Multi-objective Optimization of EV Charging and Discharging for Different Stakeholders

Shaofeng Lu, Bing Han, Fei Xue, Lin Jiang, *Member*, *IEEE*, and Kejun Qian

***Abstract*—As a dynamic energy storage system, electric vehicles (EV) play important roles in future power grids. In this paper, a model for EV aggregator participation in the electricity market has been built with a focus on the feasibility issue of the model arising from economic interest inconsistencies between different stakeholders: EV owners and aggregator. In the model, the EV aggregator attends day-ahead energy and reserve markets for profit maximization by scheduling charging and discharging behaviors of EVs. This issue exists since different stakeholders have different interests which are not necessarily consistent, e.g. profit maximization leads to increasing EV owners' charging fee. To investigate the economic relationship between the two stakeholders, two multi-objective optimization methods (weighted sum and ε-constraint methods) are proposed to take the aggregator profit and EV owners' charging fee into account in the model. A sensitivity analysis is applied to examine the aggregator profit under different price scenarios, which reveals the internal relationship between EV owners' charging fees and aggregator profit. The proposed EV charging and discharging strategy in this paper could be used to determine the settlement price between the aggregator and owners to ensure the feasibility of participation from both EV owners and stakeholders in electricity markets.**

***Index Terms*—Aggregator, economic inconsistency issue, electricity market, EV owners, EV, multi-objective optimization.**

I. Introduction

THE utilization of electric vehicles (EV) is regarded as a promising solution to mitigate exhaust gas emission problems in transportation systems. With the integration of large-scale renewable sources in power grids, more clean energy consumed by EVs could further reduce the exhaust gas emissions on the electricity generation side. Also, EVs have other advantages such as low noise. In this case, the deployment of EVs grows rapidly in recent years. Based on the EV global outlook report, there were 10 million EV globally at the end of 2020 with China overtaking the largest EV market. In the first-quarter of 2021, there were around 200,000 EVs sold in China. It is estimated there will be 200 million EVs in China by 2050 and two-thirds of light-duty vehicles in the U.S. will be EVs by 2040 [2].

However, as the penetration rate of EVs increases in the power grid, the charging behavior of EVs brings new challenges to operation of the power grid. Due to random charging behavior and the charging load of a huge amount of EVs, safe operation of the power grid will be affected. This causes various potential problems, such as power quality, voltage fluctuations and overloading [3]–[5]. To mitigate the negative impact of uncoordinated charging behaviors of EVs on the power grid, a coordinated EV charging strategy is necessary.

On the other hand, massive EVs integration to the grid also brings new opportunities. That is, EVs can participate in operation of the grid as battery energy storage systems. The development of Vehicle-to-Grid (V2G) technology enables charging and discharging behaviors of EVs to provide peak shaving, frequency regulation and auxiliary services to the power grid. EVs fleets are able to enhance resilience of the power grids and promote the integration of renewable energy sources [6], [7]. However, the battery capacity of a single EV is limited, and the charging and discharging of a single EV is insufficient to affect operation of the grid. Therefore, the concept of an EV aggregator is developed. The EV aggregator coordinates charging and discharging behaviors of EVs as a group, and participates in operation of the grid. As a third party between grid and EV owners, the EV aggregator needs to meet the driving requirements of each EV owner. At the same time, the EV aggregator can participate in electricity markets, i.e., regulation and reserve, to obtain profit by coordinating charging and discharging power of the EV [8], [9].

The research of EV charging and discharging optimization can be divided into three categories from the perspective of stakeholders: EV owners, EV aggregator and the grid, as shown in Fig. 1. EV owners are concerned about the charging fee during the parking of EVs, which consists of three parts: charging cost, discharging income and corresponding battery degradation cost. EV owners could schedule the charging and discharging power of EV based on real-time electricity prices to achieve charging fee minimization. The aggregator coordinates multi-EVs and they perform as energy storage systems in electricity markets. From the viewpoint of the grid operator, EVs are treated as a flexible load, which could make response based demand response programs, such that the stability of the power grid could be improved and generation cost/loss can be minimized.

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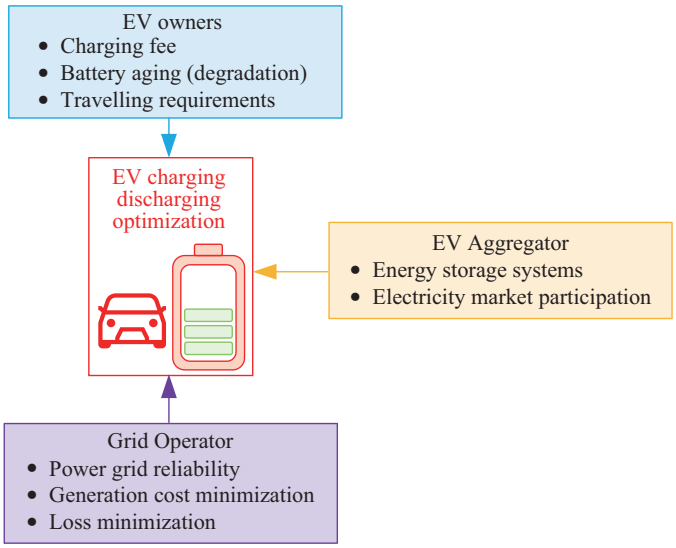

Fig. 1. Three stakeholders relate to EV charging and discharging optimization: EV owners, EV aggregator and the grid operator.

Considering charging fee minimization for EV owners, authors in [10] proposed an accurate charging model of EV battery both for normal and fast charging modes. In [11], the authors included battery aging cost in EV charging and discharging. Results show that battery degradation has a significant impact on the optimal charging and discharging strategy of EVs. Reference [12] considered the lifetime of EVs in participation in power grid operation. Results indicated that the EV battery pack capacity fade and power fade are able to be reduced up to 9.1% and 12.1% respectively. The authors in [13] used a stochastic optimization method to analyze the impact of different demand response programs on aggregator profit. The authors in [14] proposed a two-stage scheduling strategy to maximize EV aggregator profit, by considering coordination between EV charging and discharging and renewable energy. Authors in [15] considered EV charging from PV, and providing regulation service to the grid. Results show that significant charging cost reduction can be achieved. In [16] and [17], the authors proposed a bi-layer optimization strategy of EVs to consider the temporal and spatial characteristics of EVs and power girds.

To consider different stakeholders, the authors in [18] proposed a multi-objective optimization method to operation cost and voltage deviation minimization by considering solar power and EV in microgrids. Reference [19] considered the EV aggregator participating in the electricity market (regulating the market), and the EV owners' charging cost and aggregator profit are both considered. The author introduced the acceptable charging cost for owners as a constraint and this constraint is used in the aggregator profit maximization model. However, the acceptable charging cost of EV owners is not investigated.

It is found that existing research mainly focused on the charging and discharging scheduling strategies of EVs from single stakeholder perspective. Fewer studies mentioned the economic relationship between relevant stakeholders in EV scheduling. This issue is that scheduling strategies are not applicable in real-world scenarios, if the economic benefits of some stakeholders are sacrificed. Since EVs belong to EV owners, the charging fee EV owners need to pay is an important factor in evaluating the relationships between different stakeholders, which cannot be ignored.

According to the issue in the existing research, this paper specifically focuses on exploring the economic relationship between EV aggregator and owners. Two main functions of the aggregator are considered in this study: representing multi-EVs participating in the reserve and energy electricity markets for profit maximization; and meeting driving requirements, and guaranteeing EV owners' economic benefits at the same time. Multi-objective optimization methods are used to consider the economic benefits for EV owner charging fees and aggregator profits. The main contributions of this paper are summarized as follows:

- This paper considers the economic inconsistency issue between the two stakeholders: EV owners and aggregator in the electricity market. Further, the economic relationship between charging fee minimization and profit maximization is studied.
- In order to mitigate the raised issue between stakeholders, this paper adopts the multi-objective optimization methods: weighted-sum method and ε-constraint method to achieve minimization of EV owners' charging fee and maximization of aggregator profit simultaneously. The proposed method guarantees EV owners' benefit while aggregator profit is maximized, such that economic inconsistency between stakeholders is mitigated.
- This paper studies the impact of different electricity price scenarios on aggregator profit. Under the condition that the EV owners' charging fee is not greater than that in self-scheduling, maximum aggregator's profit is obtained under different electricity price scenarios. These results could be used as a reference in designing a reasonable settlement price between aggregator and EV owners.

This research is based on a previous study in [20], where a rebate factor is proposed between owners and the aggregator to guarantee owners benefits in aggregator scheduling. This research further investigates the economic relationship between owners with the aggregator, i.e., changes of EV owners charging fee and aggregator profits at different scenarios are presented. Besides, a sensitivity analysis of electricity prices in affecting charging fee and profits is presented.

The remainder of this paper is organized as follows. Section II gives an introduction to a mechanism of EVs participation in electricity markets and the relationship between EV owners, EV aggregator and the grid. Sections III and IV discuss the modeling of EV charging/discharging optimization from EV owners and EV aggregator viewpoints, respectively. Section V presents the proposed two multi-objective optimization methods. Section VI shows the scheduling results and the performance of the proposed methods are evaluated. Section VII makes the conclusions of this paper.

II. EVs Participation in Electricity Markets

The EV aggregator could obtain profit by participating in electricity markets such as energy, regulation, and reserve

markets. In the PJM energy and reserve markets, the EV aggregator needs to submit the EV charging and discharging plan and reserve capacity plan to the grid in the day-ahead market. Once the proposed plan is accepted, the EV aggregator could receive reserve capacity income. In the real-time reserve market, the proposed reserve capacity could be required to deploy, when there is a mismatch between generation and load. That is, EV charging load is reduced (or increase discharging power of EVs). Finally, the balance between power generation and load demand in the power grid could be achieved. Similarly, when generation is greater than the load demand, the reserve down capacity will be called [21], [22]. The balance between generation with the load could be achieved by calling the reserve up and down capacities. This paper only considers the EV aggregator participation in the energy and reserve markets in the day-ahead market, and the grid calling for the reserve in the real-time market is not considered.

In EV aggregator scheduling, the driving requirements of EV owners should be satisfied, and also the economic concerns (charging fee) of EV owners should be taken into account [20]. In order to ensure the benefits of EV owners, this paper proposes two multi-objective optimization methods, weighted-sum method and ε–constraint method, to address the economic relationship between EV owners and aggregator according to the existing owner–aggregator settlement mechanism [23]. Fig. 2 illustrates the settlement mechanism between EV owners, aggregator and the grid in the electricity market [19].

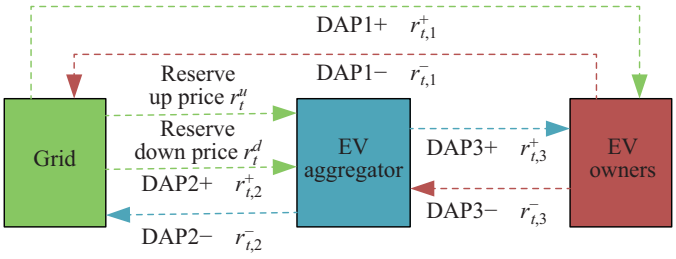

Fig. 2. Price between EV owners with the grid (DAP1), aggregator with the grid (DAP2), and EV owners with aggregator (DAP3). + and − represent charging and discharging, respectively.

In the EV charging and discharging optimization problem, EV owners have two choices: self-scheduling and aggregator scheduling. As shown in Fig. 2, in self-scheduling, the EV owners receive the charging/discharging prices ($r^+_{t,1}$ and $r^-_{t,1}$) from the grid. Considering battery degradation, it is assumed the feed-in tariff is applied to encourage EV to operate in discharging status, so the discharging price is higher than the charging price, i.e., $r^-_t = r^+_t + r, \forall t$ [24], [25]. EV owners can schedule charging and discharging power of EVs according to the electricity price. In aggregator scheduling, EV aggregator could participate in both day-ahead energy and reserve markets. Compared with scheduling of single EV, multi EVs have relatively higher power and capacity ranges. Therefore, the EV aggregator can provide reserve services to the grid and it receives reserve capacity prices (r^u_t and r^d_t) and charging/discharging prices from the grid ($r^+_{t,2}$ and $t^-_{t,2}$). The charging/discharging prices between the EV aggregator with EV owners are represented by $r^+_{t,3}$ and $r^-_{t,3}$.

III. Charging Fee Minimization for EV Owners

This section discusses the charging and discharging of EVs under the self-scheduling strategy. EV owners could obtain minimum charging fee under this strategy, and the scheduling results under this strategy are used as a reference as the settlement between EV owners with the aggregator.

A. Objective Function

EV owners' charging fee consists of two parts: (1) energy purchasing (charging) cost and energy selling (discharging) income to the grid; and (2) the corresponding battery degradation cost in EVs' charging and discharging. The objective function under self-scheduling strategy, that is owners determine the charging strategy of EVs, is given in (1a):

$$\min \quad J_{1,n} + J_{2,n} \tag{1a}$$

$$J_{1,n} = \sum_{t=1}^{M} (r^+_{t,1} p^{+,e}_{n,t} - r^-_{t,1} p^{-,e}_{n,t}) \Delta T \tag{1b}$$

$$J_{2,n} = \sum_{t=1}^{M} D_n (p^{+,e}_{n,t} + p^{-,e}_{n,t}) \Delta T \tag{1c}$$

where $J_{1,n}$ stands for the charging cost and discharging income, and $J_{2,n}$ denotes battery degradation cost of EV owner n, respectively. M and N stand for the scheduling time horizon and the total number of EVs. $p^{+,e}_{n,t}$ and $p^{+,e}_{n,t}$ represent the charging and discharging variables of EV n at time t under self-scheduling strategy, with unit kW. D_n is the parameter of the battery degradation cost, with unit \$/kWh. ΔT is the scheduling time interval, with unit h.

B. Constraints

Equations (2) and (3) guarantee that EV n only can operate in charging or discharging status during available time ($t^a_n \le t < t^d_n$). The charging and discharging power are forced to zero when $t < t^a_n$ or $t \ge t^d_n$), because EV are off the grid during these times.

$$i^+_{n,t} = \begin{cases} 0 & 1 \le t < t^a_n \text{ Before arrival} \\ \{0,1\} & t^a_n \le t < t^d_n \text{ Available} \\ 0 & t^d_n \le t \le M \text{ After departure} \end{cases} \quad \forall t, n \tag{2}$$

$$i^-_{n,t} = \begin{cases} 0 & 1 \le t < t^a_n \text{ Before arrival} \\ \{0,1\} & t^a_n \le t < t^d_n \text{ Available} \\ 0 & t^d_n \le t \le M \text{ After departure} \end{cases} \quad \forall t, n \tag{3}$$

$$i^+_{n,t} + i^-_{n,t} \le 1 \forall t, n \tag{4}$$

Binary variables $i^+_{n,t}$ and $i^-_{n,t}$ indicate whether EV n operates in charging status ($i^+_{n,t} = 1$, $i^-_{n,t} = 0$), discharging status ($i^+_{n,t} = 0$, $i^-_{n,t} = 1$), or idling status ($i^+_{n,t} = 0$, $i^-_{n,t} = 0$). Parameters t^a_n and t^d_n stand for the arrival and departure time of EV n.

The charging and discharging power of EV n is limited by maximum charging and discharging power $\overline{P}_n$. These two constraints are given (5) and (6):

$$0 \le p^{+,e}_{n,t} \le \overline{P}_n i^+_{n,t} \quad \forall t, n \tag{5}$$

$$0 \le p^{-,e}_{n,t} \le \overline{P}_n i^-_{n,t} \quad \forall t, n \tag{6}$$

Considering EV battery capacity, constraints (7) and (8) are used to prevent the EV battery being over-charged or over-discharged, i.e., at each time the battery SOC is limited by the upper/lower bounds:

$$\mathrm{SOC}_{\mathrm{n}}^{\mathrm{a}}+\frac{\sum_{t=1}^{\mathrm{m}}\left(p_{n,t}^{+,e}-p_{n,t}^{-,e}\right)\Delta T}{E_n}\leq\overline{\mathrm{SOC}}\forall n,m \tag{7}$$

$$\mathrm{SOC}_{n}^{a}+\frac{\sum_{t=1}^{\mathrm{m}}\left(p_{n,t}^{+,e}-p_{n,t}^{-,e}\right)\Delta T}{E_n}\geq\underline{\mathrm{SOC}}\forall n,m \tag{8}$$

where SOC_n^a represents the battery SOC of EV n at arrival time; $\overline{\mathrm{SOC}}$ and $\underline{\mathrm{SOC}}$ are the upper and lower bounds of the EV battery SOC; E_n is battery capacity; m is any time between 1 to M.

To satisfy driving requirements of EV owner n, constraint (9) is used to limit the EV battery SOC to not less than the target value SOC_n^d at the departure time:

$$\mathrm{SOC}_{n}^{a}+\frac{\sum_{t=1}^{T}(p_{n,t}^{+,e}-p_{n,t}^{-,e})\Delta T}{E_n}\geq\mathrm{SOC}_{n}^{d}t=t_{n}^{d} \tag{9}$$

IV. Profit Maximization for EV Aggregator

The EV aggregator's participation in the day-ahead electricity markets for profit maximization is discussed in this section. Without taking into account the economic interests of EV owners, the EV aggregator can maximize profit by optimizing charging and discharging variables of EVs and the corresponding reserve up and down capacity variables.

A. Objective Function

Aggregator profit in attending day-ahead electricity markets consists of three parts: (1) I_{res} is the reserve income for providing reserve service to the grid; (2) C_{gri} is the cost of the EV aggregator in purchasing and selling energy with the grid; and (3) I_{own} represents EV aggregator income in purchasing and selling energy with EV owners. (10a) is the objective function of EV aggregator profit:

$$\mathrm{Max}I_{\mathrm{res}}-C_{\mathrm{gri}}+I_{\mathrm{own}} \tag{10a}$$

Reserve capacity profit in (10a) is determined based on the proposed amount of reserve capacity and prices:

$$I_{\mathrm{res}}=\sum_{t=1}^{M}\sum_{n=1}^{N}(r_t^u p_{n,t}^{\mathrm{up}}+r_t^d p_{n,t}^{\mathrm{dw}})\Delta T \tag{10b}$$

where r_t^u, r_t^d are reserve up/down prices at time t; $p_{n,t}^{\mathrm{up}}$ and $p_{n,t}^{\mathrm{dw}}$ are variables for day-ahead reserve capacity for EV n at time t.

C_{gri} in (10a) stands for the energy purchasing cost and selling income to the grid based on electricity prices, which is represented in (10c):

$$C_{\mathrm{gri}}=\sum_{t=1}^{M}\sum_{n=1}^{N}(r_{t,2}^{+}p_{n,t}^{+}-r_{t,2}^{-}p_{n,t}^{-})\Delta T \tag{10c}$$

where $p_{n,t}^{+}$ and $p_{n,t}^{-}$ represent charging and discharging power under aggregator scheduling strategy. $r_{t,2}^{+}$ is the purchasing price from the grid and $r_{t,2}^{-}$ is the selling price to the grid at time t.

I_{own} in (10a) is the purchasing cost and selling income to EV owners based on prices $r_{t,3}^{+}$ and $r_{t,3}^{-}$, which is shown in (10d):

$$I_{\mathrm{own}}=\sum_{t=1}^{M}\sum_{n=1}^{N}(r_{t,3}^{+}p_{n,t}^{+}-r_{t,3}^{-}p_{n,t}^{-})\Delta T \tag{10d}$$

B. Constraints

Constraint (11) and (12) illustrate the charging/discharging power and reserve capacity are limited by the maximum power. For EV n at time t, the difference between the charging/discharging power with the reserve up capacity should equal greater than the maximum discharging power, and the summation between the charging/discharging power with the reserve up capacity should equal less than the maximum charging power.

$$p_{n,t}^{+}-p_{n,t}^{-}+p_{n,t}^{\mathrm{dw}}\leq\overline{P}_n\quad\forall t,n \tag{11}$$

$$p_{n,t}^{+}-p_{n,t}^{-}-p_{n,t}^{\mathrm{up}}\geq-\overline{P}_n\quad\forall t,n \tag{12}$$

The range of the reserve up and down capacities of the EV are defined in constraint (13) and (14):

$$p_{n,t}^{\mathrm{up}}=\begin{cases}0 & 1\leq t<t_n^a\ \text{Before arrival}\\ [0,2\overline{P}_n] & t_n^a\leq t<t_n^d\ \text{Available}\\ 0 & t_n^d\leq t\leq M\ \text{After departure}\end{cases}\quad\forall t,n \tag{13}$$

$$p_{n,t}^{\mathrm{dw}}=\begin{cases}0 & 1\leq t<t_n^a\ \text{Before arrival}\\ [0,2\overline{P}_n] & t_n^a\leq t<t_n^d\ \text{Available}\\ 0 & t_n^d\leq t\leq M\ \text{After departure}\end{cases}\quad\forall t,n \tag{14}$$

In addition, the relationship between the charging/discharging power, reserve capacity with SOC limits are formulated in constraints (15) and (16):

$$\mathrm{SOC}_{n}^{a}+\frac{\sum_{t=1}^{\mathrm{m}}\left(p_{n,t}^{+}-p_{n,t}^{-}\right)\Delta T+p_{n,t}^{\mathrm{dw}}\Delta T}{E_n}\leq\overline{\mathrm{SOC}}\quad\forall m,n \tag{15}$$

$$\mathrm{SOC}_{n}^{a}+\frac{\sum_{t=1}^{\mathrm{m}}\left(p_{n,t}^{+}-p_{n,t}^{-}\right)\Delta T-p_{n,t}^{\mathrm{up}}\Delta T}{E_n}\geq\underline{\mathrm{SOC}}_{n,m}\quad\forall m,n \tag{16}$$

Considering driving requirements of EV owners, the minimum SOC of EV n at each time m $\underline{\mathrm{SOC}}_{n,m}$ used in (16) is determined based on (17):

$$\underline{\mathrm{SOC}}_{n,m}=\max\left\{\underline{\mathrm{SOC}},\mathrm{SOC}^{d}-\frac{\overline{P}_n(t_n^d-m)\Delta T}{E_n}\right\}\forall t,n \tag{17}$$

In this constraint, the minimum SOC should be no less than the lower bound $\underline{\mathrm{SOC}}$. Besides, the battery SOC at time m should not be less than $\frac{\overline{P}_n(t_n^d-m)\Delta T}{E_n}$, so the battery could be charged to the target SOC during the remaining available time $(t_n^d-m)\Delta T$ before departure.

V. Multi-Objective Optimization

In this section, the relationship between EV owners charging fee and aggregator profit are analyzed. According to the proposed settlement mechanism between grid, aggregator and owners in Fig. 2, two multi-objective optimization methods, weighted-sum method and ε-constraint method are used to explore the economic relationship between EV owners and the EV aggregator.

A. Weighted-sum Method

According to the weighted-sum method, charging fee minimization and profit maximization are presented in one objective function by multiplying weight factors w for each objective, as it is given in (18a):

$$\max \quad w_1(I_{\text{res}} - C_{\text{gri}} + I_{\text{own}}) - w_2 \sum_{n=1}^{N} (J'_{1,n} + J'_{2,n}) \quad (18a)$$

$$J'_{1,n} = \sum_{t=1}^{M} (r^{+}_{t,3} p^{+}_{n,t} - r^{-}_{t,3} p^{-}_{n,t}) \Delta T \quad (18b)$$

$$J'_{2,n} = \sum_{t=1}^{M} D_n (p^{+}_{n,t} + p^{-}_{n,t}) \Delta T \quad (18c)$$

where w_1 and w_2 are weights for each objective, with $w_1 + w_2 = 1$. $J'_{1,n}$ and $J'_{2,n}$ are the charging/discharging cost and battery degradation cost of EV n under aggregator scheduling strategy in weighted-sum method.

In weighted-sum method, constraints (2)–(9) and (11)–(17) need to be satisfied. Variables $p^{+,e}_{n,t}$ and $p^{-,e}_{n,t}$ in (5)–(9) are substituted by $p^{+}_{n,t}$ and $p^{-}_{n,t}$, respectively.

B. ε-Constraint Method

The ε-constraint method is applied to analyze the economic relationship between EV owners and the aggregator, where the objective function (19) is to maximize aggregator profit:

$$\max \ I_{\text{res}} - C_{\text{gri}} + I_{\text{own}} \quad (19)$$

subject to: (2)–(9), (11)–(17).

Constraint (20) is used to guarantee the EV owner charging fee should not exceed the results obtained from self-scheduling:

$$\sum_{n=1}^{N} \sum_{t=1}^{M} \left[(r^{+}_{t,3} p^{+}_{n,t} - r^{-}_{t,3} p^{-}_{n,t}) \Delta T + D_n (p^{+}_{n,t} + p^{-}_{n,t}) \Delta T \right] \leq \varepsilon \sum_{n=1}^{N} \left(J^{*}_{1,n} + J^{*}_{2,n} \right) \quad (20)$$

where $J^{*}_{1,n}$ and $J^{*}_{2,n}$ are the optimal solution under self-scheduling. Similarly, the variables $p^{+,e}_{n,t}$ and $p^{-,e}_{n,t}$ in (2)–(9) are substituted by $p^{+}_{n,t}$ and $p^{-}_{n,t}$.

VI. Case Studies

A. Parameter Settings

The charging and discharging optimization of one hundred EVs ($N = 100$) is considered in case studies. Optimization is applied for twenty-four hours ($M = 24$) from 13:00 to 13:00, and the optimization interval is set to one hour ($\Delta T = 1$h). The hourly charging price between the grid with EV owners $r^{+}_{t,1}$ and the reserve capacity price are available in [22]. The parameter of the feed-in tariff is assumed as $r = 0.16$ \$/kWh. It is assumed the price between the grid with EV owners is the same with the grid with EV aggregator, i.e., $r^{+}_{t,2} = r^{+}_{t,1}$ and $r^{-}_{t,2} = r^{-}_{t,1}$. One assumption is made that the aggregator provides discounted charging prices to EV owners to attract their participation in aggregator scheduling, such that $r^{+}_{t,3} = 0.9 r^{+}_{t,1}$.

EV information, i.e. arrival time, departure time and initial SOC of each EV is generated based on the truncated Gaussian distribution, and relevant parameters are available in [13]. It is assumed that EVs in the case study are all with BYD e6 type; the battery parameters of EVs are summarized in Table I.

TABLE I
EV Battery Parameters

Parameter	Parameter	Value
Maximum power	$\overline{P}_n$	8 kW
Battery capacity	E_n	64 kWh
Battery degradation	D	0.083 \$/kWh
Lower bound SOC	$\underline{\text{SOC}}$	0.1
Upper bound SOC	$\overline{\text{SOC}}$	1
Target SOC	SOC^{d}	0.95

B. Economic Inconsistency Issue

The charging and discharging results of EVs under the self-scheduling strategy are shown in Fig. 3. It can be seen from the figure that, from 13:00–17:00 the charging power of EVs is relatively low, because most EVs are off the grid. Since the charging price is low, most EVs connected to the grid, operate in charging status during these periods. Then, during peak load periods (18:00–23:00), EVs have the maximum discharging power of 684 kW at 19:00, but less than maximum charging power of 784 kW at 1:00. There are two main reasons: first, some EVs are off the grid at 19:00, and the second reason is some EVs are with relative low SOC, so these EVs could not operate in discharging status. In 22:00–7:00, most EVs

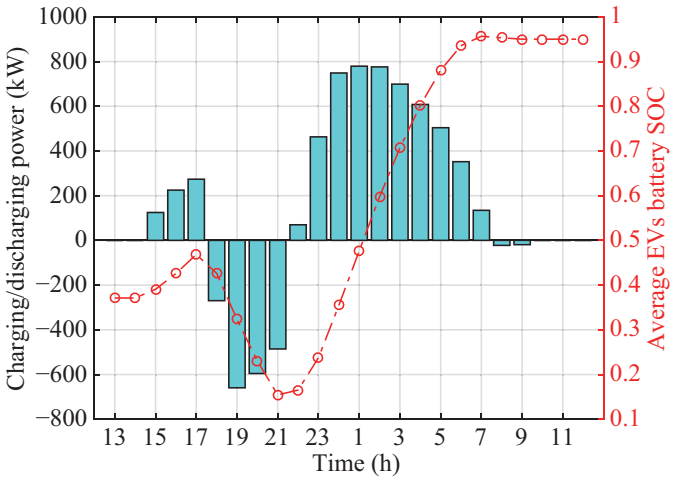

Fig. 3. EVs charging/discharging results under EV owners' self-scheduling strategy.

operate in charging status because the charging price is low during these periods. After 7:00, only a few EVs operate in discharging status.

Figure 4 shows the results of the charging and discharging of EVs under aggregator scheduling without taking into account the interests of EV owners. By comparing the results of Fig. 3, it can be seen there is a significant difference in the charging and discharging power of EVs between self-scheduling and aggregator scheduling. Since aggregators participate in both reserve and energy markets, charging and discharging power of EVs and corresponding reserve capacities are optimized simultaneously.

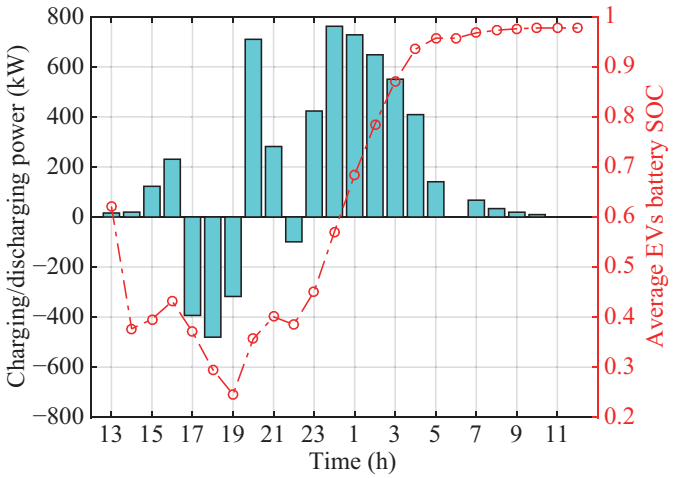

Fig. 4. EVs charging/discharging results under aggregator strategy.

Table II shows the charging fee of EV owners under self-scheduling and aggregator scheduling respectively. Results in the table suggest the total charging fee of 100 EVs under self-scheduling is $ 327.71, and $ 362.26 under aggregator scheduling. Compared with self-scheduling results, the charging fee of EV owners in the aggregator scheduling increased by 9.87%, because the objective function in aggregator scheduling is to maximize profit without taking into account the EV owner's economic benefits. It proves there exists an economic inconsistency issue between EV owners and the EV aggregator. That is, under aggregator scheduling, the charging fee of EV owners is higher than in self-scheduling. Therefore, the economic benefits of EV owners cannot be guaranteed in aggregator scheduling, resulting in EV owners not participating in aggregator scheduling.

TABLE II
EV OWNERS CHARGING FEE AND EV AGGREGATOR PROFIT

Description	Self-scheduling	Aggregator scheduling	Increment percentage
EV owners' charging fee ($)	329.71	362.26	9.87%
EV aggregator profit ($)	N/A	63.86	N/A

C. Pareto Front of Stakeholders' Interests

The economic relationship between the two stakeholders is presented by Pareto front, and the Pareto front shown in Fig. 5 is obtained based on the weighted-sum and ε-constraint methods, respectively. In the weight sum method, the values of weight w_1 increases from 0 to 1 with 0.01 intervals. Optimization results in Fig. 5 show that as weight w_1 changes from 0 to 1, both the EV owners' charging fee and aggregator profit increases. In this figure, the marginal point is defined as the EV owners' charging fee being the same under the two strategies, aggregator strategy and self-scheduling strategy (green dashed line). The right side of the marginal points suggests the EV owners' charging fee is higher than in self-scheduling strategy, while the left side is lower. When weights are $w_1 = 0.33$ and $w_2 = 0.67$, the marginal point can be achieved, where the EV owners' charging fee and aggregator profits are $ 329.60 and $ 51.80, respectively.

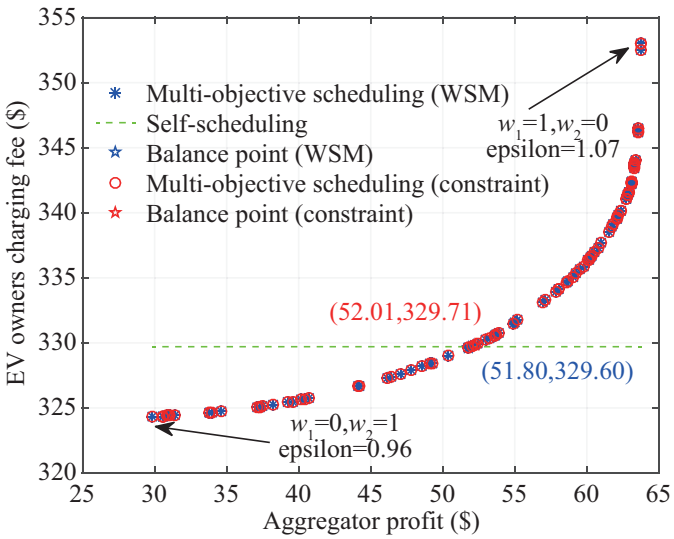

Fig. 5. Pareto front of aggregator profit and EV owners' charging fee including self-scheduling results.

In the ε-constraint method, both aggregator profit and EV owners' charging fee increase as ε increases from 0.96 to 1.07. The marginal point is achieved when $\varepsilon = 1$; at this point, the EV owners' charging fee and aggregator profit are $ 329.71 and $ 52.01, respectively. Table III summarizes the EV owner charging fee and the aggregator profit at marginal points obtained based on the two multi-objective optimization methods.

TABLE III
MARGINAL POINTS OBTAINED BASED ON WEIGHTED-SUM AND ε-CONSTRAINT METHODS

Description	Weighted-sum method ($w_1 = 0.33$, $w_2 = 0.67$)	ε-constraint method ($\varepsilon = 1$)
EV owners' charging fee ($)	329.60	329.71
EV aggregator profit ($)	51.80	52.01

On the left-hand side of the marginal point, aggregator profit significantly reduces when w_1 or ε decreases. These results could be used as a reference in balancing the economic interests of the two stakeholders and thus design a reasonable settlement mechanism between EV owners and aggregator.

Moreover, it can be seen from Fig. 5 the EV owners' charging fee increases significantly with the values of w_1

or ε decreases on the right-hand side of the marginal point. Aggregator profit reduces significantly, on the left-hand side of the marginal point, when the values of w_1 or ε decrease. These results reveal the economic interests between owners and aggregator, which can be used as reference in designing a reasonable settlement between them.

D. Sensitivity Analysis of Price with Aggregator Profit

This section discusses changes in aggregator profit and EV owners' charging fee under different price scenarios. It is assumed DAP1+ is fixed, and DAP2+ and DAP3+ are adjusted linearly with DAP1+ (DAP2+ and DAP3+ are with different percentages of DAP1+). Table IV shows maximum profit of the aggregator under different price scenarios of DAP2+ and DAP3+ under the condition that the EV owner's charging fee is not greater than in self-scheduling.

TABLE IV
SENSITIVITY ANALYSIS OF THE AGGREGATOR PROFIT UNDER DIFFERENT PRICE SCENARIOS. DAP3+ AND DAP2+ ARE WITH DIFFERENT PERCENTAGE OF DAP1+

Profit ($)		DAP3+				
		60%	70%	80%	90%	100%
DAP2+	60%	70.80	77.63	77.90	73.29	57.50
	70%	63.70	69.53	70.73	67.53	52.30
	80%	57.47	62.94	64.75	62.17	47.11
	90%	52.05	57.03	58.98	57.05	41.91
	100%	47.07	51.57	53.69	52.01	36.84

It can be seen from Table V, minimum profit of the aggregator is $ 36.71 (DAP2+ and DAP3+ are both 100%) and maximum profit of the aggregator is $ 77.90 (DAP2+ is 60% and DAP3+ is 80%). It is found that aggregator profit decreases with DAP2+ rises. This indicates a higher price between the aggregator with the grid could lead to lower aggregator profit. With DAP3+ increases from 60% to 100%, aggregator profit rises first and then falls. The aggregator could obtain maximum profit when DAP3 is 80%. Results in Table V show that reserve capacity income increases first and decreases with DAP3+ increases.

According to constraint (20), increasing of DAP3+ results in a reduction of feasible solutions. Thus the ability of the aggregator to participate in the reserve market decreases and reserve capacity income decreases. On the other hand, with DAP3+ increases, the price difference between the DAP3+ and DAP2+ is significant. EV aggregator could receive a lower purchasing/selling cost from EV owners. Therefore, when the DAP3+ is 80%, the total income (reserve capacity profit and purchasing/selling cost) reaches a maximum of $ 53.69. Results show a reasonable price between the aggregator and EV owners is of great significance for improving aggregator profit.

VII. CONCLUSION

This paper proposes a model for EVs participation in electricity markets. The economic relationship and the issues between two stakeholders (EV owners and aggregator) are discussed. Two multi-objective optimization methods are used to show the relationship between EV owner charging fee and aggregator profit, and the balance between the EV owners' charging fee minimization and the aggregator profit maximization is achieved.

The main findings of this paper are summarized as follows:

- An economic inconsistency issue exists between EV owners and aggregator. EV owners' benefits are sacrificed in aggregator scheduling. Case studies show that EV owners' charging fee increases by 9.87% in aggregator scheduling.
- The impact of different price scenarios of DAP2+ and DAP3+ on aggregator profit is analyzed. The proposed multi-objective optimization methods could be used for different price scenarios, and the price which maximum profit could be determined.
- The proposed method could be used to determine a reasonable price between aggregator and the EV owner, and the economic inconsistency issue could be mitigated.

The proposed method in this paper only considers the relationship between EV owners and EV aggregator, but disregards the benefit to the grid. In real-world scenarios, EV owners transport in the transportation network and charge their EVs in the power grid network. Such that, the transportation and grid networks are coupled by charging stations (EV aggregators). It is worth investigating the relationship between the three stakeholders in real-work scenarios.

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TABLE V
COMPOSITION OF EV OWNERS' CHARGING FEE AND AGGREGATOR PROFITS UNDER DIFFERENT SCENARIOS OF DAP3+ (DAP2+ IS 100% OF DAP1+)

Scenario	Aggregator			EV owners		
	Reserve capacity income ($)	Purchasing/selling cost ($)	Total income ($)	Purchasing/selling income ($)	Battery degradation cost ($)	Total fee ($)
DAP3+ is 60% of DAP1+	65.70	18.62	47.07	121.38	451.09	329.71
DAP3+ is 70% of DAP1+	67.37	15.80	51.57	186.05	515.76	329.71
DAP3+ is 80% of DAP1+	64.01	10.31	53.69	212.51	542.22	329.71
DAP3+ is 90% of DAP1+	56.99	4.98	52.01	242.29	572.00	329.71
DAP3+ is 100% of DAP1+	36.84	0	36.84	324.14	653.85	329.71

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