デマンドレスポンスのための電力市場価格予測手法の比較

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A Comparison of Electricity Market Price Forecasting Methods for Demand Responses

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１． Introduction

Introducing the demand response (DR) to the power system to help maintain the generation and load balance is an effective option. Normally, DR can participate in system load balancing via various electricity markets, such as the energy spot market or the ancillary market. Since the electricity markets are generally day-ahead or hour-head auction markets where the actual price cannot be known until the bidding and cleaning process is finished, the DR owner needs to predict the price in advance for the resources' optimal scheduling to maximize their profits.

In this paper, the performances of three price forecasting methods are examined. The paper focuses on comparing the influence of different forecasting methods on DR's market revenue, which hasn't been clearly discussed in the existing literature. The target market of this paper is Japan's JEPX spot market and the Replacement Reserve (三次調整力, RR) market. The JEPX spot market is a day-ahead energy wholesale market, and the RR market is an ancillary market providing tertiary frequency regulation under different time scales.

２． Forecasting Methods

The three forecasting methods to be examined are as follows:

・**Yesterday**: simply assuming that today's price will be exactly the same as yesterday's.

・**SARIMA**: a time series analysis model that forecasts future values based on merely the historical values without extra information input.

・**Machine Learning**: complicated model trained with not only historical price data but also extra data that has a direct impact, such as weather conditions.

The **Yesterday** method is a brutal but somehow effective method when other forecasting models are hard to obtain, or other forecasting results are poor (1).

The **SARIMA** model is a commonly used forecasting method for either the energy market or the frequency regulation market (2-3). It can also be easily implemented in a model predictive control scheme: the model parameters can be updated every time new data is received, which makes the SARIMA model capture the latest dynamics of the forecasting price.

The **Machine Learning** method is generally based on deep neural networks incorporating big data and is expected to produce prediction results with high accuracy (4). However, training a new model and updating the existing model can be extremely effort-costing.

3. Demand Response Schedule Optimization

This paper focuses on a battery storage system that intends to purchase charging power from the JEPX spot market and sell the power back to the spot market or the RR market to gain profit.

The daily operation schedule optimization problem is described as follows:

$$\text{Maximize } P_{max}\sum_{t=1}^{48}\left[State_{3_1}(t)Price_{3_1}(t) + State_{3_2}(t)Price_{3_2}(t) + State_{JEPX\_}(t)Price_{JEPX}(t) - State_{JEPX_+}(t)Price_{JEPX}(t)\right] - \varepsilon\sum_{t=1}^{48} State_{State_{JEPX_+}}(t) \quad (1)$$

s.t.

$$SOC(t) = SOC_{initial} - P_{max}\sum_{\tau=1}^{t}\left[State_{3_1}(\tau) + State_{3_2}(\tau) + State_{JEPX\_}(\tau) - State_{JEPX_+}(\tau)\right] \quad (2)$$

$$0 \le SOC(t) \le 1 \quad (3)$$

$$0 \le State_{3_1}(t) + State_{3_2}(t) + State_{JEPX\_}(t) + State_{JEPX_+} \le 1 \quad (4)$$

$$\begin{cases} State_{3_1}(1) = State_{3_1}(2) = \cdots = State_{3_1}(6) \\ \vdots \\ State_{3_1}(43) = State_{3_1}(44) = \cdots = State_{3_1}(48) \end{cases} \quad (5)$$

$$\begin{cases} State_{3_2}(1) = State_{3_2}(2) = \cdots = State_{3_2}(6) \\ \vdots \\ State_{3_2}(43) = State_{3_2}(44) = \cdots = State_{3_2}(48) \end{cases} \quad (6)$$

Eq. (1) is DR's one day revenue to be optimized where $Price_{3_1}$, $Price_{3_2}$ and $Price_{JEPX}$ is the predicted price of the RR market ①, ② and the JEPX spot market, respectively. Notice that currently the RR market is a multi-price auction market, therefore the maximum price is predicted. $State_{3_1}, State_{3_2}, State_{JEPX\_} \in [0,1]$ and $State_{JEPX_+} \in \{0,1\}$ are the discharge and charge power percentage at each time step. The total time slot per day is 48 since that the time step of the JEPX spot market is 30 minutes. ε is the charging loss coefficient.

Eq. (2) calculates the SOC of the battery and ensures there is enough energy left in the battery whenever discharge is scheduled. Given that the time step of the RR market is 3 hours, Eq. (5) and

Eq. (6) make sure that the operation for the RR market is consistent during every 3 hours.

4. Simulation Result

The JEPX spot Price and the RR market ①, ② price in Kyushu area are predicted from May to September, 2023. The R-squared values of the forecast results are given in Table 1, 2 and 3. For JEPX spot price forecast, the **Machine Learning** model is developed by the Japan Weather Association, utilizing historical price data, weather data and calendar data (5).

Table 1. The R-squared values of the JEPX spot price forecast results

	May	June	July	Aug.	Sep.
Yesterday	0.46	0.08	0.06	0.49	0.43
SARIMA	0.54	0.34	0.43	0.50	0.40
ML	0.67	0.55	0.62	0.68	0.56

Table 2. The R-squared values of the RR market ① price forecast results

	May	June	July	Aug.	Sep.
Yesterday	0.39	-0.55	0.63	0.51	0.60
SARIMA	0.55	0.07	0.68	0.61	0.67

Table 3. The R-squared values of the RR market ② price forecast results

	May	June	July	Aug.	Sep.
Yesterday	-0.92	-0.67	-0.43	-0.96	-0.53
SARIMA	-0.07	0.06	0.12	0.03	0.16

In the simulation, the DR will first optimize its operation schedule as introduced in Section 3 based on the forecast results, then the DR will submit its bidding to the markets based on the optimized operation plan. The actual revenue from the market will be calculated and compared to examine the effects of the forecast results. Notably, in the RR market, the predicted price is taken as the bidding price. When the predicted price is lower than the actual maximum price, or when the system demand is smaller than the total bidding capacity in the market, the bid is considered successful. Otherwise, the bid is considered not taken by the market and there is no profit for the DR.

The DR's revenue in July is shown in Table 4. The DR's capacity is 10 MWh with 10 MW maximum power output. The **Oracle** is a benchmark case that the DR makes perfect prediction on market prices and obtains the theoretically highest revenue.

Although the **Machine Learning** has the highest R-squared value in JEPX spot price forecast, the JEPX revenue is highest when **SARIMA** is applied. For DRs, the most important information is to know the timing of the highest and lowest price, which is not evaluated by the conventional R-squared value. Meanwhile, the RR market is a multi-price market where the revenue depends on the participant's own bidding price. Even if **Yesterday** method produces 'incorrect' forecast higher than the actual price, the bid might still be taken by the market when the system demand is insufficient. Therefore, extra revenue is gained compared to the **SARIMA** forecast.

Table 4. The revenue in July

RR Forecast	JEPX Forecast	RR① Revenue (万円)	RR② Revenue (万円)	JEPX Revenue (万円)	Total Revenue (万円)
Oracle	**Oracle**	948.6	133.8	379.2	1461.5
Yesterday	**Yesterday**	948.6	86.1	156.5	1191.2
SARIMA	**SARIMA**	658.8	7.5	226.7	893.0
Yesterday	**ML**	948.5	86.1	215.4	1250.0
SARIMA	**ML**	662.5	0	194.9	857.4
Yesterday	**SARIMA**	948.5	86.1	261.0	1295.6

5. Conclusion

The conventional R-squared value cannot evaluate the performance of the forecast result for market participating DRs correctly. In a multi-price market environment, the bidding strategy might have a greater effect on DR's revenue compared to forecast result accuracy. Using **SARIMA** method and **Yesterday** method to predict the JEPX spot price and the RR maximum price respectively brings highest revenue according to the simulation result.

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文　献

(1) E. Sortomme and M. A. El-Sharkawi, "Optimal scheduling of vehicleto-grid energy and ancillary services," IEEE Transactions on Smart Grid, vol. 3, no. 1, pp. 351–359, 2011.

(2) 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 transactions on power systems, vol. 20, no. 2, pp. 1035–1042, 2005.

(3) S. Cai, and R. Matsuahshi," Model Predictive Control for EV Aggregators Participating in System Frequency Regulation Market, "in IEEE ACCESS, vol. 9, pp. 80763-80771, Jun. 2021

(4) R. Zhang, G. Li and Z. Ma, "A Deep Learning Based Hybrid Framework for Day-Ahead Electricity Price Forecasting," in IEEE Access, vol. 8, pp. 143423-143436, 2020.

(5) 日本気象協会，プライス予測（電力取引価格予測），https://www.jwa.or.jp/service/weather-and-data/weather-and-data-03/