Day-Ahead Electric Vehicle Aggregator Bidding Strategy using Stochastic Programming in an Uncertain Reserve Market

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Abstract: Electric vehicle as dynamic energy storage systems could provide ancillary services to the grids. The aggregator could coordinate the charging/discharging of electric vehicle fleets to attend the electricity market to get profits. However, the aggregator profits is threaten by the uncertainty of the electricity market. In this paper, an electric vehicle aggregator bidding strategy the day-ahead market is proposed, both reserve capacity and reserve deployment are considered. The novelty of this paper is that, (1) The uncertainty of the reserve developments are address in terms of both time and amount. (2) Scenario-based stochastic programming method is used to maximize the average aggregator profits based on one-year data. The proposed method jointly consider the reserve capacity in the day-ahead market and the reserve deployment requirements in the real-time market. (3) The risk of the deployed reserve shortage is addressed by introducing a penalty factor in the model. (4) An owner-aggregator contract is designed, which is used to mitigate the economic inconsistency issue between EV owners and the aggregator. Results verify the performance of the proposed strategy, that is the average aggregator profits are guaranteed by maximizing reserve deployment payments and mitigating the penalties in RTM and thus the reserve deployment requirements uncertainty is well managed.

Nomenclature

Indices	
n	Number of EVs from 1 to N
t	Time from 1 to M
m	Any time between 1 and M
ω	Number of scenarios form 1 to Ω
q	Number of days from 1 to Q
Parameters	
M	The total time intervals

N	The total number of EVs
Ω	The total number of scenarios
Q	Number of days for Monte Carlo simulation
V_ω	The number of days for scenario ω
π'_t	The hourly probability of reserve deployment at time t
π_ω	The probability of reserve deployment for scenario ω
ΔT	Duration of each time interval
$\overline{\mathrm{P}}_{\mathrm{n}}$	EV maximum charging/discharging power of EV n (kW)
E_n	Battery capacity of EV n (kWh)
$\underline{\mathrm{SOC}}$, $\overline{\mathrm{SOC}}$	The lower/upper battery SOC boundaries
$\mathrm{D_d}$	The battery degradation parameter ($/kWh)
SOC_n^a	The SOC of EV n at arrival time
$\mathrm{SOC^d}$	The SOC at departure time of all EVs
$\underline{SOC}_{t,n}$	The minimum SOC of EV n at time t
t_n^a, t_n^d	The arrival/departure time of EV n
α^u, α^d	The penalty for reserve up/down deployment shortage ($/kWh)
K	The charging cost discount parameter
H	Rebate to each EV owner for attending aggregator scheduling in reserve market ($)
$\widetilde{r}_t^u, \widetilde{r}_t^d$	Deployed up/down reserve price at time t ($/kWh)
r_t^+, r_t^-	The charging/discharging real-time prices at time t ($/kWh)
g_t^u, g_t^d	The reserve up/down capacity prices at time t ($/kWh)
$\lambda_{t,\omega}^u$, $\lambda_{t,\omega}^d$	The amount of the reserve up/down capacity is required to deploy at time t of scenario ω
$x_{t,q}^u$	Reserve up deployment requirement at time t of day q
$\widetilde{x}_{t,\omega}^u, \widetilde{x}_{t,\omega}^d$	Reserve up/down deployment requirements at time t of scenario ω
Variables	
$p_{n,t}^{+,e}$, $p_{n,t}^{-,e}$	Charging/discharging operations of EV n at time t under self-scheduling strategy (kW)
$p_{n,t}^{+,DA}$, $p_{n,t}^{-,DA}$	The DA base load plan for EV n charging/discharging operations at time t (kW)
$p_{n,t}^{u,DA}$, $p_{n,t}^{d,DA}$	The DA plan of reserve up/down capacities of EV n at time t (kW)
$\widetilde{p}_{n,t,\omega}^u$, $\widetilde{p}_{n,t,\omega}^d$	The deployed up/down reserve of EV n at time t in scenario ω (kW)
$\Delta p_{n,t,\omega}^+$, $\Delta p_{n,t,\omega}^-$	The charging/discharging power deviations of EV n at time t in scenario ω (kW)
$s_{t,\omega}^u$, $s_{t,\omega}^d$	Reserve up/down deployment shortage at t of scenario ω (kW)

1. Introduction

With the deterioration of situations arising from global warming and energy crisis, governments have proposed plans to increase the penetration level of Plug-in Electric Vehicles (PEVs) [1], e.g., a national plan "ten cities and thousand units" has been proposed by the Chinese government to promote the penetration level of PEVs with the aim of five million PEVs adoptions in 2020 in China [2]. As an alternative transportation tool, EV has the advantage of zero exhaust gases emission and minimal noises. However, the development of EV is facing many technological limitations at present, such as high initial cost, greenhouse gas emission during manufacturing and disposal [3]. In addition, the mass charging behaviors of EVs could cause serious problems in power grids operation, such as unbalanced load conditions, harmonic distortions, transformer overloading and voltage fluctuations [4]. Thus, the exponential growth of EV will become a crucial issue of power grids operation in the future.

On the other hand, it is estimated that most of the time (95%) EVs are parked [5]. In this case, from power grids operation viewpoint, the EV battery can be regarded as a Battery Energy Storage Systems (BESS), rather than a traditional energy consuming load. EV battery is suitable for providing regulation service due to its fast ramp speed characteristics compared with conventional thermal generators. Vehicle-to-Grids (V2G) technology enables the integration of EVs in power grids and it makes EVs possible to provide ancillary services to the power grids [6]. However, there are three main issues for EVs to provide ancillary services to the grids. Firstly, the primary role of EV is to work as a transportation tool and the EV traveling behavior is randomness. It makes EV cannot make the response to the grids all the time. The second issue is that single EV cannot meet the current electricity market regulations that the minimum bidding size in the MW range [7]. The third issue is that ancillary services require battery charge and discharge frequently, which leads to a degradation problem for the EV. In this circumstance, the aggregator is required to work as a mediate agent between EVs and the power grids to participate in energy and ancillary markets [8].

1.1. Literature Review

The EVs charging and discharging scheduling problem in electricity markets has been studied in several papers, and it could be mainly categorized from stakeholders' viewpoints into three parts [9]. In [10, 11, 12], the EVs charging/discharging are scheduled from the power grids viewpoint to reduce the total operating cost or ensure the power grids stability by reducing power fluctuation level. The power grids constraints such as total load limits, voltage drop and phase balances are involved in these models. The cooperative EVs charging with power grids and transportation networks have been widely investigated [13]. Authors in [14] proposed a stochastic security constrained unit commitment model coupled with a traffic model, which jointly consider the EVs charging impact to power grids and the traffic network. In [15], an EV charging station planning scheme is proposed by coupling transportation network and distribution network. A spatial-temporal model is built in [16] to investigate the optimization problem of generators, EVs and wind power in transmission and distribution systems.

Another viewpoint is for aggregator profits maximization. It has been shown that the EV aggregator could get higher profits from providing ancillary services or attending different demand response programmes compared with charging EVs during low electricity price hours [17, 18]. The EVs charging/discharging can be scheduled from EV owners viewpoint, such as charging fee minimization including battery degradation cost [19]. Reference [20] proposed a distributed EVs charging algorithm to minimize the charging cost. This paper focuses on the aggregator profits maximization in the electricity market.

The aggregator profits maximization problem in the electricity market is threatened by uncertainties. The information gap between the predicted and the actual prices are considered in [21] and the uncertainty of RT price is addressed by using robust optimization method [22]. Besides the deviation of electricity prices, some literature focused on the cooperation between the aggregator or BESS with renewable energy sources and uncertainty of renewable is represented by scenarios in the model [23]. In addition, EVs owners' driving behaviors are naturally random. The stochastic programming method was utilized to consider the uncertainty of EVs driving characteristics [24, 25]. Furthermore, the uncertainty from the electricity market includes ancillary services such as reserve deployment requirements.

To address the uncertainty of ancillary services, the robust optimization method is used in [26] to deal with the uncertain amount of reserve deployment requirements. It is claimed that the probability density function of the amount of reserve deployment requirements is hard to build due to the characteristic of regulation and reserve markets. A probability-based model is applied in [27] to assess the aggregator's capability in providing ancillary services to power grids. Two types probabilities (i.e., the probability of the DA bidding is accepted in DAM and the probability of the reserve is required to deploy in RTM) are utilized in the model to represent the market environment by taking battery degradation into consideration. A scenario-based model is built in [28] to deal with the uncertainty prices, and the probability of each price scenario is calculated based on Monte Carlo simulation. Nevertheless, the common issue in the probability-model based and the scenario-based model is that the relationship between the proposed reserve in DAM with the deployed reserve in RTM is not presented and also different amount of reserve deployment requirements is not taken into account. The impact of the uncertainty of reserve deployment requirements are addressed by using stochastic programming in [29, 30] and additionally considered uncertainty of EV owners' behaviors and market prices. The risk of the deviation between the DA bidding and the RT operation is considered in [31] and it is assumed that the aggregator will be penalized if there is any difference between the RT based load with the DA bidding base load plan.

To summarize, several papers discussed the EVs charging/discharging scheduling problem from three stakeholders viewpoints to minimize the network cost and loss (power grids viewpoint), maximize profits by providing ancillary services in electricity market (EV aggregator viewpoint) and minimize charging fee including discharging income and battery degradation cost (EV owners viewpoint). To specific, some researchers investigated the aggregator profits maximization in the electricity market by considering the uncertainty of prices, EV owners' driving behaviors, renewable energy sources and reserve deployment requirements. However, there are four issues in the EVs scheduling problem are ignored in the existing researches:

- First, fewer papers considered the uncertainty of reserve deployment requirements in terms of time and amount aspects. In [26], a robust optimization method is used to take the uncertainty of the reserve deployment times in one day into account. However, it only considered the worst scenario which makes the results too conservative and the uncertainty of the amount is not considered.

- Second, fewer papers investigated the relationship between the DA bidding with different reserve deployment requirements in RTM. That is, the impact of the reserve deployment in RTM to the DA bidding is neglected. Authors in [29, 30] discussed the EV bidding strategy in DAM and reserve market using stochastic programming method, however the relationship between the DAM and reserve market is not considered.

- Then, the risk of reserve deployment shortage due to the uncertain RTM is not appropriatey evaluated in most references. Moreover, the impact of the reserve deployment on EVs charging/discharging is less discussed, such as [26, 29, 31].
- Finally, most existing studies simplicity focused on the EVs charging/discharging from single stakeholder's viewpoint but neglect the economic relationship between different stakeholders, such as [27, 32]. The aggregator profits is maximized while the EV owners economic benefits are sacrificed (charging fee increase). The economic inconsistency issue between the aggregator and EV owners is not fully addressed , which make the aggregator scheduling results unrealistic since the EV owners are unwilling to attend the aggregator schedule.

1.2. Main Contributions

In this paper, a stochastic DA aggregator bidding strategy in power grids reserve market is proposed while taking the reserve deployment requirements uncertainty into account. The main contributions of this paper are summarized as follows:

- In order to address the uncertain reserve market in terms of both amount and time of reserve deployment requirements, stochastic programming method is used in this work.
- The relationship between the proposed reserve capacity in DAM and the deployed reserve in RTM is formulated and the impact of reserve deployment shortage is considered by introducing a penalty factor in the model.
- To mitigate the economic inconsistency issue between owners and the aggregator, a newly proposed owner-aggregator contract is designed in this paper, i.e., the EV owners' economic benefits are guaranteed meanwhile the aggregator profits are maximized.

1.3. Paper Organization

The rest of the paper is organized as follows: Section 2 presents a scenario-based reserve deployment model. Section 3 build the EVs scheduling model from owners and aggregator viewpoints, respectively. Section 4 presents scheduling results and discussions. Section 5 draws the conclusions.

2. Electricity Markets

2.1. Reserve Market Participation

The primary role of the aggregator in attending electricity markets is to satisfy EV owners' driving requirements, after that it could provide ancillary services to power grids to maximize profits [27].

Fig. 1 illustrates the framework of the aggregator participation in the reserve market. According to the electricity markets operation mechanism, the aggregator needs to submit a reserve up/down capacities and base load plans to power grids in DAM. If the plan is accepted, the aggregator receives income for stand-by reserve capacity. In RT operation of power grids, when the generation cannot meet the demand, the reserve up capacity proposed by the aggregator could be required to deploy to offset such imbalances. If the demand is less than the generation, then the reserve down capacity will be deployed, that is to increase aggregator charging power (or decrease discharging power) and thus accommodate the imbalances. The aggregator operates in RTM should

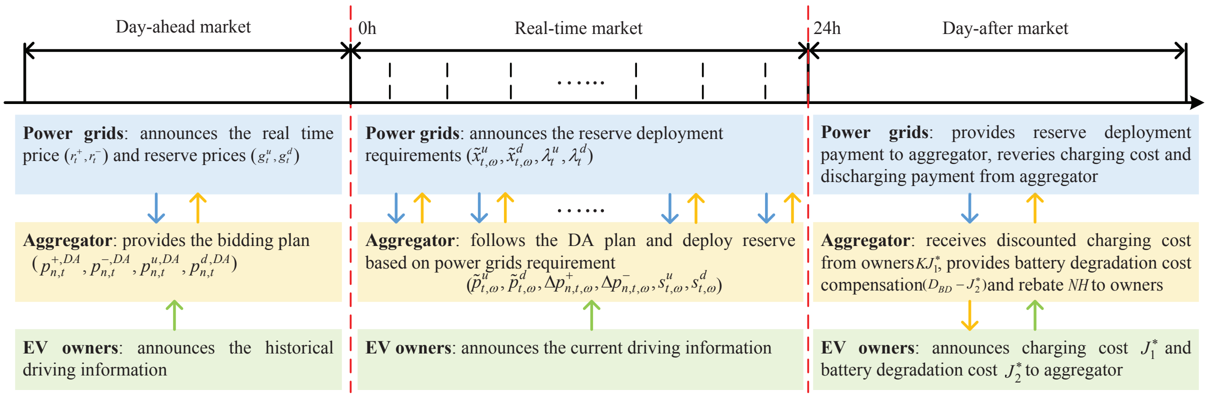

Fig. 1. *Framework of the aggregator participation in reserve market*

deploy enough reserve according to power grids requirements in RTM. The aggregator can receive additional payments as a rebate for reserve deployment [27].

This paper is based on the reserve market model proposed in [24, 33] and previous work [35]. In additionally consider the impact of uncertain reserve deployment requirements in RTM on the DA aggregator bidding. Moreover, the risk of the aggregator not being able to deploy enough reserve (shortage) is considered in the model. Thus, a reserve deployment shortage penalty factor is introduced in the model, which means the aggregator will receive penalty according to the difference between the deployed reserve and the power grids requirements. For the primary role of the aggregator, not only the EV owners driving requirements should be met but also the economic benefits (charging and battery degradation cost) of each owner should be guaranteed [9].

To mitigate the economic inconsistency issue between EV owners and the aggregator, an owner-aggregator contract is implemented after DAM and RTM. The aggregator receives a discounted charging/discharging cost to each EV owner and also offer additional battery degradation compensation to each owner. Moreover, the aggregator provides a rebate to each EV owner for attending reserve market.

2.2. Uncertainty of Reserve Deployment Requirements

Reserve service is essential to ensure the security and reliability of the grids [34] by requiring deploy reserve. That is, the aggregator should change the EVs operation temporally based on power grids reserve deployment requirements. In this case, the EVs charging and discharging scheduling problem is complicated by the uncertain reserve deployment requirements.

The uncertainty of reserve deployment requirements in twenty-four hours can be represented by a series of scenarios and the probability of each scenario. Binary numbers are used to represent whether the reserve is required to deploy or not. It is assumed that only reserve up is deployed in the model, and different reserve deployment requirements scenarios can be generated based on the Monte Carol simulation method.

Fig. 2 illustrates the procedure to generate the reserve deployment requirements data for Q days. At each time a random number i is generated between 0 to 1 and compared with the hourly reserve deployment probability π'_t [29]. If the hourly probability is equal to or greater than the random number, the reserve up capacity is deployed ($x^u_{t,q} = 1$). Otherwise, the reserve is not deployed ($x^u_{t,q} = 0$). After that, all scenarios in Q days can be represented by $[\widetilde{x}^u_{1,\omega}, ..., \widetilde{x}^u_{M,\omega}], \forall\omega \in \Omega$.

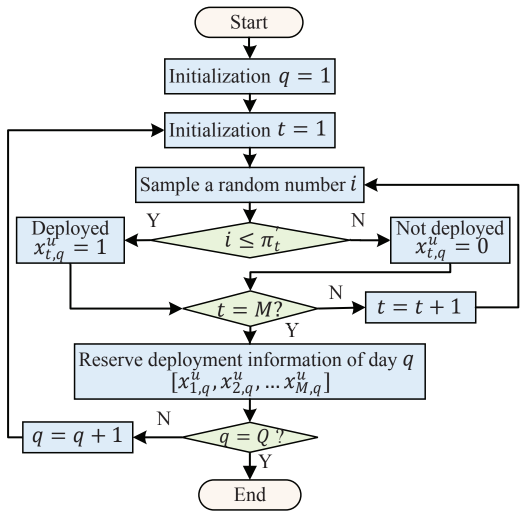

Fig. 2. *Flowchart of reserve deployment requirements scenarios generation approach based on Monte Carlo simulation*

Finally, the probability of each scenario can be calculated based on (1):

$$\pi_\omega = \frac{V_\omega}{Q} \qquad \forall \omega \tag{1}$$

and the probability π_ω with the reserve deployment requirements of each scenario will be involved in the stochastic programming of the DA aggregator bidding model.

3. EVs Scheduling Strategy

This section describes the EVs scheduling strategy from EV owner and aggregator viewpoints, respectively.

3.1. EV Owners' Scheduling (Self-Scheduling) Strategy

3.1.1. Charging fee minimization: The objective function of the self-scheduling strategy is formulated in (2a):

$$\text{Min} \quad J_1 + J_2 \tag{2a}$$

$$J_1 = \sum_{t=1}^{M} \sum_{n=1}^{N} (r_t^+ p_{n,t}^{+,e} - r_t^- p_{n,t}^{-,e}) \Delta T, \tag{2b}$$

$$J_2 = \sum_{t=1}^{M} \sum_{n=1}^{N} \mathrm{D_d} (p_{n,t}^{+,e} + p_{n,t}^{-,e}) \Delta T. \tag{2c}$$

where J_1 is the charging cost/discharging income and J_2 is the corresponding battery degradation cost.

3.1.2. Self-Scheduling Constraints:

Power limits: When EVs are not connected to the grid, EVs charging/discharging power limits are represented in constraint (3) and (4):

$$p_{n,t}^{+,e} = \begin{cases} 0 & 1 \leq t < t_n^a \\ [0, \overline{\mathrm{P}}_\mathrm{n}] & t_n^a \leq t < t_n^d \\ 0 & t_n^d \leq t \leq M \end{cases} \quad \forall n, t, \tag{3}$$

$$p_{n,t}^{-,e} = \begin{cases} 0 & 1 \leq t < t_n^a \\ [0, \overline{\mathrm{P}}_\mathrm{n}] & t_n^a \leq t < t_n^d \\ 0 & t_n^d \leq t \leq M \end{cases} \quad \forall n, t, \tag{4}$$

where the EVs charging/discharging operations are restricted between 0 to $\overline{\mathrm{P}}_\mathrm{n}$ when EVs are connected to the grid. When EVs are off the grid, EVs cannot be scheduled and thus the charging/discharging power are both set to 0.

SOC limits: Constraints (5) and (6) are used to guarantee EV battery will not be overcharged or discharged at each time,

$$SOC_n^a + \frac{\sum_{t=1}^{m}(p_{n,t}^{+,e} - p_{n,t}^{-,e})\Delta T}{E_n} \leq \overline{\mathrm{SOC}} \quad \forall n, m \tag{5}$$

$$SOC_n^a + \frac{\sum_{t=1}^{m}(p_{n,t}^{+,e} - p_{n,t}^{-,e})\Delta T}{E_n} \geq \underline{\mathrm{SOC}} \quad \forall n, m \tag{6}$$

To meet EV owners' next day driving requirements, constraint (7) is used to make sure EVs are charged to desired values at departure time,

$$SOC_n^a + \frac{\sum_{t=1}^{M}(p_{n,t}^{+,e} - p_{n,t}^{-,e})\Delta T}{E_n} \geq \mathrm{SOC_d} \quad \forall n. \tag{7}$$

The battery degradation parameter $\mathrm{D_d}$ is calculated based on the battery capital cost, cycle time and depth-of-discharge (DoD), which has been discussed in [37]:

$$\mathrm{D_d} = \frac{C_{cap}}{L_c E_s DoD} \tag{8}$$

where C_{cap}, L_c and E_s are the initial investigation cost of the battery ($), battery lifetime in cycles and battery capacity (kWh).

3.2. Stochastic DA Aggregator Bidding Strategy

This section shows the stochastic DA aggregator bidding strategy based on different scenarios.

3.2.1. Expected Aggregator Profits Maximization: The objective function of the aggregator is to maximize the expected profits in energy and reserve markets by taking all scenarios into account (9a):

$$\text{Max} \quad \underbrace{D_{RC} - D_{CD}}_{DAM} + \underbrace{\sum_{\omega=1}^{\Omega} \pi_\omega (R_{RD,\omega} - R_{PE,\omega} - R_{DE,\omega})}_{RTM} + \underbrace{\mathrm{K}J_1^* - (D_{BD} - J_2^*) - \mathrm{NH}}_{contract}, \tag{9a}$$

where the aggregator profits come from three aspects: DAM, RTM and the owner-aggregator contract.

In DAM, D_{RC} (9b) represents the DA reserve capacity plan income. It represents the available stand-by reserve, which could be deployed in RTM,

$$D_{RC} = \sum_{t=1}^{M}\sum_{n=1}^{N}(g_t^u p_{n,t}^{u,DA} + g_t^d p_{n,t}^{d,DA})\Delta T. \tag{9b}$$

D_{CD} in (9c) represents the charging cost and discharging income of the DA base load plan. The aggregator will submit the EVs charging/discharging plan in DAM to power grids for DA base load bidding. D_{BD} in (9d) is the battery degradation cost due to charging/discharging,

$$D_{CD} = \sum_{t=1}^{M}\sum_{n=1}^{N}(r_t^+ p_{n,t}^{+,DA} - r_t^- p_{n,t}^{-,DA})\Delta T, \tag{9c}$$

$$D_{BD} = \mathrm{D_d}\sum_{t=1}^{M}\sum_{n=1}^{N}(p_{n,t}^{+,DA} + p_{n,t}^{-,DA})\Delta T. \tag{9d}$$

In RTM, $R_{RD,\omega}$ in (9e) represents the reserve deployment profits: the aggregator receives additional payments by deploying reserve based on power grids requirements. $R_{PE,\omega}$ in (9f) represents the penalty for reserve deployment shortage,

$$R_{RD,\omega} = \sum_{t=1}^{M}\sum_{n=1}^{N}(\widetilde{r}_t^u \widetilde{p}_{n,t,\omega}^u + \widetilde{r}_t^d \widetilde{p}_{n,t,\omega}^d)\Delta T, \tag{9e}$$

$$R_{PE,\omega} = \sum_{t=1}^{M}(\alpha^u s_{t,\omega}^u + \alpha^d s_{t,\omega}^d)\Delta T. \tag{9f}$$

The last term $R_{DE,\omega}$ (9g) represents the cost of charging/discharging deviations in RT operation due to the uncertain reserve deployment requirements. It is assumed that the aggregator could adjust the proposed DA base load plan in RT operation only after the reserve is deployed,

$$R_{DE,\omega} = \sum_{t=1}^{M}\sum_{n=1}^{N}(r_t^+ \Delta p_{n,t,\omega}^+ - r_t^- \Delta p_{n,t,\omega}^-)\Delta T. \tag{9g}$$

In owner-aggregator contract, J_1^* and J_2^* represent the optimal charging/discharging cost and battery degradation cost from self-scheduling respectively. $\mathrm{K}J_1^*$ stands for the discounted charging/discharging fee received from EV owners. Moreover, the aggregator provides additional battery degradation payments to EV owners ($D_{BD} - J_2^*$).

3.2.2. Aggregator Scheduling Constraints: The maximum range of EVs charging/discharging operations at each time is defined in constraint (10) and (11):

$$p_{n,t}^{+,DA} = \begin{cases} 0 & 1 \le t < t_{a,n} \\ [0, \overline{\mathrm{P}}_\mathrm{n}] & t_{a,n} \le t < t_{d,n} \\ 0 & t_{d,n} \le t \le M \end{cases} \quad \forall n, t, \tag{10}$$

$$p_{n,t}^{-,DA} = \begin{cases} 0 & 1 \le t < t_{a,n} \\ [0, \overline{\mathrm{P}}_\mathrm{n}] & t_{a,n} \le t < t_{d,n} \\ 0 & t_{d,n} \le t \le M \end{cases} \quad \forall n, t, \tag{11}$$

Power limits: The relationship between EVs charging/discharging operations with reserve up/down capacities are described in constraints (12) and (13):

$$p_{n,t}^{+,DA} - p_{n,t}^{-,DA} - p_{n,t}^{u,DA} \geq -\overline{\mathrm{P}}_{\mathrm{n}} \quad \forall t, n, \tag{12}$$

$$p_{n,t}^{+,DA} - p_{n,t}^{-,DA} + p_{n,t}^{d,DA} \leq \overline{\mathrm{P}}_{\mathrm{n}} \quad \forall t, n, \tag{13}$$

and these equations suggest that the EVs charging/discharging power with corresponding reserve up/down capacities should not be greater than the maximum charging power or the maximum discharging power for each EV n at each time t.

Reserve limits: Constraint (14) and (15) are used to make sure the summation of the deployed reserve and the charging/discharging deviations are less than its reserve capacity when the reserve is deployed for each scenario,

$$0 \leq \widetilde{p}_{n,t,\omega}^{u} + \Delta p_{n,t,\omega}^{-} \leq \widetilde{x}_{t,\omega}^{u} p_{n,t}^{u,DA} \quad \forall t, n, \omega, \tag{14}$$

$$0 \leq \widetilde{p}_{n,t,\omega}^{d} + \Delta p_{n,t,\omega}^{+} \leq \widetilde{x}_{t,\omega}^{d} p_{n,t}^{d,DA} \quad \forall t, n, \omega. \tag{15}$$

Constraint (16), (17) and (18) suggest that the DA reserve up/down capacities of each EV, the deployed reserve and the power deviation at each time should not be less than zero,

$$p_{n,t}^{u,DA} \geq 0, \quad p_{n,t}^{d,DA} \geq 0 \quad \forall n, t, \tag{16}$$

$$\widetilde{p}_{n,t,\omega}^{u} \geq 0, \quad \widetilde{p}_{n,t,\omega}^{d} \geq 0, \quad \forall n, t, \omega, \tag{17}$$

$$\Delta p_{n,t,\omega}^{+} \geq 0, \quad \Delta p_{n,t,\omega}^{-} \geq 0 \quad \forall n, t, \omega. \tag{18}$$

SOC limits: The relationship between EV battery SOC limits with EVs the DA charging/discharging power, DA reserve capacities, RT deployed reserve and the RT charging/discharging deviations are formulated in constraint (19) and (20):

$$\begin{aligned} SOC_n^a &+ \frac{\sum_{t=1}^{m-1}(p_{n,t}^{+,DA} - p_{n,t}^{-,DA} - \widetilde{p}_{n,t,\omega}^{u})\Delta T}{E_n} + \frac{\sum_{t=1}^{m-1}(\widetilde{p}_{n,t,\omega}^{d} + \Delta p_{n,t,\omega}^{+} - \Delta p_{n,t,\omega}^{-})\Delta T}{E_n} \\ &+ \frac{(p_{n,m}^{+,DA} - p_{n,m}^{-,DA} + p_{n,m}^{d,DA})\Delta T}{E_n} \leq \overline{\mathrm{SOC}} \quad \forall n, m, \omega, \end{aligned} \tag{19}$$

$$\begin{aligned} SOC_n^a &+ \frac{\sum_{t=1}^{m-1}(p_{n,t}^{+,DA} - p_{n,t}^{-,DA} - \widetilde{p}_{n,t,\omega}^{u})\Delta T}{E_n} + \frac{\sum_{t=1}^{m-1}(\widetilde{p}_{n,t,\omega}^{d} + \Delta p_{n,t,\omega}^{+} - \Delta p_{n,t,\omega}^{-})\Delta T}{E_n} \\ &+ \frac{(p_{n,m}^{+,DA} - p_{n,m}^{-,DA} - p_{n,m}^{u,DA})\Delta T}{E_n} \geq \underline{SOC}_{n,m}, \forall n, m, \omega. \end{aligned} \tag{20}$$

Moreover, to guarantee that EVs are charged at the desired value at departure time, the minimum SOC of EV n at each time is calculated based on (21):

$$\underline{SOC}_{n,m} = \max\{\underline{\mathrm{SOC}}, \mathrm{SOC_d} - \frac{\overline{P}(M-m)\Delta T}{E_n}\} \quad \forall m, n. \tag{21}$$

Deviation balance: The relationship between the deployed reserve, charging/discharging deviations, reserve shortages and the power grids reserve deployment requirements at time t scenario ω are shown in (22) and (23):

$$s^u_{t,\omega} + \sum_{n=1}^{N} \widetilde{p}^u_{n,t,\omega} = \Delta p^-_{n,t,\omega} + \lambda^u_t \widetilde{x}^u_{t,\omega} \sum_{n=1}^{N} p^{u,DA}_{n,t}, \forall t, \omega, \tag{22}$$

$$s^d_{t,\omega} + \sum_{n=1}^{N} \widetilde{p}^d_{n,t,\omega} = \Delta p^+_{n,t,\omega} + \lambda^d_t \widetilde{x}^d_{t,\omega} \sum_{n=1}^{N} p^{d,DA}_{n,t}, \forall t, \omega, \tag{23}$$

The reserve down deployment is not considered in this model, thus value of reserve down deployment amount and the reserve down deployment requirements are both set to zero, that is $\lambda^d_t = \widetilde{x}^d_{t,\omega} = 0, \forall t, \omega$.

The reserve deployment shortage variables at each time and scenario is defined in (24):

$$s^u_{t,\omega} \geq 0, \quad s^d_{t,\omega} \geq 0 \quad \forall t, \omega. \tag{24}$$

3.3. Deterministic DA Aggregator Bidding Strategy

The objective function of DA bidding strategy under deterministic reserve deployment requirements is shown in (25):

$$\sum_{\omega=1}^{\Omega} \pi_\omega (D_{RC,\omega} - D_{CD,\omega} - D_{BD,\omega} + R_{RD,\omega} - R_{PE,\omega} - R_{DE,\omega}) + \mathrm{K} J^*_1 + J^*_2 - \mathrm{NH}, \tag{25}$$

subjects to: (10)-(24). Since this section shows the deterministic strategy, the DA bidding plan is unique for each scenario. In this case the variables in $p^{+,DA}_{n,t}$, $p^{-,DA}_{n,t}$, $p^{u,DA}_{n,t}$ and $p^{d,DA}_{n,t}$ in stochastic strategy are substituted by $p^{+,DA}_{n,t,\omega}$, $p^{-,DA}_{n,t,\omega}$, $p^{u,DA}_{n,t,\omega}$ and $p^{d,DA}_{n,t,\omega}$ in the deterministic strategy.

3.4. No-Deployment-Considered Bidding Strategy

The objective function of the no-deployment-considered strategy is the same with the stochastic strategy, that is with objective function (9a-9g) subjects to constraints (10)-(24). Since no-reserve-deployment is considered in this strategy, the variables represents reserve deployment in the model are set to zeros, that is $\widetilde{p}^u_{n,t,\omega} = \widetilde{p}^d_{n,t,\omega} = 0, \forall n, t, \omega$. Algorithm 1 show calculation process of the aggregator average profits under no-reserve-deployment considered strategy.

Table 1 EV types

EV type	Charging rate	Capacity	Proportion
BYD e6	8kW	64kWh	40%
Tesla model S	10kW	100kWh	30%
Nissan Leaf	6.6kW	30kWh	30%

Algorithm 1 Average profits under No-Deployment-Considered Bidding Strategy

Input: Price information, EV information
Output: Average profits
Initialize price and EV information in DAM;
 Submit the DA bidding plan based on $p_{n,t}^{u,DA}, p_{n,t}^{d,DA}, p_{n,t}^{+,DA}, p_{n,t}^{-,DA}, \forall n, t$;
 Receive profits for reserve capacity D_{RC}
 for $q = 1; q \leq Q; q++$ **do**
  for $t = 1; t \leq T; t++$ **do**
   if $x_q^t = 1$ **then**
    Penalty: $R_{PE,q,t} \leftarrow \alpha^u \lambda_t^u \sum_{n=1}^{N} p_{n,t}^{u,DA}$
   else
    No penalty: $R_{PE,q,t} \leftarrow 0$
   end
  end
  Penalty in q day $R_{PE,q} \leftarrow \sum_{t=1}^{M} R_{PE,q,t}$
end
Total penalty $R_{PE} \leftarrow \sum_{q=1}^{Q} R_{PE,q}$;
 Average profits: $D_{RC} - D_{CD} - D_{BD} - R_{PE}/Q + \mathrm{K}J_1^* + J_2^* - \mathrm{NH}$;

4. Scheduling Results and Discussions

The proposed self-scheduling strategy and the aggregator bidding strategies are formulated as linear programming problems and these problems are solved by the CPLEX [36].

4.1. Parameters and Settings

One hundred EVs in a residential community are considered in the model from 13 pm to 13 pm next day with one hour each interval (N=100, M=24, ΔT=1h). The hourly charging RT price and the hourly reserve capacities prices are available in [27], and the aggregator could receive an additional reward at the time for injecting energy back to the grids[19]. Reserve shortage penalty values are set as $\alpha^u = \alpha^d = 0.13$\$/kWh. Three types of EVs characteristics and proportion are summarized in Table 1. It is assumed that all EVs have the same battery degradation parameter, $\mathrm{D_d} = 0.083$\$/kWh [19].

The EV owners driving patterns are assumed to follow the Gaussian distributions, i.e. the arrival time, departure time and the battery SOC at arrival time follow the Gaussian distributions. Table 2 illustrates the EVs driving information parameters.

Table 2 EV Information Model Data

	Mean	Variance	Min	Max
Initial SOC	0.3	0.1	0.1	1
Arrival time	18:00	2h	13:00	13:00 next day
Departure time	07:00	2h	13:00	13:00 next day

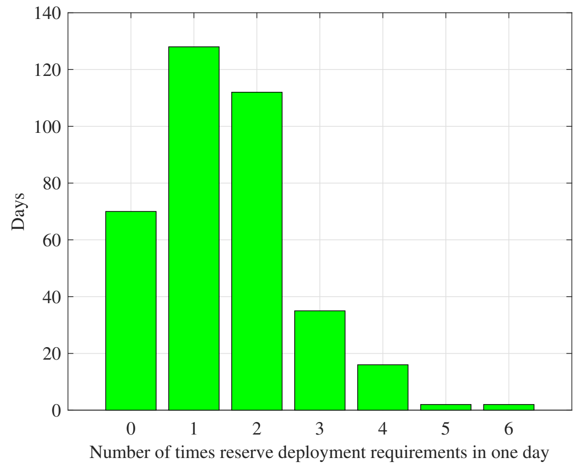

Fig. 3. *A summary of number of times reserve deployment requirements in one day among 365 days*

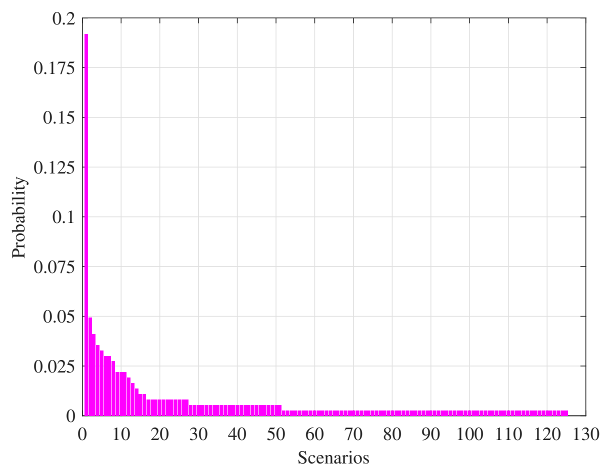

Fig. 4. *Probability of each scenario*

4.2. Scenario-based Reserve Deployment Requirements

A summary of reserve deployment requirements times in one day among 365 days is shown in Fig. 3. It suggests that within 365 days, there are 70 days that no reserve is required. There are 128 and 112 days for the reserve is required once and twice in one day, respectively There are 35 days that reserve is required three times and 16 days for four times. In the end, there are only 2 days that reserve is required five and six times in one day respectively.

According to the statistical information, the probability of each scenario π_ω is illustrated in Fig.

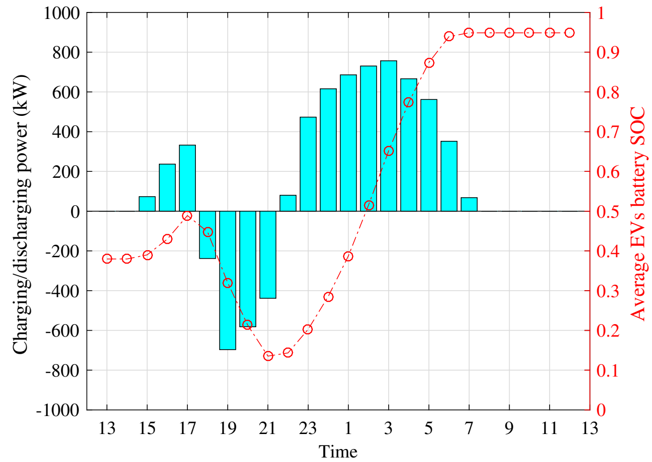

Fig. 5. *Charging/discharging of EVs results and the average EVs battery SOC under self-scheduling strategy*

4. In total, there 125 scenarios in 365 days, i.e. $\Omega = 125$. Scenario 1 represents that no reserve is required, which has the highest probability $\pi_1 = 0.19$.

4.3. Self-Scheduling Strategy

In this section, the EV owners' scheduling strategy results are presented. In Fig. 5, EVs have less charging power at the beginning (13pm-17pm) due to the reason that most EVs are off the grid, i.e. most EVs are not available during these time. For the available EVs, they operate in charging mode because the charging price is relatively lower. For operating in charging mode during these time, it could make EVs prepare enough energy to discharge in the following peak hours and thus get revenue. After that, during peak hours (16pm-21pm), EVs operate in discharging mode to inject energy back to the grid to receive revenue. However, the maximum discharging power appears at 19pm, with 687.80kW which is lower than the peak charging power (732.20kW) at 2am. There are two reasons, the first reason is that there are still some EVs not arriving at the community at 19pm, and the second reason is that some EVs battery SOC are too low to operate in discharging mode. During 23pm-7am, most EVs operate in charging status because these periods are in off-peak time. Finally, after 7am, only a few EVs operate in discharging mode, because the battery SOC is enough to satisfy owner driving requirements. Before departure, the RT price starts to raise which is higher than mid-night, and it leads to some EVs to operate in discharging mode.

The average battery SOC of the available EVs is also presented in Fig. 5. It can be seen from the figure that at each time, the SOC is strictly bounded between 0.1 to 1 which guarantees that EVs will not be overcharged or discharged. Moreover, in the morning of the next day (around 7am), the average SOC reaches 0.95 which guarantees EV owners next days driving requirements.

4.4. Aggregator Profits under Deterministic Strategy

The scheduling results of the aggregator profits under deterministic reserve deployment requirements are presented in Fig. 6. The results show that the minimum profits of the aggregator within 365 days is 21.72$, under the condition that no reserve is required in twenty-four hours. The reason is that for no-reserve-deployment, the aggregator cannot get additional payments from RTM,

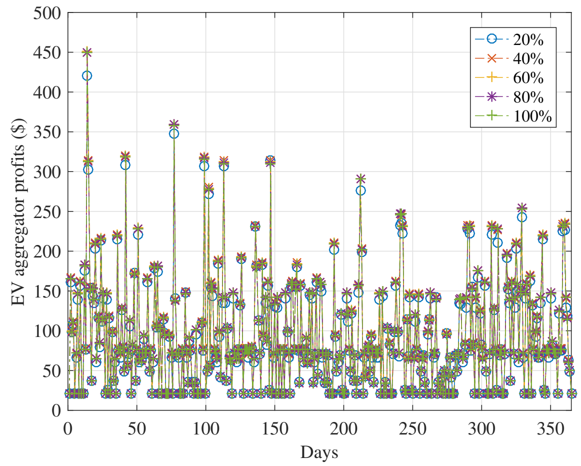

Fig. 6. *Aggregator profits with different reserve deployed amount under deterministic DA bidding strategy*

even though there is no charging/discharging deviation or deployed reserve shortage penalties in RT operation.

For reserve deployment with 20%, 40%, 60%, 80% and 100%, it can be seen from the figure that the highest profits could reach 450.39$ which is significantly greater than the scenario without reserve deployed (21.72$). The reason is that the aggregator could receive additional reserve deployment payments from RTM. Moreover, the aggregator will not receive any penalties for reserve deployment shortage due to the reason that the reserve deployment requirements are deterministic, and there are already taken into account in the aggregator DA bidding plan.

4.5. Aggregator Profits under Stochastic Strategy

Fig. 7 presents the DA base load plan with different amount of reserve deployment requirements in 24 hours. It suggests that EVs are mainly work in discharging mode during peak hours (17pm-21pm) and charging mode during off-peak hours (23pm-3am). For the different amount of reserve deployment requirements, it has less impact on DA base load plan. The DA base load plan is similar to the charging/discharging plan under self-scheduling strategy in Fig. 5, except that the maximum discharging power of the stochastic programming method (324.44$) is less than the self-scheduling (687.80kW). It due to the reason that, in order to deploy reserve capacity during peak hours, the proposed (DA plan) discharging power during this time is reduced.

The DA reserve up capacity plan is shown in Fig. 8. It can be seen that the higher reserve deployment amount, the less reserve up capacity will be proposed in the DA plan. The reason is that the aggregator will propose less reserve capacity in order to reduce the risk of reserve deployment shortage in RTM.

Fig. 9 illustrates the aggregator profits in 365 days under different amount of reserve deployment requirements. In DA scheduling, the DA bidding plan is made based on 125 scenarios. In this case, once the DA bids plan is determined, it is suitable for all scenarios in RT operation. The results in Fig. 9 show that the highest profit aggregator could get is 443.02$ which is slightly less than the deterministic strategy (450.39$). In addition, the lowest profit is -15.37$ which is much less than the deterministic strategy (21.72$).

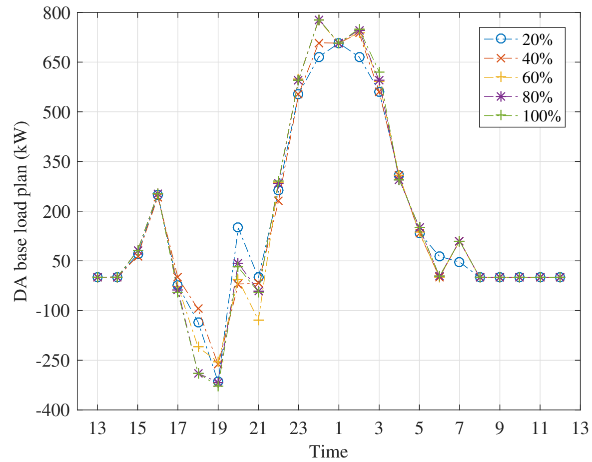

Fig. 7. *DA base load plan with different amount of reserve deployment requirements under stochastic programming strategy*

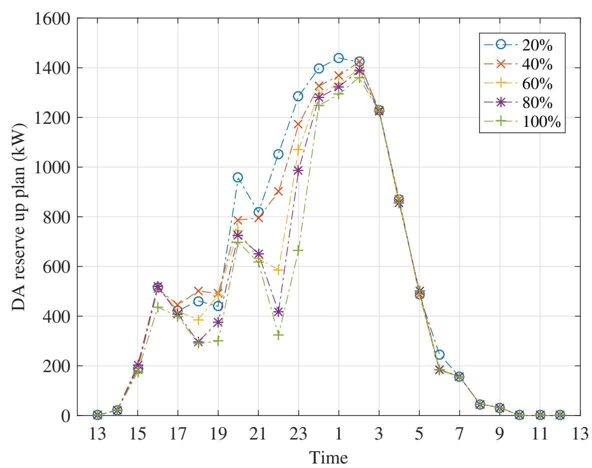

Fig. 8. *DA reserve up capacity plan with different amount of reserve deployment under stochastic programming method*

4.6. Aggregator Profits under No-Reserve-Deployment Considered Strategy

In order to make a comparison with the deterministic and stochastic strategies, the scheduling results of aggregator profits without considering reserve deployment in DA scheduling are presented in Fig. 10. It can be seen from the figure that, the highest aggregator profits could get is 21.72$ which is mulch less than the stochastic (443.02$) and deterministic strategies (450.39$). The lowest profit is -357.66$ which is much lower than the deterministic and stochastic strategies. The reason is that the aggregator will not deploy reserve in RTM and thus lead to penalty. Therefore the profit is much lower than the deterministic and stochastic strategies.

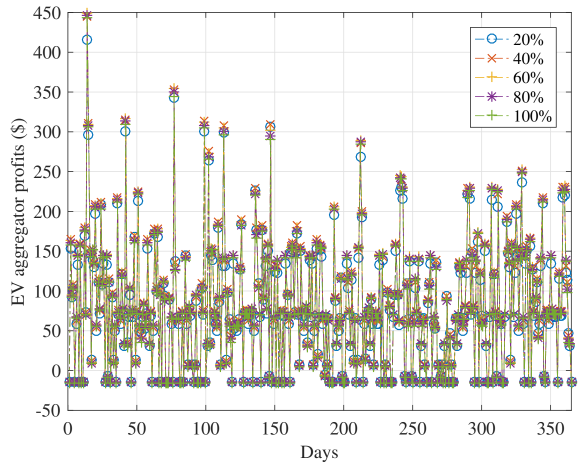

Fig. 9. *Aggregator profits with different reserve deployed amount under stochastic DA bidding strategy*

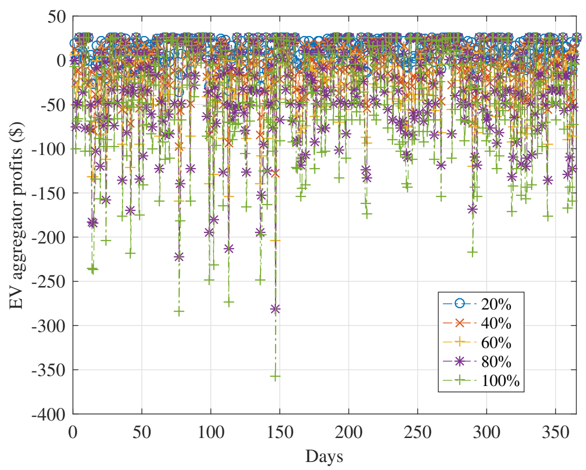

Fig. 10. *Aggregator profits with different reserve deployed amount under DA bidding strategy without considering reserve deployment*

4.7. Effectiveness of the Stochastic Strategy

According to the results in previous sections, the aggregator could get the highest profits under the deterministic strategy. However, this is not practical in the real world, since the aggregator cannot estimate the reserve deployment requirements twenty-four hours ahead accurately. It is more practical to apply the stochastic strategy. In this case, this section makes a comparison between the stochastic strategy and the deterministic strategy.

Fig. 11 illustrates the average aggregator profits in 365 days under different amount of reserve deployment requirements. For 10% requirements, the aggregator profit of stochastic strategy is 71.53$ and deterministic strategy is 84.47$. The aggregator gets highest profits with 50% requirements with 80.08$ and 93.46$ for two strategies, respectively. For the no-reserve-deployment considered strategy, the higher amount reserve is required to deploy, the lower profits aggrega-

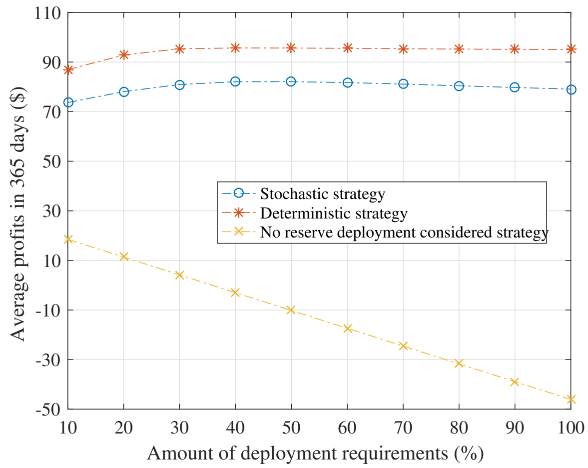

Fig. 11. *Average aggregator profits of the stochastic, deterministic and no-reserve-deployment considered strategies under different amount of reserve deployment requirements*

tor will receive. Since there is no-reserve-deployment in this strategy, the aggregator will receive penalty based on the amount of reserve deployment requirements.

4.8. Discussions

This section discusses the main findings of the paper. By making a comparison between Fig. 6 and Fig. 9 under deterministic and the stochastic strategies, both strategies achieve the lowest profits when no reserve is required to deploy in one day. The main difference between two strategies is that, when no reserve is required the profits under stochastic strategy is much less than the deterministic (-15.37$ and 21.72$), respectively. It is found that the stochastic strategy aims to optimize the average profits based on one-year data, with a sacrifice on profits under the no-reserve-required scenario.

Referring to Fig. 11, the one-year average profits under stochastic strategy is 14.31%-16.77% less than the deterministic strategy, due to the uncertainty of the reserve deployments in RTM. On the other hand, with the reserve deployment amount range from 30%-100%, the aggregator profits under stochastic strategy slightly reduced. The reason is that, the aggregator could obtain more income with the reserve deployment amount increase, but is faced with the risk of not being able to provide reserve also increases which leads to the aggregator receive more penalty.

5. Conclusions

In this paper, a DA aggregator bidding strategy in uncertain reserve market is proposed. The uncertainty of reserve market is addressed in terms of amount and time of reserve deployment requirements based on stochastic programming method. The risk of the aggregator not being able to deploy enough reserve is considered by introducing a penalty factor in the model. Moreover, an owner-aggregator contract is designed in this paper to mitigate the economic inconsistency issue between EV owners (charging fee minimization) and the aggregator (profits maximization).

The scheduling results verify the proposed stochastic programming strategy effectively managed the uncertainty of the reserve deployment requirements that the average aggregator profits are 14.31%-16.77% less than the optimal average profits under the deterministic strategy based on one-year data.

The future work will focus on the EV aggregators in distribution systems in different locations. That is, to build a spatial and temporal model of EV aggregators scheduling strategy in a distribution system.

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