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Optimal operating regime of an electric vehicle aggregator considering reserve provision

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Abstract

The number of electric vehicles (EVs) is growing rapidly due to environmental concerns and political supports. To better coordinate the charging behaviors of large numbers of EVs, the EV aggregator is an important intermediate between the electricity market and the EVs. This work proposes a two-stage optimal operational regime for an EV aggregator who participates in multiple markets under multiple uncertainties. In the day-ahead stage, a joint offering model is proposed to help the aggregator concurrently participate in both the energy and reserve markets under market price uncertainties. The concept of reserve capacity ratio is introduced in the joint offering model to allow different decisions for aggregators with various risk preferences. In the real-time stage, a rolling horizon control-based multi-resolution scheduling model is proposed to minimize the energy deviation cost under reserve deployment uncertainty. The uncertainties are modeled using representative scenarios and the stochastic optimization approach is applied to acquire the optimal solutions. The numerical results suggest that the proposed operational regime can significantly improve the profitability of the studied EV aggregator. The impact of reserve capacity ratios is also analyzed.

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Keywords: EV aggregator; Energy and reserve markets; Reserve capacity ratios; Reserve deployment uncertainty; Multi-stage; Multi-resolution

1. Introduction

The increase of greenhouse gas is contributing to climate change [1] that can lead to catastrophic outcomes. Thus, transforming the energy consumption structure to reduce carbon emission is becoming a worldwide consensus of human society. As an important part of human activity, transportation is producing substantial greenhouse gas by burning fossil fuels using internal combustion engine vehicles (ICEVs) [2]. To limit climate change, replacing the ICEVs with electric vehicles (EVs) is a promising solution that has been intensively studied.

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The rapid development of EVs can cast great challenges to the electricity network if their charging behavior is uncontrolled [3]. Also, studies have shown that the time EVs are parked and connected usually exceeds the time that is required for charging [4], thus, leading to charging flexibilities for effective demand-side management. In the literature, the possibility of EV aggregators utilizing the charging flexibility for economic purposes has been widely investigated. To reduce the charging fee paid to the utility grid, efforts have been made to help the EV aggregator actively participate in the day-ahead energy market to purchase energy at a relatively lower price. In [5], a bidding strategy is proposed for an EV aggregator to purchase energy in the day-ahead market under both the centralized and decentralized modes, uncertainties in energy market price are addressed using the stochastic optimization approach. To further utilize the charging flexibilities of the EVs, reserve provision has been considered in some works to improve the benefits of the EV aggregators. In [6], a bidding strategy that enables the EV aggregator to participate in joint day-ahead energy and reserve market is proposed, the energy and reserve market price uncertainties are handled using the stochastic optimization method. Also, because the information gap between different stages can have negative impacts on the EV aggregator profit, some works make operational decisions in an online fashion based on real-time information to mitigate such impacts. In [7], a bidding strategy is proposed for an EV aggregator who participates in the real-time energy market to minimize the charging cost, the market price uncertainty is handled using the stochastic optimization approach. In [8], a two-stage EV charging scheduling strategy is proposed, the studied aggregator procures energy in the day-ahead market, reserve market is not considered in this work and the optimization model is deterministic.

Indeed, previous works have made fruitful achievements in studying the economic operations of EV aggregators and the operational models are becoming more and more realistic. However, an optimal operational regime that simultaneously considers energy and reserve markets in the day-ahead stage, as well as involves the reserve deployment uncertainty in the real-time stage is still missing in the literature. To fill up this gap, this work proposes an optimal two-stage EV aggregator operational regime to help the EV aggregator bid in the joint energy and reserve market under price uncertainties in the day-ahead stage, as well as schedule the charging power of the EVs under reserve deployment uncertainty in the real-time stage. To handle the uncertainties, representative scenarios are generated, and the stochastic optimization approach is used to obtain the optimal solutions. The main contributions of this work can be summarized as follows:

(1) To propose an optimal two-stage operational regime for the studied EV aggregator who participates in multiple markets under multiple uncertainties based on stochastic optimization.

(2) To introduce the concept of reserve capacity ratios that allow EV aggregators to make reserve offering decisions according to their risk preferences.

(3) To involve the uncertainty in reserve deployment into the real-time stage operational problem.

The rest of this paper is organized as follows: Section 2 describes the problem and gives the general operational structure of the EV aggregator. Section 3 presents the formulations for both the day-ahead offering problem and the real-time charging scheduling problem. Numerical results are provided and discussed in Section 4. Section 5 concludes this paper.

2. Problem description

This section describes the market structure, the uncertainty model, and the operational regime of the EV aggregator.

2.1. Market structure

This work considers three markets, including the energy market, reserve market, and balancing market. In the day-ahead energy and reserve markets, the aggregator acts as a price-taker. In the balancing market, the aggregator is treated as a deviator. For the day-ahead energy and reserve markets, the clearing resolution is one hour, for the balancing market, the clearing resolution is half an hour. In the day-ahead stage, the EV aggregator procures energy in the energy market and sells its reserve capacity in the reserve market. In the reserve market, on the one hand, the aggregator receives payment for providing the capacity and deploying up-reserve. On the other hand, the aggregator only receives capacity payment for providing and deploying down-reserve, as stated in [9]. The reserve deployment

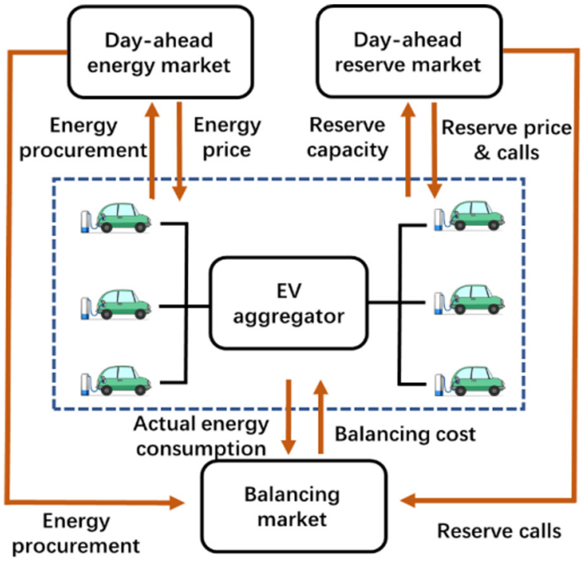

Fig. 1. The studied market structure.

resolution is thirty minutes, the same as the thirty-minute reserve in the PJM market. The balancing market settles the real-time energy deviations in an *ex-post* fashion at penalty prices [10] defined by (1)–(4):

$$\lambda^{+}_{BM,H} = \alpha\lambda_{m,H} \tag{1}$$

$$\lambda^{-}_{BM,H} = \beta\lambda_{m,H} \tag{2}$$

$$\alpha > 1 \tag{3}$$

$$\beta < 1 \tag{4}$$

where $\lambda_{m,H}$ is the day-ahead energy market-clearing price (MCP) at hour H. The penalty prices for positive and negative deviations are denoted as $\lambda^{+}_{BM,H}$ and $\lambda^{-}_{BM,H}$, respectively. The penalty parameters α and β indicate the market attitude towards energy deviations. The relationships between the EV aggregator and different markets are displayed in Fig. 1.

2.2. Uncertainty modeling

The uncertain factors include the day-ahead energy and reserve market prices, the reserve deployment uncertainty in the real-time operational stage, and the EV charging information. In the proposed operational regime, the uncertainty related to EVs is described using deterministic scenarios that are generated from the Monte-Carlo-Simulation method introduced in [11]. To describe the uncertainties in market price and reserve deployment, we first utilize ARIMA models to acquire the forecast values, then generate large quantities of scenarios based on the probability distribution of forecast errors. Finally, to reduce the computational burden, the k-means clustering method is applied to acquire influential scenarios that contain the characterizing information of the original scenarios [12].

2.3. Two-stage EV aggregator operational regime

The proposed operational regime includes the day-ahead joint offering model and the real-time scheduling model. In the day-ahead stage, according to the generated EV and price scenarios, the aggregator concurrently determines the energy procurement and the reserve provision to minimize the total operational cost. For the aggregator, joint offering in both the energy and reserve markets is more reasonable because the charging flexibility that can be sold to the reserve market is related to the charging power scheduled in the energy market. In the real-time operation stage, based on the received reserve calls and the generated future reserve call scenarios, the aggregator optimally

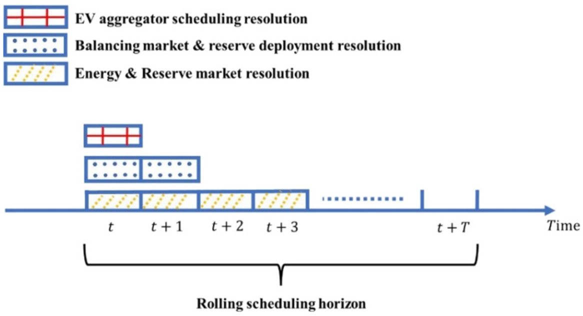

Fig. 2. Illustration of the multi-resolution real-time scheduling model, each block represents a 15-minute interval.

schedules the charging power of the parked EVs to minimize the energy deviation costs. To handle the uncertain arrival and departure of the EVs this work utilizes a rolling horizon control strategy, whose look-ahead length T is 8-hours, and the scheduling resolution is fifteen minutes. To this end, the market-clearing, reserve deployment, and scheduling resolutions are all different, as illustrated in Fig. 2. Thus, the proposed real-time operational model is a multi-resolution model, which is closer to the real-world operation. To keep the EV charging information consistent with the rolling horizon control model, only the first step in the rolling horizon solution will be implemented.

3. Problem formulation

This section presents the optimization problem formulations for both the day-ahead joint offering problem and the multi-resolution real-time scheduling problem.

3.1. Day-ahead joint offering problem

In the day-ahead stage, the EV aggregator optimally schedules the EV charging load to simultaneously minimize the energy market procurement cost and maximize the reserve market capacity revenue. Given that the infrastructure for vehicle-to-grid operation is still less developed, this work only considers the grid-to-vehicle mode. The reserve capacity sold to the reserve market can be expressed as:

$$R_{up,H} = \gamma_{up} \sum_{t \in H} \sum_{k} P_{k,t} \tag{5}$$

$$R_{down,H} = \gamma_{down} \sum_{t \in H} \sum_{k} (P_k^{max} - P_{k,t}) \tag{6}$$

where $P_{k,t}$ is the charging power of the kth EV at interval t, P_k^{max} is the maximum charging power of the kth EV. The up- and down-reserve capacities are given by $R_{up,H}$ and $R_{down,H}$, respectively. Terms γ_{up} and γ_{down} are the ratios of the reserve capacities sold to the market and the total available capacity. It should be noted that selling larger reserve capacity to the reserve can simultaneously increase the reserve market revenue and the risk of interrupting the original scheduling. When large γ_{up} is selected, the EV aggregator may have to reduce the charging power at some low-price hours and shift the charging load to high-price hours as positive deviations, which will lead to significant profit losses. When large γ_{down} is selected, the aggregator may not have enough capacity to fulfill the reserve deployment requests. Therefore, different γ_{up} and γ_{down} should be selected according to the aggregator's attitude towards risks.

The day-ahead joint offering problem can be formulated as follow:

$$\min_{P_{k,t}, P_{M,H}, R_{up,H}, R_{down,H}} \sum_{s1 \in S1} \pi_{s1} \sum_{s2 \in S2} \pi_{s2} \sum_{t} \{f_M^{s1}(P_{M,H}) - f_R^{s2}\left(R_{up,H}, R_{down,H}\right)\} \tag{7}$$

s.t.

$$\text{Constraints (5), (6)} \tag{8}$$

$$f_M^{s1}\left(P_{M,H}\right) = P_{M,H}\lambda_{m,H}^{s1} \tag{9}$$

$$f_R^{s2}\left(R_{up,H}, R_{down,H}\right) = R_{up,H}\lambda_{R,H}^{s2} + R_{down,H}\lambda_{R,H}^{s2} \tag{10}$$

$$P_{M,H} = \sum_{t\in H}\sum_{k} P_{k,t} \tag{11}$$

$$0 \le P_{k,t} \le P_k^{max} \tag{12}$$

$$SOC_{k,t+1} = SOC_{k,t} + \frac{\eta}{Cap_k}P_{k,t} \tag{13}$$

$$SOC_{k,min} \le SOC_{k,t} \le SOC_{k,max} \tag{14}$$

$$SOC_{k,dep} = SOC_{k,max} \tag{15}$$

where $s1$ and $s2$ represent the energy and reserve capacity price scenarios that belong to the generated price scenarios sets $S1$ and $S2$, respectively. The probabilities of the price scenarios are given by π_{s1} and π_{s2}. The energy procurement cost and reserve provision revenue are given by $f_M^{s1}\left(P_{M,H}\right)$ and $f_{up}^{s2}\left(R_{up,H}, R_{down,H}\right)$, respectively. The energy capacity of the kth EV is represented by Cap_k. The state-of-charge (SOC) of the kth EV at time t is given by $SOC_{k,t}$, whose lower and upper bounds are $SOC_{k,min}$ and $SOC_{k,max}$, respectively. The charging efficiency of the EVs is given by η.

In this formulation, the objective function aims to find a day-ahead joint offering solution such that the total expected operational cost is minimized. Constraint (12) gives the energy procurement at hour H. Constraint (13) limits the charging power of the EVs. Constraints (13)–(15) present the SOC limits of the EVs.

3.2. Real-time multi-resolution operation

In the real-time stage, the EV aggregator aims to minimize the energy deviation cost in the balancing market given the EV charging scenarios and the reserve deployment uncertainties. Suppose the reserve deployment scenarios and scenario set are given by s_3 and S_3, respectively, the real-time optimal scheduling problem can be formulated as:

$$\min_{P_{k,t}} \sum_{s3\in S3} \pi_3 \sum_{t\in T}\{f_{BM,h\in H}^{s3}\left(P_{d,h}^{s3}\right) - f_{up}^{s3}(R_{up,h}^{s3})\} \tag{16}$$

s.t.

$$\text{Constraints (1), (2), (13)–(15)} \tag{17}$$

$$P_{d,h}^{s3} = \sum_{t\in h}\sum_{k} P_{k,t} + R_{up,h}^{s3} - R_{down,h}^{s3} - P_{M,H} \tag{18}$$

$$f_{BM,h\in H}^{s3}(P_{d,h}^{s3}) = \begin{cases} P_{d,h}^{s3}\lambda_{BM,H}^{+}, & P_{d,h} \ge 0 \\ P_{d,h}^{s3}\lambda_{BM,H}^{-}, & P_{d,h} < 0 \end{cases} \tag{19}$$

$$f_{up,h\in H}^{s3}\left(R_{up,h}^{s3}\right) = \lambda_{m,H}R_{up,h}^{s3} \tag{20}$$

where the subscript h represents the hth half-hour. The energy deviation and balancing cost in the hth half-hour under the reserve call scenario $s3$ is given by $P_{d,h}^{s3}$ and $f_{BM,h\in H}^{s3}(P_{d,h}^{s3})$, respectively. Terms $R_{up,h}^{s3}$ and $R_{down,h}^{s3}$ are the up- and down-reserve calls for the hth half-hour under scenario $s3$. The objective is to identify a scheduling decision such that the expected profit loss due to the energy deviation is minimized. Constraint (18) provides the energy deviation of the hth half-hour. Constraint (19) gives the balancing cost. In (19), for the over-consumed part of energy, the aggregator needs to pay a higher price than the MCP; For the non-consumed part of energy, the aggregator can only sell it at a price lower than the MCP. The up-reserve deployment revenue is given by constraint (20).

4. Case study

This section presents the numerical results and discussions. The formulated stochastic optimization models are efficiently solved using the commercial solvers Gurobi 9.1.2 [13] interfaced with Matlab language.

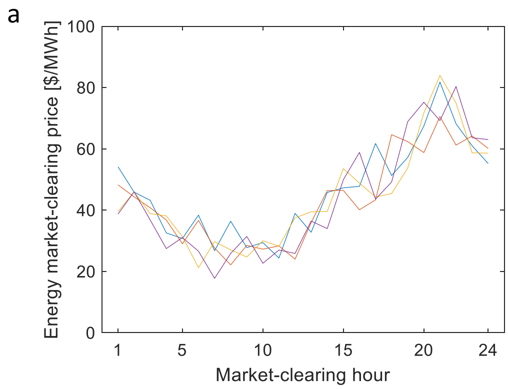

Fig. 3. Day-ahead (a) energy and (b) reserve market price scenarios.

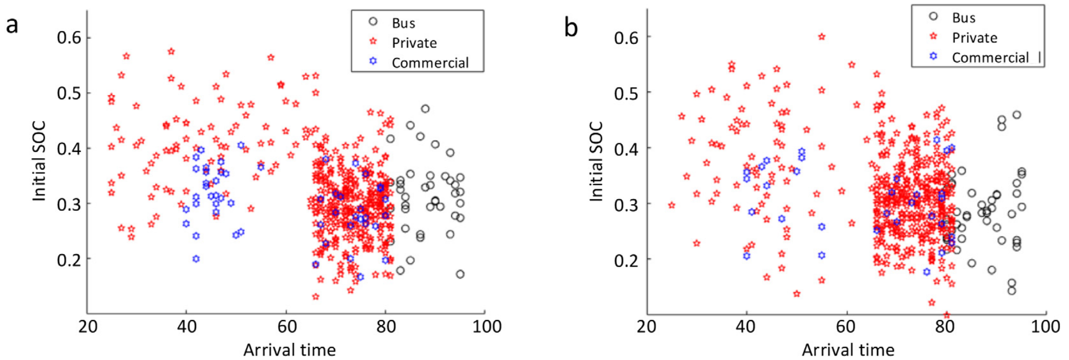

Fig. 4. The generated EV charging scenarios for the (a) day-ahead offering stage and (b) the real-time operation stage.

4.1. Basic data

The historical data for day-ahead energy and reserve market prices are obtained from the PJM market [14]. The price scenarios generated using the procedure described in Section 2 are presented in Fig. 3. Using the data provided in [11], 1000 EV charging scenarios are generated, in which 500 scenarios are used as forecast information for day-ahead offering decision-making, and the rest are used as real-time operational scenarios. The generated day-ahead EV charging scenarios and real-time EV scenarios are presented in Fig. 4. for all the EVs, the charging efficiency η is set to be 0.95. To avoid severe interruption induced from the reserve calls, γ_{up} and γ_{down} are set to be 0.2 and 0.4, respectively. The market penalty factors are set to be $\alpha = 1.5$ and $\beta = 0.5$.

4.2. Results and discussions

The scheduling results of the aggregator in both the day-ahead energy and reserve markets are presented in Figs. 5 and 6. In Fig. 5, the aggregator scheduled most of its energy consumption between midnight and morning (hours between 23 and 7 of the next day). This is because the energy market prices are relatively low during these hours. At hours 20 to 22, no energy is bought from the market because these hours have the highest forecast prices. At hours 8 and 9, most of the parked EVs have left and only a few new EVs come to charge, as can be observed from Fig. 4. Therefore, the energy scheduled for hours 8 and 9 is less than its adjacent hours. For hours 17 and 18, though the market price is high, a certain amount of energy must be scheduled to charge the EVs that are about to leave.

Also, it can be observed that the energy scheduling during hours 23 to 7 is not completely determined by the energy market price. The energy procurement for some high-price hours (such as hour 24) is even more than some

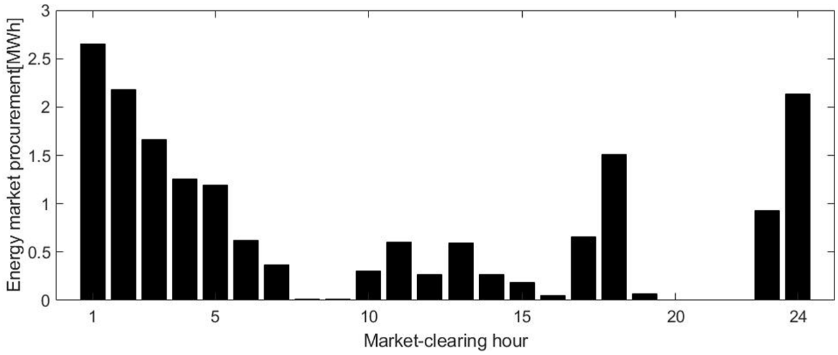

Fig. 5. Energy market procurement result.

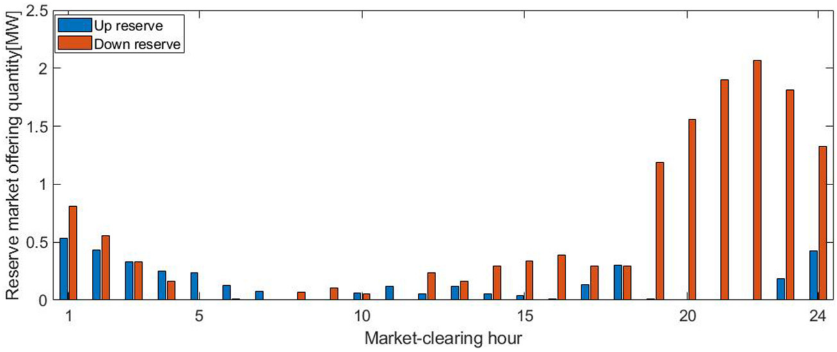

Fig. 6. Reserve market offering results.

low-price hours (such as hours 4 and 5). The rationale behind this result is that the energy scheduling for the aggregator is affected by both the energy and the reserve market prices. Since the capacity ratio for reserve-up is smaller than reserve-down, scheduling less energy means more reserve capacity can be sold to the reserve market, as can be concluded from (5) and (6). Therefore, when the reserve market price is high and the energy market price is low, the aggregator may still prefer to reduce its charging load to sell more reserve capacity.

The real-time charging scheduling result, the called reserve deployment, and the energy deviations are presented in Fig. 7. It should be noted that the power deviation is inevitable because that on the one hand, there is an

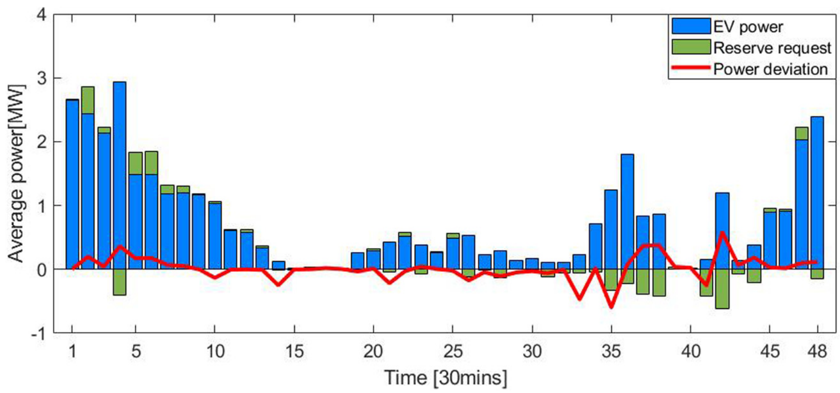

Fig. 7. The real-time scheduled EV power, the reserve request, and the power deviations.

Table 1. Cost comparison between different cases.

Capacity ratios $\gamma_{up}/\gamma_{down}$	Day-ahead cost ($)	Real-time cost ($)	Total cost ($)
Case 1	702.8	215.0	917.8
Case 2	702.8	243.9	946.7
Case 3	785.5	214.6	1001.1

Table 2. Cost details for the selected reserve capacity ratio combinations.

Capacity ratios $\gamma_{up}/\gamma_{down}$	Day-ahead cost ($)	Real-time cost ($)	Total cost ($)
0.1/0.3	725.4	197.9	923.3
0.2/0.4	702.8	215.0	917.8
0.3/0.5	680.0	217.6	897.6
0.4/0.6	657.0	251.2	908.2
0.5/0.7	635.3	295.6	930.9
0.6/0.8	612.8	338.8	951.6
0.7/0.9	590.3	376.4	966.7

information gap between the day-ahead forecast EV charging scenarios and the real-time EV charging information, on the other hand, the reserve deployment calls are uncertain. In Fig. 7, one can observe that the power deviations are very small most of the time. However, in some operational periods, the deviations are comparable to the scheduled energy, which is resulted from large forecast errors of both the EV charging scenarios and the reserve deployment requests.

The cost details for the proposed operational regime (Case 1), the case where reserve uncertainty is not considered in the real-time stage (Case 2), and the case where the reserve market is not considered (Case 3) are presented in Table 1. By comparing cases 2 and 3, one can conclude that under the proposed joint offering strategy, the provision of reserve is profitable for the EV aggregator. By selling reserve capacity to the reserve market, the day-ahead cost is reduced by 83.3$. However, the real-time cost is also increased by 29.3$ due to the interruption of uncertain reserve calls. Compare case 1 with case 2, it is evident that the proposed real-time operational model can significantly reduce the balancing cost by properly taking the reserve deployment uncertainty into account. To this end, the effectiveness of both the proposed day-ahead joint offering strategy and the multi-resolution real-time scheduling model is demonstrated.

To analyze the impact of the reserve capacity ratios γ_{up} and γ_{down}, several reserve capacity ratio combinations are selected for evaluation, and the resulted costs are presented in Table 2. By comparing the costs, one can observe that as the capacity ratios increase, the day-ahead cost is reduced. This is because that more reserve capacity is sold in the reserve market and the corresponding revenue has been improved. However, in the real-time operational stage, the interruption of reserve deployment requests become more significant, which leads to larger balancing cost. In the beginning, the total cost decreases because the reserve revenue improvement is more significant than the balancing cost increment. After the turning point, the impact of the balancing cost becomes dominant, and the total cost increases with larger scheduled reserve capacity. As a result, the total cost is V-shaped with increasing reserve capacity ratios, as displayed in Fig. 8.

5. Conclusion

In this work, an optimal operational regime for an EV aggregator who participates in multiple markets under multiple uncertainties is proposed. Unlike previous works, the proposed regime contains a day-ahead joint offering model and a multi-resolution real-time operational model. The numerical results demonstrate that the joint offering model in the proposed operational regime can effectively capture the arbitraging opportunities in the reserve market and reduce the total operational cost of the aggregator. In the real-time stage, though the power deviation is inevitable due to the uncertainties in EV charging information and reserve deployment calls, it can be efficiently reduced by properly incorporating the reserve uncertainty under the proposed real-time operational model. Finally, the sensitivity analysis on the selection of reserve capacity ratios suggests that offering more reserve capacity can simultaneously

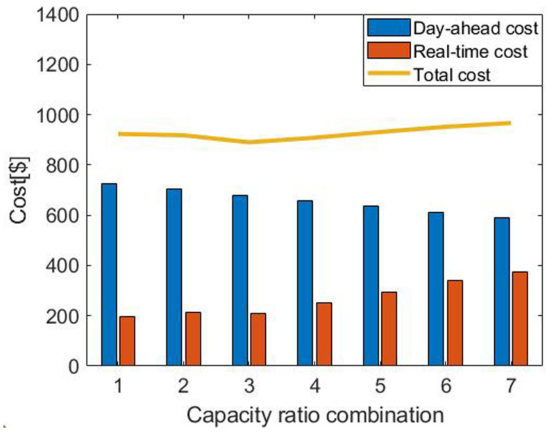

Fig. 8. Sensitivity analysis for different combinations of reserve capacity ratios.

increase the reserve revenue and the balancing cost, thus, the selection of reserve capacity ratios should be based on the aggregator's risk preference.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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