Case 5, P2P, SD, and total cost improve 14%, 16%, and 5%, respectively.

Furthermore, in terms of computational difficulty, in both
Case 1
- DN
- Electricity price & Demand profile
- Individual EV load profile
- Aggregated EV load profile
- Averaged EV profile & Incentive signal
- Public charging events
- Private charging events

Case 2
- DN
- Scenario 2: To assess the impacts of different EV objective functions on the final demand profile, various combinations of these objective functions have been studied in private and public charging events. In all cases in Scenario 2, CDP is the EV charging platform, and load variance minimization (LVM) is the EV As’ objective function. In addition, V2G capability is observed in this scenario. Table 4 displays all cases and their impacts on EVAs and EVs’ metrics. It can be observed from the table that BDM has a higher negative impact on aggregators’ metrics compared to EBC. The reason is that BDC changes with the amount of dis/charged power instead of changing based on the TOU price profile. It should be noted that DN defines the daily price profile according to network policies to make the load profile smoother, so the adverse effects of EBC on the P2P and SD are not as high as BDC. For instance, a comparison between Case 2 and Case 12 confirms that electricity bill minimization (EBM) improves P2P and SD metrics in Case 12 when the EBM is added to the EVs’ objectives.

Even though compared to BDM, EBM does not have as much adverse effects on P2P, the results confirms that by ignoring the EBM in the EV optimization, the P2P value improves (reduces). In terms of the EVAs metrics, Case 3, Case 4, and Case 16 show the best P2P and SD values. However, Case 1 shows a higher P2P value compared to these three cases because both private and public sides have

V2G and No-V2G conditions, Case 5 only needs two more iterations the Case 2 to reach convergence. Since the study is conducted for the day ahead EV scheduling, the extra iterations due to the EVAs’ collaboration can be neglected.

Scenario 2: To assess the impacts of different EV objective functions on the final demand profile, various combinations of these objective functions have been studied in private and public charging events. In all cases in Scenario 2, CDP is the EV charging platform, and load variance minimization (LVM) is the EVAs’ objective function. In addition, V2G capability is observed in this scenario. Table 4 displays all cases and their impacts on EVAs and EVs’ metrics. It can be observed from the table that BDM has a higher negative impact on aggregators’ metrics compared to EBC. The reason is that BDC changes with the amount of dis/charged power instead of changing based on the TOU price profile. It should be noted that DN defines the daily price profile according to network policies to make the load profile smoother, so the adverse effects of EBC on the P2P and SD are not as high as BDC. For instance, a comparison between Case 2 and Case 12 confirms that electricity bill minimization (EBM) improves P2P and SD metrics in Case 12 when the EBM is added to the EVs’ objectives.

Even though compared to BDM, EBM does not have as much adverse effects on P2P, the results confirms that by ignoring the EBM in the EV optimization, the P2P value improves (reduces). In terms of the EVAs metrics, Case 3, Case 4, and Case 16 show the best P2P and SD values. However, Case 1 shows a higher P2P value compared to these three cases because both private and public sides have
focused on EBM and do not efficiently collaborate to each other to preform the LVM.

In terms of the total cost index, Case 15 has the best condition, followed by Case 1. The results in Case 1 show the high impact of EBC on total costs. Furthermore, Case 2 demonstrates the highest total cost because EVs look at BDC as their primary objective function.

Fig.5 depicts the individual charging profile of public and private EVAs separately. A comparison between Fig.(5a) and (5b), between 6pm to 10pm (peak hours) reveals that by making collaboration between EVAs, each EVA can contribute in LVM up to a certain level, and there is no need for it to do the LVM all by itself.

### TABLE 4. Scenario 2: Simulation Parameters

| Case num | Evs' Objectives | EVAs' indices | EVs' indices | EVs' indices |
|----------|----------------|---------------|--------------|--------------|
|          | Pu | Pr | P2P (kW) | SD | EVC_Pu (S) | EVC_Pr (S) | EVC_P2P (S) | EVC_EBC (S) | Total Cost (S) |
| 1        | EBM | EBM | 233 | 68.73 | 0.28 | 0.71 | 402.33 | 54.42 | 457.73 |
| 2        | BDM | BDM | 242 | 82.24 | 0 | 0 | 451.85 | 135.82 | 587.66 |
| 3        | BDM | 208.27 | 68.97 | 0.18 | 0.73 | 432.41 | 54.42 | 487.74 |
| 4        | EBM | 208.63 | 68.64 | 0.28 | 0.69 | 402.33 | 69.54 | 472.84 |
| 5        | BDM | 226.13 | 79.14 | 0.25 | 0.67 | 421.43 | 135.82 | 557.69 |
| 6        | BDM | 211.18 | 71.77 | 0 | 0.7 | 452.66 | 57.38 | 510.74 |
| 7        | EBM | 233 | 79.03 | 0.33 | 0 | 0.7 | 402.33 | 135.82 | 538.48 |
| 8        | BDM | 211.12 | 71.77 | 0 | 0.7 | 456.13 | 54.42 | 511.25 |
| 9        | EBM | 233.01 | 68.76 | 0.26 | 0.7 | 402.33 | 54.42 | 457.73 |
| 10       | EBM | 212.07 | 71.78 | 0 | 0.7 | 459.91 | 54.42 | 515.03 |
| 11       | EBM | 233.04 | 68.81 | 0.26 | 0.7 | 402.33 | 54.42 | 457.72 |
| 12       | BDM | 238.59 | 79.37 | 0.26 | 0.7 | 402.33 | 135.82 | 538.41 |
| 13       | EBM | 208.47 | 68.96 | 0.19 | 0 | 433.09 | 54.42 | 488.39 |
| 14       | EBM | 208.47 | 68.96 | 0.19 | 0 | 433.09 | 54.42 | 488.39 |
| 15       | EBM | 233 | 68.84 | 0.26 | 0.7 | 402.33 | 54.42 | 457.71 |
| 16       | BDM | 208.32 | 68.97 | 0.18 | 0.69 | 425.54 | 59.91 | 486.33 |

**FIGURE 5. Scenario 2: (Dis)charging profile in Case 16 (base case), (a) Public (dis)charging profile; (b) Private (dis)charging profile; (c) Total (dis)charging profile**

**Scenario 3:** To show the impacts of EVs constraints on the final demand profile and the importance of using the MIQP model over a QP model, four cases considered in this scenario, where $\gamma_i = 0 \forall i$. In case 1, the simulation is performed without considering energy constraints and (dis)charging efficiency for each EV optimization problem; in case 2 using a QP model, energy constraints are considered, but we still do not view the charging and discharging efficiency. Considering all EVs’ batteries’ energy and efficiency constraints, the effects of different charging and discharging tariffs are assessed in Case 3, via a MIQP model. In Case 3 the $\pi_{i,t}^{ch}$ is considered as 80% charging price. Finally Case 4 is employed as a benchmark, where CDP includes all EVs’ batteries’ constraints, where $\pi_{i,t}^{dis} = \pi_{i,t}^{ch}$. Comparing Case 1 and Case 2 can prove the vital role of energy constraints on the final load profile. Fig.6 shows that considering the discharging capability in case 1, during the peak hours, the demand profile almost becomes flat, which is not a realistic scenario even considering the discharging ability. Comparing Case 2 with Case 4, we can see the charging and discharging efficiency effects on the load profile. It should be noted that using the MIQP method allows considering different values for charging and discharging efficiency. Although the demand profile of Case 1 is much smoother than other cases, the load profile in Case 2 and Case 3 is almost the same as the benchmark (Case 4). The reason is that each aggregator compensates for other EVA to smooth the load profile.

Fig.7 shows the individual impact of each EVA on the total load profile in Case 1 and Case 4. The results clearly illustrate the great impact of private charging events on the load profile’s smoothness, especially when the discharging capability is considered. That is because most EV users connect their EVs to their home chargers every day after only 25-30 miles of commute. Therefore, the remaining battery charge lets them participate in the load management programs [39]. Comparing Fig.(7b) and (7e) also illustrates the great influence of EV battery constraints on the total load profile. Moreover, comparing Fig.(7) displays the great impact of V2G on EVs’ potential to participate in the EVAs’ LVM programs.

Fig.8 depicts the total cost in all cases when we consider V2G. According to this figure, the price in Case 1 is significantly lower compared to Case 2. 6 also shows that considering the (dis)charging battery efficiency plus the energy constraints in Case 4 increase the total cost compared to Case 2. Besides, investigating the effects of different charging and discharging tariffs reveals that lower discharging price in Case 3 increases the total cost compared to the benchmark.

To have a clearer view of the calculation burden caused by the MIQP model, we compared the simulation run-time in Case 1, which is a QP, to the MIQP optimization problem in Case 4. Fig.9 depicts this comparison. It can be seen the run-time in Case 4 is almost four times of Case 1 when we consider V2G. Moreover, the run-time in both cases is less in No-V2G cases because we limit the optimization problem by not taking V2G capability into account. It is essential to know that CDP is a distributed platform that can run in parallel. Given the number of EVs, the number of iteration, and the average convergence time of all EVs at each iteration, the average computation time of each EV can be calculated. Considering the parallel structure in which each EV can solve the optimization individually using its local processor, the computation time reduces from 41 seconds to
D. DISCUSSION

This paper proposes the CDP based on ADMM, to manage the EVs charging problem and assess it in three different scenarios. Each scenario is studied from a different perspective and highlighted the paper’s contributions. Table 5 demonstrates a summary of these scenarios. The results show that the CDP has the following advantages: As opposed to centralized optimization EV charging methods, which do not allow the agents to consider their desired objective function, different agents may have various goals in the proposed model in the CDP. Therefore, the coordination between multiple EVAs decreases the total load variance around one second in CDP (Case 4), without considering the communication time.

**TABLE 5. A summary of simulation scenarios**

| Scenario | Subject |
|----------|---------|
| 1 | EV charging management platform: Comparison of CDP with locally coordinated and uncoordinated charging platforms. |
| 2 | Objective function: Analysing the effect of different EVAs and EVs objective functions on the final demand profile. |
| 3 | Optimization constraints: Analysing the effects of the V2G and energy constraints on EV and EVAs’ metrics. |

The optimization problem also investigates the profound impact of V2G on the BDC. The results confirm that when the model is executed considering BDM as the only EVs’ goal, BDC is almost zero. That is because EVs’ optimizations avoid extra dis/charging and try only to charge to meet EVs’ charging requests. Consequently, the BDC is negligible compared to when the EVs discharge and charge continuously. This paper also presents a sensitivity analysis on the effects of EVs’ constraints on the EV As’ and EVs’ metrics and reformulate the QP problem to a MIQP problem to investigate the role of bidirectional EV charging on these metrics. The simulation results prove that, without a V2G capability, the EV and EVAs’ metrics are almost the same, but the simulation time increases significantly if we use integer programming. On the other hand, executing the optimization with respect to V2G capability improves both EV As’ and EVs’ metrics. Fig. 10 displays the convergence rate primal and dual residual of the CDP when the bidirectional charging is considered.
V. CONCLUSION

In this paper, we developed a two-layer distributed control approach for the optimal discharging of EVs fleets while considering EVAs’ coordination to tackle the large-scale EVs penetration challenge in the grid. The CDP provides an opportunity for collaboration among different EVAs. It also creates a win-win situation where EVs and EVAs goals are achieved, considering the EVAs and EVs constraints. Considering the inherent uncertainty in EVs driving patterns, the proposed model also provides the opportunity for each agent to change its objective function in any iteration. The simulation results show that CDP improves the SD to the locally coordinated charging platform. Besides, there is no need to share EVs’ sensitive information, such as driving patterns with EVs. The results also illustrate the significant impact of BDM on SD. Moreover, the considerable impact of the EVs’ V2G capability is assessed through the reformulated MIQP optimization problem.

However, the offered CDP has some limitations, which will be studied in the authors’ future works. Although the distributed methods decrease run-time exponentially by distributing the problem between several agents, this paper does not consider parallel implementation. The model will be parallelized in future works through a multi-thread-multi-core implementation or be run on several machines to show the proposed charging platform’s advantages in reducing the run-time, especially for large EV numbers and EVAs with different objective functions. Moreover, finding the best trade-off value between the objective functions and developing a stochastic model to consider the electricity price and EV driver behavior uncertainty in the upcoming research.

APPENDIX. A

According to [14, 30], Eq. (1) can be reformulated where the optimal fleet charging exchange problem under an equilibrium constraint among each cluster of agents (including an EVA and its corresponding EVs) is presented by Eq. (15). To simplify the notation, the EVA index \(i\) is not shown in the formulation. However, the formulation is applied for each cluster of sub-problems.

\[
\begin{align*}
\text{minimize} & \quad \sum_{j=0}^{N} f_j(x_j) + g(z) \\
\text{subject to} & \quad x_j - z = 0 \quad j = 0, \ldots, N \quad \forall \ i.
\end{align*}
\]

where \(g\) is a regularization function is handled by the EVA. \(z_j \in \mathbb{R}^n\) is the common global variable and \(g(z)\) defined as

\[
g(z) = \begin{cases} 0 & \text{if } \sum_{j=0}^{N} z_j = 0 \\ \infty & \text{otherwise} \end{cases}
\]

This is called the global consensus problem, where all the local variables should agree on the global constraint [40]. Each term can encode constraints by assigning \(g(z) = +\infty\), when a constraint is violated. ADMM for the problem Eq. (15) can be derived directly from the augmented Lagrangian shown by Eq. (17).

\[
L_{\rho}(x_0, \ldots, x_N, z, y) = \sum_{j=0}^{N} (f_j(x_j) + y_j^T (x_j - z) + \frac{\rho}{2} \| x_j - z \|_2^2)
\]

Using \(z^k = \pi^k\), ADMM algorithm can be formulated as follows:

\[
x_j^{k+1} := \arg\min_{x_j} (f_j(x_j) + y_j^{kT} (x_j - z^k) + \frac{\rho}{2} \| x_j - z^k \|_2^2)
\]

\[
z^{k+1} := \arg\min_{z} (g(z) + \sum_{i=1}^{N} (-y_j^{kT} z + \frac{\rho}{2} \| x_j^{k+1} - z \|_2^2))
\]

\[
y_j^{k+1} := y_j^k + \rho (z_j^{k+1} - z^{k+1})
\]

The final form of ADMM formulation is shown in Eq. (6) and Eq. (7). For a useful discussion on ADMM steps and the consensus algorithms, see [14, 40].

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