Coordinated Electric Vehicle Charging Control with Aggregator Power Trading and Indirect Load Control

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Abstract—Due to the increasing concern on greenhouse gas emissions and fossil fuel security, Electric Vehicles (EVs) have attracted much attention in recent years. However, the increasing popularity of EVs may cause stability issues to the power grid if their charging behaviors are uncoordinated. In order to address this problem, we propose a novel coordinated strategy for large-scale EV charging. We formulate the energy trade among aggregators with locational marginal pricing to maximize the aggregator profits and to indirectly control the loads to reduce power network congestion. We first develop a centralized iterative charging strategy, and then present a distributed optimization-based heuristic to overcome the high computational complexity and user privacy issues. To evaluate our proposed approach, a modified IEEE 118 bus testing system is employed with 10 aggregators serving 30,000 EVs. The simulation results indicate that our proposed approach can effectively increase the total profit of aggregators, and enhance the power grid stability.

Index Terms—Electric vehicle, coordinated charging, aggregator profit maximization, inter-aggregator energy trading, power grid congestion control.

NOMENCLATURE

Sets

\( \mathcal{A} \) Set of aggregators in the system.
\( A_i \) \( i \)-th aggregator in the system.
\( V_i \) Set of Electric Vehicles (EVs) served by \( A_i \).
\( V_{i,j} \) \( j \)-th EV served by \( A_i \).
\( V_{i,u} \) \( u \)-th unidirectional charging EV served by \( A_i \).
\( T \) Time horizon of optimization.
\( T_{i,j} \) Parking time of \( V_{i,j} \).

Parameters

\( t_{0,q} \), \( t_{q} \) The current and the \( q \)-th future time slot.
\( q^{\text{max}} \) The total number of future time slots.
\( \Delta t \) Duration of each time slot.
\( t_{\text{dep}} \) The registered departure time of \( V_{i,j} \).
\( C_{i}^{\text{ch}} \) Power charging price from the power grid at \( A_i \).
\( C_{i}^{\text{dch}} \) Power discharging price from the power grid at \( A_i \).
\( C^V, C^U \) The base contract price for bi-directional and uni-directional vehicle-to-grid (V2G) charging enabled EVs.
\( \Delta C^V, \Delta C^U \) The marginal price decrease for bi-directional and uni-directional V2G charging enabled EVs.

Variables

\( T^V, T^U \) Parking time for minimal charging fee of bi-directional and uni-directional V2G charging enabled EVs.
\( P_{\text{ch}}^{\text{i,j}}, P_{\text{dch}}^{\text{i,j}} \) Maximum charging and discharging rate of \( V_{i,j} \).
\( \eta_{\text{ch}}^{\text{i,j}}, \eta_{\text{dch}}^{\text{i,j}} \) Charging and discharging efficiency of \( V_{i,j} \).
\( E_{\text{max}}^{\text{i,j}}, E_{\text{min}}^{\text{i,j}} \) Battery capacity of \( V_{i,j} \).
\( S_{\text{min}}^{\text{i,j}} \) Minimum and maximum State-of-Charge (SoC) of \( V_{i,j} \).
\( S_{\text{req}}^{\text{i,j}} \) Required SoC on departure of \( V_{i,j} \).
\( N \) Number of buses in the power system.
\( L \) Number of lines in the power system.
\( D_s \) Inelastic load on bus \( s \).
\( F_{\text{line}} \) Generation shift factor from bus \( s \) to line \( l \).
\( P_{\text{min}}, P_{\text{max}} \) Maximum power flow on line \( l \).
\( G^s_{\text{min}}, G^s_{\text{max}} \) Minimum and maximum generation output for the generator on bus \( s \).

\( t \) Current time slot.
\( R_t \) The total aggregator revenue at \( t \).
\( P_t \) Total charging power of \( A_i \).
\( P_{i,j} \) Charging power of \( V_{i,j} \).
\( \alpha_{i,j} \) Binary indicator for whether \( V_{i,j} \) is still parked after the registered departure time.
\( S_{i,j} \) SoC of \( V_{i,j} \).
\( S_{\text{min}}^{\text{i,j}} \) Minimum reserved State-of-Charge (SoC) of \( V_{i,j} \).
\( G_s \) Generation output for the generator on bus \( s \).
\( P_s \) Aggregator demand/supply on bus \( s \).
\( C_{i,j} \) Charging fee of \( V_{i,j} \) when the registered parking time is \( T_{i,j} \).
\( C^\text{trade} \) Power trading price among aggregators.
\( C_i \) Power trading price from the power grid at \( A_i \).
\( P_i \) Trade power of \( A_i \).
\( P^{\text{md}} \) Total available aggregator power supply in the trade at \( C_t \).
\( P^{\text{cap}} \) Total available aggregator power demand in the trade at \( C_i \).
\( P_i \) Trade capacity at \( C_i \).
\( C_s \) Power generation cost function for the generator on bus \( s \) when generating \( G_s \) power.
\( \lambda, \mu_t \) Lagrangian multipliers for generation cost and power flow limit constraints.

\( a_{\text{req}}^{\text{i,j}} \) Parking time for minimal charging fee of bi-directional and uni-directional V2G charging enabled EVs.
\( P_{\text{ch}}^{\text{i,j}}, P_{\text{dch}}^{\text{i,j}} \) Maximum charging and discharging rate of \( V_{i,j} \).
\( \eta_{\text{ch}}^{\text{i,j}}, \eta_{\text{dch}}^{\text{i,j}} \) Charging and discharging efficiency of \( V_{i,j} \).
\( E_{\text{max}}^{\text{i,j}}, E_{\text{min}}^{\text{i,j}} \) Battery capacity of \( V_{i,j} \).
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With the increasing concern on greenhouse gas emissions, electric vehicles (EVs) are expected to reach a significant market share in the near future. EVs can potentially alleviate the security concern on the supply of fossil fuels, and mitigate the power network instability caused by the increasing penetration of intermittent renewable energy generations [1]. However, the network security and economic operation can be significantly adversely influenced if the charging behaviors of a large number of EVs are uncoordinated [2]. Power quality degradation is also expected from the irregular demands [3]. By employing coordinated EV charging strategies, additional benefits can also be achieved such as reducing the total operational cost and mitigating the variability of the renewable energy sources [4]. Therefore, it is essential to coordinate EV charging for fleets of EVs.

Coordinated EV charging has been studied extensively. Previous research generally focused on the grid structures with aggregators managing a large number of EVs. The proposed methodologies can be classified into two groups based on where charging decisions are made: centralized and distributed methods. In the centralized methods, EVs need to send their parking and battery information to the aggregator, and then the aggregator decides how each individual EV should be charged in a centralized manner. The decision is mostly driven by the aggregator profit [5]–[7]. EV owners power cost [8]–[11], and flattening the power demand curve [12]. On the other hand, aggregators in the distributed methods send power pricing scheme and related information to EVs. The EVs then utilize their own knowledge to establish charging plans, which are later delivered to the aggregator. Usually this process repeats until an agreement or equilibrium is reached. As the charging strategies are developed on the EV side, most existing efforts employ the energy costs for EV owners as the performance metric [13]–[16]. Other common metrics include the aggregator profit [17], user utilization ratio [18], and flattening the power demand curve [19].

This paper focuses on developing a coordinated charging strategy for multiple aggregators connected to the grid. We aim at maximizing the profits of the aggregators. As operating agents in a power system, different aggregators can develop cooperative and competitive charging plans to establish a win-win situation for each participant. Different from existing approaches, such an objective can be achieved by considering two major factors: Inter-aggregator Energy Trading (IET), and Indirect Load Control (ILC) of power network congestion management. An IET scheme enables aggregators to trade excessive energy generated by the discharging behavior of EVs with others for profit maximization, while an ILC scheme better adapts the EV charging profile to the real-time power price considering the power congestion cost.

Some previous work has investigated the possible energy trades among EVs, e.g., [20], [21]. EVs attached to an aggregator can decide the amount of energy to trade with other appliances instead of discharging to the grid. They all demonstrated improved performance compared with those models without energy trade. However, IET can be more complex than EV trading because the aggregators need to keep track of a massive number of EVs with diverse dynamics and battery conditions. Besides IET, ILC of power congestion management can also contribute to increasing the social utility. There are limited efforts on power congestions when developing EV charging schedules, e.g., [15], [17], [22], [23]. They either announce charging power capacity instructions to the aggregators, or impose transformer capacity limits for congestion control, which may potentially sacrifice the possibility to exploit aggregator profits when adapting the charging schedules to the volatile network congestion condition.

In this work, we propose a coordinated EV charging strategy considering IET and Locational Marginal Pricing (LMP) based ILC for power congestion management to maximize the aggregator profit. We first formulate the centralized coordinated charging optimization problem. As the centralized problem is non-convex, we further devise a distributed optimization-based heuristic approach to solve it. The charging schedule maker is the profit-seeking aggregator in a power system.

The remainder of this paper is organized as follows. Section II presents the system framework of our proposed approach. We propose a centralized coordinated charging strategy in Section III, and Section IV demonstrates an optimization-based heuristic approach for the problem. In Section V we provide a case study to illustrate the performance of our developed approach. Finally we conclude this paper in Section VI.

II. SYSTEM ARCHITECTURE

A. Charging System Architecture

A hierarchical architecture for charging load dispatch of EVs is essential due to the rapidly increasing EV penetration rate [4]. Such a structure can efficiently reduce the computational effort in generating coordinated charging plans for EVs, as the population of EVs charging simultaneously in the same network can be huge, rendering the joint EV charging scheduling problem intractable. In addition, centralized control strategies require information aggregation at the system operator (SO) level, imposing a large burden on the information communication infrastructure. The possible communication congestion problem can also be addressed by an hierarchical architecture where EVs are clustered and the generated information are aggregated before being sent to the system operator [24].

As illustrated in Fig. 1 a typical hierarchical architecture is composed of three components: SO, aggregators, and plug-in EVs. By collecting the charging information from the clustered EVs and pricing information from SO, each aggregator develops its own optimal charging schedule such that the EV charging requirements are met while the aggregators’ profits are maximized. SO manipulates the real-time power price to balance power consumptions of each bus in the power grid to alleviate power congestion.

\[ \min_{\gamma_a} \max_{\gamma_{a'} \neq \gamma_a} \quad \text{Lagrangian multipliers for generation output limit constraints.} \]
B. Aggregators

The main objective of introducing aggregators in power markets is to unbundle the electric loads, e.g., EVs, from the power network infrastructure, and to coordinate the charging as well as possible discharging behaviors [25].

Generally speaking, aggregators are mediators between the electricity wholesale and retail markets [26]. Aggregators create profits mainly from the different cost structures between the bulk power market and the customers. In the wholesale market, aggregators compete with other market participants for optimal power consumption. By utilizing the day-ahead load prediction, aggregators place optimal power purchasing bids with the consideration of the power cost changes. In the retail market, aggregators manipulate the charging and discharging patterns of the dispatchable power appliances to meet the power consumption bids placed aforementioned. The aggregators also compete with others who offer similar services [7].

C. Electric Vehicles

In this paper we consider EVs as dispatchable power appliances whose charging rates can be adjusted by the corresponding aggregator by taking the system requirement and economic consideration into account [18]. Similar to [27], upon the arrival of an EV, we assume that its battery capacity and current SoC can be obtained by the aggregator via appropriate vehicular communication techniques. In addition, the departure time of the EV is also required by the aggregator. As the onboard batteries are utilized to perform vehicle-to-grid (V2G) operations, a positive incentive is provided to the EV owners to encourage long-time parking. One possible implementation of such incentive is to manipulate the EV charging price, where parking for a longer time can enjoy a lower price. In addition, it is also possible for the EVs to perform early departure due to emergency. In such cases, a penalty can be imposed to the EV owner [28]. For example, early departure would void the guarantee on the customers’ desired departure SoC and late departure would incur additional charges [17].

In our proposed framework, EVs are categorized into two classes by their respective charging requirements, i.e., unidirectional (grid to EV) or bi-directional (grid to EV and EV to grid) power flow. Enabling power flow from the batteries of EVs to the power grid renders a significant improvement in the ability of generating profit utilizing the power price dynamics. However V2G power flow may accelerate the battery aging process, which incurs additional cost. Aggregators may compensate the EV owners’ loss in order to encourage V2G bi-direction operation by providing contracts with lower charging cost or free battery replacement plan [24].

D. IET

The main objective of introducing IET to the coordinated charging problem is to effectively utilize the excessive energy produced from aggregators for the benefit of the grid. Instead of selling the energy to SO, the aggregators can trade with other aggregators who originally must buy power from the grid at a higher price. In this way both aggregators can increase their profits, and the power system stability can also be enhanced from the smaller charging/discharging power imposed on the grid.

**Lemma 1.** Let A1 and A2 be two aggregators in a grid. Assume A1 is charging power from the grid at $P_1 > 0$ and A2 is discharging power to the grid at $P_2 < 0$. Then there exists a possible setting for A1’s power purchasing price $C_{ch}^1$ and A2’s power selling price $C_{dch}^2$ that makes inter-aggregator energy trading profitable.

**Proof:** The total power cost for the aggregators is $P_1 C_{ch}^1 + P_2 C_{dch}^2$. Suppose that A2 desires to sell $P_{trade}^2 > 0$ power to A1 at $C_{trade}^2$ price. Then the power cost for A1 is $(P_1 - P_{trade}^2) C_{ch}^1 + P_{trade}^2 C_{trade}^2$ and A2 is $(P_2 + P_{trade}^2) C_{dch}^2 - P_{trade}^2 C_{trade}^2$, rendering a total cost at $P_1 C_{ch}^1 + P_2 C_{dch}^2 + (C_{dch}^2 - C_{ch}^1) P_{trade}^2$. To increase the total profit of the aggregators, we have

$$C_{dch}^2 - C_{ch}^1 < P_{trade}^2.$$  

Thus energy trading is more profitable when $C_{dch}^2 > C_{ch}^1$. ■

It can also be concluded from the proof that $P_{trade}^2$ does not influence the total profit. However, a proper $P_{trade}^2$ shall be found to encourage the trading due to the profit-seeking nature of the aggregators.

E. LMP-based ILC

In the previous research, the power congestion issue was resolved by imposing a power limit on the power flow optimization problem [17], [22]. However this direct load control method may reduce the potential aggregator profit. [15] employs a shadow-price-based ILC for congestion management, where the shadow-price was calculated based on a fixed aggregator charging power limit. [23] developed a distributed LMP-based pricing scheme considering power flow. However, the driving pattern and battery information of EVs need to be aggregated at the central SO upon calculation. As only unidirectional EV charging is considered in [23], the optimization formulated is a linear program which can be easily solved. In this paper we employ the LMP strategy in a deregulated
power market as ILC to handle the power congestion issue with the consideration of EV privacy and battery discharging behavior. To preserve privacy, the EV information is locally maintained at the corresponding aggregators for protection. The only information that SO obtains from the grid is the power injection of each aggregator. As EV discharging behavior is also studied in this work and the discharging price is usually different from the charging price, the power price function is consequently piecewise linear, making the problem more complex. The corresponding control is conducted in an iterative manner, and is elaborated in Section III.

III. CENTRALIZED CHARGING PROBLEM

In this section we propose a model-based forward-control optimization problem to maximize the aggregator profits. Different from the previous research, we introduce IET and LMP based ILC to further enhance the potential profits. We employ a model predictive control method to develop charging control strategies of the immediate time slot, taking future EV departures and power market profile into account. Specifically, the optimization is performed over a finite time-horizon $T = \{t_0, t_1, \ldots, t_q, q \Delta t, q = 0, 1, \ldots, q^{\text{max}}\}$. Fig. 2 demonstrates the sliding optimization horizon. Information in the current time slot $t_0$ is considered accurate while the future information is imprecise. Since the optimized charging strategies are jointly optimal over $T$, the implemented charging strategy of the current time slot contributes to the total profit maximization over $T$, instead of one single time slot. The optimization repeats whenever the EVs in a future time slot requires charging operations, rendering the process online.

The problem is solved in an iterative manner for each time slot as shown in Fig. 3. At the beginning of each time slot, a centralized coordinated charging optimization problem is solved to generate optimal charging strategies for all EVs in the system, using the day-ahead power price. Trading among aggregators is considered during the optimization. The central controller conducting the optimization can be located along with any of the aggregators or with the SO. After the scheduled aggregated charging powers are optimized, they are reported to the SO. SO then calculates the LMP considering power line congestion, and the new power prices are sent back to the central controller. The central controller then solves the charging optimization problem again by utilizing the new power prices, and this process iterates until the charging strategy does not change or a stopping criterion is met.

A. Centralized Coordinated Charging Strategy

In the coordinated EV charging problem, a set of $m$ aggregators $A = \{A_1, A_2, \ldots, A_i, \ldots, A_m\}$ are considered. Aggregator $A_i$ serves $n_i$ EVs at a time given by $V_i = \{V_{i,1}, V_{i,2}, \ldots, V_{i,j}, \ldots, V_{i,n_i}\}$. The objective function for time slot $t$ is mathematically formulated as follows:

$$R_t = \sum_{A_i \in A} \alpha_{i,j} P_{i,j} C_{i,j} + \sum_{A_i \in A} \sum_{V_{i,j} \in V_i} (1 - \alpha_{i,j}) P_{i,j} C_{i,j}$$

$$- \sum_{A_i \in A} \sum_{V_{i,j} \in V_i} \alpha_{i,j} P_{i,j} - P_{i,\text{trade}} C_{i,j}$$

where

$$C_{i,j} = \begin{cases} C_{i,j}^{\text{ch}} & \text{if } \sum_{V_{i,j} \in V_i} \alpha_{i,j} P_{i,j} - P_{i,\text{trade}} \geq 0, \\ C_{i,j}^{\text{dch}} & \text{otherwise} \end{cases}$$

which means that the charging price is employed if the aggregator draws power from the grid. Otherwise the discharging price is used.

It is patent that the income of aggregators is composed of two parts: charging and penalty income. The first term in (2) is the charging fee imposed on the EV owners, which is arbitrarily formulated as follows:

$$C_{i,j} = \begin{cases} C_{i,j}^{\text{ch}} = C_{i,j}^{\text{ch}} \min\{(1/T_{i,j}),1\} & \text{if } T_{i,j} < 1, \\ C_{i,j}^{\text{dch}} = C_{i,j}^{\text{dch}} \min\{(1/T_{i,j}),1\} & \text{otherwise} \end{cases}$$

where the first case is for bidirectional V2G charging EVs, allowing both charging and discharging behaviors, and the second case is for unidirectional charging EVs, with only

1For the sake of simplicity, the symbol $t$ for time is omitted in the following equations when no confusion may be caused.
charging behavior enabled. Note that \( P_{\text{req}} \) is a preliminary charging fee model which only considers the duration of parking and the type of V2G operations allowed. More complicated contract formulations are available in practice and can be easily incorporated into the proposed optimization problem.

The second term in (2) is the penalty imposed on the EV owner in case of late departure. This income is analogous to the parking fee in traditional parking lots and can be removed in residential area scenarios.

The third term in (2) is the cost of the consumed power purchased from SO. The cost is firstly generated using day-ahead power prices, then taking LMP into consideration in optimizations of later time slots. If the total charging power is negative, the corresponding aggregator will perform V2G energy selling operation and this term is also negative. Besides the real time profit generation, aggregators can also utilize the dispatchable characteristics of EVs to delay the charging process to further increase the profit. This results in a multiple time slot joint optimization as follows:

\[
\begin{align*}
* \quad \max & \quad \sum_{P_{i,j,t}, P_{i,j,t}^{\text{trade}}} R_{t} \quad \text{subject to} \quad (5a) \\
& \quad P_{i,j,t}^{\text{ch}} \leq P_{i,j,t} \leq P_{i,j,t}^{\text{max}}, \quad (6) \\
& \quad 0 \leq P_{i,j,t} \leq P_{i,j,t}^{\text{in}}, \quad (7) \\
& \quad P_{i,j,t} \Delta t + (t_{i,j}^{\text{dpt}} - t - 1) P_{i,j,t}^{\text{ch}} \geq (S_{i,j}^{\text{req}} - S_{i,j,t}) E_{i,j}, \quad (8) \\
& \quad \sum_{A_i \in A} P_{i,t}^{\text{trade}} = 0, \quad (10) \\
& \quad P_{i,t}^{\text{trade}} \sum_{V_{i,j} \in V_i} P_{i,j,t} \geq 0, \quad (11) \\
& \quad \sum_{V_{i,j} \in V_i} P_{i,j,t} - |P_{i,t}^{\text{trade}}| \geq 0, \quad (12)
\end{align*}
\]

\( \forall A_i \in A, \forall V_{i,j} \in V_i, \forall t \in T. \)

Constraint (6) imposes rigid upper bounds for charging power of all EVs online. These limits are introduced according to the physical characteristics of the on-board batteries. Constraint (7) further limits the uni-directional charging EVs to perform charging only operations during the whole parking process by making the charging power consistently non-negative.

Constraint (8) ensures that the current charging power of an EV is feasible only if the battery can be charged to the required SoC when the charging powers of all succeeding time slots are set to the maximum rate. This constraint is considered when the optimization horizon \( T \) does not contain the departure time \( t_{i,j}^{\text{dpt}}, \) i.e., \( \max \{T\} < t_{i,j}^{\text{dpt}}, \forall m, i. \) The left-hand-side (LHS) of (8) is the charged energy if this plan is adopted, and its right-hand-side (RHS) is the deficit energy in the battery considering charging efficiency. If \( T \) contains the departure times of all online EVs, an alternative constraint:

\[
\begin{align*}
\sum_{t \in T} P_{i,j,t} \Delta t E_{i,j} \geq (S_{i,j}^{\text{req}} - S_{i,j,t}) E_{i,j} \quad (13)
\end{align*}
\]

is considered instead of (8). LHS of (13) is the total charged energy considering the charging efficiency, which must fulfill the departure SoC requirement (RHS). Constraint (9) prevents the battery from being over charged by limiting the current charging rate. The resultant energy in the battery after the current time slot (LHS) shall be less than or equal to the required energy (RHS). Constraints (8) and (9) cooperate to manipulate the charging rates of EVs to satisfy the SoC constraints.

Constraints (10)–(12) restrict the power trading quantity among aggregators. (10) ensures that the amount of energy bought and sold in the aggregator trading market are equal. (11) prevents the aggregators that are consuming power from the power grid from trading energy to other aggregators, and vice versa. As \( P_{i,t}^{\text{trade}} \) and \( \sum_{V_{i,j} \in V_i} P_{i,j,t} \) are independent and can be both positive and negative, (11) is a non-convex constraint and makes the optimization problem non-convex. (12) imposes a constraint that the selling aggregators cannot sell more energy than they generate through V2G discharging behaviors, and the buying aggregators cannot buy more energy than they request for fulfilling the EV charging demand.

**B. System Operator LMP Calculation**

Upon the receipt of charging power requests from the aggregators, SO needs to perform another optimization problem, i.e., the Optimal Power Flow (OPF) problem. In our proposed framework, an LMP strategy is employed to impose ILC to the aggregators for congestion control [29]. As we focus on the real-time power dispatch of the aggregators for EV charging, it is assumed that the Unit Commitment (UC) problem has been solved and all generators considered are online [4]. The SO level OPF problem can be formulated as follows:

\[
* \quad \min \quad \sum_{G_s} N \quad \text{subject to} \quad (14a)
\]

\[
\begin{align*}
& \quad \sum_{s=1}^{N} G_s - \sum_{s=1}^{N} D_s - \sum_{s=1}^{N} P_s = 0, \quad (15) \\
& \quad \sum_{s=1}^{N} F_{s-i} (G_s - D_s - P_s) \leq P_{\text{line}}^{\text{max}}, \forall l, \quad (16) \\
& \quad G_s^{\text{min}} \leq G_s \leq G_s^{\text{max}}, \forall s.
\end{align*}
\]

For ease of calculation, DC-OPF is introduced and modified in this paper. Such a formulation, although lossless, still has sufficient accuracy in comparison with AC-OPF in terms of power pricing [23]. Nevertheless, AC-OPF can also be adopted into our framework with minimal efforts.

Note that the formulation of DC-OPF is adopted from [23] and [29]. In this paper, aggregator injection \( P_s \) is introduced in the power balance constraint (15) and the line transmission limit (16), where \( P_s = \sum_{V_{i,j} \in V_i} \alpha_{i,j} P_{i,j} \) is the power injection of \( A_i \) to the grid at Bus \( s. \)

The LMP of bus \( s, \) or the cost of the incremental load, can subsequently be calculated with the partial derivative of the
Aggregators maximize their profits using the additional aggregator trading price information.

**IV. AGGREGATOR COORDINATED CHARGING STRATEGY**

In Section III, (9a)-(12) give a centralized coordinated EV charging strategy with power trade among aggregators. However, the centralized optimization problem is non-convex and becomes intractable with a large total number of EVs in the system. In addition, it requires EV information to be aggregated at SO, which causes privacy concerns. Therefore, we aim to develop a distributed aggregator-level coordinated charging strategy to alleviate the computational complexity and to preserve user privacy.

In this section we propose an optimization-based heuristic coordinated charging strategy to solve the optimization problem introduced in Section III-A, and its flow chart is shown in Fig. 4. This figure is divided into three sub-steps in Fig. 3 which correspond to the three steps of our proposed heuristic in this section: aggregator profit optimization (shaded sub-step on the left in Fig. 3), power trading (top-right), and supply and demand balancing (second top-right).

**A. Aggregator Profit Optimization**

At the beginning of each optimization iteration, all online EVs send their vehicle and battery information, including the maximum charging rate, scheduled departure time, and battery size and current SoC, to their corresponding aggregator. With this information, all aggregators maximize their profits independently using a modified formulation of (2):

\[
R_{i,t} = \sum_{V_i,j \in V_i} \alpha_{i,j} P_{i,t} C_{i,j} + \sum_{V_i,j \in V_i} (1 - \alpha_{i,j}) P_{\text{trade}}^\text{ch} C_{i,j} - \sum_{V_i,j \in V_i} \alpha_{i,j} P_{i,t} - P_{\text{trade}} \cdot C_{\text{trade}}. 
\]

The major difference between (2) and (20) lies in the introduction of the trading cost term \( F_{\text{trade}} \). \( P_{\text{trade}} \) is set to zero at the beginning of the iteration, and set to either a constant value or to \( \sum_{V_i,j \in V_i} \alpha_{i,j} P_{i,t} \) based on the supply and demand equilibrium, which will be elaborated in Section III-B. By solving

\[
\max_{P_{i,t}} \sum_{t \in T} R_{i,t} \text{ subject to } (6), (7), (8), (13), (9), \forall V_i,j \in V_i, \forall t \in T, \]

each aggregator optimizes its own profit.

It is worth noting that (21) spans over multiple time slots, where \( C_{i,t} \) and \( V_i,t \) for \( t = t_1, \ldots, t_q \) are not available at the current time slot \( t_0 \). Thus in this paper we employ the power prices in the day-ahead market for future \( C_{i,t} \) values, and no new EVs are accounted for except \( V_i \). This configuration simulates an average performance of all possible power pricing (e.g., [30], [31]) and driving pattern prediction models (e.g., [32], [33]).

This optimization problem is a mixed integer linear program (MILP) with piecewise linear objective function at first glance. However, as \( \alpha_{i,j} \) is known at \( t_0 \), the second term of (21) is a constant value in the optimization. Thus \( \alpha_{i,j} \) can be substituted by 1’s if the overtime EVs are excluded from \( V_i \). Consequently (21) is also transformed into a piecewise LP.

**B. Power Trading Heuristic**

When all aggregators have finished their profit maximization processes, they broadcast their own total power for EV charging to others in the aggregator trading market in the form of bids. In this power trading step, the aggregators utilize all the power bids generated to perform a modified second-price auction [34].

When submitting bids, each aggregator calculates its total EV charging power \( P_{i} = \sum_{V_i,j \in V_i} \alpha_{i,j} P_{i,t} \) from the optimal result of (21), and places a bid in the form of \((P_{i}, C_{i})\) pair. A positive \( P_{i} \) makes \( C_{i} = C_{\text{ch}} \), and a negative \( P_{i} \) makes \( C_{i} = C_{\text{dis}} \). The bids are broadcast to others and the auction starts in the aggregator trading market when all bids are placed and announced.
After all bids are generated, the auction evaluates the available charging (demand) and discharging (supply) power for trade at all possible trading prices \( C_{\text{trade}} \), whose values are selected from all \( C_i \) values in the bids:

\[
P_{\text{trade}}^i = \sum_{A_k \in A^{\text{spl}}} P_k, P_{\text{dmd}}^i = \sum_{A_k \in A^{\text{dmd}}} P_k,
\]

where

\[
A^{\text{spl}}_i = \{ A_k \in A | P_k < 0, C_k \leq C_i \},
\]

\[
A^{\text{dmd}}_i = \{ A_k \in A | P_k > 0, C_k \geq C_i \},
\]

and \( C_{\text{trade}} = C_i \). In this step we create a scenario that the power selling price of \( A^{\text{spl}}_i \) is lower than the power purchasing price of \( A^{\text{dmd}}_i \). Thus according to Lemma 1, extra energy trading profit can be made. The trading capacity for \( C_i \) is accordingly calculated by

\[
P_{\text{cap}}^i = \min\{-P_{\text{trade}}^i, P_{\text{dmd}}^i\} \times C_i.
\]

Consequently, the value of \( C_{\text{trade}} \) is set to \( C_i \) with the maximum \( P_{\text{cap}}^i \). The design principle of this scheme is to maximize the possible trading capacity. As the power purchasing price of a buying aggregator is always larger than the trading price according to (23), the aggregator will benefit from purchasing energy at a lower cost. It is also the case for the selling aggregators where the power selling price is always smaller than the trading price according to (24).

\( C_{\text{trade}} \) is also set to some predefined values in special cases:

\[
C_{\text{trade}} = \begin{cases} 
\max\{C_i\} & \text{if } \min\{P_{\text{slice}}^i\} = 0, \max\{P_{\text{dmd}}^i\} > 0 \\
\min\{C_i\} & \text{if } \min\{P_{\text{slice}}^i\} < 0, \max\{P_{\text{dmd}}^i\} > 0 \\
0 & \text{if } \min\{P_{\text{slice}}^i\} = 0, \max\{P_{\text{dmd}}^i\} = 0
\end{cases}
\]

In such cases, all \( P_{\text{cap}}^i \) values are zero and no \( C_{\text{trade}} \) value can be determined without (26).

C. Supply and Demand Balancing

The above heuristic gives a proper global \( C_{\text{trade}} \) for power trading among aggregators, and each of them can determine the amount of power to trade with others instead of the SO. In order to maximize the additional profit contributed by the trading behavior, another round of optimization (21) is conducted with the values of \( P_{\text{trade}}^i \) and \( C_{\text{trade}} \) generated in the power trading heuristic. In this step, all aggregators try to balance the power supply and demand in the aggregator trading market. To be specific, in the cases that \( P_{\text{slice}}^i + P_{\text{dmd}}^i > 0 \) (power shortage), \( P_{\text{trade}}^i = \sum_{V_{i,j} \in V} \alpha_{i,j} P_{i,j} \) for all aggregators with \( P_i \leq 0 \). If \( P_{\text{slice}}^i + P_{\text{dmd}}^i < 0 \) (power surplus), the above formula is applied to all aggregators with \( P_i \geq 0 \). The values of \( P_{\text{trade}}^i \) for other aggregators remain zero. The design philosophy behind this scheme is to encourage the aggregators to increase charging power if the total supply is greater than the demand, and encourage discharging power if the total demand is larger.

V. Case Studies

A. Case Description and Implementation

We employ the IEEE 118 Bus system [35] to assess the profit maximization performance of our proposed approach. 10 aggregators are installed in the system on Buses 7, 14, 17, 28, 44, 58, 72, 84, 97, and 115, and as shown in Fig. 5. The settings of the system parameters are presented in Table I. The power price information is acquired from PJM [36] data on June 16–20, 2015, and aggregators are assigned with prices of different buses.

In the test system, 30,000 EVs are accommodated. We consider two models of vehicles, namely the Tesla Model S AWD-85D (Telsa Model S) and Nissan Leaf 2014 model (Nissan Leaf). We assume 60% of all EVs in the system are Tesla Model S EVs with 85 kWh batteries and 34 kWh/100 miles energy expenditure performance, and the remaining 40% are Nissan Leaf EVs with 24 kWh batteries and 31.64 kWh/100 miles energy expenditure performance. The maximum charging rates for these two models are 22 kW and 6.6 kW, respectively, and the maximum discharging rates are also set to the same values [9]. Among all EVs in the system, 80% EVs enabled bi-directional V2G operations. 5% of the EVs will perform a late departure up to a maximum of one hour. For practical situations, these parameters can be manipulated by the EV owners.

The European Commission Strategic Energy Technologies Information System reported a mobility survey on the driving and parking patterns of European car drivers [37]. It provides representative driving profiles for establishing EV charging profiles. The result of the survey are utilized to formulate the EV driving dynamics. The starting time and estimated departure time are modeled with normal distributions, and the pre-parking driving distances are modeled with lognormal distributions. Similar methods have also been adopted in the literature, e.g., [4], [26].

To solve (14) and (21), Gurobi [38], a highly efficient optimization problem solver, is adopted in this work. All simulations are performed on a personal computer with a Core i7-3770 CPU and 8GB RAM. The script is coded with Python and executed under the Windows 7 operating system.

B. Simulation Results

We perform simulations on a horizon of 72 hours, and the length of each time slot is 15 minutes. Thus the total profit of all 288 time slots are combined as the performance metric. The simulation starts from multiple days of operation ahead to ensure a stationary state. As our proposed algorithm is online, the simulation results for another 24 consecutive hours are...
Fig. 5. The modified IEEE 118 bus system.

Fig. 6. Total charging loads for all time slots.

generated but not used in the performance evaluation. In order to demonstrate the efficacy of our proposed approach, we also consider four variants of the approach:

1) The No-Trading mode (NoTrade) removes all possible trades between aggregators. Only EV-coordinated charging and LMP-based ILC are considered. This mode works like a user information encapsulated and V2G enabled version of [23].

2) The No LMP Adaptation mode (NoLMP) removes the LMP-based ILC step. For each time slot only one iteration is performed, including aggregator maximization, power trading, and supply and demand balancing steps. The final profit, however, still considers the power price changes caused by congestion.

3) The Only Planning mode (Plan) removes both trading steps and the LMP-based ILC step. The aggregators optimize their local profits and directly send the charging powers to the SO for power allocation. This mode works similar to a V2G-enabled version of [7].

4) The Greedy mode (Greedy) performs the greedy charging strategy. Upon the arrival of an EV, it is charged at the maximum rate until the SoC requirement is met.

Table II presents the total profits generated by the compared charging approaches. Here the “All” mode is our proposed hierarchical charging strategy considering aggregator trading

| Mode    | All     | NoTrade | NoLMP   | Plan   | Greedy |
|---------|---------|---------|---------|--------|--------|
| Profit ($) | 134295.1 | 110269.8 | 118534.4 | 109750.6 | 75678.9 |
and LMP-based ILC. It can be easily concluded that our proposed approach can significantly increase the aggregator profits, and both the aggregator trading and LMP-based ILC have a positive influence on the profit maximization process when compared with the Greedy mode.

In addition, the computational time of the proposed approach is also crucial as the algorithm is supposed to be online. With 30,000 EVs in the system and 24 optimized time slots, each iteration of our proposed algorithm can be finished in 9.13 seconds. All time slots can be optimized within a maximum of six iterations, i.e., one time slot can be finished in one minute. Note that the communication time is considered negligible comparing with the optimization time.

As our proposed approach in Section IV (“All” mode) is an approximation of the original optimization problem discussed in Section III, it is interesting to discover the optimality of the solutions found. Since the original problem (5) is non-tractable, we develop an upper bound of the optimal solution for indirect comparison. To do this, we convexify the problem (5) by ignoring the non-convex constraint (11). The relaxed problem can be easily solved. From the same set of test data, the optimal objective value of the relaxed problem is $139,357.8, which is just 3.7% higher than that determined with the “All” mode with value of $134,295.1 (see Table II). As the true optimal of problem (5) must be between these two values, the gap between the true optimal and our approximation must be even smaller. We can see that our heuristic is effective. Furthermore, the average simulation time for each iteration of the centralized approach is 109 seconds. This indicates that the centralized approach is more computationally expensive, and a larger number of EVs or a smaller time slot may prevent the approach from being executed in an online manner.

In addition to the profit maximization performance comparison, we also investigate the behavior of aggregators in response to the power price. Fig. 6 demonstrates the total charging power dynamics of our proposed approach with the changes on the average power purchasing price. We can observe that the charging power is mostly high when the price is relatively low. This shows the efficacy of the multiple time slot optimization in saving aggregators’ power cost. One may note that the correlation is not always strict. A possible reason for this situation is that the optimization horizon in the simulation is 24 time slots, i.e., 6 hours. It may also be due to the EV dynamics; there are less EVs affiliated with aggregators when the power price is low.

The impact of introducing the proposed strategy on the grid is also illustrated in Fig. 7 where the “congestion LMP ratios” for some buses are presented. For instance, assume that the power price is $20/MWh and the congestion LMP induced by the aggregators is $2/MWh. Then the congestion LMP ratio is 10%. This metric evaluates the impact of the aggregator charging behavior on the grid stability. In this test the ratios for Buses 44, 59, 72, and 98 are presented. Buses 44 and 72 are installed with aggregators, and the simulation demonstrates the impact of the approach on these directly connected buses. Bus 98 is adjacent to bus 97 which is connected an aggregator, and bus 59 is topologically far from all aggregators. From the figure it can be concluded that our proposed strategy (“All” mode) can more efficiently increase the power grid stability by shifting and shaving the congestion peaks compared with the uncoordinated charging strategy (“Greedy” mode). By comparing the subplots we may also observe that adjacent buses to aggregators will be influenced more by the power line congestion, which is represented in the form of LMP changes.
VI. CONCLUSION

In this paper we propose a coordinated charging strategy for maximizing the profit of multiple aggregators in the grid, considering two new schemes, i.e., IET and LMP-based ILC. A model predictive control based centralized iterative approach is devised to find the optimal EV charging strategies for profit maximization. Considering the non-convexity nature of the optimization problem and user information privacy issues, we develop an aggregator-level coordinated charging heuristic to construct EV charging schedules. To exploit the potential of employing energy trade among aggregators for profit maximization, we propose an auctioning heuristic to handle the trading details. In addition, the iterative approach utilized by our developed strategy can further adapt the EV charging schedules to the grid congestion cost. To validate the performance of the proposed approach, we employ a ten-aggregator system with 30,000 EVs for simulation. The system is installed on an IEEE 118 bus system, and the simulation is performed on a 72 hours time span. The charging schedule developed by our proposed approach can create more profit for the aggregators than the compared strategies. In addition, the impact of the proposed approach on the grid stability is investigated, and the result indicates that the system can maintain a high stability considering the power line congestion situations.

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