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**Paper**

# Cooperative Optimal Bidding Strategy for Demand-side Responses Participating in JEPX Spot Market and Replacement Reserve Market

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With the establishment of the Japan Electric Power eXchange market (JEPX) and the Replacement Reserve market (RR), the demand-side response (DR) is encouraged to participate in daily system operation with traditional generation resources. Since electricity markets are generally day-ahead or hour-ahead auction markets where the actual price is announced after the bidding and clearing process, the DR owner needs to predict the market price in advance for the resources' optimal scheduling to maximize profits. However, due to the market mechanism and the characteristics of DRs, simply forecasting the market prices with minimum error values cannot guarantee a good profit for the DRs. This paper designs a cooperative bidding strategy that considers both DR's operation and market characteristics to maximize the profit when participating in the JEPX spot market and RR market simultaneously. Rather than treating the bidding strategy as a combined optimization problem, a novel criterion is applied to select the most profitable forecast result of the JEPX spot price, and an extra procedure to predict the sufficiency of the RR demand capacity is proposed. Results comparing the proposed cooperative bidding strategy and conventional co-optimization strategy are reported, and a significant economic improvement is observed through market simulation.

**Keywords:** demand-side responses, electricity market, price forecast, ARIMA models, deep learning

## 1. Introduction

The integration of substantial renewable energy sources (RES) into traditional power systems has introduced numerous challenges. Given that RES generation, such as photovoltaic (PV) and wind turbines, is heavily dependent on weather conditions, maintaining the supply-demand balance within the system is becoming increasingly difficult. In addition to relying on conventional thermal generation units to maintain this balance, demand-side response (DR) offers an additional degree of flexibility nowadays. Modern affordable communication infrastructure and embedded systems make it relatively easy to be involved and align with the system's operation[(1)].

The progress of electricity market deregulation has enabled the fair participation of the DRs. Both the generation side and the demand side can submit bids and prices for selling and purchasing electricity to the energy trading pool, with the market operator determining the electricity price upon market clearing. Furthermore, ancillary services, such as frequency regulation, can also be procured through market auctions, where the system operator acquires regulation capacity based on system operational needs. The electricity market currently plays a critical role in the operation and management of modern power systems, and grid performance is directly influenced by market participants. Therefore, designing operational strategies for DRs using available market information is a vital step toward the effective integration of demand-side resources into the power grid.

Under such circumstances, the prices for electricity and ancillary services can fluctuate significantly based on the actions of individual participants. Meanwhile, prices are only revealed once the market has been cleared. Most existing markets operate on a day-ahead or hour-ahead basis to accommodate the non-storable nature of electricity, making prediction tasks extremely complex.

Nevertheless, market prices are critical for participants. Decision-making processes, such as optimizing bidding strategies and scheduling self-operation, heavily rely on accurate price information. To address this problem, various techniques have been employed. Among them, time-series models that predict based on historical data without additional inputs are found cost-effective[(2)]. The auto-regressive integrated moving average (ARIMA) model has been used in electricity price forecasting[(3)]. To account for seasonal trends, the seasonal auto-regressive integrated moving average (SARIMA) model has also been applied[(4)(5)]. Additionally, signal analysis techniques, such as wavelet transforms, are used for processing historical data to perform stochastic time-series forecasts[(6)].

The rapid development of machine learning has introduced new and promising approaches as well. Machine learning models can autonomously detect and extract correlations from large datasets. Forecasting methods based solely on neural networks are reported in Refs. (7)–(9), while hybrid

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approaches combining neural networks with stochastic time-series analysis are discussed in Refs. (10), (11). Advanced deep learning techniques, including the convolution neural networks (CNN) and the long short term memory (LSTM) networks, have been utilized[(12)–(14)]. Besides, a random forest regression model has been developed for forecasting New York electricity prices in Ref. (15).

The DRs, being equipment owned by the demand side, typically do not prioritize market participation. As a result, they are highly sensitive economically. This paper's main contribution is the development of a cooperative bidding strategy for DRs to jointly participate in the Japan Electric Power eXchange market (JEPX) and the Replacement Reserve market (RR). The proposed strategy focuses on addressing the problem from an economic perspective by selecting the forecast result most likely to maximize the DR's profit from the market, a topic rarely explored in the existing literature. Additionally, it introduces a sufficiency forecast using a deep learning classification model for bidding optimization, an innovative approach not previously proposed in the literature. The proposed strategy is designed to enhance DR profitability, thereby increasing their incentive to participate in the markets and, in turn, provide extra operational support to the system.

The rest of this paper is organized as follows: the necessity of an exclusive strategy for the DR's cooperative bidding is explained in Section 2. Section 3 presents the overall structure of the proposed strategy and a deep-learning-based forecast method of RR demand capacity sufficiency. Simulation with the real historical price of the JEPX spot market and the RR market is demonstrated to validate the profit improvement with the proposed strategy in Section 4, followed by the conclusion in Section 5.

## 2. Challenge of Cooperative Bidding

**2.1 Challenge in the JEPX Spot Market** The JEPX spot market is a day-ahead single-price auction energy market. Forecast methods for the JEPX spot price have been reported in many recent works[(16)–(18)]. These studies focus on minimizing the sum of the forecast error values and evaluate the forecast results by the mean-absolute-error (MAE) or the root-mean-square-error (RMSE). Intuitively, the smaller the sum of the errors, the better the result should be. Similarly, the R-squared coefficient converts the sum of forecast errors to a coefficient below 1. A forecast result is deemed more accurate if its R-squared coefficient is closer to 1.

Generally, this is the case for single-price market forecasts, whether in stock or electricity markets, as a good forecast result is expected to be as close as possible to the actual values. For a generation company or an electricity retailer whose generation schedule or electricity purchase/sell plan covers the whole day, a precise forecast on every time step is desirable.

The situation is different for DRs for two main reasons. Firstly, DRs, such as water heat pumps, electric vehicles (EVs), and air conditioners, are household equipment and are unlikely to participate in the market over long periods. These devices serve specific purposes and cannot always respond to system demands. Even battery storage systems have limited charging and discharging durations, typically lasting only a few hours. Secondly, the capacity of a DR resource is generally quite small compared to other market resources, even when aggregated. As a result, DR resources typically act as price takers in the market and do not directly influence market prices like larger generation or consumption resources.

It is first reported in Ref. (19) that an EV aggregator gains 88.3% of the theoretical maximum revenue from the frequency regulation market during the parking time with a 'poor' prediction whose RMSE reaches 19.79$/MW. Likewise, Ref. (20) finds out that a Machine Learning forecast of JEPX spot price with a high R-squared value is less profitable for a demand-side battery system compared to a simple SARIMA forecast result which has a lower R-squared value. Hence, the conventional error-value-based criterion cannot correctly evaluate the forecast result's benefits for market-participating DRs. A profit-oriented criterion is needed for the DRs to distinguish the performance from an economic aspect.

**2.2 Challenge in the RR Market** The RR market is a multi-price market operated by the Electric Power Reserve eXchange (EPRX) for maintaining the slower load balance. Only the upward-regulation product is currently available in the market[(21)]. The RR market has two types of products, namely the normal RR(RR ①) and the RR-FIT(RR ②) with different required response time and control signals[(22)]. Recently, the trading of the normal RR market has been paused from December 2023 to March 2024 due to the review of the demand capacity estimation methods[(23)]. Besides, the normal RR product is in a week-ahead market and it is extremely difficult for participants like the DRs to arrange their schedule one week before. Hence, this paper will focus on the RR-FIT product which is day-ahead like the JEPX spot market.

In a multi-price market, the revenue depends on each participant's own bidding price rather than the unified single clearing price. In such a case, forecasting the highest price of the successful bid in the market is informative, but submitting the bid price as the forecast price can also lead to profit loss since the bid might have been accepted for a higher price if the demand exceeds the supply in the market. The requirement amount of the RR-FIT was not satisfied for 19.93% and 8.78% of the time in 2022 and 2023 respectively. In such a case, the actual value of RR-FIT capacity is higher than the market price exhibits. Incorrect forecasts resulting in a high price bid accidentally might gain extra revenue compared to a precise forecast[(20)]. Generally, most common forecast methods are based on fitting or learning algorithms that tend to ignore the big bias points and produce "smoother" results than the actual data. Consequently, submitting the bidding price directly as the forecast data will likely induce a profit shortfall.

## 3. Cooperative Optimal Bidding Strategy

**3.1 Extremum Timing Accuracy** As many forecast methods with relatively fair results on the JEPX spot price have been proposed in existing literature, the problem remains on how to choose the most profitable forecast method for the DR.

Given the 2 inherent characteristics of the DRs stated in

Section 2.1, the conventional evaluation metrics like RMSE and the R-squared coefficient may not be suitable, as they rely solely on the total error across all forecast points. As highlighted in Ref. (20), in a single-price auction market, the most crucial information for the DRs from a profitability standpoint is the timing of the market price peaks and dips. These moments represent the most profitable opportunities, prompting the DRs to schedule their participation in the market accordingly. Therefore, when evaluating forecast results, it is essential to consider the accuracy of predicting the timing of price peaks and dips.

Refs. (24), (25) have proposed to forecast the appearance of the lowest price separately to further reduce the forecast error. However, whether such an approach can have economic improvement is not proved and the forecast on the appearance of the highest price is not discussed either. To assess forecast accuracy based on the critical timing aspects of peaks and dips, the Extremum Timing Accuracy (ETA) metric is proposed as follows[26]:

$$ETA = \frac{\sum_{i\in L^F_{\max}} T(i) - \sum_{i\in L^F_{\min}} T(i)}{\sum_{i\in L^A_{\max}} T(i) - \sum_{i\in L^A_{\min}} T(i)} \cdots\cdots\cdots\cdots (1)$$

$T$ is the actual price in the time series. $L_{\max}$ and $L_{\min}$ represent the indexes of the local maximum and local minimum point, and the superscript $F$ and $A$ stand for the forecast result and the actual price respectively. Like the R-squared coefficient, ETA is a unit value with 1 indicating most profitable and 0 indicating unprofitable.

An example of the application of the ETA is presented here. Assume the target DR is a battery storage system that aims to charge at the lowest price and discharge at the highest price based on the forecast results. The duration for a full charge or discharge is 1 time-step, and only one single charging cycle is permitted to prevent battery deterioration. The DR forecasts the clearing price in a single-price market and submits bids as a price taker, ensuring that the bids are accepted by the market. The profit of the DR is calculated using the actual clearing price.

Two forecast results are illustrated in Fig. 1, with the details of this example summarized in Table 1. At first glance, Prediction 2 appears superior with an R-squared value of 0.87, compared to Prediction 1, which has an R-squared value of only 0.19. However, the timing of the highest and lowest prices in Prediction 2 is completely incorrect. For the target DR, which is restricted to a single charging cycle, Prediction 2 results in a profit of only 0.62. In contrast, Prediction 1 accurately predicts the timing of the highest and lowest prices, allowing for full profit realization. The ETA for Prediction 1 is 1, while for Prediction 2, it is 0.3, aligning with the profit outcomes.

In conclusion, a forecast result with a high ETA value can be considered more profitable for DR operation scheduling and can be used as a criterion to select the forecast method on the JEPX spot price. With the help of the ETA, the DRs can easily identify the most profitable forecast under different situations without needing to develop a detailed operation model and perform simulations to calculate and compare the actual profit directly.

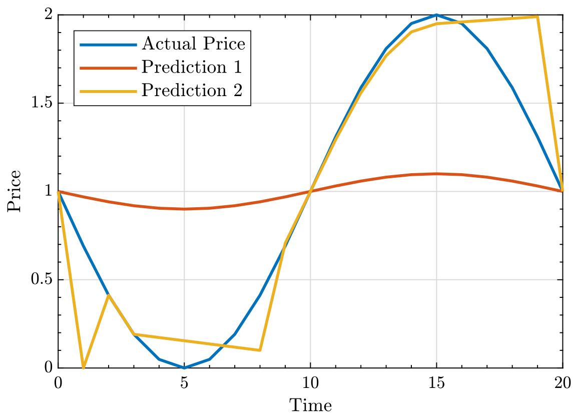



Fig. 1. Example of price forecast result comparison

Table 1. Operation schedule and profit: an example

| | Charge Time | Discharge Time | $R^2$ | ETA | Profit |
|---|---|---|---|---|---|
| **Actual** | 5 | 15 | 1 | 1 | 2 |
| **Prediction 1** | 5 | 15 | 0.19 | 1 | 2 |
| **Prediction 2** | 1 | 19 | 0.87 | 0.3 | 0.62 |

**3.2 Sufficiency Forecast** As Section 2.2 points out, extra processes are needed rather than market price forecasts to avoid potential profit loss. To avoid underestimating the value of RR capacity when system demand is inadequate, it is advantageous to perform an additional binary state forecast on RR demand capacity sufficiency besides the market price forecast.

The proposed sufficiency forecast models the system state as a binary classification problem. The system state is defined as “insufficient” when the total capacity of the accepted bids is smaller than the system requirement for the corresponding time step. Otherwise, the system state is classified as “sufficient.” The simplest approach for such a forecast is to assume that today’s system state is identical to yesterday’s. On the other hand, traditional time-series analysis models, such as SARIMA, are not well-suited for binary classification tasks. To address this, a deep learning classification network is developed to forecast the system state as shown in Fig. 2.

The proposed classification network utilizes three historical input features: the total capacity of accepted bids, the system demand capacity, and the sufficiency state. The historical data for the total capacity of accepted bids and system demand are published regularly by EPRX, and the past sufficiency state is derived from these two variables. The network’s architecture incorporates a softmax activation function in the output layer to compute the probabilities of the system being in either “insufficient” or “sufficient” and make predictions of the future system state.

**3.3 Overall Structure** The overall structure of the proposed cooperative optimal bidding strategy is depicted in Fig. 3.

In the JEPX spot market, the DR acts as a price taker who accepts whatever the prevailing price is in the market. Since the profit is determined by the clearing price rather than the bidding price, the DR can submit a very low bidding price for selling or a very high bidding price for purchasing to ensure that the bid will be taken at the desired time slot. For this part, the DR chooses the JEPX spot price forecast with the highest ETA value instead of the conventional RMSE or R-squared

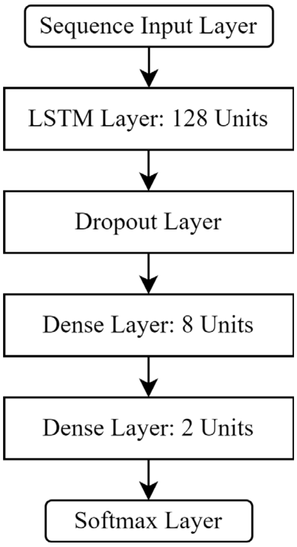



Fig. 2. Deep learning classification network for sufficient state forecast

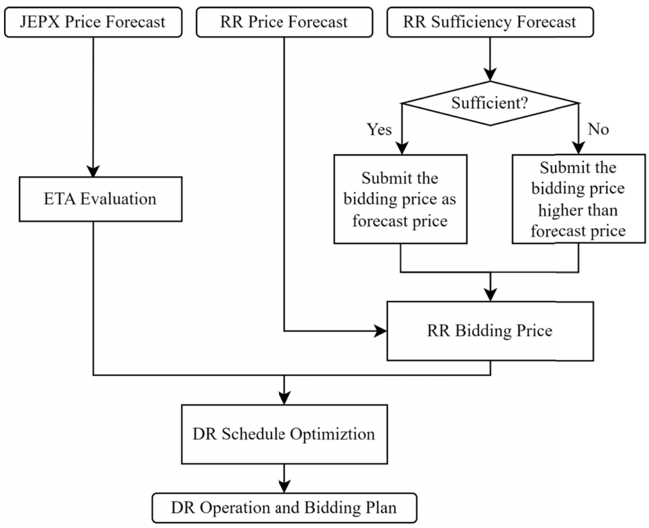



Fig. 3. Overall structure of the proposed cooperative optimal bidding strategy

coefficient to enhance profitability.

For the RR market side, the highest bidding price in the market is predicted first, then the DR modifies the bidding price according to the RR sufficiency forecast. If the system state is predicted to be "insufficient", the bidding price can be set higher than the forecast price to boost profit. Conversely, if the system state is predicted to be "sufficient", the bidding price can be submitted at the forecast price to maintain market competitiveness.

Finally, the optimal operation and bidding strategy are determined by co-optimization according to the JEPX forecast price with the highest ETA value and the modified RR bidding price.

## 4. Simulation

**4.1 DR Model** This paper focuses on a battery storage system that aims to purchase charging power from the JEPX spot market and sell the power back to either the spot market or the RR-FIT market to generate profit. The daily operation schedule co-optimization problem is formatted as follows:

$$\max_{\substack{B_{RR}(t)\\B_{JEPX-}(t)\\B_{JEPX+}(t)}} \Delta T \cdot P_{max} \sum_{t=1}^{48} \Big\{ B_{RR}(t) Y_{RR}(t) + \big[B_{JEPX-}(t) - B_{JEPX+}(t)\big] Y_{JEPX}(t) - \epsilon B_{JEPX+}(t) \Big\} \quad (2)$$

subject to

$$0 \le B_{RR}(t) \le 1 \quad (3)$$

$$0 \le B_{JEPX-}(t) \le 1 \quad (4)$$

$$B_{JEPX+}(t) \in \{0, 1\} \quad (5)$$

$$SOC(t) = SOC_{ini} - \Delta T \cdot \frac{P_{max}}{C} \sum_{\tau=1}^{t} [B_{RR}(\tau) + B_{JEPX-}(\tau) - B_{JEPX+}(\tau)] \quad (6)$$

$$0 \le SOC(t) \le 1 \quad (7)$$

$$0 \le B_{RR}(t) + B_{JEPX-}(t) + B_{JEPX+}(t) \le 1 \quad (8)$$

$$\left.\begin{array}{c} B_{RR}(1) = B_{RR}(2) = \cdots = B_{RR}(6) \\ \vdots \\ B_{RR}(43) = B_{RR}(44) = \cdots = B_{RR}(48) \end{array}\right\} \quad (9)$$

$$\sum_{t=1}^{48} B_{JEPX+}(t) \le n \quad (10)$$

The objective function Eq. (2) is to maximize the DR's one-day profit. $Y_{JEPX}$ is the forecast JEPX spot clearing price and $Y_{RR}$ is the RR bidding price. $P_{max}$ and $C$ denote the maximum power output and the total energy capacity of the DR respectively. $B_{RR}$, $B_{JEPX-}$, and $B_{JEPX+}$ represent the discharge and charge power percentages to the RR and JEPX spot market at each time step. Given that the time step for the JEPX spot market $\Delta T$ is 30 minutes, the total number of time slots per day is 48. The term $\epsilon$ is a small coefficient introduced to prevent unnecessary charges and discharges at the same price.

Eq. (6) calculates the state of charge (SOC) of the battery, ensuring there is always sufficient energy remaining whenever discharge is scheduled. Eq. (8) prevents simultaneous bidding. Given that the time step of the RR market is 3 hours, Eq. (9) ensures that the operations for the RR market remain consistent during each 3-hour interval. The number of charging cycles is limited by Eq. (10) to prevent significant battery deterioration, where $n$ represents the number of charging cycles permitted per day.

Note that the SOC at the 48th slot will always be 0 to maximize profit within a single day, which also sets the initial SOC for the following day to 0. While extending the optimization period beyond 1 day could yield a more profitable operation schedule, it would require a longer price forecast, which becomes increasingly less accurate as the forecast window expands. Given that both the RR-FIT market and the JEPX spot market are day-ahead markets, the optimization period is therefore set to 1 day.

In the RR market, when a submitted bid is accepted, the

DR must adjust the power output according to a control signal (in kW) sent by the system control center for the 3-hour RR time slot. If the DR fails to respond to the signal, it will incur a penalty, and in the worst case, may be banned from the market(22). The control signal's maximum value will not exceed the bidding capacity, which is given by $P_{max} \cdot B_{RR}$. Therefore, it is assumed in the optimal scheduling process that the battery will be discharged at full power of $P_{max} \cdot B_{RR}$, ensuring that there is enough electricity left in the battery during real-time operation and that the DR can always respond to the control signal.

### 4.2 Forecast Result

**4.2.1 Market Price Forecast** For the market price forecast, three methods are tested in this paper to forecast the market price from April 2023 to March 2024: yesterday, SARIMA, and deep learning.

The yesterday method is simply using the day-ahead price as the forecast. The SARIMA forecast model in this paper is developed using the Econometrics Toolbox in MATLAB. The SARIMA forecast is implemented in a rolling window scheme to capture the latest dynamics of the forecasting price. The historical price data of the past 1 year is used to fit a new model every day and forecast the price for the next day.

The structures of the deep learning model for the JEPX spot clearing price and the RR-FIT highest bidding price are shown in Fig. 4. Since training a new deep learning network or updating the existing model can be extremely effort-costing, the network is trained only once with the training period data from April 2022 to March 2023. The forecast is also performed on a daily basis, utilizing historical data from the past two weeks as input to predict the price for the following day. The time steps of the JEPX spot market and the RR market are 30 minutes and 3 hours respectively, hence the last dense layer contains 48 units and 8 units for one day's price forecast correspondingly.

A portion of the forecast result is plotted in Fig. 5 and Fig. 6. The actual RR-FIT price is the highest price within TSO, published by ERPX. The performance of the three forecast methods is summarized in Table 2. The ETA value is listed exclusively for the JEPX spot price forecast, as it is designed for single-price markets where the DR acts as a price-taker. As discussed in Section 2.2, the RR market is currently a multi-price market due to the relatively small number of participants. In such a market, the revenue depends on each participant's own bidding price rather than a unified clearing price. Therefore, the ETA is not suitable for evaluating the RR market price forecast, and it has not been applied in this context.

The R-squared coefficient of the deep learning model is better than that of the SARIMA model since it is a regression network trained to reduce the RMSE. However, the SARIMA model has a higher ETA value, suggesting it is more profitable for the DR despite its relatively lower R-squared value. Notably, due to the extremely volatile price movements, forecasting the RR-FIT price is much more difficult for all three methods compared to forecasting the JEPX spot price. All the forecast results are poor, with the deep learning forecast being the best method, achieving an R-squared value of only 0.16.

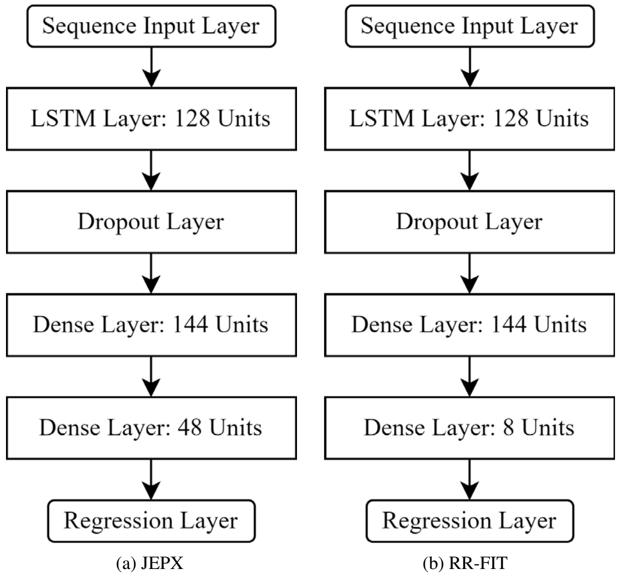



Fig. 4. Deep learning regression network for price forecast

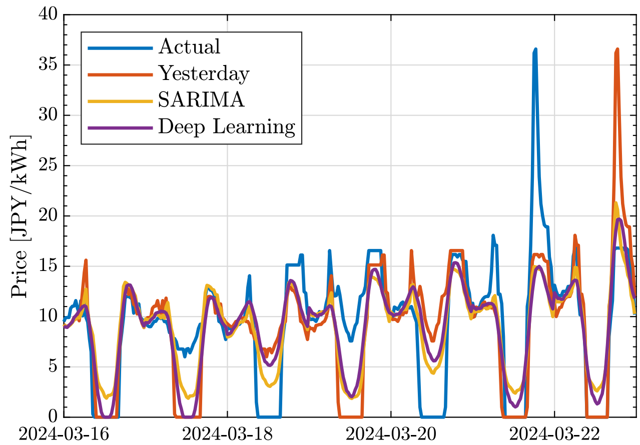



Fig. 5. Forecast result of the JEPX spot market

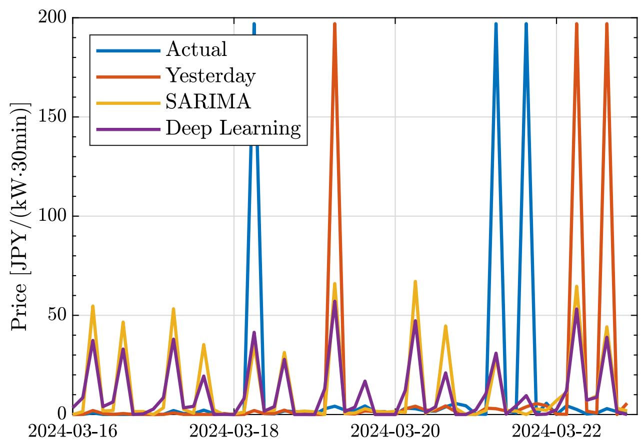



Fig. 6. Forecast result of the RR-FIT market

**4.2.2 Sufficiency Forecast** The accuracy of the sufficiency forecast from April 2023 to March 2024 with the yesterday method and the proposed deep learning network is given in Table 3. Similar to market price forecasting, the deep learning classification network is trained using historical data from April 2022 to March 2023. It performs daily forecasts by utilizing data from the past two weeks as input to predict

Table 2. The performance of the forecast results

(a) The JEPX spot market forecast

| | Yesterday | SARIMA | Deep Learning |
|---|---|---|---|
| $R^2$ | 0.47 | 0.59 | 0.62 |
| ETA | 0.60 | 0.71 | 0.65 |

(b) The RR-FIT market forecast

| | Yesterday | SARIMA | Deep Learning |
|---|---|---|---|
| $R^2$ | -0.37 | 0.07 | 0.16 |

Table 3. The accuracy of the sufficiency forecast

| | Yesterday | Deep Learning |
|---|---|---|
| Accuracy | 0.87 | 0.92 |

Table 4. The JEPX spot market profit

| | Oracle | Yesterday | SARIMA | Deep Learning |
|---|---|---|---|---|
| Profit (Million JPY) | 58 | 43 | 49 | 46 |

the system sufficiency state for the next day.

The sufficiency state exhibits a strong daily repetitive pattern and the accuracy of the yesterday forecast already reaches 87%. The proposed deep learning forecast further improves the accuracy to 92%.

**4.3 Market Profit** In this section, the DR's capacity is set to 10 MWh with a maximum power output of 10 MW, allowing for 2 charging cycles per day. The initial SOC is 0. The optimization is performed daily using Mixed Integer Linear Programming, and the market profit is calculated based on the optimization results. The simulation period is 1 year from April 2023 to March 2024.

**4.3.1 JEPX Spot Only** The annual profit of the DR when only participating in the JEPX spot market with different JEPX spot price forecasts is provided in Table 4.

The Oracle case serves as a benchmark, representing a perfect forecast where the DR's profit reaches the theoretical upper limit. The deep learning forecast, with the highest R-squared value of 0.62, is conventionally considered the best forecast. However, its ETA value is only 0.65. In comparison, the SARIMA forecast has an R-squared value of 0.59 but a higher ETA of 0.71, suggesting it is the most profitable forecast. The actual profit calculations confirm the ETA evaluation, with the SARIMA forecast yielding 49 million JPY, achieving 84.4% of the theoretical limit. In contrast, despite its high R-squared value, the deep learning forecast only generated around 46 million JPY. The simulation result proves the effectiveness of selecting the forecast methods by ETA evaluation.

A detailed operation schedule of the DR on May 23rd, 2023, is presented in Fig. 7 to demonstrate the general applicability of ETA. The bars represent the energy bids submitted to the JEPX spot market for purchasing or selling energy. The forecast results are summarized in Table 5. Contrary to the R-squared value, the ETA shows strong concordance with the profit. The peak of the forecasted price by SARIMA at 5:00 aligns more closely with the actual peak at 5:30 compared to the deep learning forecast, which predicts the peak at 4:30. The lower precision in forecasting the peak with the deep learning model results in a lower ETA and undesirable profit losses. The high R-squared value for the deep learning model

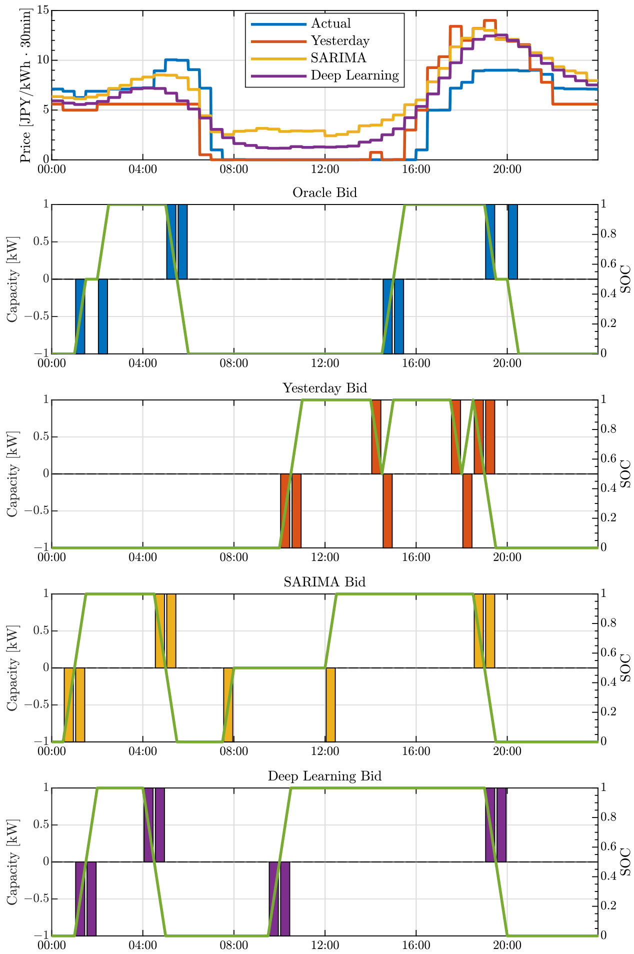



Fig. 7. The DR's operation schedule on May 23rd, 2023

Table 5. The JEPX spot price forecast on May 23rd, 2023

| | Yesterday | SARIMA | Deep Learning |
|---|---|---|---|
| ETA | 0.73 | 0.90 | 0.77 |
| $R^2$ | 0.66 | 0.47 | 0.53 |
| Profit (Thousand JPY) | 86.65 | 118.80 | 105.05 |

primarily comes from its consistently low forecast values between 8:00 and 16:00. However, this numerical precision does not provide critical information for the DR, as the DR only needs to know the optimal timing for charging (e.g., at noon when prices are low) rather than the exact value of the low prices.

**4.3.2 Cooperative Bidding** In the RR market, it is reasonable to believe that a bid would be accepted when system demand exceeds the total capacity of all bids in the market. Therefore, it is assumed that the RR market will accept a bid when the system state is "insufficient" or the bidding price is lower than the highest price in the market.

However, it is unlikely that a bid will always be accepted regardless of its price. In March 2024, the ERPX published a regulation setting price caps for some of its products[27]. Although there is currently no price cap for RR-FIT, similar constraints might be set in the future. The maximum price of an accepted RR-FIT bid from April 2023 to March 2024 was 197 JPY/(kW·30 min). Therefore, in this section, it is assumed that there is a price cap of 197 JPY/(kW·30 min)

Table 6. The bidding status in the RR-FIT market when no sufficiency forecast is applied

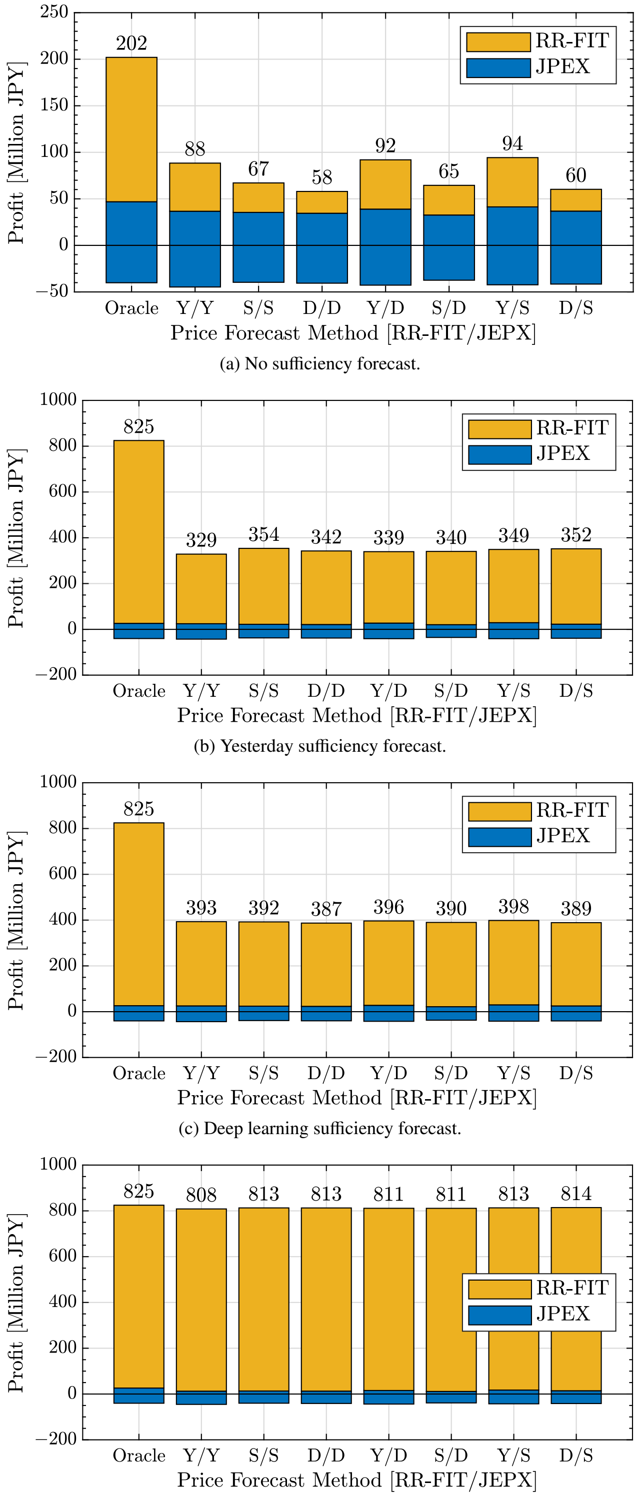
| | Y/Y | S/S | D/D | Y/D | S/D | Y/S | D/S |
|---|---|---|---|---|---|---|---|
| **Total Bid** | 92 | 204 | 189 | 88 | 241 | 86 | 159 |
| **Fail Bid** | 59 | 161 | 143 | 59 | 195 | 57 | 118 |
| **Accepted Bid** | 33 | 43 | 46 | 29 | 46 | 29 | 41 |
| **Bid Acceptance Rate** | 35.87% | 21.08% | 24.34% | 32.95% | 19.09% | 33.72% | 25.79% |
| **Average Accepted Bidding Price JPY/[kW·30 min]** | 2.59 | 2.11 | 1.40 | 2.62 | 2.15 | 2.62 | 1.37 |

in the RR-FIT market, and the DR will submit the bid at this price cap when the system state is predicted to be "insufficient."

Fig. 8 compares the profits under different forecasting and bidding strategies. The x-axis represents the combination of methods used for forecasting the highest RR-FIT bidding price and the JEPX spot clearing price: "Y" stands for yesterday, "S" for SARIMA, and "D" for deep learning. The Oracle case represents an ideal situation where the JEPX Spot price, RR-FIT price, and Sufficiency are all perfectly accurate. Fig. 8(a) to 8(d) show the profits using different sufficiency forecast methods. The yellow bar and blue bar denote the profit earned from the RR-FIT market and the JEPX spot market, respectively.

When no sufficiency forecast is applied, it is assumed that the DR submits the RR-FIT forecast price as the bid price. The highest profit is achieved by using the yesterday method for RR-FIT price forecasting and SARIMA for JEPX spot price forecasting. As analyzed in Section 4.3.1, SARIMA is more beneficial in the JEPX spot price forecasting as it has the highest ETA value among all three methods. The bidding status in the RR-FIT market is summarized in Table 6. The results show that the acceptance rate of bids is higher when the yesterday method is applied for RR-FIT price forecasting. Moreover, the average accepted bidding price is also significantly higher compared to other methods. While the yesterday method has the lowest accuracy in RR-FIT price forecasting, it is more likely to produce "incorrect" forecasts that are higher than the actual price. Those high-price bids may still be accepted when the system demand is insufficient, resulting in additional revenue from the RR-FIT market as shown in Fig. 8(a).

The profit drastically increases, particularly from the RR-FIT market, when the sufficiency forecast is introduced, due to the high RR-FIT price cap and the frequent "insufficient" system state. The proposed deep learning classification forecast further boosts the profit by around 10% compared to the simple yesterday sufficiency forecast. For both sufficiency forecast cases, the most profitable JEPX spot price forecast is the SARIMA forecast as identified by the ETA value. However, the most profitable RR-FIT price forecast varies. With the yesterday sufficiency forecast, the SARIMA forecast is most profitable for the RR-FIT price, while with the deep learning classification sufficiency forecast, the yesterday forecast is most profitable. The difference may be attributed to the specific results of the RR-FIT price and sufficiency forecasts, making it difficult to provide an accurate qualitative analysis of how the combination of forecast methods affects the profit when a sufficiency forecast is applied. When




(a) No sufficiency forecast.

(b) Yesterday sufficiency forecast.

(c) Deep learning sufficiency forecast.

(d) Oracle sufficiency forecast.

Fig. 8. Profits under different forecasting and bidding strategies

the perfect oracle sufficiency forecast is applied, the deep learning forecast becomes the most profitable RR-FIT price forecast, as it is the most accurate forecast method shown in Table 2(b). Overall, the impact of the RR-FIT price forecast on profit is very limited, accounting for only about 3%, compared to the much larger impact of the Sufficiency forecast.

**4.4 Sensitivity Analysis** This subsection provides a

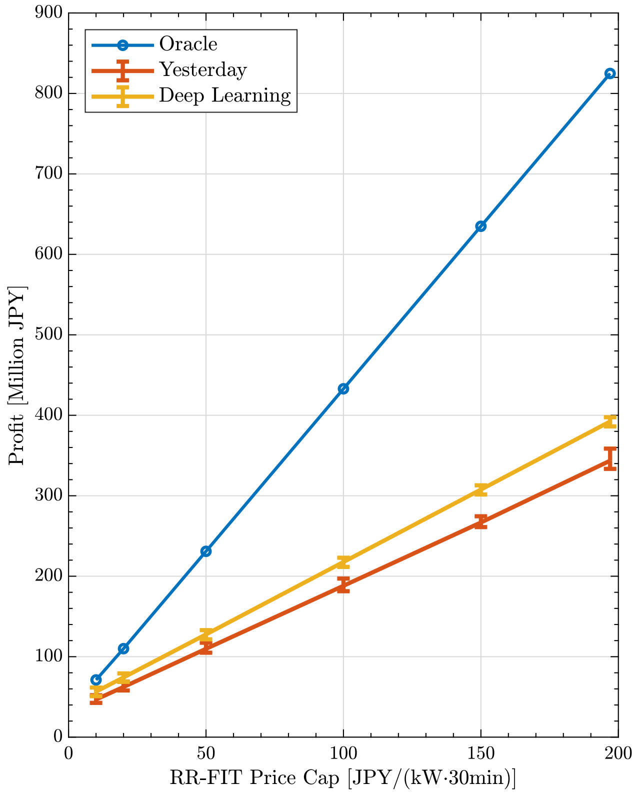



Fig. 9. Sensitivity analysis on the RR-FIT price cap

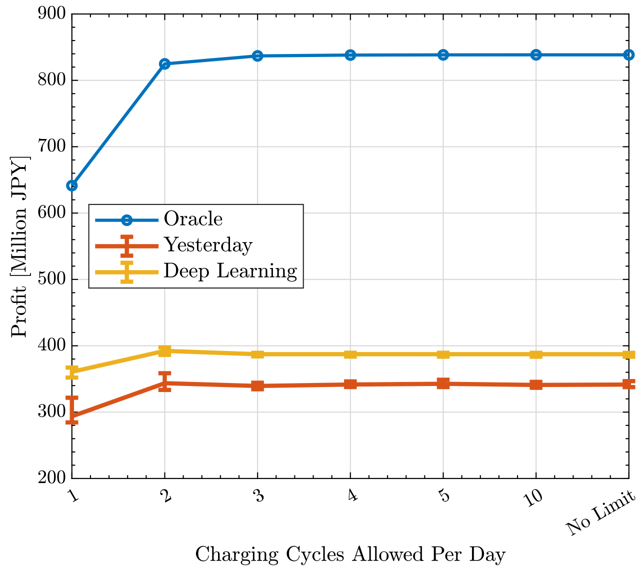



Fig. 10. Sensitivity analysis on charging cycles allowed per day

Table 7. The most profitable price forecast combination

| Price Cap JPY/[kW·30 min] | 10 | 20 | 50 | 100 | 150 | 197 |
|---|---|---|---|---|---|---|
| Yesterday | S/S | S/S | S/S | D/S | D/S | S/S |
| Deep Learning | Y/S | Y/S | Y/S | Y/S | Y/S | Y/S |

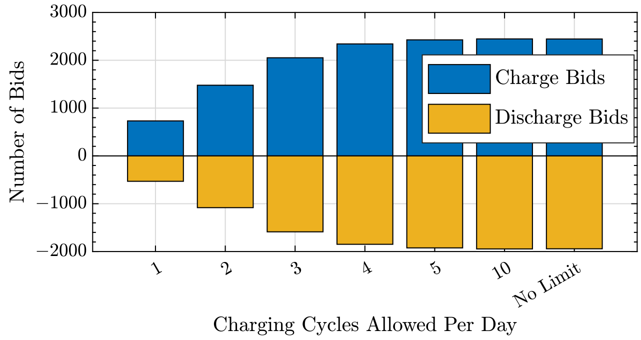
sensitivity analysis of the RR-FIT price cap, the number of charging cycles allowed per day, and the DR's maximum power output.

The impact of the RR-FIT price cap is illustrated in Fig. 9. The three lines represent different sufficiency forecast scenarios. The error bars indicate the range between maximum and minimum profits across various price forecast combinations, with the center point marking the average profit of all combinations. While the profits increase with a higher price cap, the influence of the price forecast combination is relatively minor compared to the effect of the sufficiency forecast. The advantage of selecting a particular price forecast method is easily outweighed by using a better sufficiency forecast since all the RR-FIT price forecast results are poor. A good sufficiency forecast can boost profits even when the price forecast is inaccurate. The most profitable combination of the price forecast is detailed in Table 7. The SARIMA forecast consistently proves to be the most profitable JEPX spot price forecast method, whereas the most profitable method for RR-FIT varies across cases due to its strong dependence on not only the price cap but also the specific sufficiency and price forecast results.

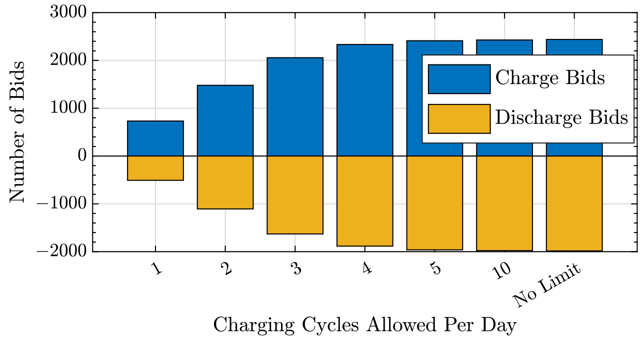
The impact of the charging cycles allowed per day is illustrated in Fig. 10. The oracle line indicates that profit increases slow down when more than two cycles are permitted per day, under a perfect sufficiency forecast. Profits even decrease when applying the yesterday and the deep learning classification forecasts. The average number of bids across all combinations of price forecast methods is shown in Fig. 11 and Fig. 12. While the total submitted bids in the RR-FIT market increase as the number of allowable charging cycles rises from 2 to 4, the number of accepted bids remains largely unchanged. Allowing more charging cycles enables more bids to be submitted, but it also increases the likelihood of unaccepted bids, reducing profits. Additionally, the number of bids in both the JEPX spot and RR-FIT markets stops increasing when the number of allowable charging cycles exceeds 4. Since profit depends on price differences, and only a few significant price differences occur within a day, additional charging cycles will not create further bidding opportunities. Consequently, too many charging cycles are not preferable, as they not only cause severe battery deterioration but also fail to provide additional economic benefits.

The lower the maximum power output, the longer the time required to fully charge the battery. Fig. 13 shows that profits decline as the maximum power output decreases because the biddable capacity reduces accordingly. Notably, the advantage of an accurate sufficiency forecast also diminishes with reduced maximum power output, as the degree of bidding flexibility decreases. Equipment with high power capacity is preferred by DRs, especially when they are confident in the sufficiency forecast results and can fully capitalize on the advantages of its high accuracy.

**4.5 Extra Energy Management** In the above simulation, to ensure that there is enough electricity left in the battery during real-time operation so that the DR can always respond to the RR control signal, it is both necessary and advantageous to assume that the battery will be discharged at full power of $P_{max} \cdot B_{RR}$ in the optimal scheduling process. As a result, the actual SOC may differ from the optimized schedule. Currently, the RR control signal is not officially published by ERPX, and it is impossible to estimate the amount of electricity that will be discharged during real-time response. However, since it is conservatively assumed that the battery will discharge at full power of $P_{max} \cdot B_{RR}$, there

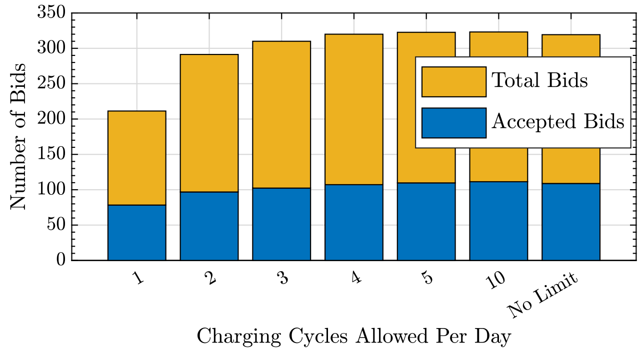



(a) Yesterday sufficiency forecast

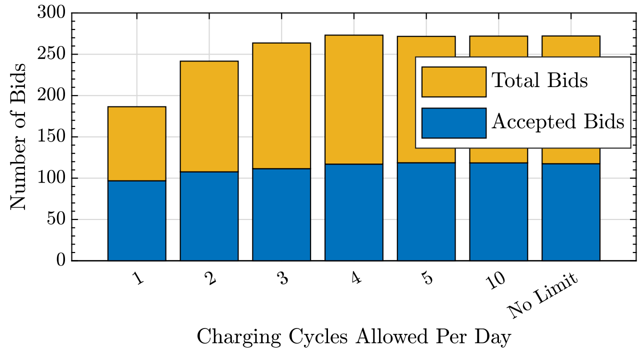



(b) Deep learning sufficiency forecast

Fig. 11. Average number of bids in the JEPX spot market




(a) Yesterday sufficiency forecast




(b) Deep learning sufficiency forecast

Fig. 12. Average number of bids in the RR-FIT market

will likely be extra electricity remaining in the battery after real-time operation, even though still within the SOC constraints of (7). Additionally, in real-time operation, some submitted RR-FIT bids may not be accepted, preventing the battery from being discharged as planned. This may result in a situation where the battery becomes fully charged and cannot absorb further electricity from subsequent JEPX spot market purchases.

For a battery system of the size considered in this study, discarding surplus energy generated under either of the above circumstances is not a feasible option. To mitigate operational disruptions without incurring financial penalties, the following two-step approach is proposed for managing surplus energy remaining in the battery:

(1) Sell the extra energy in the JEPX intraday market. The JEPX intraday market is an hour-ahead electricity wholesale market that enables energy trading up to one hour prior to operation. Unlike the JEPX spot market, which operates as a single-price auction market, the JEPX intraday market applies a continuous multi-price trading mechanism. Market participants may submit their bids from 17:00 on the previous day until one hour before the intended trading time[28]. Since both JEPX spot and RR-FIT market bids are determined on a day-ahead basis, it is possible to identify the time of RR bid failure, denoted as $t_{\text{fail}}$, and its potential impact on subsequent JEPX spot purchases day-ahead. A corresponding sell bid can then be submitted to the JEPX intraday market one hour before $t_{\text{fail}}$. Likewise, for the additional energy remaining due to partial discharge during real-time RR operation, the following algorithm can be used to determine the amount and timing of intraday market bids:

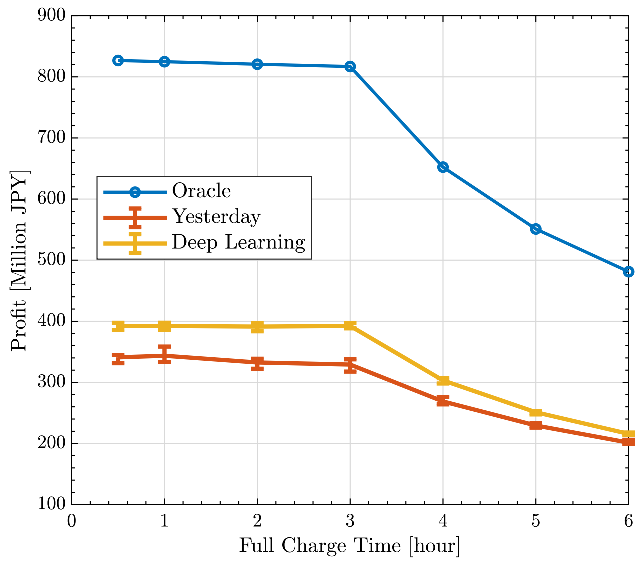



Fig. 13. Sensitivity analysis on maximum power output

**Algorithm 1** Sell Real-time Extra Energy in Battery

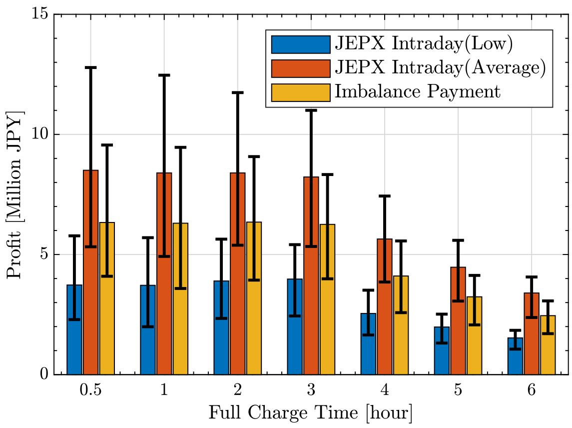
**procedure**
At the current operation time at $t$, the remaining energy in the battery is $Q_{\text{Battery}}(t)$
Find next nearest JEPX purchase $Q_{\text{JEPX}}(t_x)$
**if** $Q_{\text{Battery}}(t) + Q_{\text{JEPX}}(t_x) > C$ **then**
Submit a sell bid of $C - Q_{\text{JEPX}}(t)$ to the JEPX intraday market at one hour before $t_x$
**end if**
**end procedure**

Currently, the minimum allowable bid price in the JEPX intraday market is 0.01 JPY/kWh, and most trades occur at higher prices. While selling surplus energy at a low price might not be the most profitable strategy to handle the remaining energy, it is an effective method to avoid disruptions in real-time operation.

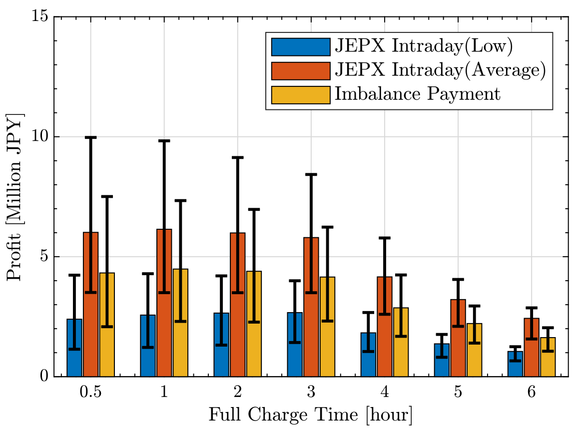
(2) Settle the extra energy as surplus imbalance ex-post. In extreme cases where JEPX intraday bids are unsuccessful(e.g., due to a lack of buyers at $t_{\mathrm{fail}}$ or if $t_{\mathrm{fail}}$ occurs within less than one hour before the operation time $t$), the excess energy scheduled for purchase but not utilized due to battery constraints will be classified as an imbalance by the system operator(29). Specifically, it is treated as a surplus imbalance, since actual electricity consumption is lower than scheduled. Under the current imbalance settlement system, surplus imbalances are purchased by the system operator to compensate for shortage imbalances elsewhere on the grid. Settlement is performed ex-post, and the DR receives compensation for the surplus imbalance rather than incurring additional costs.

By adopting the above procedures, surplus energy resulting from RR operations can be effectively managed without incurring penalties, and in fact, may generate additional revenue. Thus, the economic feasibility of the proposed cooperative optimal bidding strategy is maintained.

Assuming 2 charging cycles per day, Fig. 14 illustrates the additional profit derived from surplus energy management under different trading schemes: selling to the JEPX intraday market at low prices, selling at average prices, and settling via surplus imbalance payments. The height of each bar represents the average profit across various price forecast combinations. The error bars indicate the range between the maximum and minimum profits, capturing the variability in outcomes due to different price forecast scenarios. The additional profits are less than 2% of the total profit shown in Fig. 13, and further profit optimization is possible through more advanced strategies. However, the development of such strategies falls outside the scope of this paper and will be explored in future research.




(a) Yesterday sufficiency forecast




(b) Deep learning sufficiency forecast

Fig. 14. Profit from the extra energy

## 5. Conclusions

This paper proposes a cooperative optimal bidding strategy for DRs participating in both the JEPX spot market and the RR market. The strategy employs ETA as the criterion for selecting the forecast method for the JEPX spot market and introduces sufficiency forecasts for the RR-FIT market.

Given the present circumstances of high demand in the RR market and the relatively low number of market participants, there is a greater economic opportunity for DRs to engage in the RR market jointly rather than solely participating in the JEPX spot market. By utilizing the sufficiency forecast, the proposed method enables DRs to achieve higher profits, especially from the RR market, within the current multi-price market mechanism.

Determining the optimal RR market price forecast method when a sufficiency forecast is involved remains a key challenge. Future research will focus on understanding the relationship between the sufficiency forecast and the price forecast in the RR market to further enhance profits. The actual SOC of the battery system is affected by the received RR control signal. Real-time SOC management, considering RR discharge electricity estimation and the JEPX intraday market co-optimization, is also an important future research topic.

The ETA presented in this paper does not account for the duration of peak or dip periods, which could impact DRs with longer operation periods. Incorporating the duration of peak or dip periods into ETA could potentially enhance the concordance its concordance with profit. Additionally, the ETA, currently applied as an evaluation metric after prediction, shows potential for guiding forecast model development. Integrating ETA into the forecast model training process, such as loss functions and cross-validation also represents a promising direction for future work.

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## References

(1) P. Palensky and D. Dietrich: “Demand side management: Demand response, intelligent energy systems, and smart loads”, *IEEE Trans. Ind. Informatics*, Vol.7, No.3, pp.381–388 (2011)

(2) G.E. Box, G.M. Jenkins, G.C. Reinsel, and G.M. Ljung: Time Series Analysis: Forecasting and Control, John Wiley & Sons (2015)

(3) T. Jakaša, I. Andročec, and P. Sprčić: “Electricityprice forecasting—ARIMA

model approach", 2011 8th International Conference on the European Energy Market (EEM), pp.222–225 IEEE (2011)
( 4 ) P. Rajan and K.V. Chandrakala: Statistical Model Approach of Electricity Price Forecasting for Indian Electricity Market, 2021 IEEE Madras Section Conference (MASCON), pp.1–5 IEEE (2021)
( 5 ) S. Cai and R. Matsuhashi: "Model predictive control for EV aggregators participating in system frequency regulation market", *IEEE Access*, Vol.9, pp.80763–80771 (2021)
( 6 ) A.J. Conejo, M.A. Plazas, R. Espinola, and A.B. Molina: "Day-ahead electricity price forecasting using the wavelet transform and ARIMA models", *IEEE Trans. Power Syst.*, Vol.20, No.2, pp.1035–1042 (2005)
( 7 ) D. Singhal and K. Swarup: "Electricity price forecasting using artificial neural networks", *Int. J. Electr. Power & Energy Syst.*, Vol.33, No.3, pp.550–555 (2011)
( 8 ) D. Keles, J. Scelle, F. Paraschiv, and W. Fichtner: "Extended forecast methods for day-ahead electricity spot prices applying artificial neural networks", *Appl. Energy*, Vol.162, pp.218–230 (2016)
( 9 ) D. Wang, H. Luo, O. Grunder, Y. Lin, and H. Guo: "Multi-step ahead electricity price forecasting using a hybrid model based on two-layer decomposition technique and BP neural network optimized by firefly algorithm", *Appl. Energy*, Vol.190, pp.390–407 (2017)
(10) N. Amjady and F. Keynia: "Day ahead price forecasting of electricity markets by a mixed data model and hybrid forecast method", *Int. J. Electr. Power & Energy Syst.*, Vol.30, No.9, pp.533–546 (2008)
(11) J.C.R. Filho, C.M. Affonso, and R.C. Oliveira: "Energy price forecasting in the North Brazilian market using NN-ARIMA model and explanatory variables", 2014 IEEE Symposium on Computational Intelligence for Engineering Solutions (CIES), pp.171–175 IEEE (2014)
(12) P.-H. Kuo and C.-J. Huang: "An electricity price forecasting model by hybrid structured deep neural networks", *Sustainability*, Vol.10, No.4, p.1280 (2018)
(13) K. Wang, M. Yu, D. Niu, Y. Liang, S. Peng, and X. Xu: "Short-term electricity price forecasting based on similarity day screening, two-layer decomposition technique and Bi-LSTM neural network", *Appl. Soft Computing*, Vol.136, p.110018 (2023)
(14) F.H. Mohammadreza Heidarpanah, and M. Fazeli: "Daily electricity price forecasting using artificial intelligence models in the Iranian electricity market", *Energy*, Vol.263, p.126011 (2023)
(15) J. Mei, D. He, R. Harley, T. Habetler, and G. Qu: "A random forest method for real-time price forecasting in New York electricity market", 2014 IEEE PES General Meeting—Conference & Exposition, pp.1–5 IEEE (2014)
(16) M. Omura, Y. Fujimoto, Y. Hayashi, T. Sawa, H. Sasaki, N. Fukuyama, and Y. Nishino: Forecast of Area Prices in Japanese Day-Ahead Electricity Market using Open Data, *IEEJ Trans. PE*, Vol.141, No.5, pp.366–373 (2021)
(17) N. Kaneko and T. Inoue: "Sparse Modeling Approach for Day-Ahead Electricity Price Forecast and Factor Analysis in the Japanese Spot Market", *J. Jpn Soc. Energy & Resources*, Vol.44, No.4, pp.160–170 (2023)
(18) T. Matsumoto: "Electricity Spot Price Forecasting Using Principal-Component-Guided Sparse Regression", Proc. of the 2022 Autumn Research Conference Operations Research Society of Japan (2022)
(19) S. Cai and R. Matsuhashi: "Model Predictive Control for EV Aggregators Participating in System Frequency Regulation Market", *IEEE Access*, Vol.9, pp.80763–80771 (2021)
(20) S. Cai, M. Mae, and R. Matsuhahi: "A Comparison of Electricity Market Price Forecasting Methods for Demand Responses", The 2024 Annual Meeting of The IEEJ (2024)
(21) Electric Power Reserve eXchange: Trading Guide (All Products), 4th edition edition (2024), https://www.eprx.or.jp/outline/docs/guide_240401.pdf
(22) Electric Power Reserve eXchange: Overview of the EPRX Market and Product Requirements, 4th edition edition (2024), https://www.eprx.or.jp/outline/docs/gaiyoushouhin_ver.4_20240401.pdf
(23) Electric Power Reserve eXchange: Commencement of Efficient Procurement of Required Volume for Replacement Reserve (2023), https://www.eprx.or.jp/j_information/202311271516r2_news.pdf
(24) S. Nakayama, A. Shiota, Y. Mitani, and M. Watanabe: "GIS based JEPX spot prices forecasting system using solar power generation focusing on lowest prices", *Energy Reports*, Vol.9, pp.240–244 (2023)
(25) S. Nakayama: "Construction of Electricity Market Spot Prices Forecasting System Using GIS", PhD thesis, Kyushu Institute of Technology (2024)
(26) S. Cai, M. Mae, and R. Matsuhashi: "A Novel Criterion of Electricity Price Forecast for Demand-Side Responses Participating in the Electricity Market", 2024 20th International Conference on the European Energy Market (EEM), pp.1–5 (2024)
(27) Electric Power Reserve eXchange: Price Cap for ΔkW in the EPRX Market (2024), https://www.eprx.or.jp/information/20240315_%E9%9C%80%E7%B5%A6%E8%AA%BF%E6%95%B4%E5%B8%82%E5%A0%B4%E3%81%AE%E4%B8%8A%E9%99%90%E4%BE%A1%E6%A0%BC%E3%81%AB%E3%81%A4%E3%81%84%E3%81%A6.pdf
(28) Japan Electric Power eXchange: Japan Electric Power eXchange Trading Guide (2019), https://www.jepx.jp/electricpower/outline/pdf/Guide_2.00.pdf?timestamp=1744881758877
(29) Electricity and Gas Market Surveillance Commission: Imbalance Price System (2022), https://www.emsc.meti.go.jp/info/public/pdf/20220117001b.pdf

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