A Hybrid Incentive Program for Managing Electric Vehicle Charging Flexibility

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***Abstract*—With the mass roll-out of electric vehicles (EVs) and rapid progress in battery technology, utilizing EV charging flexibility has become a promising solution for supporting economic and secured power system operations. This work proposes a novel hybrid incentive program, which encourages EV owners to sell their charging flexibility to a charging station (CS) and achieve a win-win situation for both EV owners and the CS. Unlike existing approaches, the proposed hybrid incentive program is simultaneously featured with simplicity, consistency, and controllability. To determine the incentive payment parameters, an optimal incentive price selection model is developed. In the solution methodology, we first linearize the original problem, then develop an adaptive ADMM algorithm to efficiently solve the formulated problem. Case studies confirm the superiority of the proposed hybrid incentive program over the state-of-the-arts, achieving 22.51% of EV owners' cost reduction, 31.18% of energy market bill reduction, and 64.13% of potential charging flexibility utilization.**

***Index Terms*—EV charging flexibility, incentive program, optimal incentive price selection, adaptive ADMM**

I. Introduction

CLIMATE change is one of the biggest challenges for mankind [1], which has seen the global response to reduce carbon emissions across all sectors of the economy in the last decade [2]. Transportation is one of the largest emitting sectors of greenhouse gas largely due to the internal combustion engine vehicles (ICEVs) [3]. Hence, shifting from ICEVs to electric vehicles (EVs) has been widely recognized as one of the most effective means to decarbonize the transportation sector because EVs can be powered by electricity generated from renewable sources.

The EV charging demand has grown dramatically over the past few years [4]. This is contributed by the mass roll-out of EVs and the advances in EV battery technology. The increased charging demand can impose significant challenges to the power network operation if the EV charging behavior is uncontrolled and unregulated [5]. Previous research reveals that the EV parking time is often longer than that is required for charging in many scenarios [6], which leads to charging flexibility that can support economic and secured power system operations in the future [7].

Due to the distributed nature and large quantities of EVs, direct control of EV charging by the system operator is computationally challenging. Hence, EV charging coordination is often accomplished by intermediary agents including EV aggregators, parking lots, charging stations (CS), virtual power plant (VPP) operators, and microgrid operators. For these intermediary agents, the EVs under their control can act as flexible demand response resources to generate revenues and benefits in many ways, such as participating in the energy market to reduce the energy procurement cost [8]–[10], providing ancillary services to generate income [11]–[13], and gaining remunerations by responding to the demand response signals [14], [15]. The underlying assumption in these works is that the intermediary agents can utilize EV charging flexibility without incentivizing EV owners, which is bluntly unrealistic as scheduled charging may bring considerable inconvenience to EV owners, and convenience is the primary motivation for personal ownership of vehicles. Hence, the design of incentives for EV owners is vital for the intermediary agents to acquire EV charging flexibility.

Since EV owners tend to charge their EVs as quickly as possible [16], incentive programs are needed to remunerate EV owners for acquiring their charging flexibility and reshaping EV charging load. Otherwise, EV owners will not be motivated to participate in the demand response programs (DRP). In a demand response incentive program, the DRP operator should specify what kinds of EV owners' actions will be rewarded and how much will be paid for these actions. Hence, this work is specifically focused on the design of EV owners' remunerable actions and the pricing methods for these actions.

In the literature, a variety of incentive programs have been proposed for inspiring EV owners to participate in DRPs managed by intermediary agents. These incentive programs, though varying from one to another, can be categorically classified as static programs and dynamic programs from the incentive signal update frequency angle.

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The incentive signal update frequency of static incentive programs is relatively low, which keeps the incentive programs unchanged over a relatively long period. The advantages of such programs are that they are consistent and simple for implementation, EV owners can easily use them as a reference for scheduling their charging plans.

Practices of static incentive programs include time-of-use (TOU) pricing and critical peak pricing (CPP). In [17], an optimal TOU tariff plan decision model is proposed to shift the EV charging load from high-price hours to low-price hours. In [18], an optimal TOU tariff plan is proposed by evaluating various aspects of EV charging behavior under the TOU tariff. In [19], several strategies including TOU tariff is applied to EV charging load to mitigate the transformer burden imposed by the high penetration level of EVs. In [20], a TOU charging price program with a price reduction strategy is applied to reduce the energy procurement costs and distribute the benefits between EV owners and charging infrastructure operators. In [21], both TOU and CPP mechanisms are applied to the EVs to improve the VPP's profitability. Similarly, both TOU and CPP programs are used in [22] to increase the profit of a distribution company. In static incentive programs, consumers are allowed to sacrifice a certain degree of convenience in return for reduced charging fees in a simple way. However, existing static programs do not offer the intermediary agents the controllability to maximize their benefit from the short-term market and system fluctuations.

Compared with static programs, dynamic programs update incentive signals more frequently in response to short-term market and system information, which enables more controllable actions to handle short-term market and system fluctuations, hence encouraging more proactive participation of EV owners in offering flexibility services to the power grid through intermediary agents.

The most popular dynamic programs are dynamic pricing and transactive control programs. In [23], a CS uses real-time energy and reserve price signals to incentivize EV owners for altering their charging schedules. In [24], an EV aggregator sends dynamic price signals to encourage EV owners to change their charging plan or authorize the battery access right to the aggregator. In [25], a dynamic pricing model is proposed for multiple CSs to coordinately shift EV charging load from residential load peaks. A dynamic pricing framework for CSs is proposed in [26] to concurrently maximize the profit of CSs and reduce the peak load. In [27], the EV aggregator manages the charging load by clearing the transactive market according to the day-ahead energy procurement and real-time requests of EV owners. The charging load in [28] is controlled through a transactive market to which EV owners need to submit their real-time charging requirements and preference setting of demand response. A sensitivity-based real-time transactive control framework is proposed in [29] to coordinate the EV charging behavior through a local energy market.

Although dynamic programs are more controllable, they lack simplicity and consistency compared to static programs. Besides, dynamic incentive programs assume that EV owners can actively respond to the price signals and alter their charging behavior responsively [30], which is too optimistic as it takes effort and specific knowledge to complete these tasks. Furthermore, in order to make the optimal decisions to maximize the benefit, EV owners have to be constantly updated with the latest market information, which demands extra effort from the EV owners.

Considering the pros and cons of existing EV incentive programs, we propose a hybrid incentive program for a CS that aims to offer incentives to the EV owners to share their charging flexibility. The proposed hybrid incentive program combines static incentives with dynamic control. Under the proposed hybrid incentive program, the consistency and simplicity of static programs are retained, while the controllability of dynamic programs can be achieved. Table I compares the key features of the proposed incentive program with both static incentive programs and dynamic incentive programs.

TABLE I
KEY PROPERTIES OF DIFFERENT TYPES OF INCENTIVE PROGRAMS

	Simplicity	Consistency	Controllability
Static programs [17]–[22]	Medium	High	Low
Dynamic programs [23]–[29]	Low	Low	High
Proposed program	High	High	Medium

The considered CS faces volatile day-ahead wholesale market-clearing prices (MCP) and variability of EV owners' willingness to sell their charging flexibility. For the CS, the incentive prices can affect both the incentive payment and the amount of charging flexibility that can be acquired to reduce energy bills. Therefore, the selection of incentive prices is crucial for the performance of the proposed hybrid incentive program. To maximize the CS's benefit while encouraging proactive participation of the EV owners, an optimal incentive price selection model is developed in this paper to determine the incentive prices for the EV charging flexibility.

As the proposed hybrid incentive program needs to retain consistency for a relatively long period, market price patterns at different times should be considered in the optimization model to ensure unbiased incentive price selection. Increasing the number of price scenarios leads to a larger number of EVs under consideration, which makes the solution process computationally challenging. In confronting the dimensional problem for large EV fleets, distributed and meta-heuristic methods are the most popular approaches in the literature [31]. Compared with meta-heuristic approaches, distributed methods are more specific and take less time to converge [32]. Hence, a distributed solution process based on the ADMM method is developed in this paper to guarantee computational efficiency in solving the optimal incentive price selection problem.

The major contributions of this work are as follows:

- A hybrid incentive program is proposed to encourage EV owners to sell their charging flexibility to the CS. The proposed hybrid incentive program combines the advantages of both static and dynamic incentive programs, namely, it has the features of simplicity, consistency, and controllability.
- An optimal incentive price selection model is developed to minimize the CS's cost in the electricity market and the DRP. The optimization results of the proposed model can serve as a reference for policymakers who adopt the proposed hybrid incentive program.
- An ADMM with adaptive penalty (ADMM-AP) solution algorithm is presented to efficiently solve the problem in a distributed manner for large EV fleets.

The remainder of this paper is organized as follows. Section II gives an overview of the CS operational framework. Section III provides the details of the proposed hybrid incentive program. Section IV presents the optimal incentive price selection model. The proposed solution methodology is detailed in Section V. Section VI presents the numerical results and discussions. Section VII concludes this paper.

II. Charging Station Operational Framework

The configuration of the CS's operational framework is presented in Fig. 1.

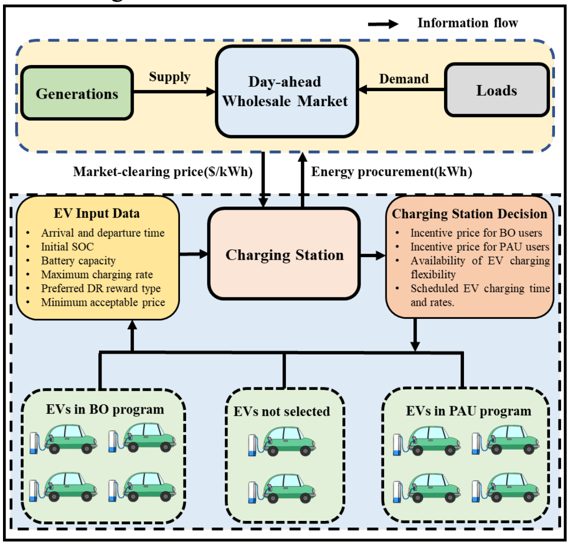


Fig. 1. Operational framework of the charging station.

The CS under consideration is a public CS, which can directly control the charging rates of its charging piles. To acquire the information about the EV owners' demand response preferences, it is assumed that EV owners can directly communicate with the CS in advance before they choose to park and charge there. In the day-ahead wholesale market, the clearing resolution is one hour, and the CS is a price-taker who purchases energy at the MCP to satisfy EV energy requirements. Due to market entrance requirements, the considered CS may not be able to have access to the wholesale market and benefit from competitive wholesale prices. Hence, an intermediary agent that can integrate the CS and access the wholesale market (e.g., EV aggregators or virtual power plants that can integrate the charging stations) is needed in the energy procurement process. Since the CS cannot affect the market price, it is motivated to shift the EV charging load from high-price hours to low-price hours to reduce the energy bills.

Under the TOU pricing scheme, EV owners who want to reduce their charging fee must wait for low-price hours to park and charge, which reduces the simplicity of the incentive program by significantly limiting EV owners' convenience. Hence, to minimize the restrictions on EV owners' traveling and parking plans, a flat charging price is applied in the CS. The charging loads are shifted through the CS's DRP, which provides certain remuneration to EV owners in exchange for the access right to EV batteries. The DRP managed by the CS includes the buy-out (BO) program and pay-as-use (PAU) program, which correspond to different incentive payment calculation methods in the proposed hybrid incentive program.

The CS needs to set up proper incentive prices to encourage EV owners to sell their charging flexibility. Also, the CS is responsible for scheduling the charging flexibility to minimize the energy procurement cost. For EV owners, they only need to claim their charging demands and DR preferences upon arrival. Besides the dwelling time, other battery information including the initial state-of-charge (SOC), battery capacity, and maximum charging rate can be directly acquired from the battery management system (BMS) of the EVs. The DR preference information includes which incentive they want to receive and the minimum prices they can accept for authorizing the battery access rights.

There are several advantages to apply such a flat pricing and incentive DRP operational framework. Firstly, EV owners do not have to wait for low price hours to park and charge. Secondly, EV owners do not need to actively respond to the incentive signals during the charging duration. Instead, they only need to clarify their DR preferences upon arrival. Thirdly, the negotiation process for real-time demand response is avoided since all the information needed to approach the optimal solution is pre-communicated.

Because the infrastructure for the vehicle to grid (V2G) operation is still an underdeveloped area and frequent discharging of the EVs will accelerate battery degradations, only the grid to vehicle operation mode is considered in this work.

III. Proposed Hybrid Incentive Program

A. *Discussion on Key Properties of Incentive Programs*

In this work, an incentive program is considered to be simple if the required actions from the EV owners are minimal. Consistency of an incentive program means that EV owners' knowledge about the incentives does not have to be updated frequently. Besides, controllability of incentive programs refers to the ability to match the charging load with short-term market price variations. Simplicity and consistency can be difficult to quantify because the criteria can vary from person to person. One example of simple and consistent incentive programs is the TOU pricing, where prices for peak-flat-valley periods are stable for a relatively long period to allow decision-making simple and straightforward. An opposite example is the transactive control program, where EV owners need to actively respond to the incentive signals that change in real-time. For controllability, a controllability index (CI) is defined in this work to quantitatively reflect how controllable a DRP incentive program is:

$$CI(\$/kWh) = \frac{Energy\ Bill\ Reduction(\$)}{Effective\ Flexibility(kWh)} \tag{1}$$

where energy bill reduction is the reduced energy procurement cost (measured in \$) in the wholesale market, and effective flexibility (measured in kWh) is the flexibility that is utilized. Larger CI implies more efficient utilization of each unit of effective flexibility, which can be achieved by more exactly matching the charging load with the variable market price.

For EV owners, simplicity and consistency are favorable properties for an incentive program. From the CS's point of view, controllability is a desirable property as it can achieve more benefits. However, achieving controllability may contradict the simplicity and consistency if EV owners have to actively respond to incentive signals. To address this contradiction, we propose a hybrid incentive program for the CS, which consists of the BO incentive and the PAU incentive. The prices for both the BO and PAU incentives will remain unchanged for a relatively long period. Under the proposed hybrid incentive program, if EV owners accept the CS's offer, they would receive payments for the access right of their EV batteries. With the access right to the batteries, the CS can achieve accurate EV charging load control under the constraint of satisfying EV charging demand. Specifically, by directly controlling the operation of its charging piles, the CS can determine the charging time and charging rates of EVs which are chosen to participate in the DRPs.

Towards this end, the proposed hybrid incentive program features simplicity in terms of EV owners' participation, while consistency is retained regarding the incentive price update frequency. Moreover, controllability can be achieved by the dynamic charging control of the CS.

B. BO Incentive

For EV owners who accept the offers from the BO program, they will receive a payment to buy out all the potential charging flexibility (measured in kWh), which may or may not be used in the charging scheduling. Since the battery charging rates are assumed to be continuously controllable [33], the potential flexibility f_i of the ith EV can be calculated as:

$$\tau_i = t_{i,out} - t_{i,in} \tag{2}$$

$$E_i = (SOC_i^{max} - iSOC_i)Cap_i \tag{3}$$

$$f_i = \min\{E_i, \tau_i P_i^{max} - E_i\} \tag{4}$$

where i is the index for EVs in the BO program. The plug-in and plug-out times are represented by $t_{i,in}$ and $t_{i,out}$, respectively. Term τ_i denotes the total parking time. The energy requirement E_i is calculated using the initial SOC (*iSOC*) and battery capacity Cap_i through Eq (3), in which SOC_i^{max} represents the maximum SOC. The potential charging flexibility f_i is given by Eq (4), which states that f_i is the maximum shiftable load. The calculation of f_i is schematically illustrated in Fig. 2.

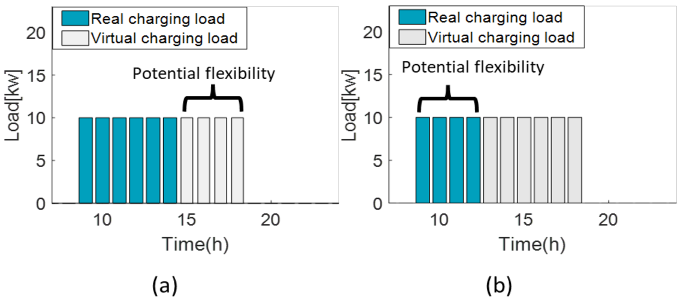


Fig. 2. EV Flexibility in the BO program.

Fig. 2 displays two possible charging scenarios for a typical EV whose parking time is longer than the time required for charging. Real charging load represents the energy that the EV consumes when parking; virtual charging load is the energy that the EV is parking but not consuming because the battery is already fully charged. In both scenarios, the real charging load can be shifted to the virtual charging load, which yields potential EV charging flexibility. In Fig. 2a, only part of the real charging load can be shifted to the virtual charging load, whereas all real charging load can be shifted to virtual charging load in scenarios illustrated in Fig. 2b. When only part of the real charging load can be shifted to the virtual charging load, the potential charging flexibility is given by the totality of the virtual charging load. Otherwise, the potential flexibility is restricted by the real charging load. For EVs with the required charging time less than the parking time, their potential charging flexibility is 0.

C. PAU Incentive

Unlike paying for all the potential flexibility in the BO program, the remuneration in the PAU program depends on effective flexibility. Hence, to calculate the payment in the PAU program, the uncontrolled load profile for each EV must be identified. In the uncontrolled charging scenario, the EV will charge at the maximum rate before reaching the battery capacity Cap_j:

$$P_{j,t}^{uc} = P_j^{max}, \left(SOC_{j,t-1} + \frac{P_j^{max}\Delta t}{Cap_j}\right) \leq SOC_j^{max} \tag{5}$$

where j is the index for EVs in the PAU program. The uncontrolled charging rate of the jth EV at time t is given by $P_{j,t}^{uc}$, whose upper bound is P_j^{max}. The scheduling interval is given by Δt. $P_{j,t}^{uc}$ with superscript '*uc*' stands for the charging power under the uncontrolled charging scenario.

When the EV is about to be fully charged, it will charge at a rate such that the EV just reaches the maximum SOC:

$$P_{j,t}^{uc} = \frac{(SOC_j^{max} - SOC_{j,t-1})Cap_j}{\Delta t}, \frac{P_j^{max}\Delta t}{Cap_j} \geq SOC_j^{max} - SOC_{j,t-1} \tag{6}$$

After the EV is fully charged, the charging rate becomes 0 because discharging is not considered:

$$P_{j,t}^{uc} = 0, \quad SOC_{j,t-1} = SOC_j^{max} \tag{7}$$

As Eqs (5) – (7) are derived for uncontrolled EV charging of the PAU program, they also apply to the BO program. After acquiring the uncontrolled charging profile, the change in charging power can be obtained as the difference between the uncontrolled charging power $P_{j,t}^{uc}$ and the scheduled charging power $P_{j,t}^{s}$:

$$\Delta P_{j,t} = P_{j,t}^{s} - P_{j,t}^{uc} \tag{8}$$

To avoid double remuneration, only the downward power change will be accounted for when calculating the incentive payment. Hence, the power change in the PAU program is divided into downward $\Delta P_{j,t}^{d}$ and upward $\Delta P_{j,t}^{u}$ changes:

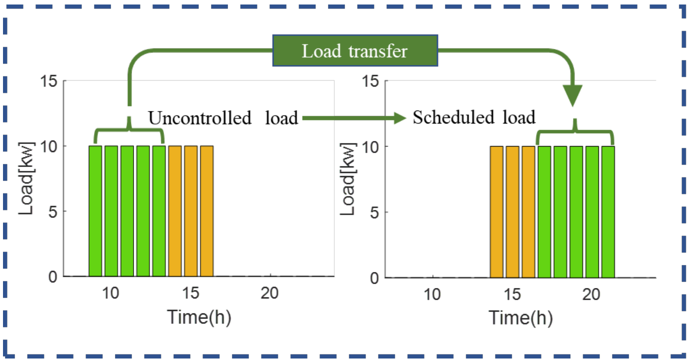
$$\Delta P_{j,t} = \Delta P_{j,t}^{u} - \Delta P_{j,t}^{d} \tag{9}$$

$$\left[\Delta P_{j,t}^{u}, \Delta P_{j,t}^{d}\right] \geq 0 \tag{10}$$

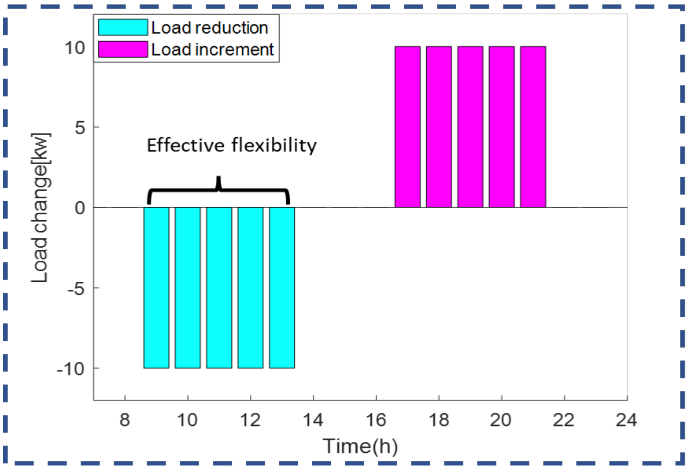
Thus, the power changes are obtained as:

$$\Delta P_{j,t}^{u} - \Delta P_{j,t}^{d} = P_{j,t}^{s} - P_{j,t} \tag{11}$$

The flexibility calculation for the PAU program is schematically depicted in Fig. 3.



(a) Uncontrolled and scheduled load scenarios.



(b) Load change result

Fig. 3. EV flexibility in the PAU program.

Fig. 3a shows the uncontrolled (left) and scheduled (right) charging load profiles for a typical EV. Comparing the uncontrolled load with the scheduled load, it is observed that only the charging loads between hours 9 and 13 are shifted to hours between 17 and 21, whereas the loads at hours 14, 15 and 16 remain unchanged. The load change result from the uncontrolled charging scenario to the scheduled charging scenario is summarized in Fig. 3b, which shows that only the reduced load is counted as remunerable effective flexibility.

D. Participation Status Decision

As the price threshold for authorizing the battery access right can vary among a large group of EV owners, it is not likely that all the EVs will be involved in the DRP. Instead, only EV owners with minimum acceptable prices (MAP) lower than the incentive prices are willing to sell their charging flexibility. Besides, the price for each unit of charging flexibility in each incentive program should be uniform to ensure fairness. Hence, the incentive prices must be determined before EV owners can decide if they want to join the DRP.

In the proposed hybrid incentive program, two prices need to be specified. In the BO program, the incentive price α represents the financial incentive paid to EV owners for each unit of potential flexibility they can provide. In the PAU program, the incentive price β is the financial incentive paid to EV owners for each unit of effective flexibility.

Once the incentive price information becomes available, the participation status of each EV can be determined through the following relationship:

$$y_i(\alpha - \omega_i) \geq 0 \tag{12}$$

$$y_j(\beta - \omega_j) \geq 0 \tag{13}$$

$$[y_i, y_j] \in \{0,1\} \tag{14}$$

where ω_i and ω_j are the MAPs for EV owners to authorize their battery access right in the BO and PAU programs, respectively. Correspondingly, binary terms y_i and y_j are availability indicators for the battery access rights in the BO and PAU programs, respectively. As stated in (12) and (13), EV owners will allow the CS to control their EV charging rates only if the incentive price is higher than their MAPs.

In real-life applications, the MAPs of EV owners depend on their specific features. Hence, the CS needs to perform surveys of its consumers in order to determine the prices that would yield the best outcome.

IV. Optimal Incentive Price Selection Model

From the CS's perspective, higher incentive prices can encourage more EV owners to share their charging flexibility, which allows the CS to reduce the energy procurement cost. Meanwhile, the financial incentives paid to EV owners will also increase due to uplifted incentive prices and a larger purchased flexibility volume. Hence, the selection of incentive prices α and β is of vital importance to the performance of the proposed hybrid incentive program.

To determine the optimal incentive price set (α,β) that will maximize the CS's overall benefit, an optimal incentive price selection model is developed in this section. In the developed optimization model, the objective is to minimize the total cost from the wholesale energy market and the DRP. Therefore, before presenting the optimal incentive price selection model, the incentive payment of EV owners needs to be calculated. The payments of EV owners are calculated as follows:

$$\gamma_i^B = \alpha f_i \tag{15}$$

$$\gamma_j^P = \sum_t \frac{\beta \Delta P_{j,t}^d}{R} \tag{16}$$

where γ_i^B and γ_j^P are the payments in the BO and PAU programs, respectively. The term R is the ratio between one hour and the scheduling resolution of the CS.

After obtaining the incentive payment of EV owners, the optimization problem can be formulated as:

$$\min_{\alpha,\beta,y_i,y_j,\Delta P_{i,t},\Delta P_{j,t}^u,\Delta P_{j,t}^d,E_{M,t}} \{\sum_t \lambda_t E_{M,t} + \sum_i \gamma_i^B y_i + \sum_j \gamma_j^P\} \tag{17}$$

s.t.

$$(2) - (7), (10) - (16) \tag{18}$$

$$(P_{i,t} + P_{j,t} + \Delta P_{i,t} + \Delta P_{j,t}^u - \Delta P_{j,t}^d)\Delta t = E_{M,t} \tag{19}$$

$$0 \leq P_{i,t} + \Delta P_{i,t} \leq P_{i,max} \tag{20}$$

$$-y_i P_{i,max} \leq \Delta P_{i,t} \leq y_i P_{i,max} \tag{21}$$

$$0 \leq P_{j,t} + \Delta P_{j,t}^u - \Delta P_{j,t}^d \leq P_{j,max} \tag{22}$$

$$[\Delta P_{j,t}^d, \Delta P_{j,t}^u] \leq y_j P_{j,max} \tag{23}$$

$$\sum_t \Delta P_{i,t} = 0 \tag{24}$$

$$\sum_t (\Delta P_{j,t}^d - \Delta P_{j,t}^u) = 0 \tag{25}$$

$$0 \leq \alpha \leq \bar{\alpha} \tag{26}$$

$$0 \leq \beta \leq \bar{\beta} \tag{27}$$

where λ_t and $E_{M,t}$ represent the MCP and energy purchased from the market at time t, respectively. The time interval for one charging scheduling period is given by Δt. The objective function contains the energy procurement cost and the incentive payments. Parameters $\bar{\alpha}$ and $\bar{\beta}$ are upper bounds for the incentive prices, which are selected as the highest MAPs of EV owners so as not to affect the optimality of the problem.

Constraint (19) is the power balance constraint. Constraints (20) – (23) represent the battery charging rate limitations under the EV participation status restrictions. Constraints (24) and (25) ensure that EV charging demands are satisfied across the scheduling horizon. Constraints (26) and (27) provide reasonable ranges for the incentive prices to reduce the searching domain and ensure problem convergence.

V. Proposed Solution Methodology

The proposed optimization model has bilinear terms $\beta \Delta P_{j,t}^d$ from the PAU program and αy_i from the BO program. Besides, the solution process for EV charging scheduling under large EV fleets is challenged by the curse of dimensionality issue. Hence, in this section, we first provide a linear reformulation of the original problem, then develop an ADMM-AP algorithm to efficiently solve the reformulated problem for large EV fleets.

A. Problem Linearization

The bilinear term αy_i is the product of a bounded continuous variable α and a binary variable y_i. According to the method proposed in [34], this term can be modeled by introducing a new continuous variable σ_i and the following constraints:

$$\alpha y_i = \sigma_i \tag{28}$$

$$\alpha - (1 - y_i)M \le \sigma_i \le \alpha + (1 - y_i)M \tag{29}$$

$$-y_i M \le \sigma_i \le y_i M \tag{30}$$

where M is a large enough positive constant.

Another bilinear term $\beta\Delta P_{j,t}^d$ is the product of two bounded continuous variables β and $\Delta P_{j,t}^d$. To handle this term, we first use the optimality condition to transform the variable $\Delta P_{j,t}^d$ into the product of a binary variable $y_{j,t}^d$ and a constant $P_{j,t}^{uc}$ derived in (5) – (7), then model this new term $\beta y_{j,t}^d P_{j,t}^{uc}$ by the method proposed in [34].

Firstly, when $\Delta P_{j,t}^d > 0$, from the objective function one can conclude that:

$$\lambda_{j,out} - \lambda_{j,in} > \beta \tag{31}$$

where $\lambda_{j,out}$ is the market price when the load is shifted out, and $\lambda_{j,in}$ is the market price when the load is shifted in. In this case, the profit improvement $\Delta Profit$ from shifting the load $\Delta P_{j,t}^d$ is:

$$\Delta Profit = \Delta P_{j,t}^d\left(\lambda_{j,out} - \lambda_{j,in} - \beta\right) \tag{32}$$

which is an increasing function of $\Delta P_{j,t}^d$. Hence, in the optimal solution, the value of $\Delta P_{j,t}^d$ is either 0 or its maximum possible value $P_{j,t}^{uc}$. To this end, the continuous variable $\Delta P_{j,t}^d$ can be transformed into the product of a binary variable $y_{j,t}^d$ and a constant $P_{j,t}^{uc}$.

The new term $\beta y_{j,t}^d P_{j,t}^{uc}$ is the bilinear product of a bounded continuous variable β, a binary variable $y_{j,t}^d$, and a constant $P_{j,t}^{uc}$. Similarly, the term $\beta y_{j,t}^d P_{j,t}^{uc}$ can be modeled by introducing a new continuous variable $\varphi_{j,t}^d$ and the following constraints:

$$\beta y_{j,t}^d P_{j,t}^{uc} = \varphi_{j,t}^d P_{j,t}^{uc} \tag{33}$$

$$\beta - \left(1 - y_{j,t}^d\right)M \le \varphi_{j,t}^d \le \beta + \left(1 - y_{j,t}^d\right)M \tag{34}$$

$$-y_{j,t}^d M \le \varphi_{j,t}^d \le y_{j,t}^d M \tag{35}$$

where the bilinear term $\beta y_{j,t}^d$ is replaced by the auxiliary variable $\varphi_{j,t}^d$ bounded by constraints (34) and (35).

Hence, the original problem can be reformulated as:

$$\min_{\alpha,\beta,y_i,y_j,\Delta P_{i,t},\Delta P_{j,t}^u,\Delta P_{j,t}^d,E_{M,t},\sigma_i,\varphi_{j,t}} \left\{\sum_i \sigma_i f_i + \sum_t \left(\frac{\sum_j \varphi_{j,t}}{R} + \lambda_t E_{M,t}\right)\right\} \tag{36}$$

s.t.

$$(18) - (35) \tag{37}$$

B. A Distributed Solution Algorithm

As the numbers of price scenarios as well as EVs need to be large enough to obtain statistically significant results, the dimensional disaster in EV charging scheduling problem is hardly avoidable. To address this challenge, the original problem (36) – (37) is decomposed into a distributed form based on the ADMM algorithm. In the distributed problem, EVs are divided into different groups according to the date they park in the CS. Specifically, EVs that are parked on the same day will be clustered as a group. In the ADMM method, the primary problem is responsible for coordinating the optimal incentive prices from different groups. By using the scaled form of the ADMM method, the primary problem in the $(v+1)th$ iteration can be written as:

$$\min_{\alpha,\beta,y_i,y_j} \Big\{\sum_i y_i(\alpha f_i - CR_{i,v}) + \sum_j y_j\left(\beta\ \Delta P_{j,v}^d - CR_{j,v}\right) + \sum_g \Big[\left(\alpha - \boldsymbol{\alpha}_g^v\right)^2 + \left(\beta - \boldsymbol{\beta}_g^v\right)^2 + \frac{\boldsymbol{\rho}_g^v}{2}||\alpha - \boldsymbol{\alpha}_g^v - \boldsymbol{A}_g^v||_2^2 + \frac{\boldsymbol{\rho}_g^v}{2}||\beta - \boldsymbol{\beta}_g^v - \boldsymbol{B}_g^v||_2^2\Big]\Big\} \tag{38}$$

s.t.

$$(2) - (4), (12) - (14) \tag{39}$$

$$\Delta P_{j,v}^d = \frac{1}{R}\sum_t \Delta P_{j,t,v}^d \tag{40}$$

$$CR_{i,v} = -\frac{1}{R}\sum_t \Delta P_{i,t,v}\lambda_t \tag{41}$$

$$CR_{j,v} = \frac{1}{R}\sum_t \left(\Delta P_{j,t,v}^d - \Delta P_{j,t,v}^u\right)\lambda_t \tag{42}$$

$$\min\{\boldsymbol{\alpha}_g^v\} \le \alpha \le \max\{\boldsymbol{\alpha}_g^v\} \tag{43}$$

$$\min\{\boldsymbol{\beta}_g^v\} \le \beta \le \max\{\boldsymbol{\beta}_g^v\} \tag{44}$$

where $\Delta P_{j,v}^d$ is the total power reduction of the jth EV calculated in the vth iteration. The cost reductions $CR_{i,v}$ in the BO program and $CR_{j,v}$ in the PAU program are also calculated values obtained from the scheduling results of the secondary problems by using Eqs (41) and (42). The optimal incentive price set to be coordinated is represented by (α ,β). Incentive price set ($\boldsymbol{\alpha}_g^v$, $\boldsymbol{\beta}_g^v$) are the optimal values of the gth group obtained in the vth iteration. The term $\boldsymbol{\rho}_g^v$ is the penalty for the gth group in the vth iteration. Terms $\boldsymbol{A}_g^v$ and $\boldsymbol{B}_g^v$ are scaled dual variables in the ADMM method. The ranges of the coordinated optimal incentive prices are given by Eqs (43) and (44). The bilinear terms in (38) are handled in a similar way as (28) - (30).

Upon receiving the optimized values of (α^{v+1} ,β^{v+1}) from the primary problem, each group re-calculates the incentive prices using the secondary problem that considers the deviation penalty from the coordinated optimal incentive prices:

$$\min_{\boldsymbol{\alpha}_g,\boldsymbol{\beta}_g,y_i,y_j,\Delta P_{i,t},\Delta P_{j,t}^u,\Delta P_{j,t}^d,\sigma_i,\vartheta_{j,t},E_{M,t}} \Big\{\sum_i \sigma_i f_i + \sum_t \left(\frac{\sum_j \vartheta_{j,t}}{R} + \lambda_t E_{M,t}\right) + \sum_g \Big[\left(\alpha^{v+1} - \boldsymbol{\alpha}_g\right)^2 + \left(\beta^{v+1} - \boldsymbol{\beta}_g\right)^2 + \frac{\boldsymbol{\rho}_g^v}{2}||\alpha^{v+1} - \boldsymbol{\alpha}_g - \boldsymbol{A}_g^v||_2^2 + \frac{\boldsymbol{\rho}_g^v}{2}||\beta^{v+1} - \boldsymbol{\beta}_g - \boldsymbol{B}_g^v||_2^2\Big]\Big\} \tag{45}$$

s.t.

$$(18) - (35) \tag{46}$$

where $\boldsymbol{\alpha}_g$ and $\boldsymbol{\beta}_g$ are incentive prices to be optimized by group g. Notably, the penalty terms are not included in the secondary problems in the first iteration.

By solving the primary and secondary problems, the scaled dual variables ($\boldsymbol{A}^{v+1}$,$\boldsymbol{B}^{v+1}$) are updated:

$$\boldsymbol{A}_g^{v+1} = \boldsymbol{A}_g^v + \alpha^{v+1} - \boldsymbol{\alpha}_g^{v+1} \tag{47}$$

$$\boldsymbol{B}_g^{v+1} = \boldsymbol{B}_g^v + \beta^{v+1} - \boldsymbol{\beta}_g^{v+1} \tag{48}$$

The convergence of the problem is declared when the change in scaled dual variables falls below a certain criterion:

$$\sqrt{||\boldsymbol{A}^{v+1} - \boldsymbol{A}^v||_2^2 + ||\boldsymbol{B}^{v+1} - \boldsymbol{B}^v||_2^2} \le \varepsilon_{ADMM} \tag{49}$$

C. Adaptive Penalty Factors

The conventional ADMM method applies the same penalty factors to all groups, which cannot reflect different qualities of the obtained incentive price sets. To accelerate the convergence of the solution process, an adaptive algorithm is proposed in this work to adjust the penalty factors at the early stages of the consensus optimization problem. The proposed adaptive algorithm assigns heavier penalties to price sets with better qualities to increase their significance in the coordination process. The quality of each price set is evaluated by calculating the CS's final gain $\boldsymbol{F}_g^v$ using that price set:

$$\boldsymbol{F}_g^v = \sum_i y_i(\boldsymbol{\alpha}_g^v f_i - CR_{i,v}) + \sum_j y_j(\boldsymbol{\beta}_g^v \Delta P_{j,v}^d - CR_{j,v}) \quad (50)$$

The first and second terms represent the CS's gains from the BO and PAU programs, respectively. In (50), the values of $\{\boldsymbol{\alpha}_g^v, \boldsymbol{\beta}_g^v, f_i, \Delta P_{j,v}^d, CR_{i,v}, CR_{j,v}\}$ are optimized results of the secondary problems for each group. Besides, the participation status $\{y_i, y_j\}$ in the BO and PAU programs can be determined through Eqs (12) – (14). Hence, the CS's gain under each group incentive price set can be obtained from a simple calculation process that only takes negligible computation time.

After obtaining the qualities of the price sets, the adaptive weight $\boldsymbol{\varphi}_g^v$ of each group is acquired from (51) – (53):

$$F_{max}^v = max\{\boldsymbol{F}_g^v, g \in G\} \quad (51)$$

$$F_{min}^v = min\{\boldsymbol{F}_g^v, g \in G\} \quad (52)$$

$$\boldsymbol{\varphi}_g^v = \frac{F_g^v - F_{min}^v}{F_{max}^v - F_{min}^v} \quad (53)$$

where F_{max}^v and F_{min}^v denote the CS's maximum and minimum gains under different price sets in the vth iteration. The adaptive weight $\boldsymbol{\varphi}_g^v$ is calculated based on the quality of each group by using (53).

Denote ρ_0 as the initial penalty factor, the penalty factors for different groups in each iteration can be acquired by:

$$\begin{cases} \rho_g^{v+1} = \rho_0(1 + \boldsymbol{\varphi}_g^v) & \forall v < v_{max} \\ \rho_g^{v+1} = \rho_0 & \forall v \geq v_{max} \end{cases} \quad (54)$$

where v_{max} is the iteration threshold, after which the adaptive update of the penalty factors is terminated.

D. ADMM-AP Convergence Discussion

In the early stages of the consensus optimization problem, the optimized incentive prices among different groups deviate hugely from each other, resulting in large quality variations. By using the adaptive algorithm, the qualities of different price sets are accounted for to accelerate the convergence. After some iterations, such quality differences become insignificant. Hence, the adaptive update of penalty factors is not needed, and the subsequent iterations work as the standard ADMM method to guarantee the convergence of the solution process.

In this work, we propose an event-triggered mechanism to determine the timing v_{max} for switching from the pre-event stage to the post-event stage without requiring pre-knowledge on the problem convergence speed. The switch between stages occurs when the maximum quality difference among the price sets falls below a given threshold:

$$\frac{F_{max}^v - F_{min}^v}{F_{min}^v} \leq \varepsilon_{adaptive} \quad (55)$$

After the switch of stage, the adaptive update of penalty factors is terminated, and the solution process enters the post-event stage for convergence. To this end, the ADMM-AP algorithm can be summarized as follows:

Algorithm 1: Solution algorithm based on ADMM-AP

1. **Initialize:** $\varepsilon_{ADMM} = 0.0001$, $\rho_0 = 100$, $\varepsilon_{adaptive} = 0.01$
2. **While** (49) is not **True**
3. **Obtain** ρ_g^{v+1} for each group from (50) – (55)
4. **Solve** (38) – (44) and **Derive** $(\alpha^{v+1}, \beta^{v+1})$
5. **Solve** Problem (45) – (46) for each group and **Derive** $(\boldsymbol{\alpha}_g^{v+1}, \boldsymbol{\beta}_g^{v+1})$
6. **Update** $\boldsymbol{A}^{v+1}$ and $\boldsymbol{B}^{v+1}$ using (47) – (48)
7. **End While**

VI. Case Study

A. Basic Data

The case study considers 24 operating days that are uniformly distributed over the year 2020. The price data for 24 days from the Nord Pool UK day-ahead market [35] is shown in Fig. 4.

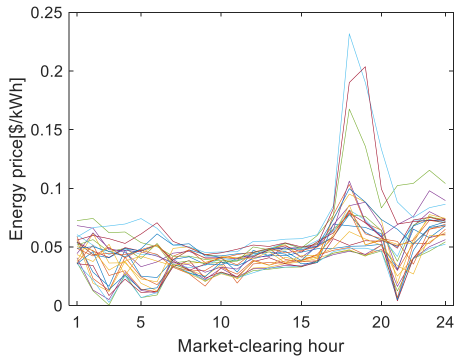


Fig. 4. Day-ahead price data for 24 operating days.

Four typical EV models displayed in Table II are selected to generate EV charging scenarios through the Monte-Carlo-Simulation method introduced in [36]. For each EV, the charging efficiency is assumed to be 0.95 and the maximum SOC is 0.95 [37]. A total of 2,400 EV charging scenarios are generated and evenly distributed to the selected 24 operating days. Among the 2,400 EV charging scenarios, it is assumed that half of the EV owners prefer the BO program and the rest prefer the PAU program. In the BO program, EV owners' MAPs are assumed to follow the normal distribution with mean and variance equal to 25% of the average energy market price. Since the PAU incentive is risker than the BO incentive, the MAPs for EV owners in the PAU program are assumed to be 50% higher than the BO programs. The scheduling resolution of the CS is set to be 15 minutes [38].

TABLE II
EV MODEL PARAMETERS

Model	Tesla model Y	Tesla model 3	BYD Qin plus	Volkswagen ID.4
Capacity	66 kWh	62 kWh	57 kWh	62 kWh
Charging rate	11.5 kW	11.5 kW	11 kW	11 kW

B. Results and Discussions

The potential flexibility distributions of the generated EV charging scenarios are displayed in Fig. 5 regarding different flexibility amounts and EV arrival times. The distribution of EV charging flexibility amount is provided in Fig. 5a, which shows that most EVs can provide an amount of charging flexibility between 30 kWh and 45 kWh. Given the battery capacities shown in Table II, it can be concluded that most of the EV charging demand in this work can be treated as flexible loads. The potential flexibility distribution regarding different EV arrival times is shown in Fig. 5b. The peaks in Fig. 5b correspond to the time windows when most EVs come and charge, one is from hour 8 to hour 9, and the other is between hours 18 and 21. Especially, the second peak covers the price spikes shown in Fig. 4, which makes this part of flexibility extremely valuable. Hence, the amount and value of EV charging flexibility make it promising for supporting the economic operation of the CS.

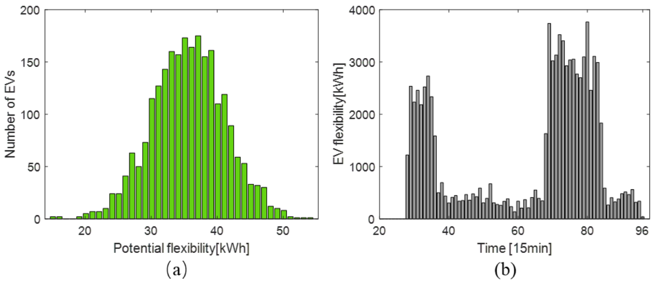


Fig. 5. Flexibility distributions for a) different flexibility amounts and b) different EV arrival times.

Fig. 6a displays the optimal incentive price selection results together with the MAP distributions. By considering the typical price scenarios over a year, the incentive prices that can maximize the CS's benefit are selected to be 0.0114 $\$/kWh$ and 0.0177 $\$/kWh$ in the BO and PAU programs, respectively. In the PAU program, all the remunerated charging flexibility is effective for reducing the energy procurement cost of the CS. However, in the BO program, the CS must pay for potential charging flexibility that may not be useful. Hence, the BO incentive price is lower than the PAU incentive price. Fig. 6b shows the participation status of EV owners. Under the selected incentive prices, 44% and 46% of EV owners are involved in the BO and PAU programs, respectively. In total, 90% of EV owners are incentivized to offer their EV charging flexibility.

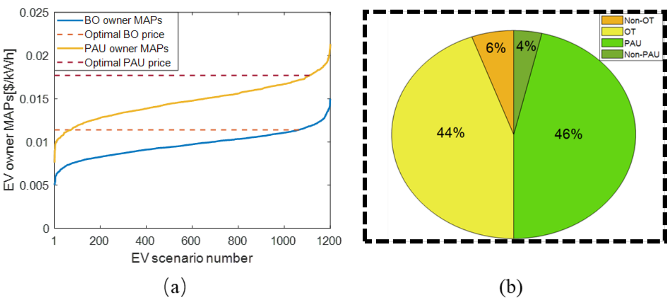


Fig. 6. a) EV owner MAPs and optimized incentive prices, b) participation results.

In the case study, 1,066 EV owners are participating in the BO program. Because the BO program remunerates EV owners based on their potential charging flexibility, all the participating owners are paid even if their charging flexibility is not utilized during the charging scheduling. Thus, the average incentive payment is \$0.42 per EV owner in the BO program. On the other hand, 1,113 EV owners are participating in the PAU program. However, since the PAU program only considers effective charging flexibility, some EV owners are not rewarded because their charging flexibility is not used during the charging scheduling. Consequently, only 762 EV owners are paid in the PAU program with an average incentive payment of \$0.57 per EV owner, and a total of 351 EV owners participating in the PAU program are not rewarded at all. From the EV owners' perspective, this result implies that the PAU program is a more risky program but with a higher average return. Hence, for conservative EV owners, the BO program can be a better choice because it offers a stable return. For risk-seeking EV owners, the PAU program may be preferable because it has a higher average return.

An important criterion to assess the incentive programs is the potential flexibility utilization ratio (PFUR), which can reflect the effectiveness of incentive programs in motivating the utilization of potential charging flexibility:

$$PFUR = \frac{Effective\ Flexibility(kWh)}{Potential\ Flexibility(kWh)} \tag{56}$$

In the optimization result, the PFUR for individual EVs in both the BO and PAU programs are displayed in Fig. 7. The PFUR distribution for EVs in the BO program is shown in Fig. 7a. The number of EVs whose potential flexibility is not utilized at all is 134, which is in line with the participation status displayed in Fig. 6b. In the BO program, the PFUR for 699 EVs reaches 100%, which implies that all their potential charging flexibility is utilized to reduce the energy procurement cost. It is also shown that the PFURs for some EVs are distributed between 0% and 100%, indicating that their potential flexibility is not fully utilized. Since utilizing the purchased potential flexibility will not induce extra costs to the CS, the only reason for this result is that some potential flexibility is useless in terms of reducing the CS's energy procurement cost. In total, 71.05% (31,328 kWh out of 44,091 kWh) of the potential flexibility is used by the CS through the BO incentive program.

Fig. 7b illustrates the PFUR distribution for EVs in the PAU program. Similar to the BO program, two peaks are observed at PFUR equals to 0% and 100%, respectively. However, the number of EVs whose potential flexibility is not utilized is 438, which exceeds the number of EVs that are not selected in the PAU program (87 EVs). This is because the utilization of charging flexibility in the PAU program will lead to extra costs. The utilization of charging flexibility depends on the competing result of the flexibility price and energy bill reduction. Hence, though some EVs are involved in the PAU program, their flexibility is not utilized because the reduced energy procurement cost cannot cover the incentive payment. In the PAU program, there are also some EVs with PFUR distributed between 0% and 100%. The reason for this situation is twofold, one is that some flexibility cannot be used to reduce the energy cost, and the other is that the cost of utilizing some flexibility is larger than the benefit. Overall, 59.06% (25,072 kWh out of 42,452 kWh) of the potential EV charging flexibility is deployed through the PAU incentive program.

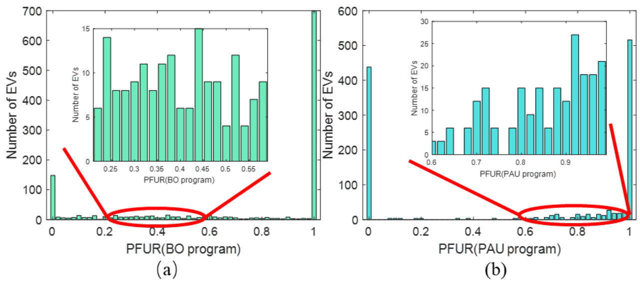


Fig. 7. PFUR distribution for individual EV owners in a) BO program and b) PAU program.

The convergence rates of the proposed ADMM-AP and the conventional ADMM approaches using different numbers of groups are shown in Fig. 8. It can be seen that the convergence speed of the proposed ADMM-AP algorithm becomes more accelerated as the number of groups increases. This is due to the fact that a larger number of groups leads to larger variations of EV charging information and market price data among different groups, and hence reflecting the quality of different price sets becomes more important in the algorithm design.

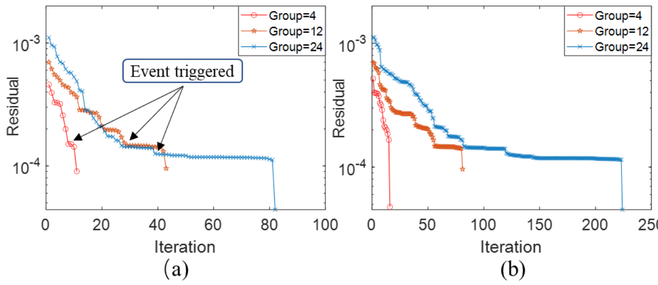


Fig. 8. Convergence rates of a) the proposed ADMM-AP algorithm and b) the conventional ADMM algorithm.

C. Comparative Case Studies

To demonstrate the performance of the proposed hybrid incentive program, we compare it with the TOU program and transactive control program in this subsection. In the comparative case studies, typical day price data from the Nord Pool market is used to evaluate these incentive programs. The flat and TOU prices [39] at the CS are presented in Fig. 9a. In the proposed hybrid incentive program, EV owners with MAPs lower than the incentive prices (i.e., 0.0114 $\$/kWh$ in the BO program and 0.0177 $\$/kWh$ in the PAU program) will be involved in the DRP. In the TOU program, EV owners with MAPs lower than the peak-flat-valley price differences will participate in the DRP. In the transactive control program, the CS determines the price signals to shift EV charging load based on the relationship between the load change and incentive price signal λ_{inc}, which is illustrated in Fig. 9b [27]. The comparative cases are tested using 200 EV charging scenarios shown in Fig. 10.

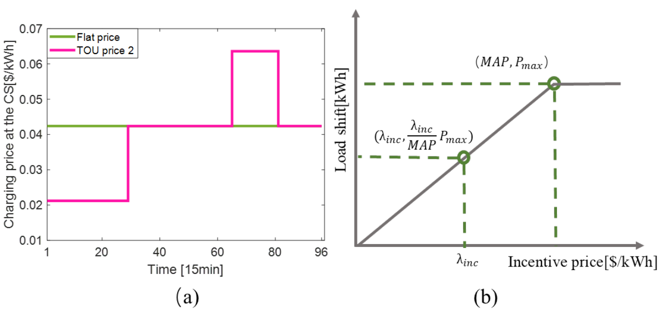


Fig. 9. a) Charging prices at the charging station. b) EV response curve in the transactive control program.

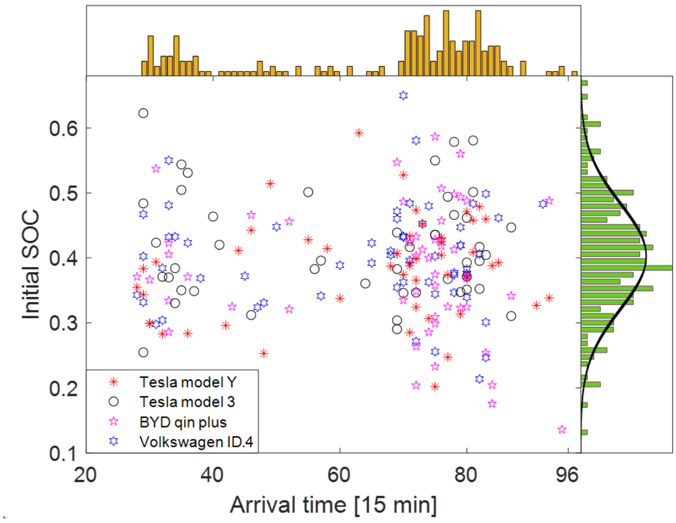


Fig. 10. EV charging scenarios.

The energy market price and net load change in the TOU program are displayed in Fig. 11, in which one can observe that the load is only shifted from hours between 16 and 24 to hours between 1 to 4 of the next day. No load shift is observed in other periods of the day because the charging load is shifted based on the fixed TOU price, which cannot accurately reflect the short-term market price fluctuations. Notably, in some flat-price periods, there are both loads shifted in from higher price hours and loads shifted out to lower price hours, which cancel each other in the net load change result. Hence, the net load change is less than the deployed charging flexibility.

In the TOU program, the CS's revenue and energy bill for charging the EVs are \$260.90 and \$227.46, respectively. Compared to the uncontrolled charging scenario, the CS's revenue and energy procurement cost have been reduced by \$44.95 and \$65.84, respectively. In total, the CS's profit is increased by \$20.89 (from \$12.55 to \$33.44). Meanwhile, by shifting the charging load in the TOU program, EV owners' cost is reduced by \$44.95.

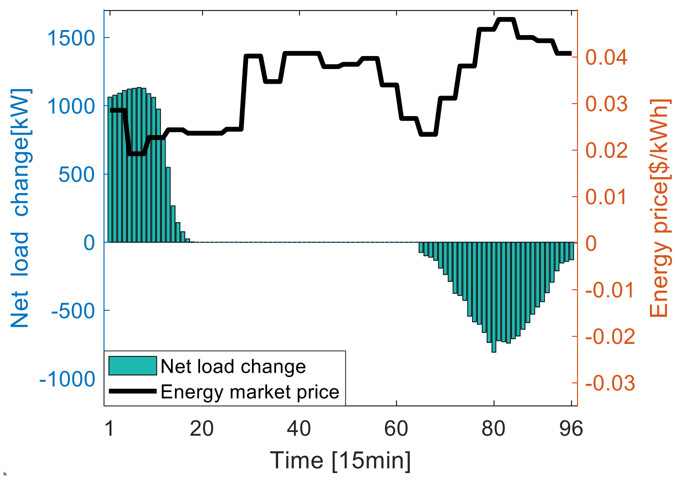


Fig. 11. Load shift results in the TOU pricing program.

The net load change and optimized incentive price signals in the transactive control program are shown in Fig. 12. Compared to the load shift in the TOU program, the load change in the transactive control program can more accurately capture the market price variations. For instance, in the transactive control program, the load increment is more concentrated at hours 2 and 3, which have lower energy prices. Also, the transactive control program shifts loads from high-price hours (10 to 14) to low-price hours (15 to 17), whereas the TOU program does not react to the price differences during this period.

When the market price is high, the CS uses high incentive prices to shift the EV charging load. At low-price hours, to motivate EV owners to charge at large power, the incentive prices can be very low or even zero, such as hours 2 to 7.

In the transactive control program, the CS pays $25.06 for utilizing the charging flexibility, which reduces the energy procurement cost by $57.15. In total, the CS's profit is increased by $32.09 (from $12.55 to $44.64) compared to the uncontrolled charging scenario. For EV owners, their charging fee is reduced by $25.06 due to the incentive payment.

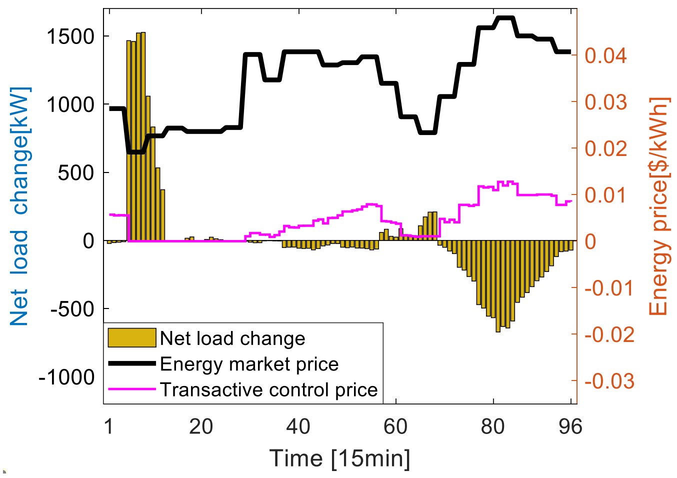


Fig. 12. Load shift results in the transactive control program.

The net load shift result in the proposed hybrid incentive program is presented in Fig. 13. In the BO program, the charging load is shifted from high-price hours to low-price hours even if the price differences are small, which can maximize the CS's gain because utilizing the charging flexibility in the BO program will not induce extra costs. In the PAU program, because shifting the load can bring extra incentive costs, the charging load is only shifted between hours with large price differences (e.g., price differences between hours 18 to 24 and hours 2 to 3) to be profitable.

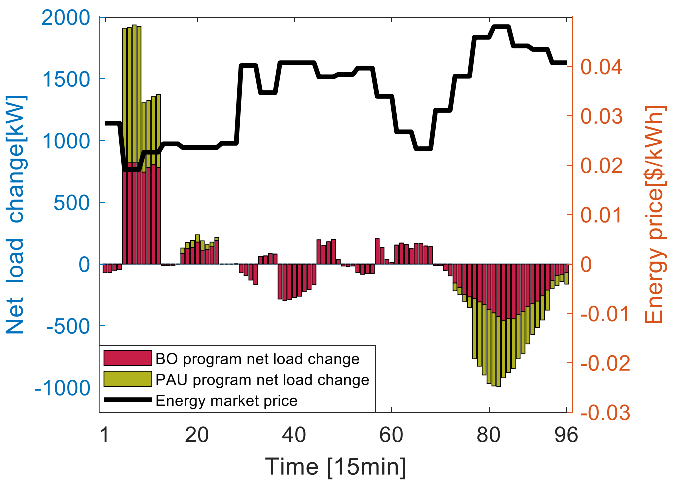


Fig. 13. Load shift results in the proposed hybrid incentive program.

By applying the proposed hybrid incentive program, the CS's electricity bill is reduced by $91.45. The incentive payments in the BO and PAU programs are $37.75 and $31.11, respectively. Overall, the CS's profit is increased by $22.59 compared to the uncontrolled charging scenario. For EV owners, their charging fee is significantly reduced by $68.86 from the proposed hybrid incentive program.

The performances of the uncontrolled charging scenario and investigated incentive programs are all summarized in Table III. Among the investigated programs, the proposed hybrid incentive program achieves the smallest EV owners' cost, which is reduced by 22.51% compared to the uncontrolled charging scenario (from $305.85 to $236.99). Hence, the proposed program is the most attractive program for EV owners. It also reduces 31.18% of wholesale market energy procurement cost for the CS (from $293.30 to $201.85), which is more than other programs. Among the investigated incentive programs, the proposed hybrid incentive program has the largest PFUR of EVs, which confirms that it is the most efficient program in encouraging the utilization of EV charging flexibility and makes it more attractive to the power system. As a simple and consistent incentive program, the controllability of the proposed hybrid incentive program is much better than the TOU program. Though the CI of the transactive control program is higher than the proposed hybrid incentive program, it has however sacrificed simplicity and consistency.

TABLE III
SCHEDULING RESULTS

	CS profit [$]	EV owner cost [$]	Market bill [$]	CI [$/kWh]	PFUR (%)
Uncontrolled charging	12.55	305.85	293.30	0	0
TOU program	33.44	260.90	227.46	0.0183	50.25
Transactive control	44.64	280.79	236.15	0.0225	35.50
Proposed program	35.14	236.99	201.85	0.0200	64.13

The CS's profit obtained from the proposed hybrid incentive program is higher than the TOU program and lower than the transactive control program. The better profitability of the transactive control program comes from the adjustability of flexibility prices. Notably, the CS's profits shown in Table III are obtained under the assumption that the numbers of EVs participating in the listed incentive programs are all the same. However, compared to the transactive control program, the proposed hybrid incentive program is simpler, more consistent, and less costly to EV owners. Hence, it is very likely that a CS adopting the proposed hybrid incentive program can attract more EVs than a CS applying the transactive control program, which can potentially increase the CS's profit.

In summary, the proposed hybrid incentive program is consistent and simple for EV owners to participate. Meanwhile, the proposed hybrid incentive program can minimize the potential restrictions and impacts on EV owners' daily plans and charging costs. Thus, the proposed hybrid incentive program can be a highly attractive and practical program for real-world EV owners that are willing to participate in the DRPs. Besides, the high potential profitability feature of the proposed hybrid incentive program makes it also attractive to the CSs facing volatile electricity prices. Hence, the proposed hybrid incentive program has a great potential for its practical implementations.

Notably, to avoid disturbances of uncertain factors, deterministic price and EV charging scenarios are used in the case studies to compare the proposed hybrid incentive program with existing methods. However, uncertainties in the variable market price and the EV charging demand are inevitable in real-world applications. These uncertainties may have several impacts on CS operations. Firstly, in the day-ahead scheduling stage, to consider the price and EV charging demand uncertainties, some uncertainty handling techniques such as stochastic and robust optimization approaches are required to determine the energy procurement in the wholesale market. Secondly, due to the information gap between the forecast and real EV charging demand, the real-time operational stage needs to simultaneously consider the deviation penalty and price differences.

VII. Conclusion

This work has proposed a novel hybrid incentive program for motivating EV owners to share their EV charging flexibility. The proposed hybrid incentive program combines the advantages of both the static and dynamic incentive programs, making it simple and consistent for EV owners, as well as controllable for the charging station. To determine the incentive prices, an optimal incentive price selection model is developed in this work. Because large EV fleets are involved in the optimization model, an improved ADMM algorithm with adaptive penalties is proposed to efficiently solve the incentive price selection problem.

The proposed hybrid incentive program is compared with the TOU and transactive control programs using real-world price data. The numerical results confirm that the proposed hybrid incentive program is highly efficient in cutting down the CS's energy market bill, reducing EV owners' charging fees, and encouraging the utilization of EV charging flexibility. The proposed hybrid incentive program has superior controllability compared to the TOU program while maintaining simplicity and consistency. Though the transactive control program is more controllable than the proposed hybrid dynamic incentive program, it is more demanding for EV owners in order to participate. The CS's profit is also improved considerably by applying the proposed hybrid incentive program. Although the improvement is not as significant as the transactive control program, the proposed hybrid incentive program is more attractive to EV owners, which may further increase the CS's profit.

Future works may consider the impacts of the V2G operation on the design of incentive programs. Also, competition among different CSs can be considered to assess the necessity of fairness in benefit distribution between the CS and EV owners.

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