Stochastic Bidding Strategy of Electric Vehicles and Energy Storage Systems in Uncertain Reserve Market

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Abstract

This paper proposes an Electric Vehicle (EV) aggregator bidding strategy in the reserve market. The EV aggregator determines the charging/discharging operations of EVs in providing reserve service for profits maximization. In the Day-Ahead Market (DAM), the EV aggregator submits a bidding plan to the Independent Systems Operator (ISO) including base-load and reserve up/down capacities plans. In the Real-Time Market (RTM), the EV aggregator should deploy reserve based on the ISO's requirements, and the EV aggregator could receive income by deploying reserve or penalty for reserve shortage. The stochastic programming method is applied to address the uncertain reserve deployment requirements in RTM in terms of time. In addition, Energy Storage Systems (ESS) are utilized by the EV aggregator to enhance the ability in providing reserve service to the grids. The aggregator–owner contract is designed to guarantee EV owners' economic benefits. Case studies show the expected profits of the EV aggregator are maximized and the risk of the reserve shortage is well managed, i.e., penalty is minimized. With the utilization of ESS, the performance of the EV aggregator in making response to the ISO's requirements is improved. That is, the required reserve percentage increases from 5.68% to 7.85%, and the deployed reserve percentage increases from 69.71% to 88.47%.

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1 Introduction

1.1 Background

Energy crisis and environmental problems become crucial issues for the whole world and urgently require human to take action to save energy and reduce the greenhouse gas emission. Over 60% of the global primary demand is from electricity generation and transportation (electricity generation accounts the major the coal demand and transportation accounts the major of the oil demand), and a significant amount of the exhaust emission is accounted by the transportation [1]. In recent years, the development of EV becomes popular, due to the reason that the EV has the advantage of dependence of fossil fuels, lower noise levels and less carbon emission compared with internal combustion engines. In the past ten years, the deployment of EV has been growing rapidly, there are more than 5.1 million EV in the world in 2018. [2]

With the rapid development of EVs, the mass amount of EVs charging behaviors bring significant negative impacts on the power grids operation such as voltage drop, energy losses and transformer overloading. Studies showed that when EVs penetration level reaches 40% under uncoordinated charging, the distribution transformers need to be replaced [3]. On the other hand, the charging behaviors of EVs are flexible which can be scheduled since 96% of time EVs are parked at home or office [4]. Consequently, coordinate charging strategies of EVs are necessary, which not only could mitigate the negative impacts of EVs charging to power grids but also EVs could work as ESS to provide ancillary services (regulation and reserve etc.) to power grids based on vehicle-to-grid technology. Furthermore, studies showed that the coordinate charging of EVs received special attention from the Independent Systems Operator (ISO), and the ISO is responsible for the power grids stability by monitoring the frequency deviation, controlling

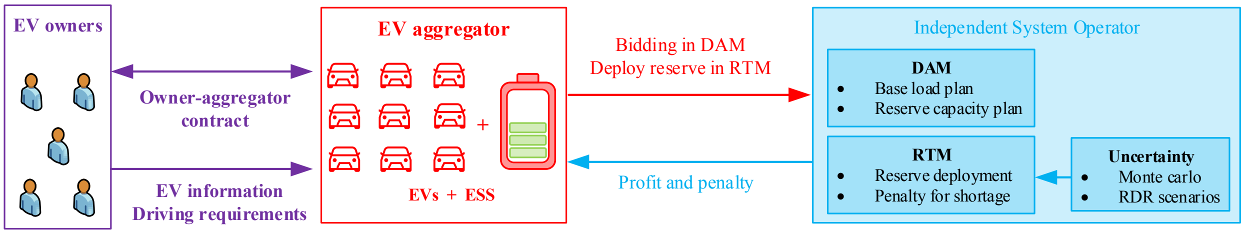

Figure 1: Relationship between stakeholders: EV aggregator and ISO with profit maximization in uncertain electricity markets. A contract is proposed between EV owners with EV aggregator to guarantee EV owners' benefits.

spinning reserves and regulation [5]. Under this circumstance, the concept of aggregator is developed, which is a central entity and it is a good candidate in attending demand response programmes by coordinating the charging/discharging behaviors of EVs fleet, such as all EVs in the parking lot. The aggregator could determine the charging/discharging power of each EV at different time based on several constraints from power grids, EV owners and the EV battery characteristics. Considering several uncertainties, such as regulation, reserve services and the EV owners' driving behaviors, it is worth considering the utilization of ESS in coordinating with EVs' charging/discharging. ESS are stationary compared with EVs, therefore the flexibility of EV aggregator could be improved.

1.2 Literature Review

The literature on EVs charging/discharging scheduling problems can be generally categorized from three stakeholder's viewpoints: EV owners, EV aggregator and ISO. From the EV owners' viewpoint, the smart charging strategy of EVs in response to real-time price has been studied in [6, 7, 8] to minimize the EVs' charging cost including energy purchasing cost and the income of injecting energy back to the grid. Authors in [9] considered the EV charging in an unbalanced electrical distribution system with distributed generations, to minimize the energy purchasing cost of EVs. In [10], the power generation limits of the AC grids and power flow issues are considered in the EVs charging scheduling. From the grid viewpoint, EVs are regarded as ESS to provide ancillary services to the grids [11, 12, 13]. Lian *et al.* [14] optimized the operation of ESS in response to frequency regulation signals from the grid. An economic analysis is performed based on the battery lifetime (degradation cost) and the UK frequency regulation market. A hierarchical framework of EVs charging is proposed in [15] to minimize the systems' peak loads at the provincial and city levels. The interrelationship between various levels are identified in terms of energy transactions and information exchange.

Moreover, some researchers used multi-objective optimization methods to address the trade-off between EV owners with the grid. Maigha *et al.* [16] applied an augmented epsilon-constraint based multi-objective optimization method to tackle the conflict between owners and systems operator in economic charging and maintaining systems load profiles. The battery degradation cost minimization is considered in the model. In [17], the operation strategy of microgrid is presented involving photovoltaics and EVs. The ε-constraint method followed with fuzzy decision making is applied to jointly minimize the operation cost of EVs and voltage deviation. The EVs scheduling in power grids are also related to traffic information. Reference [18] presented an EV charging navigation strategy, where the navigated charging station could minimize the total charging time of EVs while protecting EV owners' privacy. In [19], a hierarchical game approached is designed in EV charging navigation. The upper and lower levels are the game between charging stations and EV owners. A stochastic constrained unit commitment traffic assignment problem is proposed in [20]. Results show that the generation cost is minimized and traffic congestion is relieved. An optimization strategy of siting and sizing of the charging station is proposed in [21] considering both power and traffic network. A sensitive analysis is applied to evaluate the impact of EV population, line capacity, EV mobility to the planning results. The benefits of stakeholders, such as power grids, traffic networks, charging stations (aggregator) and EV owners, are all related to EV operation. Therefore it is worth considering the economic relationship between stakeholders.

Despite the literature discussed the EV charging/discharging scheduling problem from EV owners and the grid stakeholders' viewpoints, the research of the EV aggregator profits maximization problem is widely studied. Several papers studied the EV aggregator or ESS bidding strategy in electricity markets (regulation and reserve market) [22, 23]. In [24], the ESS providing frequency regulation to power grids in cooperating with wind power is analyzed. A real-time cooperative strategy of ESS is proposed to maximize profits in both energy and reserve markets. In this paper, the optimal bidding strategy of the ESS is made by assuming that all parameters are known in advance without uncertainty. Reference [25] considered the EV aggregator bidding strategy in both energy and reserve markets. In this paper, the acceptance of the EV owners in providing reserve is modeled, however the RT reserve deployment in impacting DA bidding is not well discussed. A two-stage stochastic programming model is proposed in [26] to minimize the net expected energy cost of the aggregator. The price deviation in the first stage (DAM) and the several possible EV parking scenarios in the second stage (RTM) are considered. However, the uncertainty of the reserve capacity call-up at different time from the ISO is not considered. In [27] and [28], authors both used robust optimization method to formulate the uncertainty of the prices, but the uncertainty of the ISO's requirements is neglected. Kazemi *et al.* [29] addressed the uncertainty of ancillary services based on robust optimization method. It assumed that the ESS should deploy reserve in RTM based on the Reserve Deployment Requirements (RDR) from the ISO, and the uncertainty of the amount of the RDR is considered in the model. However, the authors only considered the amount of RDR, the impact of the RDR at different time to the aggregator bidding and profits are neglected.

To summarize, the EVs' charging/discharging scheduling strategies are mainly categorized from three stakeholders viewpoints: charging cost minimization for owners, profits maximization for EV aggregator in electricity markets and frequency regulation purposes for the ISO. However, there are some issues in existing studies: 1) most of the papers considered EVs or ESS participation in electricity markets, but the cooperation between EVs and ESS is not investigated. The ability of EVs in attending electricity could be enhanced with the utilization of ESS; 2) No existing paper compared the performance and analyzed the ability of EVs (dynamic ESS) and ESS (stationary) in attending electricity markets; 3) Most of the existing studies simply focus on the problem from one stakeholder viewpoint but neglect the economic relationship between different stakeholders.

1.3 Main Contributions

In this paper, an EV aggregator scheduling strategy with the utilization of ESS is presented in both DA and RT energy and reserve markets. This paper applies a similar optimization model in [22] to tackle the stochastic bidding problem and conduct further extensions of study on the coordination between EVs and ESS in electricity markets. The main contributions are summarized as follows:

- The DA bidding strategy of the EV aggregator in cooperating with ESS is proposed in this paper. The strategy enables the coordination between EVs with ESS, such that the ESS can enhance the ability of EV aggregator in providing reserve services and the profit of the EV aggregator could be improved.

- The ability and the performance in participating electricity markets between EVs and ESS are analyzed. The difference between EVs (dynamic ESS) with ESS in providing reserve service is quantified in terms of the average actual deployed reserve and the reserve deployment shortage.

2 Problem Formulation

2.1 EV Aggregator Participation in Electricity Markets

It is studied that the EV aggregator could participate in electricity markets to obtain profits [25]. The model of the EV aggregator in attending DAM and RTM could be applied in the United States electricity markets, such as the performance-based regulation mechanism in PJM and ERCOT [30]. In PJM, there are energy market, capacity market and ancillary services market. The energy market is the largest in PJM, which contains DAM and RTM. In DAM and RTM, the electricity is sold and purchased to meet customers' demands. To keep the balancing of electricity generation and consumption, ancillary services market is needed and it is a vital part of energy markets. Therefore, the energy market and ancillary services market are jointly considered, i.e. the DAM and RTM (energy market) with reserve service (ancillary services market) are considered in this paper.

Figure 1 illustrates the relationship between EV owners, EV aggregator with ISO. In DAM, the ISO needs to announce the hourly electricity purchasing prices and corresponding reserve up/down prices to the EV aggregator. Then, the EV aggregator schedules the charging/discharging operation of all EVs and the ESS based on price signals received from the ISO. In addition, the corresponding reserve capacity at each hour needs to be determined. After that, the EV aggregator provides the charging/discharging operations (DA base-load plan) and the reserve up/down capacity (DA reserve up/down capacity plan) to the ISO. In RTM, the EV aggregator should follow the proposed base-load plan by purchasing/selling energy at each hour. Furthermore, the ISO could request the EV aggregator to deploy a certain amount of reserve according to the DA reserve capacity at each hour. The EV aggregator could receive additional income by providing enough reserve based on the ISO's requirements, however, it could receive penalty for not being able to deploy enough reserve (reserve shortage). By making comparison between EVs and ESS, ESS are stationary and EVs are not available all the time since each EV owner has its' own driving requirements. The EVs' information could be formulated based on EVs' mobility parameters (carpark location and EVs' route etc.) [31]. In this model, the EVs' mobility parameters of arrival/departure time and the initial SOC (EV's battery SOC at arrival time) are involved as EV aggregator scheduling parameters.

A contract is designed in Figure 1, that is the EV aggregator accounts for the economic concerns of EV owners' charging fee. The previous research indicated that there exist an economic inconsistency issue between the EV aggregator and EV owners [32]. Thus, an aggregator–owner contract is applied to mitigate the economic inconsistency issue. Under the aggregator–owner contract, the EV aggregator gets the full right to schedule the charging/discharging behaviors of EVs, each owner needs to pay the charging cost to the EV aggregator which contains the parking cost and electricity purchasing cost. Moreover, the EV aggregator reimburses the additional battery degradation cost to each owner since the EV aggregator collaborates with EVs in attending both energy and reserve markets, the frequently charging/discharging operations of EVs lead to additional battery degradation cost.

2.2 EV aggregator's DA Bidding under Uncertain Reserve Market

Reserve service is essential to ensure the security and reliability of the grid [33] by requiring deploy reserve. That is, the aggregator should change the EVs operation temporally based on the grid's RDR. In this case, the EV energy management problem is complicated by the uncertain RDR. In this section, the modeling of the uncertainty of RDR is presented.

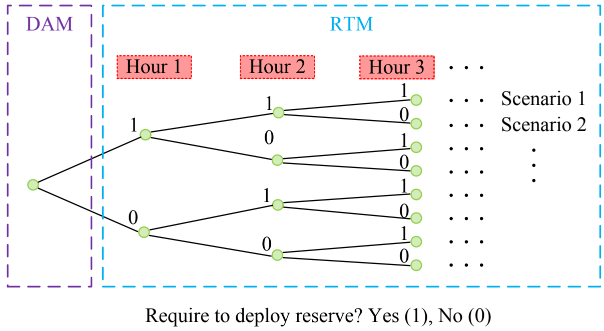

Figure 2: Branch tree structure of the reserve deployment requirements scenarios

The uncertainty of the RDR in twenty-four hours can be represented by a series of scenarios and the probability of each scenario. Figure 2 depicts a branch tree structure, where binary numbers are used to represent whether the reserve is required to deploy or not at each hour (1 or 0, respectively). Under this circumstance, there are $2^{24} = 16,777,216$ scenarios in total, which lead to a large computational burden for the stochastic programming method. It is not necessary to consider all scenarios, because most scenarios have low probability and they have a low impact on the optimization results. In order to reduce the number of scenarios in the stochastic programming method, one-year RDR data is generated. The bidding plan in the DAM is made according to the scenarios from the one-year data in RTM. Therefore, the bidding plan is suitable for one-year operation and the expected profit could be maximized.

The generation process of the RDR one-year data is shown in Figure 3. It is assumed that only reserve up is deployed in the model and different RDR scenarios can be generated based on the Monte Carol simulation method. For the scenario generation process, parameter $x^{up}_{t,q}$ indicates whether the reserve up capacity is required ($x^{up}_{t,q} = 1$) or not ($x^{up}_{t,q} = 0$). At time t in q day, a random number i with uniform distribution is generated between 0 to 1, which is compared with the hourly reserve deployment probability $\pi^{'}_t$ [34]. If the hourly probability is equal to or greater than the random number, the reserve up capacity is deployed (if $i \geq \pi^{'}_t$, then $x^{up}_{t,q} = 1$). Otherwise, the reserve is not deployed (if $i < \pi^{'}_t$, then $x^{up}_{t,q} = 0$), where Q is the total number of days in one year.

After that, the RDR one-year data $[x^{up}_{1,q}, ..., x^{up}_{M,q}], \forall q \in Q$ can be summarized to Ω

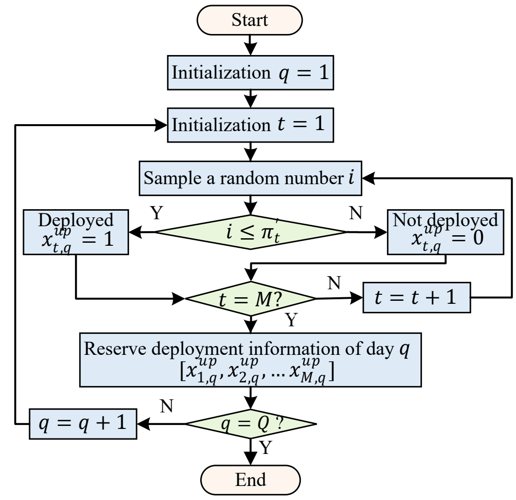

Figure 3: Flowchart of reserve deployment requirements scenarios generation approach based on Monte Carlo simulation

scenarios which are shown in (1),

$$\begin{bmatrix} \widetilde{x}_{1,1}^{up} & \widetilde{x}_{2,1}^{up} & \cdots & \widetilde{x}_{M,1}^{up} \\ \widetilde{x}_{1,2}^{up} & \widetilde{x}_{2,2}^{up} & \cdots & \widetilde{x}_{M,2}^{up} \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{x}_{1,\Omega}^{up} & \widetilde{x}_{2,\Omega}^{up} & \cdots & \widetilde{x}_{M,\Omega}^{up} \end{bmatrix} \tag{1}$$

where there are Ω scenarios among Q days and V_ω days for each scenario ($\sum_{\omega=1}^{\Omega} V_\omega = Q$).

Finally, the probability of each scenario can be calculated based on (2):

$$\pi_\omega = \frac{V_\omega}{Q} \qquad \forall \omega \tag{2}$$

and the probability π_ω with the RDR $\left[\widetilde{x}_{1,\omega}^{up}, \cdots, \widetilde{x}_{M,\omega}^{up}\right]$ of each scenario will be involved in the stochastic programming of the DA aggregator bidding model. The model is discussed in detail in Section 3.

3 EV aggregator Scheduling Strategy

In this section, the mathematical modeling of the EVs and ESS charging/discharging scheduling strategy is proposed. The variables and relevant parameters involved in the model are summarized in Table 3 and Table 1.

2pt Variables of EVs and ESS

Variables of EVs		
Binary	$i_{n,t}^{+}$, $i_{n,t}^{-}$	Charging/discharging status of EV n at time t
Continuous	$p_{n,t}^{+}$, $p_{n,t}^{-}$	Charging/discharging power of EV n at time t
	$p_{n,t}^{up}$, $p_{n,t}^{dw}$	Reserve up/down capacity of EV n at time t
	$\widetilde{p}_{n,t,\omega}^{up}$, $\widetilde{p}_{n,t,\omega}^{dw}$	Deployed reserve up/down capacity of EV n at time t in scenario ω
	$s_{t,\omega}^{up}$, $s_{t,\omega}^{dw}$	Reserve up/down shortage at time t in scenario ω
Variables of ESS		
Binary	i_t^{+}, i_t^{-}	Charging/discharging status of the ESS at time t
Continuous	p_t^{+}, p_t^{-}	Charging/discharging power of the ESS at time t
	p_t^{up}, p_t^{dw}	Reserve up/down capacity of the ESS at time t
	$\widetilde{p}_{t,\omega}^{up}$, $\widetilde{p}_{t,\omega}^{dw}$	Deployed reserve up/down capacity of the ESS at time t in scenario ω

3.1 Objective Function

The objective function of the proposed model is to maximize the expected EV aggregator profits in attending DA and RT reserve and energy market. The objective function is presented in (3a), which consists of three parts:

$$\text{Maximize} \quad DAM^{\text{ev}} + DAM^{\text{ess}} + \sum_{\omega=1}^{\Omega} \pi_\omega \left(I_\omega^{\text{ev,ess}} - C_\omega^{\text{ev,ess}}\right) + \left[(1-\beta) J_1^{\text{ev}*} + J_2^{\text{ev}*}\right] \tag{3a}$$

1) the first part DAM^{ev} and DAM^{ess} stand for the aggregator profits from DAM; 2) the second part is the expected profits in RTM with Ω scenarios; 3) the third part is the aggregator–owner contract. The aggregator receives the discounted charging fee from each EV owner and provides the additional battery degradation cost to owners. $J_1^{\text{ev}*}$ and $J_2^{\text{ev}*}$ stand for the EVs' charging fee and the battery degradation cost. These two values could be obtained based on the owners' self-scheduling strategy. [35]

In DAM, the aggregator profits from EV and ESS

Table 1: Parameters of the model

Parameters	Description
N, M	The total number of EVs and time intervals
$\overline{P}^{\text{ev}}, \overline{P}^{\text{ess}}$	Rated charging/discharging power of EV and ESS (kW)
$E^{\text{ev}}, E^{\text{ess}}$	Battery capacity of each EV and the ESS (kWh)
$S_n^a, \mathrm{S}^{\mathrm{d}}$	Initial SOC at arrival time and target SOC at departure time of EV n
t_n^a, t_n^d	Arrival/departure time of EV n
$\overline{\mathrm{S}}, \underline{\mathrm{S}}$	Upper/lower SOC boundary of each EV and ESS
S^{b}	SOC of ESS at the beginning time
$D^{\text{ev}}, D^{\text{ess}}$	Battery degradation of each EV and the ESS ($/kWh)
r_t^+, r_t^-	Charging/discharging real-time price ($/kWh)
r_t^{up}, r_t^{dw}	Reserve up/down capacity price ($/kWh)
$\widetilde{r}_t^{up}, \widetilde{r}_t^{dw}$	Deployed reserve price ($/kWh)
γ^{up}, γ^{dw}	Deployed reserve shortage penalty ($/kWh)
ΔT	Duration of each time interval (1 hour)
β	Discounted parameter of charging fee (%)

are defined in (3b) and (3c):

$$\begin{aligned} DAM^{\text{ev}} = &-\sum_{t=1}^{M}\sum_{n=1}^{N}\left(r_t^+ p_{n,t}^+ - r_t^- p_{n,t}^-\right)\Delta T \\ &+\sum_{t=1}^{M}\sum_{n=1}^{N}\left(r_t^{up} p_{n,t}^{up} - r_t^{dw} p_{n,t}^{dw}\right)\Delta T \\ &-\sum_{t=1}^{M}\sum_{n=1}^{N} D^{\text{ev}}\left(p_{n,t}^+ + p_{n,t}^-\right)\Delta T \end{aligned} \tag{3b}$$

$$\begin{aligned} DAM^{\text{ess}} = &-\sum_{t=1}^{M}\left(r_t^+ p_t^+ - r_t^- p_t^-\right)\Delta T \\ &+\sum_{t=1}^{M}\left(r_t^{up} p_t^{up} - r_t^{dw} p_t^{dw}\right)\Delta T \\ &-\sum_{t=1}^{M} D^{\text{ess}}\left(p_t^+ + p_t^-\right)\Delta T \end{aligned} \tag{3c}$$

where p_t^+, p_t^- are the charging and discharging powers of the ESS in the DAM; p_t^{up} and p_t^{dw} are the reserve up and down capacities of the ESS in the DAM. D^{ev} and D^{ess} are battery parameters, which relate to the capital cost, lifetime in cycles and depth-of-discharge of the battery [36]. The third term of (3c) stands for the daily battery degradation cost of ESS due to the installation fee of ESS.

In the RTM, the ISO declares RDR to call for the reserve based on the DA proposed reserve capacity. $I_\omega^{ev,ess}$ in (3d) represents the income by deploying the reserve under scenario ω:

$$\begin{aligned} I_\omega^{\text{ev,ess}} = &\sum_{t=1}^{M}\sum_{n=1}^{N}\widetilde{r}_t^{up}\left(\widetilde{p}_{n,t,\omega}^{up} + \widetilde{p}_{t,\omega}^{up}\right)\Delta T \\ &+\sum_{t=1}^{M}\sum_{n=1}^{N}\widetilde{r}_t^{dw}\left(\widetilde{p}_{n,t,\omega}^{dw} + \widetilde{p}_{t,\omega}^{dw}\right)\Delta T \end{aligned} \tag{3d}$$

where $\widetilde{p}_{n,t,\omega}^{up}$, $\widetilde{p}_{n,t,\omega}^{dw}$ and $\widetilde{p}_{t,\omega}^{up}$, $\widetilde{p}_{t,\omega}^{dw}$ stand for the deployed reserve up and down of EV n and the ESS at time t in the RTM.

$C_\omega^{\text{ev,ess}}$ in (3e) defines the penalty of the EV aggregator suffers from default the DA proposed reserve capacity under scenario ω (i.e., reserve shortage penalty):

$$C_\omega^{\text{ev,ess}} = \sum_{t=1}^{M}\left(\gamma^{up} s_{t,\omega}^{up} + \gamma^{dw} s_{t,\omega}^{dw}\right)\Delta T \tag{3e}$$

3.2 Scheduling Constraints

The EV aggregator needs to guarantee scheduled charging/discharging power to be strictly bounded by the maximum charging/discharging power limits during the available time ($t_n^a \le t < t_n^d$), and the charging/discharging power are both set to zero when EV is off the grid.

$$p_{n,t}^+ = \begin{cases} 0 & 1 \le t < t_n^a \\ [0, \overline{P}^{\text{ev}} i_{n,t}^+] & t_n^a \le t < t_n^d \\ 0 & t_n^d \le t \le M \end{cases} \quad \forall n, t, \tag{4}$$

$$p_{n,t}^- = \begin{cases} 0 & 1 \le t < t_n^a \\ [0, \overline{P}^{\text{ev}} i_{n,t}^-] & t_n^a \le t < t_n^d \\ 0 & t_n^d \le t \le M \end{cases} \quad \forall n, t, \tag{5}$$

Binary variables in (6) are used to make sure that the EV will not be charged or discharged simultaneously.

$$i_{n,t}^+ + i_{n,t}^- \le 1 \quad \forall n, t, \tag{6}$$

The relationship between the reserve up/down capacity with the charging/discharging power is represented in (7) and (8):

$$p_{n,t}^+ - p_{n,t}^- - p_{n,t}^{up} \ge -\overline{P}^{\text{ev}} \quad \forall t, n, \tag{7}$$

$$p_{n,t}^{+} - p_{n,t}^{-} + p_{n,t}^{dw} \leq \overline{P}^{\mathrm{ev}} \quad \forall t, n. \tag{8}$$

These two equations suggest that at each time t, the charging/discharging power of EV n with its reserve up/down capacity should not greater or lower than the maximum charging/discharging power respectively.

Constraints (9) and (10) make sure that for each scenario ω , at each time the deployed up/down reserve is not greater than the proposed reserve up/down capacity:

$$0 \leq \widetilde{p}_{n,t,\omega}^{up} \leq p_{n,t}^{up} \quad \forall t, n, \omega, \tag{9}$$

$$0 \leq \widetilde{p}_{n,t,\omega}^{dw} \leq p_{n,t}^{dw} \quad \forall t, n, \omega. \tag{10}$$

Moreover, at each time the EV aggregator needs to guarantee each EV will not be overcharged or discharged. The reserve up/down capacity of each EV is also limited by the boundary of SOC.

$$\begin{aligned} S_n^a + \frac{\sum_{t=1}^{m} \left(p_{n,t}^{+} - p_{n,t}^{-}\right) \Delta T - p_m^{up} \Delta T}{E^{\mathrm{ev}}} + \\ \frac{\sum_{t=1}^{m-1} \left(-\widetilde{p}_{n,t,\omega}^{up} + \widetilde{p}_{n,t,\omega}^{dw}\right) \Delta T}{E^{\mathrm{ev}}} \geq \underline{\mathrm{S}}_{n,m} \quad \forall m, \omega \end{aligned} \tag{11}$$

$$\begin{aligned} S_n^a + \frac{\sum_{t=1}^{m} \left(p_{n,t}^{+} - p_{n,t}^{-}\right) \Delta T + p_m^{dw} \Delta T}{E^{\mathrm{ev}}} + \\ \frac{\sum_{t=1}^{m-1} \left(-\widetilde{p}_{n,t,\omega}^{up} + \widetilde{p}_{n,t,\omega}^{dw}\right) \Delta T}{E^{\mathrm{ev}}} \leq \overline{\mathrm{S}} \quad \forall m, \omega \end{aligned} \tag{12}$$

where $\underline{\mathrm{S}}_{n,m}$ is the minimum SOC of EV n at time m to make sure that EV could be charged at the target SOC at departure time, the value of $\underline{\mathrm{S}}_{n,m}$ is defined in (13):

$$\underline{\mathrm{S}}_{n,m} = \max\{\underline{\mathrm{S}}, \mathrm{S}^{\mathrm{d}} - \frac{\overline{P}^{\mathrm{ev}} (M-m) \Delta T}{E^{\mathrm{ev}}}\} \quad \forall m, n. \tag{13}$$

The scheduling constraints of the ESS are similar to EVs except that the ESS is available all the time and the ESS has no target SOC but the final SOC. The scheduling constraints of the ESS are formulated as follows:

$$0 \leq p_t^{+} \leq \overline{P}^{\mathrm{ess}} i_t^{+} \quad \forall t \tag{14}$$

$$0 \leq p_t^{-} \leq \overline{P}^{\mathrm{ess}} i_t^{-} \quad \forall t \tag{15}$$

$$i_t^{+} + i_t^{-} \leq 1 \quad \forall t \tag{16}$$

$$p_t^{+} - p_t^{-} - p_t^{up} \geq -\overline{P}^{\mathrm{ess}} \quad \forall t \tag{17}$$

$$p_t^{+} - p_t^{-} + p_t^{dw} \leq \overline{P}^{\mathrm{ess}} \quad \forall t \tag{18}$$

$$0 \leq \widetilde{p}_{t,\omega}^{up} \leq p_{t,\omega}^{up} \quad \forall t, \omega \tag{19}$$

$$0 \leq \widetilde{p}_{t,\omega}^{dw} \leq p_{t,\omega}^{dw} \quad \forall t, \omega \tag{20}$$

$$\begin{aligned} \mathrm{S}^{\mathrm{b}} + \frac{\sum_{t=1}^{m} \left(p_t^{+} - p_t^{-}\right) \Delta T - p_m^{up} \Delta T}{E^{\mathrm{ess}}} + \\ \frac{\sum_{t=1}^{m-1} \left(-\widetilde{p}_{t,\omega}^{up} + \widetilde{p}_{t,\omega}^{dw}\right) \Delta T}{E^{\mathrm{ess}}} \geq \underline{\mathrm{S}} \quad \forall m, \omega \end{aligned} \tag{21}$$

$$\begin{aligned} \mathrm{S}^{\mathrm{b}} + \frac{\sum_{t=1}^{m} \left(p_t^{+} - p_t^{-}\right) \Delta T + p_m^{dw} \Delta T}{E^{\mathrm{ess}}} + \\ \frac{\sum_{t=1}^{m-1} \left(-\widetilde{p}_{t,\omega}^{up} + \widetilde{p}_{t,\omega}^{dw}\right) \Delta T}{E^{\mathrm{ess}}} \leq \overline{\mathrm{S}} \quad \forall m, \omega \end{aligned} \tag{22}$$

Considering the periodical operation of ESS, constraint (23) makes sure that the SOC by the end of the day is same with the beginning SOC:

$$\mathrm{S}^{\mathrm{b}} + \frac{\sum_{t=1}^{M} \left(p_t^{+} - p_t^{-} - \widetilde{p}_{t,\omega}^{up} + \widetilde{p}_{t,\omega}^{dw} \Delta T\right)}{E^{\mathrm{ess}}} = \mathrm{S}^{\mathrm{b}} \quad \forall \omega \tag{23}$$

From the viewpoint of the ISO, the grid could call for the reserve in RTM based on the DA proposed reserve capacity both for EVs and the ESS. The aggregator will receive penalty for the reserve deployment shortage. The constraints (24) and (25) indicate that summation of the deployed reserve with reserve deployment shortage equal to the required reserve capacity.

$$s_{t,\omega}^{up} + \widetilde{p}_{t,\omega}^{up} + \sum_{n=1}^{N} \widetilde{p}_{n,t,\omega}^{up} = \lambda^{up} \widetilde{x}_{t,\omega}^{up} \left(p_{t,\omega}^{up} + \sum_{n=1}^{N} p_{n,t,\omega}^{up} \right) \quad \forall t, \omega \tag{24}$$

$$s_{t,\omega}^{dw} + \widetilde{p}_{t,\omega}^{dw} + \sum_{n=1}^{N} \widetilde{p}_{n,t,\omega}^{dw} = \lambda^{dw} \widetilde{x}_{t,\omega}^{dw} \left(p_{t,\omega}^{dw} + \sum_{n=1}^{N} p_{n,t,\omega}^{dw} \right) \quad \forall t, \omega \tag{25}$$

where $s_{t,\omega}^{up}$ and $s_{t,\omega}^{dw}$ stand for the reserve shortage.

Constraint in (26) is utilized to make sure that at all time, the reserve up/down shortage variables are positive.

$$s_{t,\omega}^{u} \geq 0, \quad s_{t,\omega}^{d} \geq 0 \quad \forall t, \omega. \tag{26}$$

The block diagram in Figure 4 shows the modelling of the EV aggregator bidding strategy, including objective function, constraints of EV, ESS and the reserve deployment.

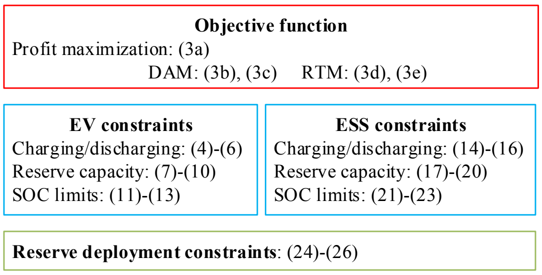

Figure 4: A block diagram of the modelling of the EV aggregator bidding strategy

Table 2: EVs and ESS Parameters

$\overline{P}^{\mathrm{ev}}$	$\overline{P}^{\mathrm{ess}}$	D^{ev}	D^{ess}	$\overline{\mathrm{S}}$
8 kW	120 kW	0.083 $/kWh	0.05 $/kWh	1
$\underline{\mathrm{S}}$	S^{d}	S^{b}	E^{ev}	E^{ess}
0.1	0.95	0.5	64 kWh	1500 kWh

4 Results

The proposed EV aggregator bidding strategy is formulated based on mixed-integer linear programming and this optimization problem is solved by IBM ILOG CPELX [37].

4.1 Parameters Setting

A residential community is considered in this model, the EV aggregator coordinates the charging/discharging of 100 EVs and the ESS from the 13:00 to 13:00 next day for twenty-four hours with one hour each interval ($M = 24$, $N = 100$, $\Delta T = 1\mathrm{h}$). The real-time price and reserve up/down capacity prices are available in [25].

All EVs are assumed with BYD e6 type, where the EV battery has the maximum charging power 8 kW and 64 kWh capacity. The ESS is assumed with the maximum charging power of 120 kW and 1500 kWh capacity. The lower and upper boundary SOC of EV and ESS are set to 0.1 and 1, respectively. The target SOC of EV S^{d} is 0.95 to guarantee EV owners' requirements. The beginning SOC of ESS S^{b} is set to 0.5 for periodical operation. The EVs and the ESS parameters are summarized in Table 2.

The EV owners' driving behaviors in a residential community are assumed to follow Gaussian distributions. To specific, the arrival time, departure time and the EV's SOC at arrival time (initial SOC) follow Gaussian distributions. These parameters are presented in Table 3.

Table 3: 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

Table 4: Hourly probability of RDR

Time	**13:00**	**14:00**	**15:00**	**16:00**	**17:00**	**18:00**
Probability	0.089	0.091	0.099	0.121	0.122	0.156
Time	**19:00**	**20:00**	**21:00**	**22:00**	**23:00**	**0:00**
Probability	0.155	0.151	0.154	0.156	0.122	0.094
Time	**1:00**	**2:00**	**3:00**	**4:00**	**5:00**	**6:00**
Probability	0.015	0.015	0.015	0.015	0.015	0.015
Time	**7:00**	**8:00**	**9:00**	**10:00**	**11:00**	**12:00**
Probability	0.029	0.055	0.078	0.081	0.083	0.084

In RTM, one-year ($Q = 365$) of RDR data are generated and the hourly probability is available in Table 4 [23]. It can be seen that the ISO has higher probabilities to require to deploy the reserve from 18:00 to 22:00. The reason is that these are peak hours in one day, there is a higher probability that the generation side cannot meet the energy consumption from the demand side. Therefore, the ISO has a high probability of reserve up capacity deployment requirements during these times to meet the generation and demand balance.

4.2 One-Year Data of Reserve Deployment Requirements

This section shows the generated one-year data for RDR based on Monte Carlo simulation. A summary of the RDR times in one-day among one-year data is shown in Figure 5. It suggests that within 365 days, there are 39 days that no reserve is required. There are 111 and 127 days for the reserve is required once and twice in one-day, respectively. There are 54 days that reserve is required three times and 22 days for four times. In the end, there are only 9 and 3 days that reserve is required five or six times in one-day respectively.

The probability of each scenario π_ω is illustrated in Figure 6, and in total there are 208 scenarios in 365 days, i.e. Ω=208. Scenario 1 represents that no reserve is required, which has the highest probability of π_1=0.101.

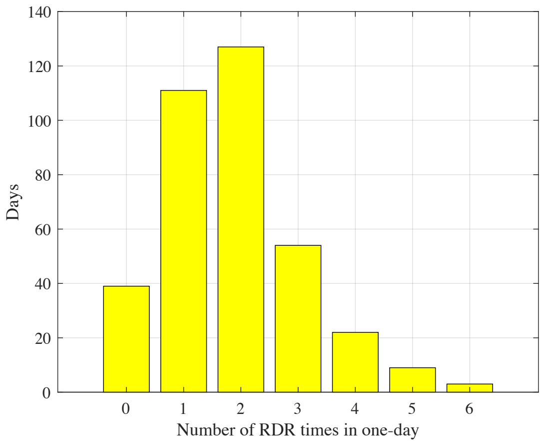

Figure 5: A summary of the number of RDR times in one-day among one-year data

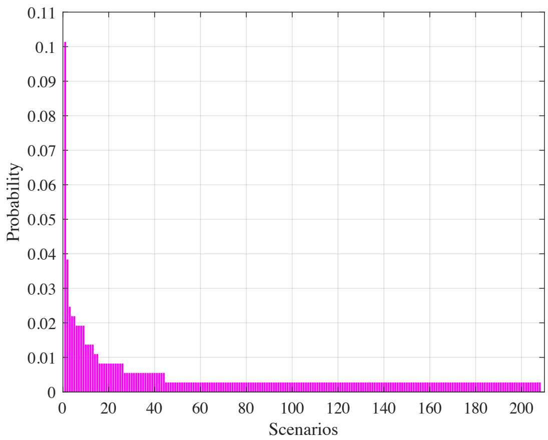

Figure 6: The probability of each reserve deployment scenario for one-year data

4.3 DA Bidding Plans of EVs and ESS

In this section, the DA bidding plan of the EV aggregator with the utilization ESS is presented, which includes the DA based load plan and the reserve up/down capacities plan. The scheduling results of the EV aggregator coordinating 100 EVs with the number of connected EVs at each time are shown in Figure 7. It can be seen that the blue curve represents the proposed charging/discharging power of all EVs in the DAM; at the beginning (13:00–16:00), the EVs have less charging power because most EVs are not connected to the grid. The RTP is relatively lower during these periods, and thus EVs operate in the charging status. After that, the peak hours are from

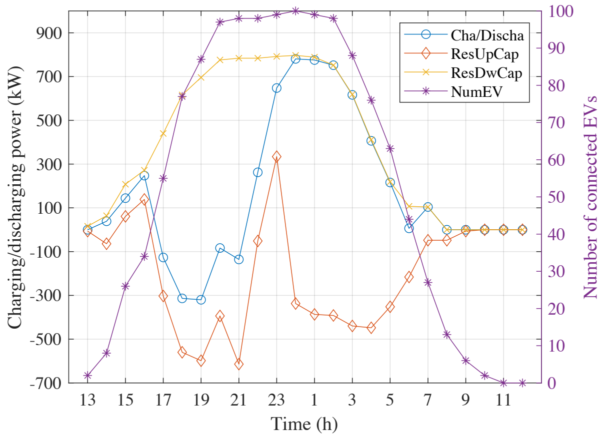

Figure 7: EVs DA bidding plan in terms of base load, reserve up/down capacities (left axis) and number of connected EVs (right axis with purple colour) over one day

18:00 to 21:00, when the total discharging power increases to inject energy back to the grid and the EV aggregator could obtain profit. Then, the maximum charging power appears at 0:00 and the EV aggregator could charge all the EVs at the lowest price. After 2:00, the total charging power decreases gradually; this indicates that some EVs have stored enough energy to meet the next day's driving requirements. The corresponding reserve up/down boundaries at each hour are also indicated in the figure. The results suggest that the EVs propose more reserve down capacity during 17:00–21:00 (most EVs operate in discharging status) and more reserve up capacity during 22:00–3:00 (most EVs operate in charging status). Because most EVs are not connected to the grid, EVs proposed less reserve up/down capacities before 17:00 or after 7:00.

Compared with the EVs' DA bidding plan, the ESS bidding plan is presented in Figure 8. The figure shows the proposed charging/discharging power at each hour and the corresponding SOC of the ESS. Unlike the EVs that charged during the off-peak hours and discharged during peak hours, the base-load plan of the ESS do not follow the RTP. The reason for this is that the ESS have more flexibility in providing reserve service to the ISO. In addition, considering the dynamic change of the ESS battery SOC, at each time the SOC is bounded between 0.1 and 1; the results indicate that the proposed strategy could effectively manage the charging/discharging of the ESS and prevent it from overcharging or discharging.

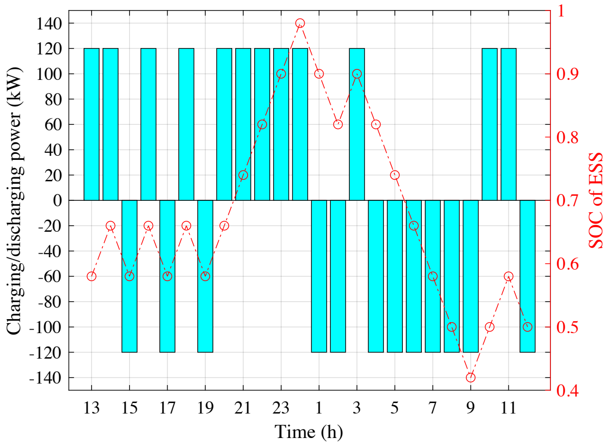

Figure 8: ESS DA bidding plan in terms of charging/discharging power of ESS (in blue bar chart) and the SOC changing profile of ESS (orange dashed line with circle point) over one day

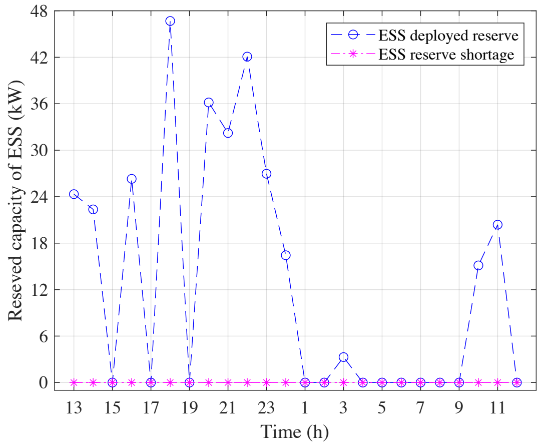

Figure 10: Average deployed reserve (blue dashed line with circle point) and reserve shortage (magenta dashed line with circle point) based on one-year data of ESS in RTM. The reserve of ESS are main deployed between 13:00–23:00) and no reserve shortage.

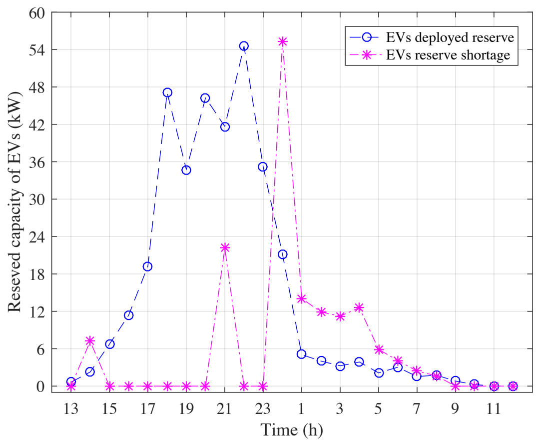

Figure 9: Average deployed reserve (blue dashed line with circle point) and reserve shortage (magenta dashed line with circle point) based on one-year data of EVs in RTM. The reserve of EVs is mainly deployed in the night (18:00-22:00). EVs mainly have reserve shortage in the midnight (0:00-4:00)

4.4 Expected Deployed Reserve and Penalty of EVs and the ESS

In this section, the performance of EVs and the ESS in the RT reserve market is discussed. According to the EV aggregator operation mechanism in the RTM, the average deployed reserve results of EVs at each time are shown in Figure 9. The average deployed reserve is calculated based on the one-year RDR data. It can be seen from the figure that, at the beginning (13:00–15:00), the reserve is less deployed; the reason for this is that most EVs are not available, i.e. EVs are not connected to the grid. As the EV information model data is given in Table 3, the mean value of arrival time is 18:00 with 2 hours variance, thus most EVs are not available during 13:00–15:00. From 17:00–22:00, the deployed reserve of EVs is greater than other time because these periods are peak hours, i.e. the ISO has a higher probability (referring to Table 4) to call for the reserve. After 1:00, the average deployed reserve decreases, because EVs cannot operate in discharging status as the EV aggregator must guarantee that each EV could be charged to the target SOC by departure time. Finally, after 9:00, no reserve is deployed because most EVs have disconnected from the grid and the proposed reserve is close to zero. The average penalty of EVs for reserve deployment shortage at each time is also represented in the figure. It can be seen that EVs receive a higher penalty between 23:00–5:00, which means EVs have a higher risk of not being able to provide enough reserve as proposed. According to the EVs charging/discharging results from Figure 7, most EVs operate in charging status during these time periods, EVs could not deploy all reserve up capacity (operate in discharging status), because they must store enough energy to meet the next day's driving requirements.

The performance of the ESS in RT reserve market is shown in Figure 10. Compared with the peak de-

The proposed, required and deployed reserve for cases with EVs only, ESS only and cooperation between EVs and ESS throughout one year. The required percentage is defined as the required reserve according to the ISO over the proposed reserve capacity and the deployed percentage is defined as the actual deployed reserve of the EV aggregator over the required reserve from the ISO.

	EVs	ESS	EVs with ESS
Proposed reserve up capacity (MWh)	3193.55	2880.00	6073.55
Required reserve up capacity (MWh)	181.45	295.23	476.68
Required percentage	5.68%	10.25%	7.85%
Actual deployed up reserve (MWh)	126.48	295.23	421.71
Deployed percentage	69.71%	100%	88.47%

ployed reserve of 100 EVs with 54.60 kWh, the peak deployed reserve of the ESS is 46.68 kWh at 18:00, which is in the peak period. In addition, the ESS reserve is mainly deployed in the periods 13:00–0:00 and 10:00–11:00, which has more flexibility than EVs. This is one of the advantages of the ESS, which is that ESS are available all the time, but EV is only available when connecting to the grid. Moreover, the ESS are much reliable than EV in providing reserve service; the results in the figure indicate that the penalty of the ESS is zero, which means that the ESS could deploy enough reserve as proposed in the DAM.

To compare the performance of the EVs and ESS in providing reserve service (assume $\lambda^{up} = 100\%$) in the RTM, a summary is shown in Table 4.4. The relationship between the proposed, required and actual deployed reserve up capacity is shown in Equation (24) , where $\lambda^{up}\tilde{x}^{up}_{t,\omega}\left(p^{up}_{t,\omega} + \sum_{n=1}^{N} p^{up}_{n,t,\omega}\right)$ is the required reserve up capacity and $\left(p^{up}_{t,\omega} + \sum_{n=1}^{N} p^{up}_{n,t,\omega}\right)$ is the proposed reserve up capacity. The total proposed reserve up capacity of the EVs in one year is 3193.55 MWh, which is greater than the ESS reserve up capacity (2880.00 MWh), because the total capacity of all EVs is greater than that of the single ESS. It can be seen that the required percentage of the EVs and the ESS are 5.68% and 10.25%, respectively. This implies that the proposed reserve of the ESS has a higher probability to be required by the ISO. According to the DA bidding plan shown in Figure 7 and the hourly RDR probability in Table 4, the most reserve capacity of EVs is proposed between 0:00–5:00; however, the ISO has lower probability to call for the reserve up capacity during these periods, and thus EVs have less required percentage compared with the ESS.

In order to meet EV owners' driving requirements, EVs should be charged to the target SOC by the departure time. In this case, EVs could not respond to the RDR all the time, and the deployed percentage of EVs is 69.71%. The deployed percentage of the ESS is 100%, which means that the ESS could deploy enough reserve according to the ISO's requirements without shortage. Based on these results, it can be concluded that the ESS are much more flexible than EVs in providing reserve services. With the utilization of ESS in the EV aggregator, the required percentage increases from 5.68% to 7.85% and the deployed percentage increases from 69.71% to 88.47%.

4.5 Profit Compositions under Stochastic Strategy

In this section, the expected daily profit of the EV aggregator is analyzed. The expected daily profit of EV aggregator is calculated based on the generated RDR one-year data. Essentially, the EV aggregator profit comes from two sides: EVs and the ESS. To be specific, EVs and the ESS can either obtain income or incur cost from the DAM and the RTM, such as reserve capacity income, charging/discharging income, and deployed reserve income. Furthermore, not only does the EV aggregator guarantee owners' driving requirements, but the economic benefits of each owner are also considered.

Table 4.5 shows the income, cost, and penalty of EVs and the ESS from the DAM, RTM, and aggregator–owner contract. The DA reserve capacity income of EVs is \$53.38, which is significantly greater than that of the ESS (\$15.42). However, compared with the deployed reserve, the income of EVs and the ESS are much closer, at \$93.48 and \$79.16 respectively. The reason is that the total capacity of all EVs is 6.4 MWh (100 EVs with 64 kWh for each vehicle), which is much greater than the ESS capacity (1500 kWh). Although EVs propose more reserve capacity than the ESS, the deployed reserve income is slightly greater than the ESS. This is because the operation of the ESS is much more flexible than that of EVs, i.e. the ESS are available for twenty-four hours, and could therefore respond to the ISO's requirements at any time. Regarding the penalty of the reserve shortage in the RTM, penalties for EVs and the ESS are only \$2.97 and \$0, respectively, which are significantly less

2pt Expected profit composition of EVs and ESS from DAM, RTM and the contract for two cases of EVs only and EVs with ESS.

Daily expected cost/income		EVs only	EVs with ESS	
		EVs	EVs	ESS
DAM	DA reserve up/down capacity income	\$53.38	\$53.38	\$15.42
	DA charging/discharging cost/income	\$144.38	\$144.38	\$230.07
	Battery degradation cost	N/A	N/A	\$-144.00
	Total	\$197.76	\$197.76	\$101.48
RTM	Deployed reserve income	\$93.48	\$93.48	\$79.16
	Reserve shortage penalty cost	\$-2.97	\$-2.97	\$0
	Total	\$90.51	\$90.51	\$79.16
Contract	Charging income/cost from owners	\$-350.57	\$-350.57	N/A
	Degradation compensation	\$143.42	\$143.42	N/A
	Total	\$-207.15	\$-207.15	N/A
Daily profit of the EV aggregator		\$81.12	\$81.12	\$180.64
			\$261.76	

than the income of the EV aggregator in participating in the DAM and RTM. Thus, these results prove that the porposed strategy could reduce the reserve shortage risk of the EV aggregator. The proposed stochastic programming method effectively accounts for the uncertainty of the reserve market in the DA bidding, and the expected profit of the EV aggregator is maximized.

Another point is that the battery degradation, i.e. the average daily installation fee, of the ESS is \$144.00. However, the EV aggregator will not be responsible for the battery degradation for all EVs, because EVs do not belong to the EV aggregator. The EV aggregator gets the full right in scheduling charging/discharging operation of EVs under the condition that it must reimburse the additional battery degradation cost to each owner compared with the degradation cost obtained from EV owners' scheduling results. In addition, the EV aggregator could receive the income from each EV owner for parking and charging EVs to the target SOC at departure time. Finally, the expected daily profit of the EV aggregator is \$261.76, including \$81.12 from EVs and \$180.64 from the ESS.

Moreover, Table 4.5 shows the profit of the EV aggregator with and without ESS utilization. It can be seen from the table that the EV scheduling results are not affected by the ESS, which means that the ESS do not cooperate with the EVs in providing reserve service to the grid, i.e. ESS cannot reduce the EVs' reserve shortage penalty, even though the ESS have more flexibility in responding to the RDR. The reason for this is that the ESS bidding strategy changes if the ESS are used to reduce the EVs' reserve shortage, and the EVs' reserve shortage penalty is less than the ESS profit reduction.

5 Conclusions

In this paper, an EV aggregator bidding strategy with ESS in DAM and RTM is proposed. The uncertainty of the reserve market in impacting the EV aggregator DA bidding is taken into consideration, and the uncertainty of the reserve market is represented by several scenarios in one-year data which is generated based on Monte Carlo simulation. An aggregator–owner contract is designed to guarantee the economic benefits of each EV owner. In case study, the bidding results of EVs and ESS are compared in terms of base-load plan, required and deployed reserve. In addition, the profit composition of ESS and EVs are analyzed. The main conclusions are summarized as follows:

- The proposed strategy could maximize profits and effectively reduce the risk of the reserve shortage of the EV aggregator. Results show that the reserve shortage penalty of the EV aggregator is \$2.97 (\$2.79 for EVs and \$0 for the ESS) and the profits are \$261.76.

- A comparison is made between EVs and the ESS in providing reserve services to the grid. Results show that the ESS have more flexibility in making response to the ISO's requirements, that is in average 10.25% is required to be deployed and it could deploy enough reserve as proposed.

- With the utilization of the ESS, the ability of the EV aggregator in providing reserve services in improved, where the required percentage increases from 5.68% to 7.85% and the deployed percentage increases from 69.71% to 88.47%. However the EVs' reserve shortage cannot be reduced by the ESS, because the bidding plan of the ESS will be affected and the total profits will be reduced.

Future work will focus on the ESS and EVs participation in both regulation and reserve markets. Detailed modeling of EV and ESS (more accurate Li-ion battery model) will be investigated. In addition, considering the capital and maintenance cost, the size of the ESS utilized by the EV aggregator will be optimized.

Acknowledgment

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