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Three-stage electric vehicle scheduling considering stakeholders economic inconsistency and battery degradation

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Abstract: This study proposes an electric vehicle (EV) aggregator operation mechanism in a residential community. The EV charging and discharging operation behaviours are scheduled to maximise the EV aggregator revenue, while EV aggregator provides reserve service for the grid. This study not only considers the energy and information interactions between three stakeholders: EV aggregator, EV owners, and power grids, but also the economic interests of aggregator and owners are considered. The aggregator-owner economic inconsistency issue (EV owners get higher charging cost in aggregator scheduling than self-scheduling) is presented. In order to mediate this issue, a rebate factor is proposed. In the first stage, the objective is to minimise the day-ahead (DA) charging cost of EV owners. Then the second stage is to maximise DA aggregator revenue with different rebate values. Finally, in the third stage, a real-time scheduling strategy is proposed to maximise aggregator revenue using the optimal rebate value. In addition, the battery degradation in influencing scheduling is formulated. Scheduling results show the effectiveness of the proposed strategy, e.g. economic inconsistency of different parties can be mediated. Significant reduction of EV owners' cost from self-scheduling can be achieved while the revenue of EV aggregator is maximised under the proposed strategy.

1 Introduction

With the tendency of green transportation develops, electric vehicle (EV) as a green transportation tool has the advantage of better energy conversion efficiency and no green gas emission compared with traditional internal combustion vehicle. According to the Chinese government announcement, a national strategic plan of electrification of transportation has been made for the year of 2011–2015. In addition, Chinese government sets a plan for 'ten cities and thousands units' to promote the penetration levels of New-Energy Vehicle (NEV) in public transportation, with the aim of five million NEVs in 2020 [1]. With the penetration level of EV increasing, uncoordinated charging of EVs brings new challenges and problems for power grids operation. Owing to the massive amount stochastic charging behaviours and huge charging power of EVs, the stability and capacity of power systems will be affected, leading to potential issues such as power quality, voltage deviation and overload problems [2]. To tackle the negative effects of EVs charging to power systems, a coordinated charging strategy of EVs should be adopted.

In modern smart grids, the concept of cyber-physical systems (CPS) provides an opportunity for physical devices realising a coordination based on information exchange. That is, by utilising advance sensors, the physical properties and information can be amalgamated. Finally, the energy use in power grids could be coordinated properly [3]. In this circumstance, the aggregator is a promising candidate in CPS, which is an intermediate system to represent all EVs' energy requirements to participate in power grids operation. In this case, energy interactions between EVs and power grids can be coordinated by the aggregator and thus the negative effects of EVs to power grids can be eliminated.

The utilisation of demand response (DR) programs provides opportunities for the information interactions between power grids, aggregator, and owners. Owners are encouraged to change their energy usage habits based on price incentives, that is to reduce and shift their demand during peak periods and thus to obtain financial incentives. Compared with residential home applicants, EV has a higher flexibility since during 95% of the period, EVs are parked and available for coordination [4]. The great flexibility of EV could satisfy various types of DR programs so to obtain financial income for EV owners. Moreover, by aggregating the massive amount of EVs together and working under the vehicle-to-grid (V2G) mode (charging and discharging), aggregator could provide a large power range to make responses to power grids, which not only eliminate the negative impacts of EVs charging behaviours but also improve power grids reliability. Despite the benefits of V2G, frequent charging and discharging of EV leads to the battery degradation increase. The battery degradation problem is the main obstacle to the widespread implementation of V2G technology [5]. The battery degradation has significant influence in EV charging and discharging operations (i.e. EV owners are unwilling to work under V2G with a high battery degradation fee). Thus, a proper battery degradation model is necessary during EVs charging and discharging scheduling, which cannot be neglected.

1.1 Main contributions

This paper introduces a three-stage EV charging and discharging scheduling strategy in a typical residential community. The proposed strategy aims to maximise EV aggregator revenue without sacrificing each EV owner economic benefit. In the first stage, EV charging and discharging operations are scheduled from EV owners' viewpoint (self-scheduling), the objective is to minimise the charging cost of each owner. The second-stage scheduling strategy aims to maximise aggregator revenue versus rebate values by taking EV owners' economic benefits into account. The third stage is to apply the optimal rebate value from the second stage in the real-time (RT) scheduling strategy. Considering the uncertainty of EV driving behaviours, a model predictive control (MPC) algorithm is applied in the third stage and a dynamic RT EV information model is proposed. These three stages are linked as follows: the first-stage scheduling results of EV owner charging cost are involved as constraints in the second-stage scheduling; then the optimal rebate value is determined in the second-stage scheduling, which will be applied in the third-stage scheduling.

The main contributions of this paper are highlighted as follows:

- The economic inconsistency issue is considered in the paper, i.e. the economic interests of EV owners and EV aggregator are analysed and the economic inconsistency issue between these two stakeholders is presented. Moreover, a sensitivity analysis of the factors in impacting economic inconsistency is presented.
- To mediate the economic inconsistency issue between aggregator and EV owners, a rebate factor is introduced in this paper. The optimal rebate value is found in the second-stage scheduling, which maximises the aggregator revenue under the condition that there is no charging cost increment for each owner compared with the results from the first-stage scheduling.

1.2 Paper organisation

The remaining of this paper is organised as follows. Section 2 presents EV charging and discharging scheduling strategies. Section 3 discusses the three-stage EV charging and discharging strategy. Section 4 introduces the day-ahead (DA) and RT EV information models and relevant model settings. Section 5 illustrates the scheduling results and discussions. Finally, Section 6 will draw the conclusions of this paper.

2 EV charging and discharging scheduling strategies

Numerous previous papers of EV charging and discharging scheduling are mainly categorised based on three stakeholders: EV owners, power grids, and EV aggregator.

In [6], an aggregator providing ancillary services to power grids is proposed. A robust algorithm is applied in the model by considering the uncertainty of energy and reserve prices based on linear programming. Further, a battery degradation cost model is presented. In [7], a two-stage scheduling strategy is proposed to maximise EV parking deck revenue. A marginal electricity price is determined in the first stage to maintain the parking deck revenue and in the second stage, an MPC-based online method is used to accommodate the uncertainty of EV driving behaviours. In [8], the authors concentrated on two objectives: maximising parking lot revenue and maximising the number of EVs fulfilling their requirements in a two layer (day-head and RT) parking lot recharging systems. In [9], Jin *et al.* jointly considered the aggregator revenue and EV owners cost demand by setting an upper bound charging cost while maximising aggregator revenue. In [10], the authors studied EVs charging with energy storage systems in the regulation market to maximise aggregator revenue based on mixed-integer linear programming (MILP) algorithm. Results showed that the aggregator revenue can be improved by 7.8% with the aid of energy storage systems. In [2], the authors used stochastic programming approach to examine the impact of different DR programs to EV parking lot profits. The results demonstrated that by participating selected combination of DR programs, the parking lot profit can be significantly increased. In [5], the battery degradation cost is involved in EVs charging and discharging scheduling model. In the model, the degradation parameter is related with total discharging energy, so that an iterative MILP algorithm is adopted. In addition, a sensitive analysis in affecting charging and discharging strategy is carried out in terms of discharging reward, charging period and battery capital cost. In [11], a micro-grid energy management system was built involving household load, EV, and renewable sources. The model aimed to minimise the economic cost of energy exchange between the micro-grid and the main grid.

Table 1 summarises the related works and the proposed work based on the five aspects: stakeholder viewpoint, objective, optimisation algorithm, time horizon and decision-making location.

Current researches mainly focus on the optimal operation of EV charging and discharging from the viewpoint of different stakeholders: EV owners, power grids, and EV aggregator. However, there is little work in investigating the relationship between these stakeholders from the economic benefits perspective. Due to the fact that EVs belong to each EV owner, the economic benefits of each EV owner is an important part in economic interactions among stakeholders. Therefore, it is not practical to consider the energy and information interactions from the viewpoint of a single stakeholder.

In [2], the objective function consists of several terms to maximise aggregator revenue, which contains the income of selling energy to EV owners and the cost of purchasing energy from EV owners. However, it is not practical that the EV owners economic benefits are integrated into the EV aggregator objective function since different stakeholders' economic interests are not same. In [9], the authors jointly considered EV aggregator and EV owner by involving EV owner's charging cost limit as the key constraint in aggregator scheduling. However, the EV owner's charging cost is a parameter and the rationale of providing this parameter is not provided. In [25], a rebate factor is introduced in the model to encourage EV owners to participate in power grids operation. However, the value of rebate factor is not determined, and the charging cost of EV owners participates in power grids operation is not discussed (EV owners economic interests are not evaluated).

Table 1 Summary for EV charging and discharging strategies

Authors	Viewpoint	Objective	Algorithm	Time horizon	Centralised decentralised
Antunez *et al.* [12]	power grids	min grid operation cost	MILP	RT	centralised
Cao *et al.* [13]	EV owners	min owner charging fee	heuristic algorithm	DA	centralised
Igualada *et al.* [11]	power grids	min grid cost	MILP	DA	centralised
Jin *et al.* [10]	aggregator	max aggregator revenue	MILP	RT	centralised
Momber *et al.* [14]	aggregator	max aggregator revenue	stochastic LP	DA	centralised
Qian *et al.* [15]	EV owners	min charging fee	LP	DA	centralised
Zheng *et al.* [16]	power grids	min power fluctuation level	genetic algorithm	DA	centralised
Gao *et al.* [17]	power grids	min grid operation cost	optimal control algorithm	DA	decentralised
Kumar *et al.* [18]	power grids	min load variation	dynamic programming	RT	centralised
Vaya and Andersson [19]	aggregator	min charging cost	MILP	DA	centralised
Mohamed *et al.* [20]	EV owners	min charging cost	fuzzy agent	real time	decentralised
Wu *et al.* [21]	power grids	min operation cost	MILP	DA	centralised
Yang *et al.* [22]	aggregator	min purchasing cost	stochastic LP	real time	centralised
Martin *et al.* [23]	power grids	max reserve profit	stochastic programming	DA	centralised
Zhang *et al.* [24]	power grids	max reserve profit	quadratic programming	RT	centralised
Guo *et al.* [7]	aggregator	max aggregator revenue	model predictive control	RT	centralised
Jin *et al.* [9]	EV owners	min charging cost	LP	DA	centralised
Melo *et al.* [6]	EV aggregator	min charging cost	robust optimisation	DA	centralised
proposed work	EV owner	EV aggregatormax aggregator revenue	MILP	DART	centralised

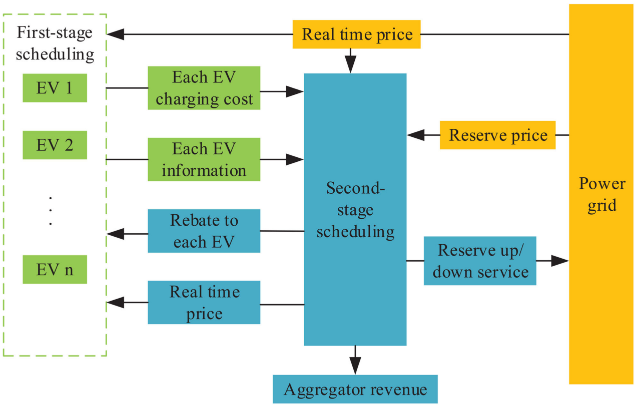

Fig. 1 *First and second stages scheduling strategy*

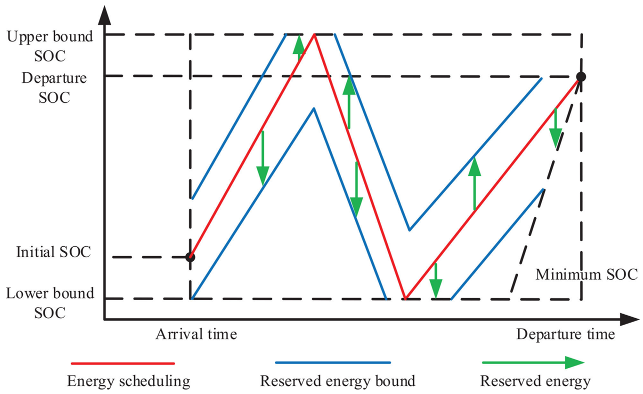

Fig. 2 *Energy scheduling and corresponding reserved energy*

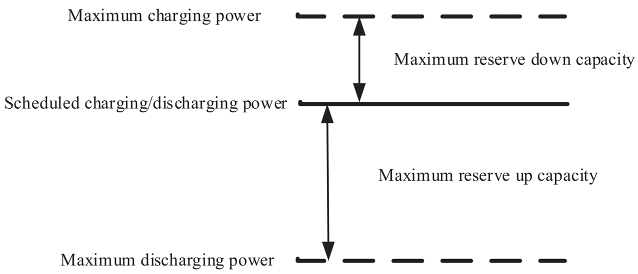

Fig. 3 *Operating power and reserve capacity (without SOC and driving constraints)*

3 Three-stage scheduling strategy

3.1 Problem definition

This section introduces the three-stage scheduling strategy. The first and second stages are DA strategies and the third stage is a RT strategy. The concepts of first and second stages are illustrated in Fig. 1.

In the first stage, the interaction between EV owner and power grids is formulated. A DA scheduling strategy (charging and discharging) is presented aiming to minimise each owner charging cost based on RT price. After that, the energy and reserve interactions between EV owners, the aggregator and power grids are modelled in the second stage where an aggregator participates in both energy and reserve markets. As a coordinator between power grids and EV owners, aggregator obtains each EV information (arrival time, departure time and initial SOC) and charging cost from EV owners. Then, aggregator schedules all EVs' charging and discharging operations based on RT price and reserve up/down prices. At the same time, the reserve up/down capacities of the aggregator are determined and submitted to power grids. Finally, aggregator gains revenue from the grid.

The relationship between energy scheduling and the reserved energy is illustrated in Fig. 2. It shows a typical single EV under V2G mode during the available time, the reserved energy (in kWh) shows the ability of EV to increase or decrease current consumption energy temporarily based on the requirement of power grids. At each time, there are three corresponding values for each single EV: operating power (charging, discharging or idling status), reserve up capacity and reserve down capacity. By evaluating reserve up and down capacities at each time, the flexibility of EV is determined. EV aggregator will submit reserve up and down capacities with multi-EVs together to power grids and thus participate in power grids reserve market. Power grids could call for reserve (reserve deployment) from EV aggregator and thus keep power girds stability.

Fig. 3 shows the relationship between operating power, reserve up capacity and reserve down capacity without considering battery SOC and EV owner driving requirements. The reserve down capacity (in kW) is defined as the difference between maximum charging power with the current operation power and the reserve up capacity (in kW) is the difference between maximum discharging power with current operation power.

3.2 First stage: EV owners' scheduling strategy

The first stage is to minimise the DA charging cost of each EV owner $J_n^d(x_{n,t}^{c,d}, x_{n,t}^{d,d}), \forall t$ under V2G based on RT price and DA EV information $[t_{a,n}^d, t_{d,n}^d, \mathrm{SOC}_{ini,n}^d], \forall n$. The EV owner charging cost consists of three terms: (i) charging fee for purchasing energy from the grid, (ii) discharging income for selling energy back to the grid and (iii) corresponding battery degradation fee both for charging and discharging. Since EV operations are independent of each other [7], the objective function of each EV owner can be integrated as follows:

$$
\begin{aligned}
\text{Min} \sum_{n=1}^{N} J_n^d = & \sum_{t=0}^{M} \sum_{n=1}^{N} p_n (r_{t,1}^c x_{n,t}^{c,d} - r_{t,1}^d x_{n,t}^{d,d}) \Delta T \\
& + \sum_{t=0}^{M} \sum_{n=1}^{N} C_d p_n (x_{n,t}^{c,d} + x_{n,t}^{d,d}) \Delta T
\end{aligned} \tag{1}
$$

where M is the total time intervals; N is the total EV number; $r_{t,1}^c$ are $r_{t,1}^d$ are purchasing and selling RT price information of owners obtained from power grids at time t; p_n stands for the maximum charging and discharging power of EV n; $x_{n,t}^{c,d}$ and $x_{n,t}^{d,d}$ are DA charging and discharging variables of the model, respectively; C_d is the degradation parameter of the battery with the unit \$/kWh and T is the time interval. To enhance the energy interactions between the EVs and the grids, EV owners will be rewarded for discharging according to feed-in-policy [5], i.e. $r_{t,1}^c = r_{t,1}^c + s$, where s is a positive real number representing the V2G reward tariff in \$/kWh to encourage EV owners to discharge energy

$$
x_{n,t}^{c,d} = \begin{cases} 0 & 0 \le t < t_{a,n}^d \quad \text{before arrival} \\ 1 & t_{a,n}^d \le t \le t_{d,n}^d \quad \text{charging} \\ 0 & t_{a,n}^d \le t \le t_{d,n}^d \quad \text{idling or discharging} \\ 0 & t_{d,n}^d < t \le \mathrm{M} \quad \text{after departure} \end{cases} \quad \forall n, \forall t \tag{2}
$$

$$
x_{n,t}^{d,d} = \begin{cases} 0 & 0 \le t < t_{a,n}^d \quad \text{before arrival} \\ 1 & t_{a,n}^d \le t \le t_{d,n}^d \quad \text{discharging} \\ 0 & t_{a,n}^d \le t \le t_{d,n}^d \quad \text{charging or idling} \\ 0 & t_{d,n}^d < t \le \mathrm{M} \quad \text{after departure} \end{cases} \quad \forall n, \forall t \tag{3}
$$

In constraints (2) and (3), $x_{n,t}^{c,d}$ and $x_{n,t}^{d,d}$ are 0, 1 integer variables to represent the charging ($x_{n,t}^{c,d} = 1$, $x_{n,t}^{d,d} = 0$), discharging ($x_{n,t}^{c,d} = 0$, $x_{n,t}^{d,d} = 1$) and idling ($x_{n,t}^{c,d} = 0$, $x_{n,t}^{d,d} = 0$) status of EV during available time. $t_{a,n}^d$ and $t_{d,n}^d$ are DA EV information for arrival time and departure time of EV n

$$x_{n,t}^{c,d} + x_{n,t}^{d,d} \le 1 \quad \forall t, \forall n \tag{4}$$

Constraint (4) makes sure EV only has one status during operation, i.e. EV cannot operate at two statuses for charging and discharging simultaneously

$$\mathrm{SOC}_n^t = \mathrm{SOC}_n^{t-1} + \frac{p_n(x_{n,t}^{c,d} - x_{n,t}^{d,d})\Delta T}{E_n} \quad \forall t, \forall n \tag{5}$$

The relationship between charging and discharging power with EV battery SOC is described in (5), where E_n is the battery capacity of EV n

$$\underline{\mathrm{SOC}} \le \mathrm{SOC}_n^t \le \overline{\mathrm{SOC}} \quad \forall t, \forall n \tag{6}$$

$$\mathrm{SOC}_n^t = \mathrm{SOC}_{\mathrm{ini},n}^d \quad t = t_{a,n}^d, \forall n \tag{7}$$

$$\mathrm{SOC}_n^t \ge \mathrm{SOC}_{\mathrm{dep}} \quad t = t_{d,n}^d, \forall n \tag{8}$$

In constraint (6), $\underline{\mathrm{SOC}}$ and $\overline{\mathrm{SOC}}$ are the lower and upper bounds for EV battery SOC, respectively, to prevent the battery from over discharging or charging. Furthermore, constraint (7) defines the initial SOC equals to $\mathrm{SOC}_{\mathrm{ini},n}^d$, where $\mathrm{SOC}_{\mathrm{ini},n}^d$ is obtained from DA EV information of EV n. To guarantee EV owners driving requirements, each EV should be charged with a level no less than the desired SOC value $\mathrm{SOC}_{\mathrm{dep}}$. In this paper, it is assumed that $\mathrm{SOC}_{\mathrm{dep}}$ is a constant for all EVs.

Battery degradation is an important parameter to be considered under V2G for EV owners. It is assumed that the EV charging and discharging behaviours both could lead to battery degradation, and the cost is formulated in the second part of the objective function (1), in which C_d represents the corresponding battery degradation cost due to EV charging and discharging behaviours and it is calculated as

$$C_d = \frac{C_c}{L_c \cdot E_n \cdot \mathrm{DoD}} \tag{9}$$

where C_c is the battery capital cost in \$, L_c is the cycling times and the DoD stands for the depth of discharge [26].

3.3 Second stage: optimal rebate value for aggregator

The second stage aims to maximise DA aggregator revenue $H^d(x_{n,t}^{c,d}, x_{n,t}^{d,d}, z_{n,t}^{up,d}, z_{n,t}^{dw,d})$ from EV aggregator's viewpoint. According to DA EV information $[t_{a,n}^d, t_{d,n}^d, \mathrm{SOC}_{\mathrm{ini},n}^d]$, the objective function of EV aggregator is formulated as

$$\mathrm{Max} \quad H^d = I_{\mathrm{res}}^d - C_{\mathrm{gri}}^d + I_{\mathrm{own}}^d - C_{\mathrm{reb}}^d \tag{10}$$

which consists of four terms: (i) reserve income I_{res}^d for providing reserve up/down services for power grids; (ii) C_{gri}^d represents the cost of aggregator-grid energy interactions (purchasing and selling energy); (iii) I_{own}^d stands for the income of aggregator-owner energy interactions and (iv) C_{reb}^d is the rebate fee provided by aggregator for each EV owner to guarantee their economic benefits.

The first term of (10) is the reserve revenue which is obtained based on reserve up/down prices, which is shown in

$$I_{\mathrm{res}}^d = \sum_{t=0}^{M}\sum_{n=1}^{N} p_n(g_t^{\mathrm{up}} z_{n,t}^{\mathrm{up},d} + g_t^{\mathrm{dw}} z_{n,t}^{\mathrm{dw},d})\Delta T \tag{11}$$

where g_t^{up} and g_t^{dw} are reserve up and down prices at time t, respectively; $z_{n,t}^{\mathrm{up},d}$ and $z_{n,t}^{\mathrm{dw},d}$ are DA reserve up and down capacities, respectively, for EV n at time t.

The second term of (10) is the energy interaction between aggregator and grids, which includes purchasing fee and selling income and it is given as

$$C_{\mathrm{gri}}^d = \sum_{t=0}^{M}\sum_{n=1}^{N} p_n(r_{t,2}^c x_{n,t}^{c,d} - r_{t,2}^d x_{n,t}^{d,d})\Delta T \tag{12}$$

where $r_{t,2}^c$ and $r_{t,2}^d$ are purchasing and selling RT prices between the aggregator and the grid, respectively.

The third term of (10) describes the energy interaction between aggregator and EV owners including purchasing fee and selling income, which is given as

$$I_{\mathrm{own}}^d = \sum_{t=0}^{M}\sum_{n=1}^{N} p_n(r_{t,3}^c x_{n,t}^{c,d} - r_{t,3}^d x_{n,t}^{d,d})\Delta T \tag{13}$$

where $r_{t,3}^c$ and $r_{t,3}^d$ are selling and purchasing RT prices between the aggregator and owner, respectively.

The last term of (10) is the rebate fee for each EV provided by the aggregator. It represents the economic interaction between the aggregator and each EV owner, which means that EV owner will receive rebate income both for charging and discharging under aggregator scheduling. The equation is formulated as

$$C_{\mathrm{reb}}^d = \sum_{t=0}^{M}\sum_{n=1}^{N} \alpha p_n(x_{n,t}^{c,d} + x_{n,t}^{d,d})\Delta T \tag{14}$$

where α stands for the rebate factor with the unit \$/kWh.

From EV aggregator stakeholder's viewpoint, the scheduling has common constraints with the self-scheduling subject to (2)–(9). Moreover, there are several constraints of aggregator for providing reserve service to power grids.

The reserve capacity is limited by the operating status and maximum charging and discharging power. Constraint (15) shows the sum of reserve down capacity and operating power should be no more than the maximum charging power. The reserve up capacity is determined based on (16), it shows that the difference between operating status and reserve up capacity should not be less than the maximum discharging power

$$x_{n,t}^{c,d} - x_{n,t}^{d,d} + z_{n,t}^{\mathrm{dw},d} \le 1 \quad \forall t, \forall n \tag{15}$$

$$x_{n,t}^{c,d} - x_{n,t}^{d,d} - z_{n,t}^{\mathrm{up},d} \ge -1 \quad \forall t, \forall n \tag{16}$$

where $z_{n,t}^{\mathrm{up},d}$ and $z_{n,t}^{\mathrm{dw},d}$ are integer variables (0, 1 and 2) of DA reserve up and down capacities of EV n at time t.

The reserve up and down capacities depend not only on the operation status but also on the upper and lower bounds battery SOC, which are shown in

$$\mathrm{SOC}_n^{t-1} + \frac{p_n(x_{n,t}^{c,d} - x_{n,t}^{d,d} + z_{n,t}^{\mathrm{dw},d})\Delta T}{E_n} \le \overline{\mathrm{SOC}} \quad \forall t, \forall n \tag{17}$$

$$\mathrm{SOC}_n^{t-1} + \frac{p_n(x_{n,t}^{c,d} - x_{n,t}^{d,d} - z_{n,t}^{\mathrm{up},d})\Delta T}{E_n} \ge \underline{\mathrm{SOC}} \quad \forall t, \forall n \tag{18}$$

In addition, the reserve up capacity is also limited by the driving requirement of EV owners, so the minimum SOC at each time SOC_t is involved to make sure that battery SOC is not less than $\mathrm{SOC}_{\mathrm{dep}}$ at departure time and the constraints are shown in

$$\mathrm{SOC}_n^{t-1} + \frac{p_n(x_{n,t}^{c,d} - x_{n,t}^{d,d} - z_{n,t}^{\mathrm{up},d})\Delta T}{E_n} \ge \mathrm{SOC}_t \quad \forall t, \forall n \tag{19}$$

$$\mathrm{SOC}_t = \max\left\{\underline{\mathrm{SOC}}, \mathrm{SOC}_{\mathrm{dep}} - \frac{p_n(M-t)\Delta T}{E_n}\right\} \quad \forall t, \forall n \tag{20}$$

where (20) determines the minimum SOC during available time. The concepts of upper and lower bounds and minimum SOC at each time are illustrated in Fig. 2.

To guarantee EV owners' economic benefits, a rebate factor is introduced in the model to make sure charging cost does not exceed the DA self-scheduling charging cost for each owner. The constraint is shown in

$$\begin{aligned}&\sum_{t=0}^{M} p_n(r_{t,3}^c x_{n,t}^{c,d} - r_{t,3}^d x_{n,t}^{d,d})\Delta T + \sum_{t=0}^{M} C_d p_n(x_{n,t}^{c,d} + x_{n,t}^{d,d})\Delta T \\ &- \sum_{t=0}^{M} \alpha p_n(x_{n,t}^{c,d} + x_{n,t}^{d,d})\Delta T \le (1-K)J_n^d \quad \forall n\end{aligned} \tag{21}$$

where K is a discount parameter offered by EV aggregator to provide a lower charging cost (compared with self-scheduling J_n^d) for EV owners and thus it can attract more EVs to participate in aggregator scheduling.

The scheduling results for the second stage is to obtain the optimal rebate value α_{opt} which maximises the aggregator revenue without sacrificing each EV owner's economic benefit. In addition, non-optimal rebate factor in a range will still work for the model, only slightly affect the revenue of aggregator.

3.4 Third stage: RT aggregator scheduling strategy

This section presents the aggregator revenue maximisation strategy in a RT scenario. The optimal rebate value α_{opt} obtained from the second stage is involved in this stage. Owing to the reason that EV owner driving behaviours are difficult to predict, the strategy needs to be re-scheduled based on the dynamic RT EV information. In this case, an MPC-based algorithm is proposed in the third stage, i.e. EV aggregator schedules the operation behaviours based on RT EV information, and only the first step is dispatched to each EV. After that, EVs update their information. Finally, EV aggregator repeats for the next step scheduling.

In this stage, all variables and parameters consist of two types in terms of fixed and predicted EV information. $[x_{q,t}^{c,f}, x_{q,t}^{c,f}, z_{q,t}^{\text{up},f}, z_{q,t}^{\text{dw},f}]$ are variables of fixed EV information $[t_{a,q}^f, t_{d,q}^f, \text{SOC}_{\text{ini},q}^f]$, and $[x_{w,t}^{c,p}, x_{w,t}^{c,p}, z_{w,t}^{\text{up},p}, z_{w,t}^{\text{dw},p}]$ are variables of predicted EV information $[t_{a,w}^p, t_{d,w}^p, \text{SOC}_{\text{ini},w}^p]$. Note that all variables and parameters in the third stage have the same format with the second stage and the objective function given as

$$\begin{aligned}\text{Max} \quad H^r = &I_{\text{res}}^f - C_{\text{gri}}^f + I_{\text{own}}^f - C_{\text{reb}}^f \\ &+ I_{\text{res}}^p - C_{\text{gri}}^p + I_{\text{own}}^p - C_{\text{reb}}^p\end{aligned} \tag{22}$$

where H^r represents the RT aggregator revenue.

The scheduling strategy is implemented as follows:

1. EV owner receives RT price from the power grid for DA self-scheduling and obtains each owner charging cost based on the objective function (1), subjects to (2)–(9).
2. EV aggregator receives RT price, reserve price, DA EV information and each owner charging cost for DA scheduling with the objective function (10), subjects to (2)–(9) and (15)–(21). The optimal rebate value is obtained.
3. EV aggregator schedules all EVs based on dynamic RT EV information, updated owner charging cost, price signals and optimal rebate value for RT scheduling.
4. Implement the results from the first step to a fixed number of EVs (in the community) and update their EV information as

$$\text{SOC}_{\text{ini},q}^f = \text{SOC}_{\text{ini},q}^f + \frac{p_q \sum_{t+1}^{t+T_0}(x_{q,t}^{c,f} - x_{q,t}^{d,f})\Delta T}{E_q} \quad \forall q \tag{23}$$

(see (24))

5. Re-predict EV information $[t_{a,w}^p, t_{d,w}^p, \text{SOC}_{\text{ini},w}^p]$, $\forall w = 1, \ldots, W$ for EVs not in the community.
6. Update the dynamic RT EV information and time based on (25). After that, repeat the MPC process from Step 3

$$t = t + T_0 \tag{25}$$

To summarise, the proposed three-stage scheduling strategy is illustrated by a flowchart given in Fig. 4.

4 Case studies

4.1 EV information model

In the first and second stages, the scheduling strategies are carried out based on DA EV information. To describe the DA EV information mathematically, a Gaussian model is applied. It is assumed that the arrival time and departure time and initial SOC of each EV follow a Gaussian distribution. The parameters of three Gaussian distributions are summarised in Table 2.

In the third stage, due to the reason that EV driving behaviours are difficult to predict, a RT EV information model is presented. An assumption is made that for EVs already in the community and will come to the community in the following T_0 period, these EVs information will not change. Otherwise, EV information is generated based on the Gaussian distribution (EVs are not in the community). The concept of the RT EV information model is shown in Fig. 5. In Fig. 5, the arrival time of EV 1 is earlier than the current time (i.e. $t_{a,1} < t + T_0$), therefore EV 1 is already in the community and its EV information is fixed. In contrast, EV 2 is not in the community since the predicted arrival time is beyond current time (i.e. $t_{a,2} > t + T_0$). Thus, the EV information of EV 2 is not fixed and it needs to be re-predicted for the next scheduling round. For EV 3, it is assumed that EV information can be predicted accurately in the following T_0 period so that its information is also fixed for the reason that the arrival time is between the current time and the next scheduling time ($t \le t_{a,3} \le t + T_0$).

4.2 Model settings

A typical residential community is considered in this paper. The total time period is 24-four hours (13:00–13:00 next day) and the scheduling interval is set to $\Delta T = 1$ h. Thus, the total time interval is $M = 24$. The performance of 100 EVs is examined in this case, $N = 100$. In the third stage, the scheduling process repeats hourly, so the receding horizon is $T_0 = \Delta T$. The upper and lower bound SOCs are $\overline{\text{SOC}} = 1$ and $\underline{\text{SOC}} = 0$ (these figures are generic and can be easily changed according to requirements) for all EVs and deep of

$$\begin{aligned}(1-K)J_q^f = (1-K)J_q^f &- \sum_{t+1}^{t+T_0} p_q(r_{t,3}^c x_{q,t}^{c,f} - r_{t,3}^d x_{q,t}^{d,f})\Delta T \\ &+ \sum_{t+1}^{t+T_0} C_d p_q(x_{q,t}^{c,f} + x_{q,t}^{d,f})\Delta T \\ &- \sum_{t+1}^{t+T_0} \alpha p_q(x_{q,t}^{c,f} + x_{q,t}^{d,f})\Delta T \quad \forall q\end{aligned} \tag{24}$$

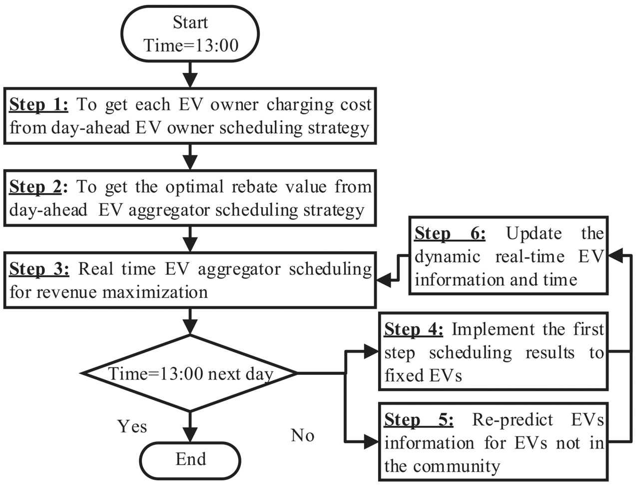

Fig. 4 *Flowchart of the three-stage scheduling strategy*

Table 2 DA EV information parameters

	Mean	Variance	Min	Max
initial SOC	0.3	0.1	0	1
arrival time	18:00	2 h	13:00	13:00 next day
departure time	07:00	2 h	13:00	13:00 next day

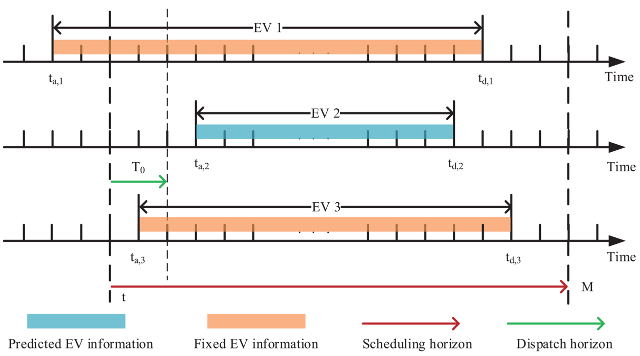

Fig. 5 *RT EV information model*

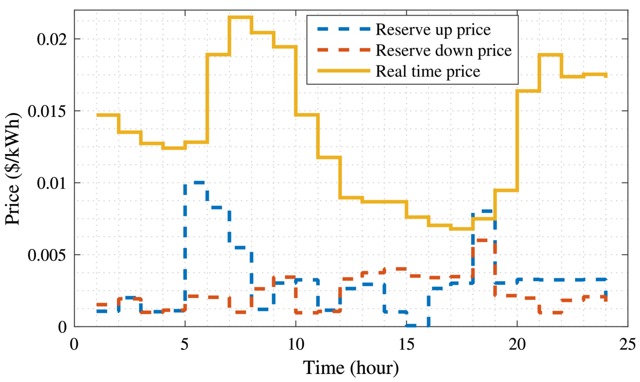

Fig. 6 *RT price and reserve prices*

discharge is set as DoD = 1. It is assumed that all EVs in the model are BYD e6 with battery capacity $E_n = 64$ kWh [27] and constant charging and discharging power $p_n = 8$ kW.

For simplification, the RT price tariff between power grids aggregator and EV owners are all with the same value (i.e. $r^c_{t,1} = r^c_{t,2} = r^c_{t,3}, r^d_{t,1} = r^d_{t,2} = r^d_{t,3}$), and the RT price (purchasing energy price) and reserve price are available in Fig. 6 [28].

5 Scheduling results

In this section, the performance of the proposed strategy is evaluated. The three-stage scheduling strategy is formulated to three MILP problems based on MATLAB and solved by CPLEX [29].

5.1 Economic interests of EV owners considering battery degradation

The EV owner self-scheduling results in the first stage are depicted in Fig. 7. To examine the charging cost of EV owners operate under V2G, different degradation values are used in the model. Compared with the RT price information, it can be observed that all EVs operate at charging status during off-peak hours (low price) and operate at discharging status during peak hours (high price) under degradation 0.083 and 0.086 $/kWh. However, there are no discharging behaviours for all EVs under degradation value 0.090 $/kWh. This is due to the reason that the V2G reward tariff cannot cover the degradation fee for EV owners to operate under V2G.

Furthermore, Table 3 shows the total charging cost for all EVs including charging fee, discharging income and degradation fee versus degradation.

It can be seen from Table 3 that, the charging fee and discharging income both decrease ($49.79 to $27.31 and $390.46 to 0) with the degradation increase. This is due to the reason that frequent energy interaction between EVs and grids leads to an increase of degradation fee. Therefore, the degradation factor has significant influence in EV charging and discharging scheduling, and EV owners would like to be involved under V2G under the condition that the V2G reward tariff provided by power grids can cover their battery degradation fee.

5.2 Economic interests of EV aggregator

In this section, only the EV aggregator economic interests are taken into account (ignore the economic interaction between the aggregator and the EV owners), so that the rebate factor in (10) and EV charging cost constraint (21) are not considered in EV aggregator scheduling. In this case, the objective function of maximising EV aggregator revenue without rebate factor is given as

$$\text{Max} \quad I_{\text{res}} - C_{\text{gri}} + I_{\text{own}} \tag{26}$$

Since it is assumed that the prices tariff between owner-aggregator and aggregator-grid are the same, two terms in (26) can be cancelled each other (i.e. $I_{\text{own}} - C_{\text{gri}} = 0$). In this case, the EV maximum aggregator revenue is deterministic since reserve prices and EV information are both fixed. The aggregator scheduling results for reserve up/down capacities are illustrated in Fig. 8. It can be seen from the figure that the reserve up/down capacities are scheduled based on corresponding prices in Fig. 6, which describes the response ability of aggregator in meeting temporary power grids requirements. That is, the reserve up/down capacities enable aggregator to decrease/increase its current operating power based on power grids demands. Fig. 9 shows both charging and

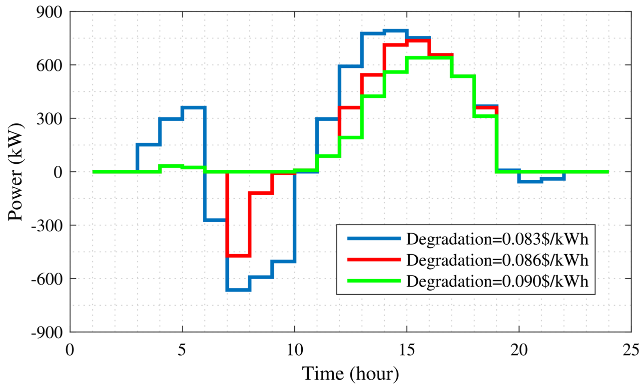

Fig. 7 *EV owners self-scheduling versus degradation*

Table 3 EV owner charging cost versus degradation

Degradation, $/kWh	0.083	0.086	0.090
charging fee, $	49.79	32.33	27.31
discharging income, $	390.46	108.76	0
degradation fee, $	646.74	400.42	311.04
total cost, $	306.06	323.99	338.35

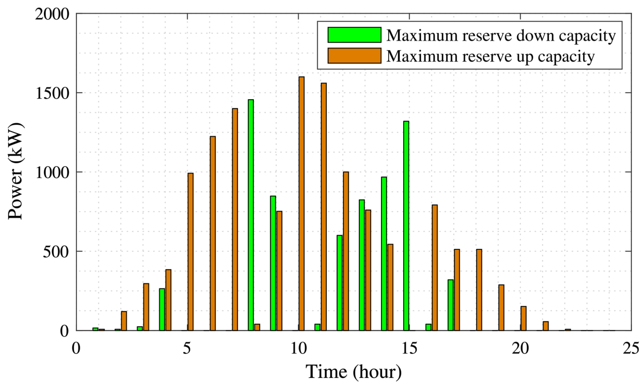

Fig. 8 *Aggregator scheduling results for reserve up/down capacities*

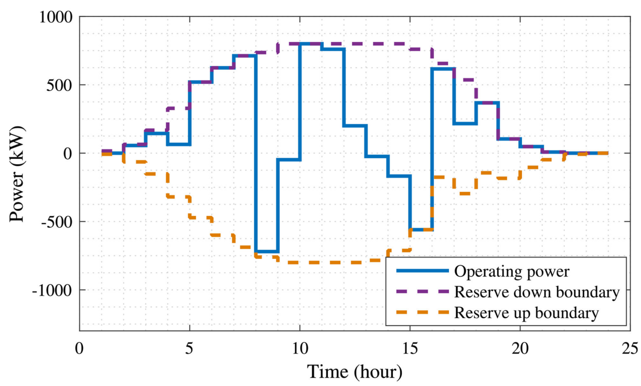

Fig. 9 *Operating power and reserve capacity for aggregator revenue maximisation*

Table 4 Economic inconsistency versus degradation

Degradation, $/kWh	0.083	0.086	0.090
self-scheduling, $	306.06	324.00	383.35
aggregator scheduling, $	369.72	393.21	424.54
increment, %	+20.80	+21.37	+25.48

discharging operations and reserve capacity results along 24 h. EV aggregator enables power grids to call for the reserve to absorb or inject energy back temporarily and thus improves power grids stability. Therefore, EV aggregator gains revenue by providing reserve up/down capacities to power grids.

5.3 Economic inconsistency between stakeholders

In this section, the economic inconsistency issue is presented which is described as the total charging cost increment percentage. A sensitive analysis of impacting economic inconsistency is illustrated in terms of degradation, maximum charging/discharging power and battery capacity.

The total cost for EV owners self-scheduling and aggregator scheduling associate with different battery degradation values are summarised in Table 4. It can be observed from Table 4 that total charging cost for self and aggregator scheduling both increase with degradation value increase. Moreover, the economic inconsistency issue becomes significant with a higher degradation value (+20.80 to +25.48%). This is due to the reason that the frequent energy interaction between EV and power grids causes high battery degradation fee.

The impact of different charging and discharging power of EVs in influencing economic inconsistency issue is shown in Table 5. The results in this table suggest that the economic inconsistency is reduced (from +20.80 to +14.59%) with the charging and discharging power increase.

In addition, the impacts of different battery capacity values are examined in the model. Scheduling results are shown in Table 6 that with the battery capacity increase, the economic inconsistency issue is reduced, that is the charging cost increment percentage decreases from +20.80 to +18.00%.

5.4 Optimal rebate value

In the previous section, the existence of economic between EV owners and aggregator is demonstrated and the impacting factors are analysed. That is EV owner charging cost increases under aggregator scheduling compared with EV owners self-scheduling. In order to mediate the economic inconsistency issue, a rebate factor is proposed in the model in the second-stage scheduling. By introducing a rebate factor in the second-stage scheduling strategy, it enables the model jointly consider two stakeholders economic interests.

The relationship between maximum EV aggregator revenue and the value of rebate factor is described in Figs. 10 and 11. These figures suggest that there exists an optimal rebate factor value which can achieve aggregator revenue maximised. The maximum aggregator revenue is obtained with $\alpha_{\text{opt}} = 0.0046$ \$/kWh, $\alpha_{\text{opt}} = 0.0056$ \$/kWh under different discount values. For a relatively smaller rebate factor, EVs charging and discharging operations mainly depend on the self-scheduling, which restrict aggregator to make a response to power grids, and aggregator has a lower flexibility to schedule EVs based on the reserve up/down prices. On the contrary, for a relatively higher rebate value, the aggregator has more incentive to involve EVs in reserve markets. However, a higher rebate value requires more rebate fee to EV owners from the EV aggregator and thus reduces aggregator revenue.

In Fig. 12, ten EV owners charging cost are presented both under self and aggregator scheduling with a different value of discount and corresponding optimal rebate values. It can be found from the figure that, each EV owner charging cost under aggregator scheduling is less than the one under self-scheduling (5 and 7.5% discount). The results verified the effectiveness of the proposed rebate factor in the second-stage scheduling. These results demonstrate the proposed strategy motivates EV owners to participate in aggregator scheduling (a lower charging cost under aggregator scheduling than self-scheduling). However, the aggregator revenue will significantly decrease under a higher discount ($37.02 with 5% discount and $32.04 with 7.5% discount in Figs. 10 and 11).

5.5 MPC-based RT scheduling strategy

In the third-stage scheduling, the stochastic driving behaviours of EV owner are considered in the model. That is, EV information cannot be predicted accurately, thus a dynamic RT EV information (fixed and predicted) is adopted during the scheduling. The scheduling results of DA and RT are presented in Fig. 13 with

Table 5 Economic inconsistency versus power

Charging/discharging power, kW	8	10	12
self-scheduling, $	306.06	324.00	383.35
aggregator scheduling, $	369.72	385.04	439.28
increment, %	+20.80	+18.84	+14.59

Table 6 Economic inconsistency versus capacity

Battery capacity, kWh	64	72	80
self-scheduling, $	306.06	324.00	383.35
aggregator scheduling, $	369.72	385.66	452.35
increment, %	+20.80	+19.30	+18.00

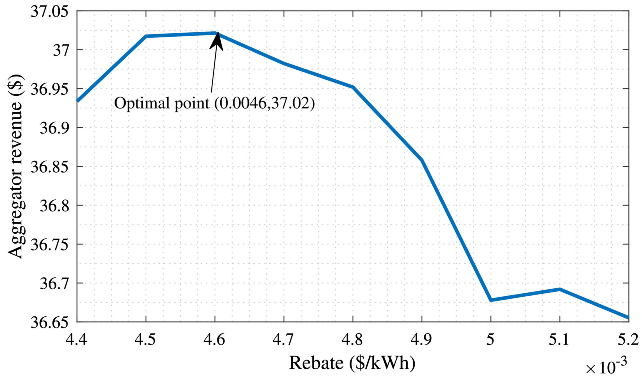

Fig. 10 *Maximum aggregator revenue versus rebate value (discount = 5%)*

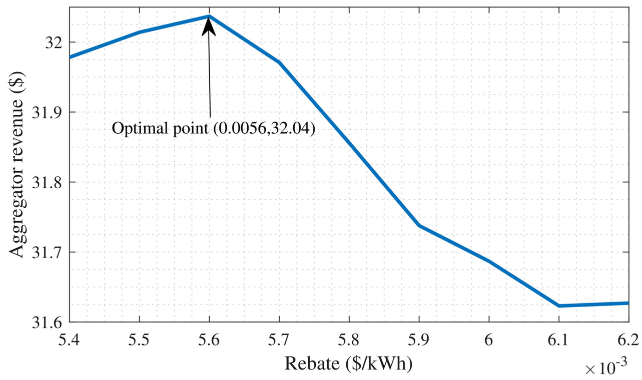

Fig. 11 *Maximum aggregator revenue versus rebate value (discount = 7.5%)*

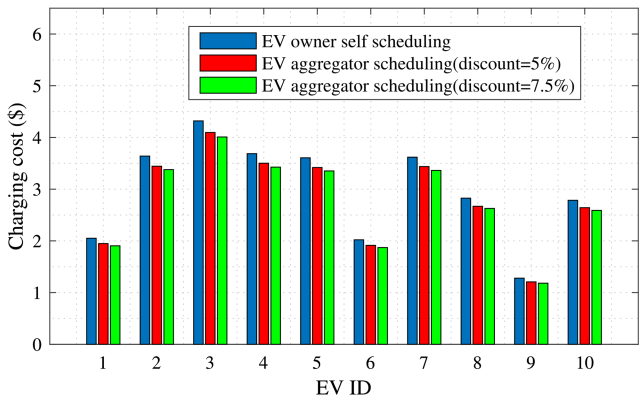

Fig. 12 *EV owner charging cost (self and aggregator scheduling) versus discount value*

degradation $C_d = 0.083$ \$/kWh and discount $K = 0.05$. Since in the DA EV information is fixed, the results of the second-stage scheduling (DA aggregator revenue maximisation) are deterministic. On the contrary, the dynamic RT EV information needs to be re-predicted due to the prediction errors. In this case, the RT scheduling results are not the same with day-head results.

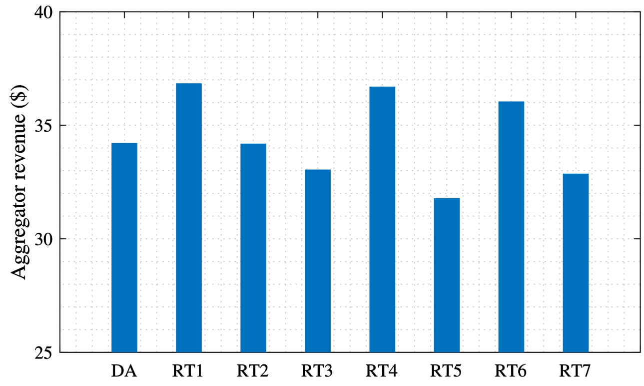

Fig. 13 *DA and RT aggregator revenue in a week*

In Fig. 13, the RT scheduling strategy is repeated for seven times to represent daily aggregator revenue in a week, i.e. from RT1 to RT7. It is assumed that the DA EV information in the whole week is the same. Based on the observation from the results, the daily RT aggregator revenue in a week are $36.85, $34.19, $33.05, $36.70, $31.79, $36.05 and $32.87. Which are not equal to DA aggregator revenue $34.22 due to the reason of RT EV information is stochastic.

6 Conclusion

In this paper, a three-stage EV charging and discharging scheduling strategy is proposed in a residential community from the viewpoint of two stakeholders (EV owner and aggregator): to minimise each EV owner charging cost and maximise aggregator revenue. The energy, reserve and economic interactions between power grids, EV aggregator, and EV owners are discussed. EV owners minimise their charging cost in energy market based on RT price and V2G reward tariff provided by power grids. Aggregator maximises its revenue by participating in reserve market. Since two stakeholders have different objectives, the economic inconsistency issue is analysed. Moreover, the stochastic driving behaviours of EV owners are considered in the model.

The main outcomes of this paper are summarised as follows:

- The model is carried out from the viewpoint of two stakeholders, respectively. In the first-stage scheduling, each EV owner charging cost is minimised and the battery degradation factor in influencing the charging cost of EV owner participating in V2G is evaluated. By implementing sufficient V2G reward tariff and the developing EV battery technology, EV owners are willing to participate in V2G to enhance energy interaction between power grids and EVs.
- The impact of degradation, maximum charging and discharging power and battery capacity in influencing economic inconsistency issue is discussed.
- To mediate the economic inconsistency issue between stakeholders, a rebate factor is proposed in the second-stage scheduling, which stands for the economic interaction between aggregator and EV owners. Results show the effectiveness of this strategy: EV owner charging cost under aggregator scheduling is less than the one in self-scheduling.
- An MPC-based RT scheduling strategy is adopted in the third stage. The stochastic driving behaviours of EV owner are considered in the model, which makes scheduling results more practical in real-world scenarios.

The future research will focus on the reserve and regulation services between aggregator and power grids. That is to say, power grids can call for reserve temporarily based on its requirement and aggregator ability. Moreover, the relationship between charging cost and participation needs to be analysed, and thus a proper discount value can be obtained.

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