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Impact of the Rapid Expansion of Renewable Energy on Electricity Market Price: Using Machine Learning and Shapley Additive Explanation [*]

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Abstract

The increase in variable renewable energy (VRE) has brought significant changes in the power system, including a decrease in the average electricity market price owing to the merit order effect (MOE). In this study, we use machine learning and Shapley additive explanation (SHAP) to comprehensively examine the drivers of market price volatility, including the interaction between VRE and demand, fuel prices, and operation capacity in the Japanese electricity market which solar power installation is expanding rapidly. The results of SHAP reveal that there is a large decline effect for market price in solar power during daytime; however, the effect varies depending on the time of day, season, and demand. In addition, the results suggest that the market price increases when demand is high and solar generation is low, such as during summer evenings, which may be because of natural gas generation with higher marginal costs. The study reveals that impact of expanded VRE will not only have the MOE which decreasing average market prices, but may also prompt structural changes in electricity supply, causing market instability and price spikes in the transition process.

Keywords: renewable energy sources, electricity spot price, transition, merit order effect, XGBoost

JEL classification:Q42, Q47, Q54

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1. Introduction

Introduction of renewable energy (RE) is progressing owing to global decarbonization. According to the International Energy Agency (IEA), the amount of RE in 2019 was approximately 2,700 GW, and its Development Scenario estimates that the amount will be approximately 7,000 GW in 2030 [1]. Europe took the lead in the introduction of RE; however, Asia is leading the effort nowadays, and China has introduced the largest amount of RE in the world.

The merit order effect (MOE) is known for the effect of expanding RE in the electricity market [2–9]. A drop in the electricity market price owing to the introduction of RE with low marginal costs has been identified in prior studies. However, the effects of variable renewable energy (VRE), such as solar and wind power, do not only decrease the market price but also the diffusion of VREs leads to other things, such as the need for adjustability to handle a sudden fluctuation (ramp-up), a backup power supply to deal with the so-called windless period when VRE output disappears, and the lack of supply capability owing to "missing money," resulting from the drop in market price in the mid to long term. These problems have been pointed out by previous studies [4,10–15]. However, the existing literature did not reveal the multidirectional effects of VRE on the electricity market, including fuel price and demand. Additionally, previous studies mainly analyzed the market in Europe and the US [16,17]. The electricity market in Asia is hardly analyzed.

This study analyzes the Japanese electricity market, where the liberalization and introduction of REs have advanced. In Japan, before the accident of Fukushima Daiichi Nuclear Power Station in 2011, 54 nuclear power stations were operating. In 2012, all of them stopped operating to review their safety measures [18]. Only 10 of them had restarted operation by October 2021 [19]. As expectations about RE heightened with the decline in the perceived reliability of nuclear energy and the introduction of the feed-in-tariff (FIT) scheme in Japan in 2012, the amount of RE introduced, mainly from solar power systems, suddenly increased. It seems that the market price (spot price) of electricity in Japan decreased as a result of the expanded diffusion of solar power, but this has not been researched in detail [20]. The average spot price in Japan in FY2019 (i.e., 2019 fiscal year 1 April to 31 March) decreased to 7.93 Yen/kWh (US$ 72/MWh[2]), but it was hit by an unprecedented price surge during the winter in 2020–2021, with a maximum price of 251 Yen/kWh [21]. For Japan, which is aiming to develop RE to achieve carbon neutrality, further clarifying the effects of RE on the market can have useful policy implications when considering a future energy policy in Japan. Furthermore, the effects of the rapid expansion of solar power on the electricity market in Japan have important implications for other regions and countries.

[2] exchange rate: 1US$ = 110 Yen (2021/3/31) based on X-RATES (https://www.x-rates.com/)

This study intends to conduct a detailed discussion of the effects of VRE in the Japanese electricity market by comprehensively evaluating the effects of demand, fuel price, and operable power facility capacity (operation capacity) by using machine learning to analyze spot prices from FY2016 to FY2020. Price formation in electricity markets follows a non-linear pattern, and the prices fluctuate because of multiple factors [8,9,22–25]. For this reason, this paper employs machine learning methods, which can detecting nonlinear relationships and interactions with high accuracy [26,27]. Additionally, in recent years, a technique of explainable artificial intelligence (XAI) [28–30] has progressed and can be used to visualize factors of the judgment of machine learning. Therefore, the estimation of machine learning fits the analysis of electricity market price trends.

In this study, we use the partial dependence plot (PDP) and Shapley additive explanation (SHAP) to investigate factors that influence the VRE market. Using these approaches, we show that VRE has different effects on electricity market price depending on the time of day or season and the lapse of time. We also show that the interaction between VRE and other variables has different effects.

The rest of this paper is as follows. Section 2 presents an overview of the status of the electricity market and the introduction of RE in Japan, and Section 3 summarizes recent studies. Section 4 first introduces the data used in this study and then explains the proposed technique. Section 5 presents the analysis results of the machine learning and the factor analysis conducted with XAI. Finally, Section 6 presents the conclusions.

2. Literature review

MOE is known for the effect of RE on the electricity market; when RE with low marginal costs enters the market, the supply curve shifts to the right, and the market price decreases. There are many studies on MOE, and most of them have confirmed a drop in the market price due to VRE [2–9].

Moreover, it has been reported that the market price of electricity is determined by multiple factors and is non-linear. For example, using the graph theory, Kyritsis et al. [6] showed that wind and solar power exhibit MOE at peak hours, and solar power generation reduces the volatility of the price of electricity and the probability of sudden price hike, whereas wind power affects the volatility of the price of electricity and causes price spike. Mosquera-López and Nursimulu [31] analyzed the German market using a threshold regression. They showed that solar power has different effects on the market price once it exceeds a certain value, and there is a possibility that MOE may temporarily change, suggesting that the dynamics of the electricity market change continuously as RE is added to the electricity generation mix progressively. Hagfors et al.

[29]analyzed the MOE of solar and wind power at each time of day using quantile regression in the German market and found that the decline in daytime price due to solar power is small, and a negative price caused by wind power is a rare phenomenon that occurs at night when demand is low. Sirin and Yilmaz [23] analyzed the MOE of run-of-river hydropower and wind power in the Turkish market using the quantile regression and showed that the MOE is different depending on the demand, price, and power generation type. Keeley et al. [33] used ordinary least squares and machine learning to analyze the German market, visualized by PDP (a type of XAI)—the relationship between MOE caused by solar and wind power and demand and found that MOE has a non-linear effect and is different depending on demand and time of day. Figueiredo and Silva [8] showed that solar and wind power have an MOE of 0.879–1.131 ct/kWh but have high volatility of MOE in the Iberia wholesale electricity market using the graph theory. Kolb et al.[9] found a high MOE in the German market—2.89 ct/kWh in 2014 and 8.89 ct/kWh in 2017. They had these results because they used a non-linear marginal cost curve where the price suddenly rises at the time of supply capability shortage for a conventional backup capacity. Although Figueiredo and Silva [8] and Kolb et al. [9] found that MOE of VRE exists, they also pointed out that the effects of RE on the market is highly volatile and risky for investors, and the supply capability of existing power stations would become insufficient in mid- to long-term, as their business conditions would turn worse due to a drop in market price. These studies showed that the scale of the effects of VRE is non-linear and different depending on demand, time of day, and prices while acknowledging a decline in market price because of VRE.

Apart from MOE, studies about the effects of multiple factors, such as fuel price, demand, existing power stations (e.g., thermal power), and RE, on a market have been performed. Moreover, the effects of the spread of RE on the income and expenditure of power generation facilities have been conducted. Bublitz et al. [14] conducted factor analyses of the changes in the market price of electricity in Germany and concluded that the decline in the market price is greatly affected by fuel price and CO2 price. Csereklyei et al. [34] reported that MOE varies with regional differences in VRE penetration; there are interactions between solar and wind MOEs, and the market price increases because of price hikes of natural gas in Australia. López Prol et al. [35] concluded that a cannibalization effect had occurred in California, where due to the decline in the market price of wind and solar power, the value of RE declined. Bushnel et al. [22] investigated how the market price of solar power changes in California depending on the time of day or season and showed the market price rises in the morning and evening because of the solar power. Fell and Kaffin [36] focused on the interaction between the price of natural gas and wind-powered electricity generation in the US to investigate the effects on the decline in coal-fired electricity generation. Antweilera and Muesgens built a theoretical model that incorporates adjustments in baseload and peak-load power capacity due to the introduce of RE, and examined the short- and long-term MOE. The results show that in the short term, the introduction of RE will lower market prices, but in the long term, the adjustment of other types of plants (i.e. baseload to peak-load) will cause to rise market price [37] . These studies were conducted mainly in Europe and the US, and although there have been recent reports about Australia, there has been no study about the effects of RE on the electricity market in Asia, including Japan. In this study, we use machine learning to clarify the effect of VRE on the market price depending on the time of day, season, and time series; changes in the market price due to demand, fuel price, and capacity of power generation facilities; and the interaction between these multiple factors. In addition, this study is highly applicable to the effects of RE on power systems in areas other than Europe and the US, such as Asia, where RE is rapidly popularized, by analyzing the electricity market in Japan, which is still in the process of liberalization.

3. An overview of the Japan electricity market

Changes in power generation by type in Japan are presented in Table 1. As explained in Section 1, nuclear power stopped after the Great East Japan Earthquake of 2011. FIT began in July 2012, and mainly solar power is being introduced rapidly. Solar power generation increased approximately 14 times from 4.8 billion kWh in FY2011 to 69 billion kWh in FY2019, and the output ratio increased to 6.7% in FY2019, which was bigger than that of nuclear power. The generation of wind power was smaller than (approximately 11%) that of solar power in FY2019.

Table 1. Changes in power generation by type (TWh)

FY	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
nuclear	288	102	16	9	0	9	18	33	65	64
coal	320	306	334	357	354	356	345	347	333	327
natural gas	334	411	432	444	455	426	435	421	403	380
oil	98	158	189	157	116	101	100	89	74	68
hydro	84	85	77	79	84	87	80	84	81	80
solar	4	5	7	13	23	35	46	55	63	69
wind	4	5	5	5	5	6	6	7	8	8
Geothermal	3	3	3	3	3	3	3	3	3	3
biomas	15	16	17	18	18	19	20	22	24	26
Total	1,150	1,090	1,078	1,085	1,058	1,040	1,051	1,060	1,051	1,024

Note: The generation includes self-consumption (e.g., private power generation and consumption and private solar power consumption estimate). Hydropower includes storage hydropower.

Source [37]

In the past, the electricity supply and distribution system in Japan was a vertically integrated system in which 10 local electric power companies in each area (Hokkaido, Tohoku, Tokyo, Chubu, Hokuriku, Kansai, Chugoku, Shikoku, Kyushu, and Okinawa) was in charge of the operation of power supply and systems and owned power stations, grids, and distribution [38–40]. The Japanese electric power system has been liberalized progressively. Retailing was fully liberalized in 2016, and power generation and distribution were separated in 2020 [39]. The current Japanese electric power system is still separated into 10 conventional areas, and except for Okinawa, all the areas are connected with a wide-area connection line (Okinawa is a remote island and independently operated) [41](See Figure S1). The supply and demand of electric power are managed by ordinary transmission system operators (TSO) in each area, and the "Organization for Cross-regional Coordination of Transmission Operators, Japan" (OCCTO) was established in 2015 and started operation in April 2016 to optimize nationwide network operation. Since then, the OCCTO oversees the flow of connected electricity and monitors nationwide power generation and the operation of the power network [39,40]. Electricity demand and the amount of RE introduced greatly vary among the regions. In Kyushu, which is in the south, solar power is introduced the most, and in Hokkaido and Tohoku, which are in the north, wind power is introduced a lot. However, demand is high in Tokyo and Kansai. The transmission of RE to urban areas is limited because the transmission capacity between areas is limited [38]. Wide-area interchange through connection lines has also been installed. However, in Kyushu, where solar power is introduced a lot, the outputs of RE facilities sometimes have restrained from October 2018 [42,43]. A spot market (day-ahead market) in the Japan Electric Power Exchange (JEPX) is a nationwide market of interconnected nine areas (10 areas minus Okinawa). A nationwide flat price (system price) occurs when all deals are made within an empty capacity depending on the capacity of the connection line, but it becomes a segmentation contract (area price) for each area when the connection lines are busy [44,45]. The lower limit price of the spot market is 0.01 Yen/kWh, and there is no negative price, and the upper limit price is 999 Yen/kWh. In the spot market, bids based on the marginal cost are tendered similar to the tendering of the electricity market in Europe, and the ranking is performed depending on a merit order. The total amount of the FIT of RE has been delivered to the market since FY2017, and RE with low marginal costs has been integrated into the market. In addition, a rule that the limit price is assumed to be the lowest price at 0.01 Yen/kWh was established for the FIT of VRE, starting from the winter of FY2018 [46]. As at FY2020, which is the target year in this study, the capacity market had not been established yet, and the market was an "energy-only market." The Japanese Government announced a target to achieve carbon neutrality by 2050 in July 2010[47] and devised a basic energy plan in October 2021 that stipulated that 36%–38% of electricity is to be provided through RE by 2030 [48]. As at October 2021, carbon pricing had not been introduced in Japan.

4. Data and methods

In this section, we explain the data used, the extreme gradient boosting decision tree (GBDT) method (the machine learning used), and XAI (a technique to interpret machine learning). We use hourly data about demand generation of solar and wind power, fuel prices, and operation capacity. The analysis was performed every hour to investigate both average changes and changes according to time of day, season, and year in the wholesale price of electricity. Furthermore, SHAP and PDP (as XAI) are used to clarify the relationship between the changes in each variable and the market price.

4.1. Data

The research period is from April 2016 to March 2021, which is after the liberalization of retail electricity. During this period, data about the amount of electricity generated, demand, and other variables are available. The spot market (day-ahead market) in the JEPX deals in nine areas nationwide (10 areas minus Okinawa) and releases each area price every 30 minutes, as well as a system price, which is the price at an intersection point of the sell and buy bid curves nationwide. We use the system price to conduct the nationwide analysis. The price varies seasonally and tends to rise in summer and winter. The transition of the market price during the target period is shown in Figure 1, and the distribution by month and fiscal year are depicted in Figure S2.

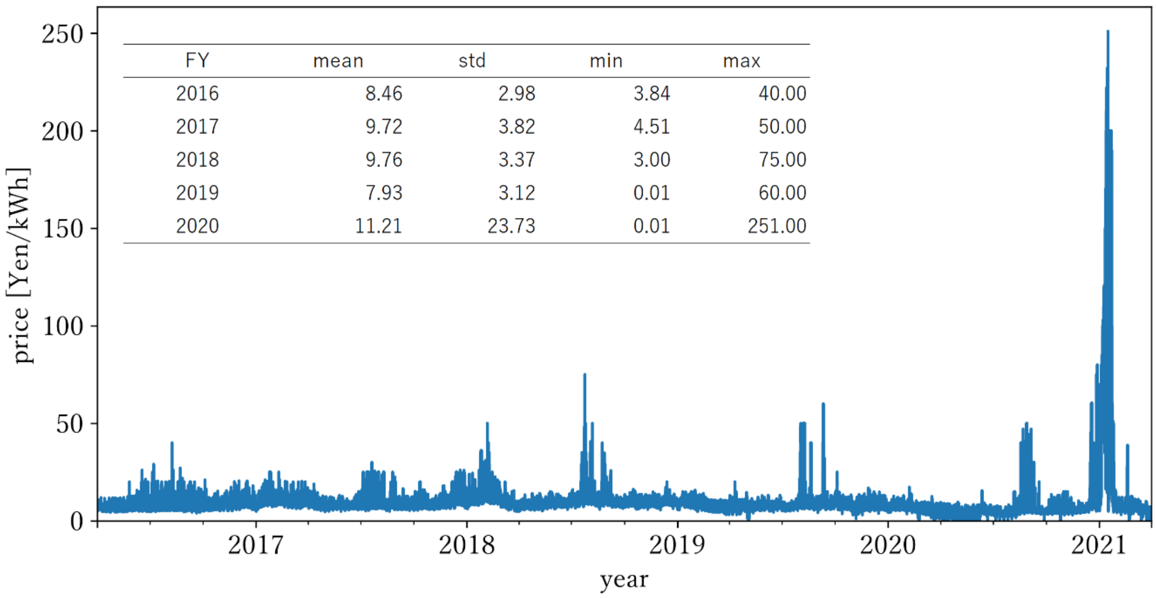


Figure 1. Time Series of spot market prices (system price) from April 2016 to March 2021

(**source** [49])

The annual average price decreased to 7.93 Yen /kWh in FY2019. From the spring of 2020 (FY2019), transactions at 0.01 Yen/kWh, which is the lowest price of the spot market, are noticeable. There was no significant price increase from 2016 to 2019, with the highest price at 75 Yen/kWh. However, the price soared up to 251 Yen/kWh from December 2020 to January 2021.

The wholesale price of electricity is affected by various factors, but the main independent variables are demand, generation from RE, and fuel price [31]. In this study, we also add operation capacity as an independent variable to consider the effects of the introduction of RE on supply capability. The data about the hourly demand and the generation with VRE (solar and wind) that TSOs in each area released are from April 2016 to March 2021, and the sum of the values of the nine areas are used as the nationwide value. Solar power does not include self-consumption. Operation capacity is defined as the capacity of operable power generation facilities that are derived from the capacities of authorized power stations minus the capacities of inactive power stations. The data about the authorized power stations and shut down (daily) are from the power generation information disclosure system (HJKS) that is released by the JEPX [50]. HJKS was started in April 2016, and data about the shut down of power stations with a capacity of 100 MW or more lasting for 24 hours or more are released. HJKS provides data for thermal, hydro (include pump-storage plants) and nuclear plants, so the value of operation capacity includes capacity of all of these power plants that constitute most of the Japanese electricity supply, exclusing VRE. Publications of information about the decline in output also began in October 2020, but it is not included in the analysis because the data periods are limited. A transition of the operation capacity is shown in Figure 2. The operation capacity had seasonal variation, decreasing in spring and fall when demand is low and increasing in summer and winter when demand is high, but the annual average consistently decreased from FY2016 to FY2020. The trend of operation capacity by power type is depicted in Figure S3.

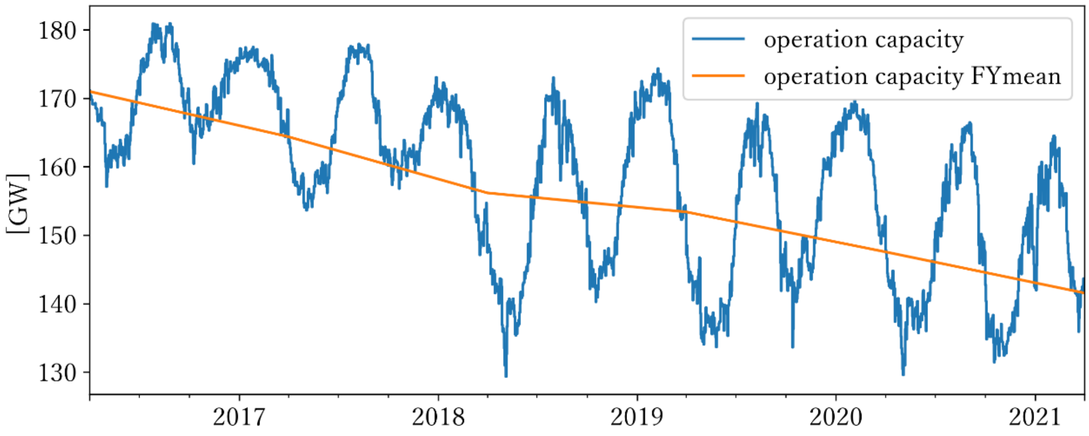


Figure 2. Transition of the operation capacity from April 2016 to March 2021

The fuel prices used are monthly import prices (CIF price) of coal, LNG, and oil in Japan and are taken from customs statistics.

To analyze hourly data, each variable is set to an hourly value; the hourly price data are extracted from spot market prices every 30 minutes; data on operating capacity are converted from daily data into 24-hour equivalents (24 hours same value), and data on fuel prices are linearly corrected monthly data and converted to daily equivalents (24 hours same value). The statistics of each variable are presented in Table 2, and the correlation coefficients between each variable are presented in Table 3. Figure S4 depicts the changes in the variables (weekly average).

Table 2. Descriptive Statistics of the Variables (April 2016 to March 2021)

	Unit	mean	std	min	max
demand	GWh	100.35	17.97	50.80	164.85
solar	GWh	6.52	9.53	0.00	47.83
wind	GWh	0.83	0.51	0.01	2.87
coal	thousand Yen/Mt	11.11	1.74	7.49	14.21
LNG	thousand Yen/Mt	50.37	7.39	30.25	65.39
oil	thousand Yen/kl	45.72	8.03	22.02	63.77
operation_capacity	GW	158.49	12.48	129.34	180.93
price	Yen /kWh	9.42	11.14	0.01	250.00

Note: *demand*, *solar*, and *wind* are hourly values

The hourly maximum solar generation during the research period was 47.83 GWh, and it occurred at 11:00 a.m. on March 24, 2021, and the nationwide demand at this time was 107 GWh, implying that approximately 45% of the demand was served by solar power. The generation with wind power was less than that with solar power, and the hourly maximum generation with wind power was 2.87 GWh, which is approximately 1/17th of that of solar power.

Table 3. Correlation Coefficients among the Variables (April 2016 to March 2021)

	price	*demand*	*solar*	*wind*	*operation capacity*	*coal*	*LNG*	*oil*
price	1							
demand	0.33	1						
solar	−0.06	0.29	1					
wind	0.09	0.09	−0.03	1				
operation capacity	0.07	0.40	−0.12	−0.09	1			
coal	−0.01	0.07	−0.06	−0.10	0.22	1		
LNG	0.05	0.07	−0.02	0.06	0.06	0.82	1	
oil	0.08	0.12	−0.04	0.07	0.03	0.72	0.71	1

4.2. Method

4.2.1. Machine learning Model

In this study, GBDT is used as a machine learning technique. We use the Python XGBoost package for GBDT analyze. XGBoost fits well even on outliers such as price spikes and improves performance significantly[51]. Thus, it is used to analyze power market prices, which fluctuate dynamically in price due to complex factors [33,52]The following empirical relationship (Eq. (1)) is used to examine the effects of RE power sources (wind and solar power) on the spot market price.

$$price_t = f(load_t, solar_t, wind_t, operation\ capacity_t, coal_t, LNG_t, oil_t) \qquad (1)$$

To prevent overfitting, early stopping and cross-validation are conducted. The sample data are divided into training samples and validation data—from April 2016 to March 2020 are the training data, and from April 2020 to March 2021 are the validation data. The training data are divided into five segments with cross-validation, and training is conducted to validate the accuracy. The parameters are estimated with the training sample, and the presence or absence of overfitting in the training sample can be examined using the mean square errors of samples other than the learning samples with the verification samples. By setting the values of various tuning parameters in the estimated samples, we prove that learned weights (parameter estimates) do not strongly depend on the estimated or training data and can be applied more generally. Furthermore, we devised a way to prevent overfitting by initiating early stopping that terminated learning when reproduction accuracy stopped improving. The optimum iterations are set using the data from April 2020 to March 2021 as the validation data.

4.2.2 Interpretation of the model

Additional analyses using feature importance plot, PDP, and SHAP are performed to determine the factors that contributed to the prediction results. PDP visualizes the average relationship between independent and dependent variables and can determine whether an appropriate form function is either monotonic, linear, polynomial, or more complicated. SHAP was proposed by Lundberg and Lee [53] as a unified framework to interpret a prediction based on the Sharpley value of the cooperative game theory. SHAP shows how much a certain variable contributes to the fluctuation of a predicted value of multiple predictors while interacting with other variables. It can show how each variable relates to the predicted value and is used in studies in the fields, for example medicine and construction [54,55]. SHAP value has the additivity property, and when the baseline (the average model output over the training data) of all predicted values and the SHAP value of each variable is added, it becomes the predicted value of the model.

SHAP can show the reason for the prediction of machine learning of each instance (in this study, every hour) and the effect caused by each variable, whereas PDP clarifies an average relationship. The SHAP value shows how individual data influences are different from the baseline. A positive SHAP value indicates an increasing effect of the baseline on the predicted price, and a negative value indicates a reducing effect.

In this study, based on the model made with XGBoost, SHAP values are calculated using the SHAP Python package. We analyze the effect of each variable on the predicted value of the market price depending on the time of day, season, and time series using a characteristic of SHAP values. In this detailed analysis, the SHAP values of coal, oil, and LNG fuel prices were summed up using the additivity property of SHAP and are summarized as SHAP values of $fuels$. This helps us to understand the effects on the predicted values across the overall fuel price. Eq. (2) shows the relationship between the forecast of prices and the SHAP value.

$$predicted\_price = baseline + load\_SHAP + solar\_SHAP + wind\_SHAP \\ + operation\_capacity\_SHAP + fuels\_SHAP \quad (2)$$

where *predicted_price* refers to the value predicted by the machine learning model; *baseline* denotes the average value of the predicted value over the training data, and *demand_SHAP*, *solar_SHAP*,*wind_SHAP*,*operation_capacity_SHAP* and *fuels_SHAP* denote the SHAP value of each variable.

Feature importance indicates the importance of an attribute. On the one hand, the feature importance of XGBoost becomes a degree of contribution to the divergence caused by the decision tree (degree of contribution to the loss function at the time of training); hence, it is not the degree of contribution to the predicted value. On the other hand, in the feature importance with SHAP, each variable becomes the degree of contribution to the predicted value (market price). We use the feature importance with SHAP because it can be understood more directly.
Using these techniques, we interpret the machine learning (so-called "black-box" model) and perform multifaceted analyses of the effects of VRE and other factors on the market price, including the interrelation with other variables and the differences depending on the time of day and season.

5. Results and discussion

In the following section, we show the result of constructing the model using machine learning, analyze the effects of VRE and other factors on the market price depending on the time of day and season using SHAP, and estimate MOE. In addition, we discuss the sharp increase in the market price during the winter of FY2020 based on the results.

5.1. Results of the machine learning (XGBoost)

The results of the machine learning by XGBoost are shown in Figure 3, and the evaluation indices including Root Mean Squared Error (RMSE), Weighted Absolute Percentage error (WAPE), correlation coefficient (cor) are presented in Table 4. The results of the XGBoost fitted very well during the training period, i.e., until March 2020. The accuracy during the verification period from April to November 2020 was also comparatively well, and the performance of the model was secured. However, the magnitude of the price surge from December 2020 was not able to be reproduced. This price surge is discussed in Section 5.5.

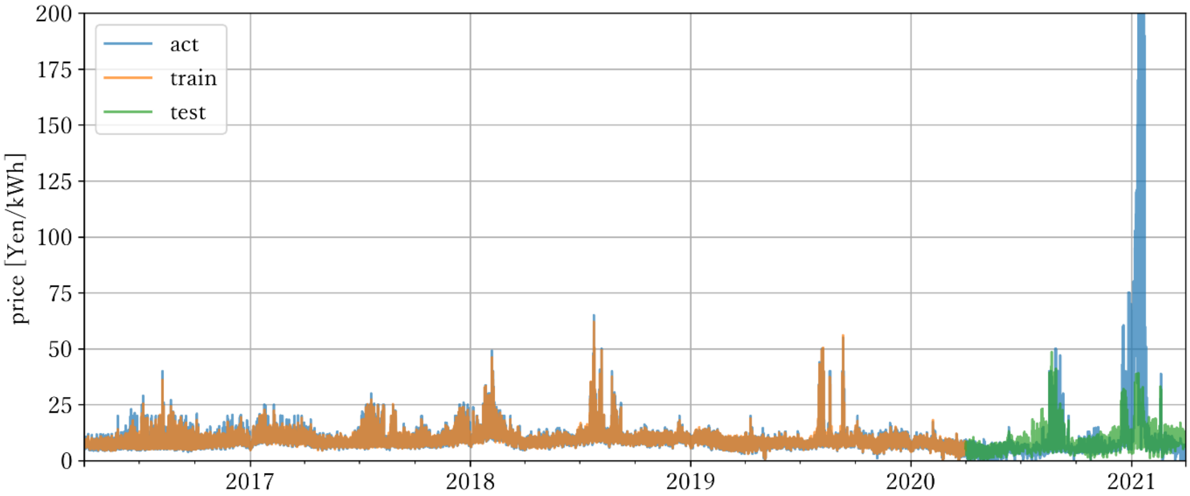


Figure 3. Results of the XGBoost model (trained from April 2016 to March 2020)

Table 4. Evaluation indices of XGBoost model prediction

	April 2016 to March 2020	April 2016 to November 2020	December 2020 to March 2021
RMSE	0.65	1.28	38.49
WAPE	0.05	0.08	0.71
cor	0.98	0.94	0.54

The SHAP baseline from April 2016 to March 2020 is 8.96 Yen/kWh and corresponds to the average market price during this period.

Feature importance with SHAP is shown in Figure 4. The variable with the largest degree of contribution to the *predicted_price* is *demand*, followed by *solar*, *operation_capacity*, and *fuel price*. On average, the *demand* contributed approximately 2 Yen/kWh to the *predicted_price*, and the contribution of *solar* was about half of that of *demand*. The results reveal that the degree of contribution of *wind* to *predicted_price* is small; this may be because of its small generation. Figure S5 shows examples of changes in SHAP value.

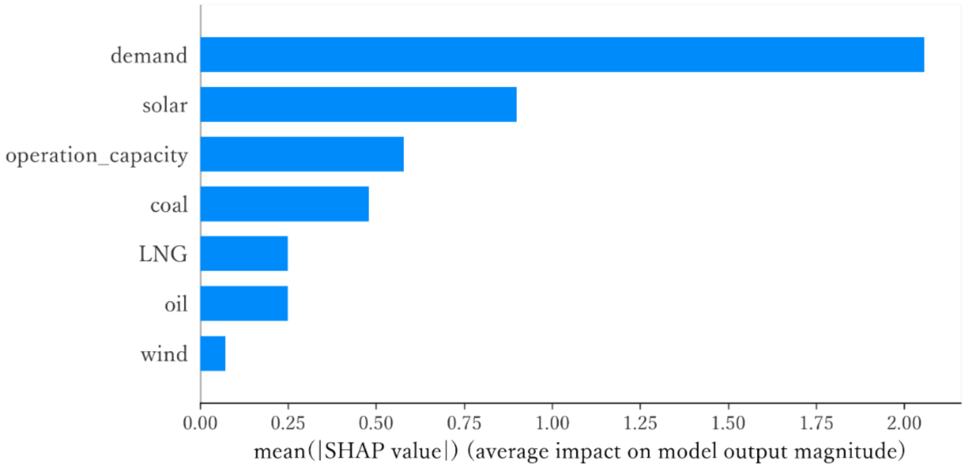


Figure 4. Feature importance with SHAP

5.2. The effects of the factors on the market price depending on the time of day and season

Figure 5 shows the average SHAP values of each variable depending on the time of day of every season and fiscal year. Since the Japanese TSOs assume that summer (July to September) and winter (December to February) are severe weather periods [56], we assume the same and set them as such; March to June are set as spring, and October and November are set as fall.

The effect of *fuels* on the *predicted_price* varied with year. For example, the rate of decline in the *predicted_price* with *fuel* increased in the winter of FY2019, which is consistent with the decline in fuel price (see Figure S4).

Demand had increasing effects on the *predicted_price* during the day and reducing effects during the night. These movements correspond to the increase and decrease in the daily electricity demand. In addition, the SHAP values of *demand* are around 0 Yen/kWh during the day in spring and autumn, whereas it has an increasing effect of 4 to 6 Yen/kWh in the peak times in summer. In the winter of 2017, the temperature was lower than that of the average of the year [57], and in the summer of FY2018, the temperature was a record high [58], so electricity demand increased, and the results of SHAP reflects it.

In contrast, *solar* decreased the *predicted_price* during the day and increased it during the night. From FY2016 to FY2019, the *predicted_price* declined due to the increase in daytime *solar*. On average, the reducing effect caused by *solar* during the daytime in FY2019 was approximately 2 Yen/kWh. The reducing effect in the summer due to the daytime *solar* was particularly high, and it was approximately 3 Yen/kWh in the summer of FY2019. In addition, an increasing effect from the baseline on the *predicted_price* due to *solar* was observed in summer evenings, and it was approximately 2 Yen/kWh during 18:00 in the summer of FY2019. In this model, we find that flexible thermal power generation, such as LNG-burning, which has high marginal costs, is essential as an adjusting force to rapidly ramp-up to supplement due to the decline in solar generation in the evening, which is consistent with the findings of Bushnell and Novan [22]. Although the reducing effect of the *predicted_price* caused by *solar* during winter increased from FY2016 to FY2017, there is almost no change after FY2017.

The wind generation was small (the high value in FY2019 was approximately 5% of the solar generation), and there was almost no effect of *wind* on the *predicted_price*.

The effect of *operation_capacity* was approximately 1 Yen/kWh, which is a reducing effect on the *predicted_price* during the summer and winter of FY2016, whereas the effect during the same season of FY2019 was around 0 Yen/kWh, which was an increasing effect on the market price. This is a reflection of the declining trend of the *operation capability*.

Therefore, we visualize the effects of VRE, excluding the effects of demand, fuel price, and operation capacity, on the market price by separating the effects of each variable on the *predicted_price* using the SHAP value. The effects caused by *solar* greatly varied according to the time of day and season. The decline in daytime *predicted_price* caused by *solar* was high, but increasing effects were also observed during summer evenings. According to Hirth [59], the larger the installation, the larger the MOE by wind power, and the reason why this analysis did not find any effect of *wind* on market prices is assumed to be due to the small amount of wind generation. Thus, we examine the effects of *solar* in the following section in detail.

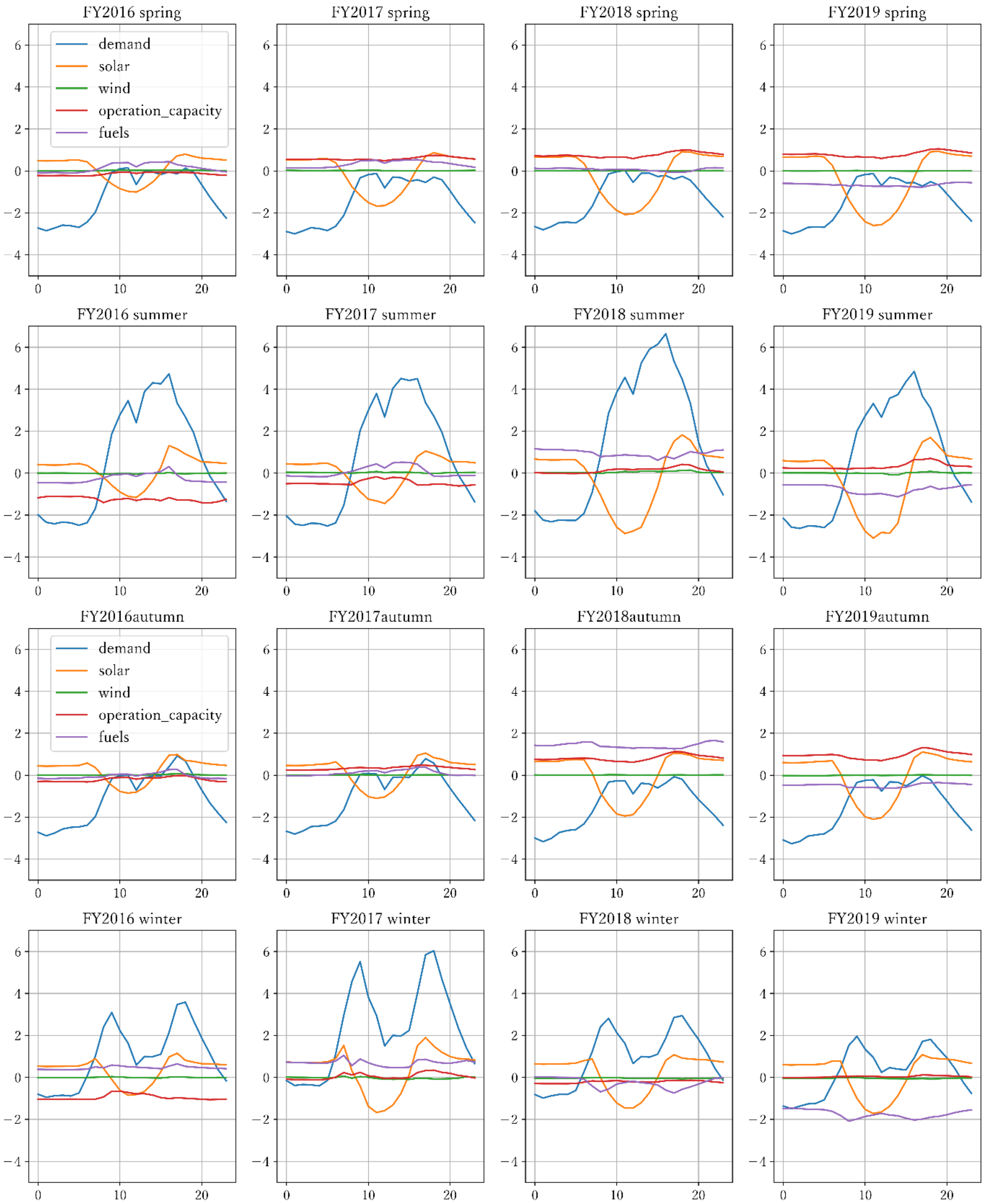


Figure 5. The effects of each variable on the predicted value for the fiscal year, season, and time of day according to SHAP (Y-axis is the SHAP value (Yen/kWh), and X-axis is the time of day (24-hour)).

5.3. MOE caused by solar power: Interaction between solar power and the demand

We analyze the degree of contribution of *solar*, which had large effects on the *predicted_price*, including the interaction between *solar* and *demand*, in Section 5.2. In Figure 6, the X-axis represents the amount of each variable, and the Y-axis represents the SHAP value which shows changes of predicted_price from baseline. *Solar* and *demand* had the highest interaction. Regarding *solar* (Figure 6 a), the *predicted_price* fell linearly as the amount of electricity generated increased. However, the effect differed depending on the magnitude of *demand*, and there was a threshold near *demand* of 125 GWh (90th percentile demand). The amount of *demand* (Figure 6b) increases the *predicted_price*. The curvature changed near the *demand* of 125 GWh (90th percentile demand), and the increasing effect on the *predicted_price* increased when the *demand* is beyond 125 GWh. In addition, when the *demand* exceeds 125 GWh, the market price changes by *solar*. The increasing effect of *demand* on the market price becomes larger when *solar* is small.

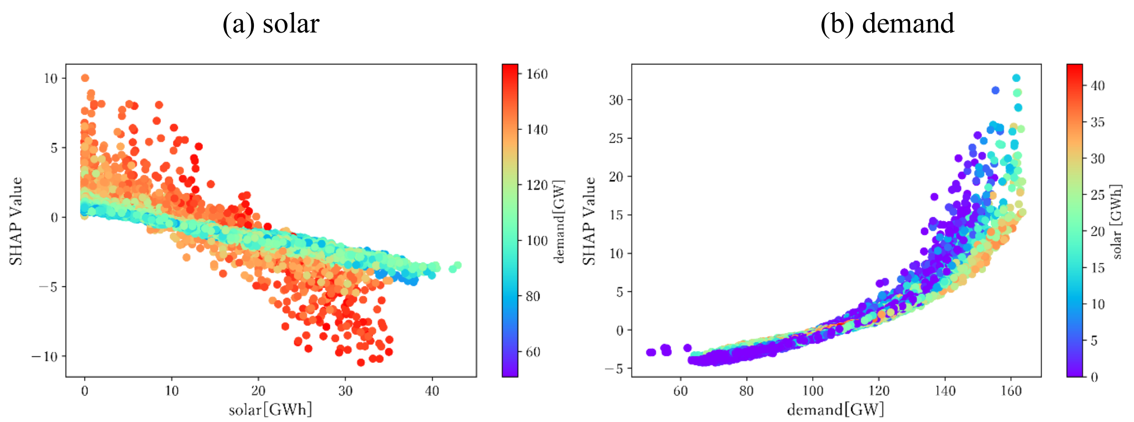


Figure 6. Contribution to the *predicted_price* of *solar* (a) and *demand* (b); the X-axis represents the amount of solar generation and the demand, and the Y-axis represents the SHAP value(changes of *predicted_price* from baseline). The values of variables whose interactions were large have been colored (low: blue; high: red).

The degree of contribution to the *predicted_price* and approximate curves of *solar* and *demand* is shown in Figure S6. For *solar* [Figure 6a and Figure S6a], the data are divided at the 90th percentile *demand*, and the approximate curve is drawn.When below the 90th percentile *demand* (*demand* <125 GWh), the dispersion was small and there was approximately 0.11 Yen/kWh reducing effect on the *predicted_price* per 1 GWh of *solar* ($R^2 = 0.96$). When the *demand* was at the upper 10% (*demand* >125 GWh), although the dispersion was large, in *solar*, for every 1GWh, there was approximately 0.20 Yen/kWh reducing effect on the *predicted_price* ($R^2 = 0.71$). These MOEs are consistent with those in the study of Zipp [7] (MOE:0.103–0.154 €/MWh). The result that the effect of VRE on price varies with the magnitude of demand is consistent with that of Sirin and Yilmaz [22]. However, when the *demand* was high (upper 10%) and *solar* was small

(<10 GWh), *solar* had an increasing effect on the *predicted_price*. This is the increasing effect on the *predicted_price* in summer evenings shown in Figure 5.

Regarding the *demand* [Figures 6b and S6b], there was approximately 0.12 Yen/kWh increasing effect on the *predicted_price* per 1 GWh of the *demand* when the *demand* was below 90th percentile (*demand* <125 GWh) (R^2=0.97), whereas the effects were different depending on the amount of *solar* when *demand* was at the upper 10% (*demand*>125GWh). When *solar* was within 75th percentile (<10 GWh), there was approximately 0.49 Yen/kWh increasing effect (R^2 = 0.78). When *solar* was 75th percentile (>10 GWh), there was approximately 0.40 Yen/kWh increasing effect on the *predicted_price* (R^2 = 0.81).

Based on these results, we estimate negative MOE of 0.11–0.20 Yen/kWh for solar generation per 1 GWh. However, its effect varied depending on the demand, and the MOE of solar power increased when the demand was high. When the demand was high and solar generation was small, an increasing effect on the price was observed.

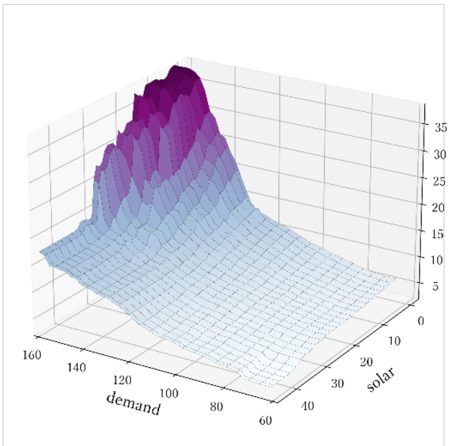
It has been reported that demand is inelastic to price in the short term [60]. However, the result of relationship between solar generation and demand shows that shifting demand to match solar output is essential in increasing the adoption of solar. In addition, the introduction of RE in Japan is biased toward solar power, and areas where solar power is installed are also unevenly distributed, so the periods during which solar power is generated (or not generated) are also concentrated. This also increases the amount of ramp-up required when the output of solar power drops, such as in the evening. To further expand RE, it will be necessary to diversify the types of RE and install them in geographically dispersed locations. Clear MOE of wind power was not observed, this may be because the amount of electricity generated by wind was small.[3]

5.4. PDP: Non-linearity of the effect factor on the market price

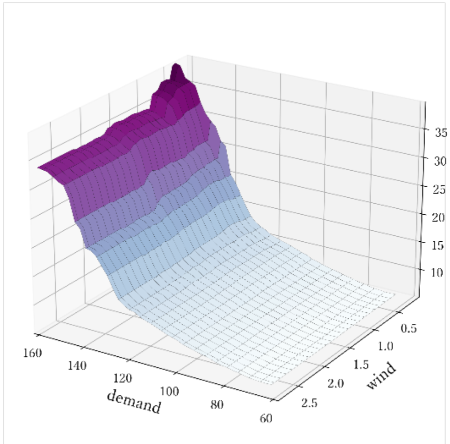
Analyses of PDP were conducted for the *demand*, *solar*, and *operation_capacity*, whose importance to the market price was high (see Section 5.1), as well as *wind* as VRE (Figure 7). The analyses were conducted to determine their relationship with the *demand* because all of them had strong interactions with the *demand*.

[3] Similar analyses were carried out for *wind*, but the correlation between the *predicted_price* and *wind* was weak (R^2 = 0.10)

(a) solar–demand



(b) wind - demand



(c) operation capacity-demand

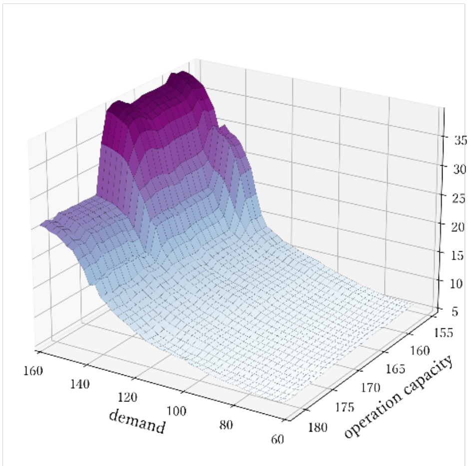


Figure 7. PDP of *solar*, *wind*, and *operation_capacity* relationship with *demand*

Solar, *wind*, and *operation_capacity* exhibited a large effect on the *predicted_price* when the *demand* was high (upper 10%, or >125 GWh). For *solar* (Figures 7a), the *predicted_price* became flat when *solar* generation was very large (>30 GWh), implying that the reducing market price effect declined. This is consistent with the result in the study of Keeley et al. [33], which showed that VRE becomes unresponsive to price once its share in the electricity market in Germany exceeded a particular threshold, suggesting that there is a limitation to the reducing market price effect. For *wind* power, Figure 7b shows that the *predicted_price* declined only when the *demand* was high (upper 10% or >125 GWh). For *operation_capacity*, Figure 7c reveals that if the *demand* is not large, the *operation_capacity* will not affect the *predicted_price*. However, when the *demand* is high (upper 10%, or >125 GWh), the rate of the increasing effect of *predicted_price* increases as the *operation_capacity* decreases. Furthermore, the *predicted_price* increases in stages by *operation_capacity*. This indicates that the market price increased progressively depending on merit order; type of power facility.

These results show that the effects of *solar*, *wind*, and *operation_capacity* on the market price are all highly non-linear. Furthermore, the effects on the market price were not by each factor alone but are largely different depending on the interaction with the *demand*. This is consistent with previous studies [23,33].

5.5. Price surge in the winter of FY2020

In Japan's spot market, the highest price from FY2016 to FY2019 was 75 Yen/kWh but soared up to 251 Yen/kWh in the winter of FY2020. This is a record high price since the spot market was established in 2005. As discussed in Section 5.1, the fluctuations of the market price of the results of machine learning were captured comparatively accurately till November 2020. However, for the results from December 2020 to January 2021, the predicted price was approximately 40 Yen/kWh, and the price surge was not captured. This infers that a phenomenon different from that during the learning period (from April 2016 to March 2020) occurred.

About the price surge, the Ministry of Economy, Trade and Industry in Japan (METI) reported that the main factors to this were an increased demand due to sudden cold weather and an LNG stock shortage [61].

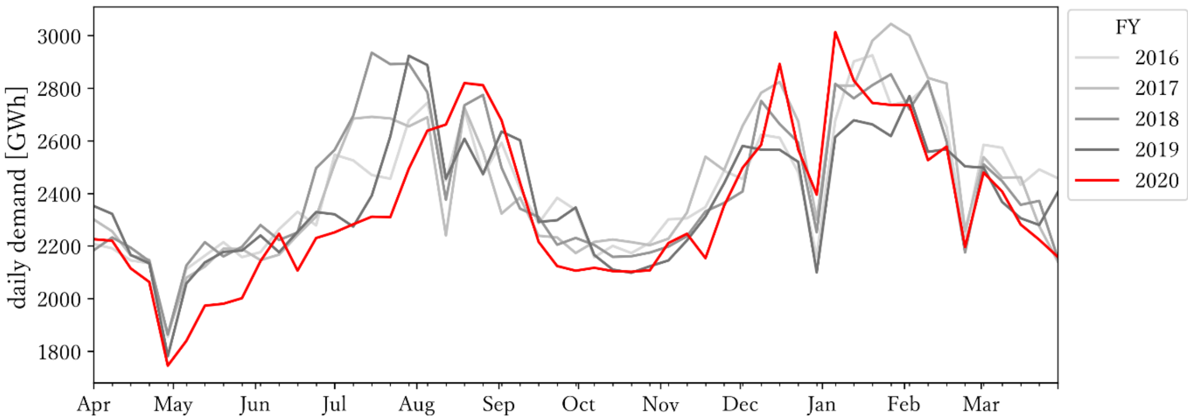


Figure 8. Seven days' average of daily demand

Figure 8 shows a yearly comparison of seven days' average of the daily demand. The daily demand in FY2020 were lower than the levels during FY2016–FY2019 until around November, except during the summer (August to September). The declining demand due to the spread of COVID-19 also may have affected this. However, the demand increased from December 2020 to January 2021. The demand in early January 2021 was 155 GWh, which exceeded the upper 10% demand of 125 GWh, that is, the threshold shown in Sections 5.3 and 5.4, where the surge rate of the market price was higher.

The LNG stock of FY2020 at the end of the month was higher than that in FY2018 and FY2019 from April to July 2020, which was approximately 2,500,000 tons but decreased to approximately 2,000,000 tons at the end of August [61]. The LNG stock increased when heading into the winter in FY2018 and FY2019. It was approximately 2,500,000 tons at the end of November in FY2018 and FY2019, and it remained low at approximately 2,000,000 tons at the end of November 2020. Power companies had planned to increase their LNG stock from December, but due to problems with supply facilities in gas-producing countries, stocks remained at low levels. Kyushu Electric Power, in which the share of solar power in the amount of electricity generated was the highest, reported an extraordinary loss because of the resale of LNG as it became overstocked because of the price decline in the electricity market in 2019 [62]. With demand slump due to the effect of COVID-19, the market structure and management environment may have been some of the factors that caused the decrease in LNG inventory at electric power companies. The LNG stock was not included in this analysis because of the lack of data.

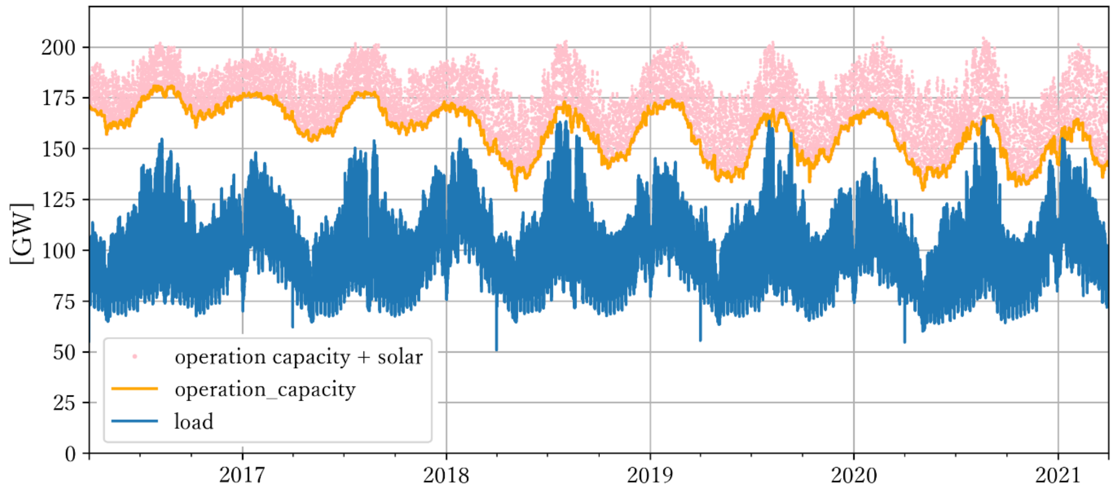


Figure 9. Relationship between *operation_capacity*, *solar,* and *demand* (Pink dot: Sum of *operation_capacity* and *solar* (hourly value); Orange line: *operation_capacity*; Blue line: *demand*)

Figure 9 shows the relationship between *operation_capacity*, *solar*, and *demand*. *Operation_capacity* consistently decreased from FY2016 through FY2020, whereas the maximum supply capability, that is, the sum of *solar* and *operation_capacity*, in the summer and winter did not change at about 200 GW because of the increase in *solar*. Normally, peak-load power plants cover their fixed costs through the gain during the higher market prices[63], but until FY 2019, market price was kept low and did not soar. In Japan, the capacity market hasn't started and there was little appetite for investment in peak-load power plants. Solar power is only generated during the daytime and does not supply power at night and during bad weather. The maximum *demand* was about 150 GW, although it varies from year to year. At the time of the price surge, the supply was insufficient because the *operation_capacity* and *demand* were at the same level. Bid curves at the time of the price surge are shown in Figure 10. For the supply curve with the merit order, the price increased progressively depending on the type of power facility. When the supply becomes insufficient, the curve becomes straight, and the market soars. As shown in Figure 10, the sell bid was sold out that time. The PDP of the *operation_capacity* shown in Section 5.4 also depicts this behavior, that is, the price increased progressively and greatly at the time the *demand* increased, and when the *operation_capacity* got below 160 GW, the price hike went up by one step. At the time of the price surge in the winter of FY2020, the *operation_capacity* was even smaller than 160 GW, and the price surge was non-linear and sudden. This is consistent with the large increase in the supply curve at the time of the insufficient supply capability described in the study of Kolb et al. [9]. In addition, since such high price data at the time of the price surge were not included in the machine learning training period, the predicted values were greatly deviated.

Furthermore, as shown in Section 5.3, it seems that there was an increasing effect on the market price when solar generation was low, and demand was high, which were the conditions that easily led to a price hike. This result is consistent with the result in the study of theoretical model by Antweilera and Muesgens [63]. Based on these results, it is assumed that the main causes of the price surge in the winter of FY2020 were the increase in demand and LNG shortage in the short term. However, in the medium- to long-term, the market price spike was probably caused by a combination of factors, including a decline in daytime market prices due to the increased adoption of *solar* power generation and a decline in operating supply capacity due to the discontinuation or shutdown of existing power plants as business shrank. Antweiler and Muesgens paper shows that the MOE is a transitory effect, and tends to decline in the long term when capacity is allowed to adjust for RE. The paper asserts that when the capacity has been adjusted (as RE increase, base-load plants capacity decline and translate to peak-load plants or power storage system) the market price will often spike if the generation of RE is low, which enables peak-load plants to cover the fixed costs through the gain during the higher market prices. Assuming such adjustments are eventually made, depending on the pace of the transition, there is a risk of supply capacity shortages Japanese market price spike in winter 2021 may be a process of this adjustment. In addition, natural gas is one of the main flexibility supplies to backup VRE nowadays. Due to rising global demand for natural gas, there are risks of price spikes, fuel shortage and geopolitical. In order to ensure a stable electricity supply and transition to decarbonization, it will be important to diversify the types of RE sources and manage the pace of RE installation and transition of conventional power plants.

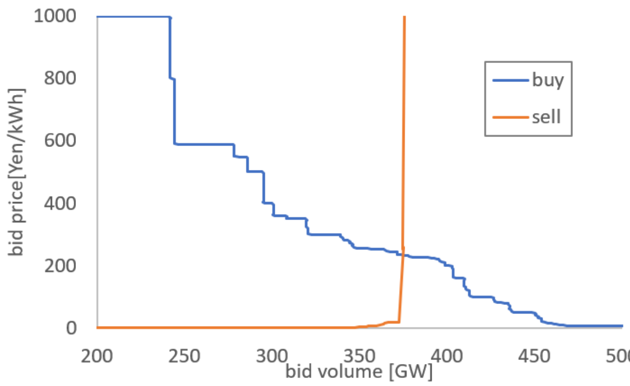


Figure 10. Bid curve at the time of the price surge in the winter of FY2020 at 16:30, January 15, 2021 and the highest market price of 251 Yen/kWh (Compiled by authors based on the data published by the JEPX) [49]

6. Conclusion

A detailed understanding of the factors affecting electricity market prices is critical to the proper design and operation of electricity markets. Since VRE is rapidly advancing globally, we conduct a detailed research about the effects of VRE on electricity market price in Japan, where the liberalization and introduction of VRE are advanced, next to that of Europe and the US, by using machine learning (XGBoost) and model interpretation (XAI (SHAP)) to perform the analysis.

This research employs the operation capacity, which is the authorization power capacity minus the capacity of the shutdown facilities, in addition to demand, the amount of electricity generated with VRE, and fuel price, which were used as variables in past studies on electricity market price, as variables. By using the operation capacity, we were able to perform detailed analyses that considered the condition of stopping facilities. Using the hourly values of these variables, we construct the model for machine learning using data from FY2016 to FY2019 as the training data and those of FY2020 as the validation data and investigated factors that influence the fluctuation of the market price.

The biggest fluctuation factor in the market was the demand, followed by solar, operation capacity, and fuel prices. Clear effects of wind power on the market price were not observed; this may be because the amount of wind power was small. The analyses based on the year, time of day, and season showed that the reducing effect of solar power on the daytime market price increased with time; the reducing effects of solar power were greatly different depending on the time of day and season, and summer evenings experienced increasing effects on the market price.

The MOE due to solar power varied depending on the demand. It was reducing effect approximately 0.11 Yen/kWh in the 90th percentile demand, and approximately 0.20 Yen/kWh at the upper 10% demand, implying that MOE also increased when demand increased. However, when demand was high, the increasing effects on the market price were observed when solar generation was small. This may be because energy sources with high marginal costs, such as natural gas, which were able to deal with the start-up or sudden fluctuation for evening ramp-up fluctuation, were used at that time. The decrease in operation capacity increased market prices. These results showed that the effects of VRE, demand and operation capacity on the market price are all highly non-linear and the effects were not by each factor alone but are largely different depending on the interaction with the demand. In addition, the PDP reveals that the market price was flat when the amount of electricity generated with solar power was very large, implying that solar's reducing price effect is limited. The power supply in mainland Japan is divided into nine areas, and each area has interchanging electricity connection lines. However, the capacities of the connection lines are limited. In Kyushu, where the share of solar power in the amount of electricity generated is the highest, RE electricity is sometimes restricted. To expand the introduction of RE further, it is important to amplify the connection lines, diversify the types of RE and install them in geographically dispersed locations..

Amid the rapid expansion of solar power in Japan, we can observe continuous decline especially for conventional power plants with 100 MW capacity or more. The solar power does not only reduce the daytime market price but which may also have reduced the operation capacity. Existing studies have shown that the decline in the market price due to MOE deteriorates the profit of the conventional power plant, leading to market price surge [8,9] and will induce changes in peak load and base load capacity [63]. In the case of Japan, we have started to observe these effects. This trend may be a natural part of the transition process toward decarbonization, but depending on the pace of the transition, there is a risk of security of electricity supply.

In the autumn of 2021, the electricity market price in Europe soared due to the lack of natural gas [64]. While demand for natural gas has increased globally due to the increasing role of gas power that can respond, which is critical for the expansion of VRE and the decarbonization trend, there are risks of price spikes, fuel shortage and geopolitical. For a smooth transition, policy support would be needed to manage the pace of power plants installation and transition, including conventional power plants, and to introduce adequate solutions that can enhance flexibility (like gas power plants, demand response, storage, grid expansion, etc.) to support RE deployment.

This paper shows that the VRE not only have the MOE which decrease average market prices, but may also prompt structural changes in electricity system dynamically. Beyond the MOE discussion, it is necessary to examine the impact of RE expansion from multiple perspectives, including changes in the transition process and take measures to minimize adverse effects.

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