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Beyond the merit order effect: Impact of the rapid expansion of renewable energy on electricity market price

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ABSTRACT

A drop in the average electricity market price owing to renewable energy with low marginal costs has been identified and explored as merit order effect. However, diffusion of variable renewable energy leads to concerns about the need for flexibility, decline of supply capacity, and volatility increase of electricity prices. For both decarbonization and stable electricity systems, understanding the drivers of market price is critical, but it is challenging because electricity markets are non-linear and affected by multiple factors. Hence, this research proposes a model based on machine learning techniques and explainable artificial intelligence (XAI) and estimates the multi-directional impact of renewable energy on the Japanese electricity market. The results reveal that the contribution of demand to market price is the largest, followed by solar generation and operable power facility capacity. This research identifies a large decline in the price triggered by solar power during the daytime; however, the effect of solar power varies by the time of day, season, and demand. Additionally, the results suggest that the market price increases when demand is high and solar generation is low, such as during summer evenings. Using XAI, this study quantitatively and visually demonstrated that interactions between solar power, demand, and operable power facility capacity are the key factors behind the high market volatility and price surge. It is important to manage the pace of plant installation and energy transition. Our study provides insights into how and when the market price changes with variable renewable energy and other policy-making factors.

1. Introduction

The introduction of renewable energy (RE) is progressing owing to global decarbonization. According to the International Energy Agency (IEA), the amount of RE in 2020 was approximately 3000 GW, and its Sustainable Development Scenario estimates that it will be approximately 8000 GW in 2030 [1]. Europe took the lead in introducing RE; however, Asia is currently leading the effort, with China having introduced the largest RE globally.

Along with the diffusion of RE, electricity supply from RE critically affects the electricity market. Particularly, as an effect of RE expansion, the merit order effect (MOE), in which the electricity supply of RE with low marginal cost lowers the average electricity market price, has been identified in prior studies [2–5]. However, diffusion of variable RE (VRE) could also increase and fluctuate the electricity market price. The VRE's electricity supply is unstable because it relies on weather conditions. Each electricity firm must balance electricity demand and supply at any time. To balance electricity demand and unstable electricity supply from VRE, Many regions have utilized natural gas power generation as flexibility [6,7]. Many previous studies reveal that natural gas prices are sensitive to factors such as geopolitics, demand, and other fuel prices [8–11]. Also, the volatility of natural gas prices has progressively become larger [12]. Therefore, the diffusion of VRE has MOE that lowers the average electricity market price, but simultaneously, it increases the volatility of electricity market price due to the electricity balancing issue.

In July 2022, in response to rising energy prices, the United Kingdom

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Nomenclature

Abbreviations

FIT	Feed-in tariffs
GBDT	Gradient boosted decision trees
IEA	International energy agency
JEPX	Japan electric power exchange
MOE	Merit order effect
OCCTO	Organization for cross-regional coordination of transmission operators, Japan
PDP	Partial dependence plot
RE	Renewable energy
RMSE	Root mean squared error
SHAP	Shapley additive explanation
TSO	Ordinary transmission system operators
WAPE	Weighted absolute percentage error
XAI	Explainable artificial intelligence
VRE	Variable renewable energy

government proposed to reform the electricity market, premised on RE and the extensive ecosystem required for RE [13]. IEA energy outlook 2021 notes that the electricity market spikes were not solely caused by the efforts to transition to clean energy but caused by broader factors related to energy security risks during the transition. The expansion of RE has a dynamic impact on electricity markets and systems. Therefore, a better understanding of its impact on electricity prices is essential when considering stable electricity supply, affordable and fair electricity systems, and institutional design.

Constructing a suitable institutional design requires more understanding of the effect of RE on electricity market price. Still, it is challenging to reveal complex relationships between RE, market price, and other factors. Previous studies suggest that price formation in electricity markets follows a non-linear pattern, and prices fluctuate because of multiple factors [5,14–16]. Most preceding studies focused on VRE or the relationship between VRE and specific elements of fuel price, CO_2 price, demand, and time of day. They analyzed them with season and time dummies, lags, and pre-set interactions [5,17–19]. This study hypothesizes that the impact of VRE on the electricity market will vary depending on the circumstances and that conventional, preconceived impact predictions are insufficient to understand market dynamics adequately. To broadly understand market price fluctuations, including the dynamic interactions of variables and conditions, employing an analytical approach that relies less on pre-determined assumptions is important. To this end, this study uses machine learning and explainable artificial intelligence (XAI).

Machine learning can detect non-linear relationships and interactions of variables with high accuracy [20,21]. Additionally, XAI [22–24] has progressed and has been used to allow users to comprehend and trust the results and output created by machine learning algorithms. This method enables detailed analysis and easy-to-understand visualization of the MOE, which indicates the average decline in electricity market prices and how electricity market prices have changed with the introduction of VRE without having pre-determined assumptions.

This study analyzes the Japanese electricity market. In Japan, after the Fukushima nuclear power accident in 2011, all nuclear power plants stopped operation to review their safety measures [25]. As expectations regarding RE heightened with the decline in the perceived reliability of nuclear energy, the amount of RE introduced rapidly increased, mainly led by solar power. While RE installations have increased, the capacity of conventional power plants has continued to decline. Investigating the impact of the rapid expansion of RE on the electricity market shows the multi-directional relationships between RE, demand, operable power facility capacity (operation capacity[1]), and market prices.

This research aims to provide a comprehensive analysis of what factors and conditions affect electricity market prices, including the rapid introduction of RE. This study goes beyond the MOE analysis and analyzes the market impact of RE, demand, fuel prices, operation capacity, and their interactions, alongside seasonal, time-of-day impact analysis using machine learning and XAI. Our methodology helps better understand the multi-directional impact of RE expansion on the market changes and informs future institutional design and policy concerning carbon neutrality.

The rest of this paper is structured as follows. Section 2 summarizes recent studies; Section 3 presents an overview of the status of the electricity market and RE in Japan; Section 4 introduces the data used and explains the proposed technique; Section 5 presents the analysis results and discussion; finally, Section 6 presents the conclusions.

2. Literature on the impact of RE on the electricity markets

One of the typical previous analyses to understand the impact of RE on an electricity market focuses on the MOE. Many studies on MOE have confirmed a drop in the average market price due to VRE [4,5,14,26,27].

However, the effects of VRE do not only decrease the market price, but also the diffusion of VREs leads to other things. For example, previous studies have pointed out 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 [28–31]. Moreover, Newbery reported the lack of supply capability owing to "missing money," resulting from the drop in market price in the mid to long term [32]. López Prol et al. [33] concluded that a cannibalization effect had occurred in California, where the value of RE declined due to the decline in the market price of wind and solar power. These preceding studies have been shown primarily in simulation and model-based studies.

Empirical analysis also shows that the increase of VRE can broadly impact electricity markets and the electricity system, not just a decline in average market prices. 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. Kolb et al. [14] found a high MOE in the German market while also pointing out that the effects of RE on the market are highly volatile and risky for investors 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. Bushnell and Novan [35] investigated how the market price of solar power changes in California depending on the time of day or season that it rises in the morning and evening. These studies focused on VRE or the relationship between VRE and specific elements and performed analyses with control variables.

The common method for analyzing the impact of VRE on electricity markets is regression analysis [5,14], which applies historical market price to estimate VRE influence ex-post. The regression model has been widely employed as a valuable method to assess the extent to which it affects the average electricity market prices, serving as a suitable approach to quantify the MOE. However, the market price of electricity is determined by multiple factors and is non-linear [5,15,17,35,36,37]. Showing the impact of VRE on market price by a simple regression model is difficult. Therefore, in recent empirical analyses, improved methods are used. For example, using GARCH analysis and Granger causality, Kyritsis et al. [27] analyzed Germany's market price volatility by wind and solar power. They showed that solar power reduces the volatility of the price of electricity and the probability of sudden price

[1] Operation capacity is defined as the capacity of operable power generation facilities that are derived from the capacities of authorized power stations minus inactive power stations.

hike, whereas wind power affects volatility and causes price spikes. Sirin and Yilmaz [17] analyzed the MOE of run-of-river hydropower and wind power in the Turkish market using quantile regression, showing that the MOE depends on the demand, price, and power generation type. These studies estimate the effect of their interest by using pre-treatment, for example, interaction, year and season dummies, and lags. It means the results rely on pre-determined assumptions. To evaluate the multi-directional impact of VRE on electricity markets, this study employs machine learning and XAI method, which enables treating non-linear relationships and interactions of variables with high accuracy. Machine learning has been criticized as a black box, making it difficult to understand why certain results are achieved. However, the recent development of XAI has brought interpretability to machine learning, making it possible to visualize the role of individual variables. A limitation of machine learning is its inability to extrapolate beyond the range of variables included in the training period. However, this characteristic can be exploited for various applications, such as change detection and anomaly detection. A few previous studies have used machine learning to estimate the impact of VRE on electricity markets. Keeley et al. [38] used ordinary least squares and machine learning to analyze the German market, visualized by Partial Dependence Plot (PDP)—a type of XAI—the relationship between MOE caused by solar and wind power and demand that MOE has a non-linear effect and depending on demand and time of day. However, they did not address differences related to factors such as fuel prices, operation capacity, and seasonality. This research aims to fill these gaps and further develop a comprehensive approach to understanding the impact of various elements on the electricity market.

This study applies the analysis framework to Japan, but the approach and insights derived are highly applicable to understanding the effects of RE on power systems in other global regions.

3. An overview of the Japanese electricity market

Changes in power generation by type in Japan are presented in Table 1. As explained in Section1, nuclear power stopped after the Great East Japan Earthquake in 2011. Feed-in Tariffs (FIT) scheme began in July 2012, and mainly solar power is being rapidly introduced. Solar power generation increased from 4.8 TWh in FY2011 to 79 TWh in FY2020, with the output ratio rising to 7.9 %, bigger than nuclear power's. The generation of wind power was smaller than (approximately 11 %) that of solar power in FY2020.

In the past, Japan's electricity supply and distribution system was vertically integrated in which ten local electric power companies in each area (Hokkaido, Tohoku, Tokyo, Chubu, Hokuriku, Kansai, Chugoku, Shikoku, Kyushu, and Okinawa) were in charge of the operation of power supply and systems and owned power stations, grids, and distribution [40–42]. Over time, this system has been progressively liberalized. Retailing was fully liberalized in 2016, and power generation and distribution were separated in 2020 [41]. The current Japanese electric power system is still separated into 10 ten conventional areas; barring Okinawa, all the areas are connected with a wide-area connection line (Okinawa is a remote island and independently operated) [43] (see Fig. 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 has overseen the flow of connected electricity and monitors nationwide power generation and the power network [41,42].

Electricity demand and the amount of RE introduced greatly vary among regions. In Kyushu, which is in the south, the share of solar power generation is the highest, and wind power is still not widely installed in Japan but is concentrated in Hokkaido and Tohoku (Fig. S2). Regarding demand, it is relatively high in Tokyo and Kansai. The transmission of RE to urban areas is limited due to limited transmission capacity between areas [40]. Wide-area interchange through connection lines has also been installed. However, in Kyushu, the outputs of RE facilities have sometimes been restrained since October 2018 [44,45]. A spot market (day-ahead market) in the Japan Electric Power Exchange (JEPX) is a nationwide market of nine interconnected areas (excludes Okinawa). A nationwide flat price (system price) occurs when all deals are made within an empty capacity [46,47]. The lower limit price of the spot market is 0.01 Yen/kWh, and there is no negative price, and the upper limit is 999 Yen/kWh. In the spot market, bids based on the marginal cost are tendered similarly to Europe, and the ranking depends 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. 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 [48]. As of FY2020 (this study's target year), the capacity market had not been established yet, and the market was an "energy-only market." In July 2010, the Japanese government announced a target to achieve carbon neutrality by 2050 [49] and devised a basic energy plan in October 2021 that stipulated that 36%–38 % of electricity is to be provided through RE by 2030 [50]. As of October 2021, carbon pricing had not been introduced.

4. Data and methods

4.1. Data

To analyze the effect of RE on electricity prices, this study used hourly data on market price, demand, generation of solar and wind power, fuel prices, and operation capacity. The research period was April 2016–March 2021 (FY2016–2020), after the liberalization of retail electricity. The spot market in the JEPX deals in nine areas nationwide and releases each area price every 30 min, including a system price, which is the price at an intersection point of the sell and buy bid curves nationwide. The system price is used for the nationwide analysis. The

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

FY	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Nuclear	288	102	16	9	0	9	18	33	65	64	39
Coal	320	306	334	357	354	356	345	347	333	327	310
Natural gas	334	411	432	444	455	426	435	421	403	380	390
Oil	98	158	189	157	116	101	100	89	74	68	64
Hydro	84	85	77	79	84	87	80	84	81	80	78
Solar	4	5	7	13	23	35	46	55	63	69	79
Wind	4	5	5	5	5	6	6	7	8	8	9
Geothermal	3	3	3	3	3	3	3	3	3	3	3
Biomass	15	16	17	18	18	19	20	22	24	26	29
Total	1150	1090	1078	1085	1058	1040	1051	1060	1051	1024	1000

Note: The generation includes self-consumption (e.g., private power generation and consumption and private solar power consumption estimate). Hydropower includes storage hydropower. Source [39].

price varies seasonally and rises in summer and winter. The transition of the market price during the target period is in Fig. 1, and the distribution by month and fiscal year are in Fig. S3.

The annual average price decreased to 7.93 Yen/kWh in FY2019. From the spring of 2020 (FY2019), transactions at JPY0.01/kWh, the lowest price of the spot market, are noticeable. There was no significant price increase across 2016–2019, with the highest price at 75 Yen/kWh. However, the price soared 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 [37]. This study adds operation capacity to consider the effects of RE introduction 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 data does not include self-consumption. As described in the Introduction section, operation capacity is defined as the capacity of operable power generation facilities that are derived from the capacities of authorized power stations minus inactive power stations. The data about the authorized power stations and shutdown (daily) are from the power generation information disclosure system (HJKS) from the JEPX [52], which was started in April 2016. HJKS provides data for thermal, hydro (including pump-storage plants), and nuclear plants, so the value of operation capacity includes all of these power plants, excluding VRE. Publications of information about the decline in output also began in October 2020, but it is not included because the data periods are limited. A transition of the operation capacity is shown in Fig. 2; it 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 across FY2016–2020. The trend of operation capacity by power type is in Fig. S4.

The fuel prices used are monthly import prices (CIF price) of coal, LNG, and oil and are taken from customs statistics [53]. In Japan, all natural gas is imported as LNG. Fuel prices (coal, LNG, oil) did not increase during the electricity market surge in the winter 2020–2021.

To analyze hourly data, each variable is set to an hourly value; the hourly price data are extracted from spot market prices every 30 min; data on operating capacity are converted from daily data into 24-h equivalents and data on fuel prices are linearly corrected monthly data and converted to daily equivalents. The statistics of each variable are in Table 2, and the correlation coefficients between each variable are in Table 3. Fig. S5 depicts the changes in the variables (weekly average).

The hourly maximum solar generation during the research period was 47.83 GWh, and it occurred at 11:00 a.m. on 24 March 2021, as the nationwide demand was 107 GWh, implying that approximately 45 % of the demand was served by solar power. The generation with wind power was less, and its hourly maximum generation was 2.87 GWh. To analyze extreme situations, the outlier is not removed.

4.2. Method

This research aims to provide a comprehensive analysis of the factors and conditions that influence electricity market prices. To achieve this goal, this study uses Gradient Boosted Decision Trees (GBDT) as a machine learning method. GBDT is an ensemble learning algorithm that combines several decision tree models using the "Gradient Boosting" technique. Decision trees are tree-like models that partition data based on features, with each node representing a feature and its threshold for data splitting [20]. Gradient Boosting is a method that trains new models based on the errors of previous models and guides them in the direction that minimizes the errors. GBDT is an appropriate method for nonlinear models that need to represent electricity prices [54].

This study uses Python XGBoost package as GBDT. XGBoost fits well even on outliers such as price spikes and improves performance significantly [54]. Thus, it is used to analyze power market prices, which fluctuate dynamically in price due to complex factors [38,55]. The following empirical relationship [Eq. (1)] is used to examine the effects of RE power sources (wind and solar) on the spot market price.

$$price_t = f(demand_t, solar_t, wind_t, operation\ capacity_t, coal_t, LN\ G_t, oil_t) \quad (1)$$

To prevent overfitting, early stopping and cross-validation are conducted. The sample data are divided into training samples (April 2016–March 2020) and validation data (April 2020–March 2021). 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 can be examined using the mean square errors of samples other than the training samples with the verification samples. By setting the values of various tuning parameters in the estimated samples, this study proves that learned weights (parameter estimates) do not strongly depend on the estimated or training data and can be applied more generally. Furthermore, this study 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 validation data. For the model interpretation, only the training samples are used.

Additional analyses using feature importance plot, PDP, and SHapley Additive exPlanation (SHAP) are performed to determine the factors contributing 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,

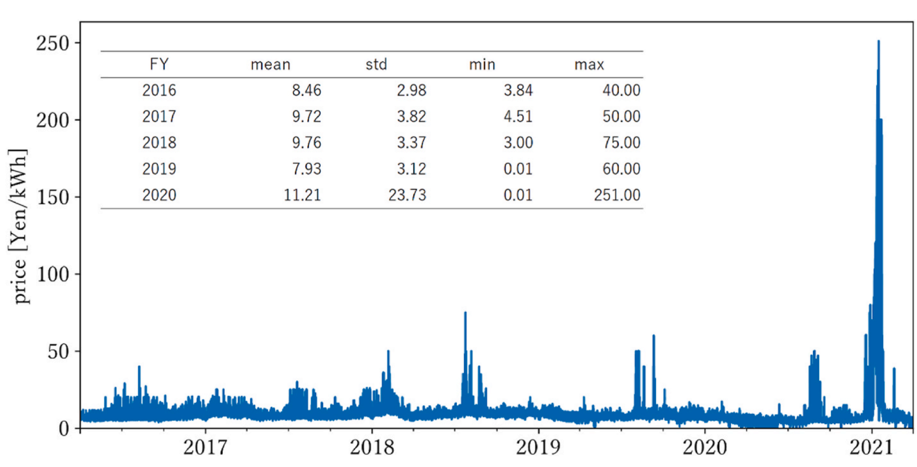

Fig. 1. Time series of spot market prices (system price) from April 2016 to March 2021 (source [51]).

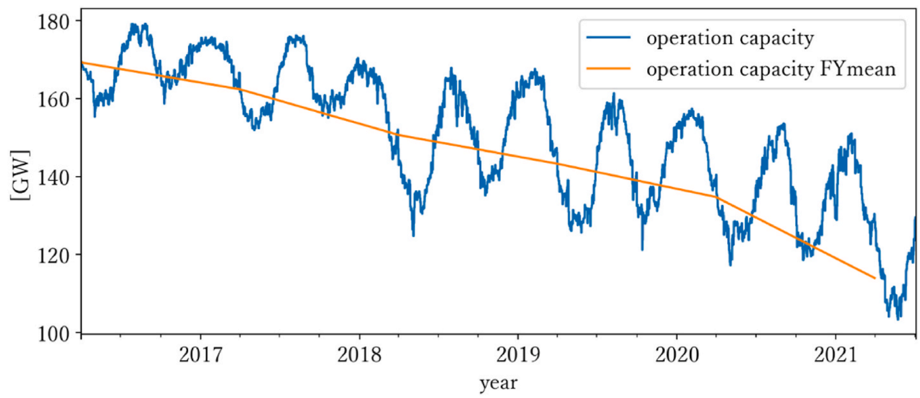

Fig. 2. Transition of the operation capacity (April 2016– March 2021).

Table 2
Descriptive statistics of the variables (April 2016–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.

polynomial, or more complicated. Lundberg and Lee [56] proposed SHAP as a unified framework to interpret a prediction based on the Sharpley value of the cooperative game theory; it 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 fields such as medicine and construction [57,58]. SHAP value has the additivity property, and the sum of the baseline (the average model output over the training data) of all predicted values and the SHAP value of each variable is the predicted value of the model.

SHAP can show the reason for the machine learning prediction 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, while a negative value indicates a reducing effect.

In this study, based on the XGBoost model, SHAP values are calculated using the SHAP Python package. This study analyzes 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, which can aggregate the effect of each variable over a specific period and also analyze the interactions, without using dummy variables. This means that broad analyses can be performed without preprocessing or assumptions.

In this detailed analysis, the SHAP values of coal, oil, and LNG fuel prices were summarized as SHAP values of *fuels*. This helps 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.

$$predicted\_price = baseline + demand\_SHAP_t + solar\_SHAP_t + wind\_SHAP_t + operation\_capacity\_SHAP_t + fuels\_SHAP_t \tag{2}$$

where *predicted_price* is 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 each variable's SHAP value.

Feature importance indicates the importance of an attribute. 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. Alternatively, in the feature importance with SHAP, each variable becomes the degree of contribution to the predicted value (market price). Thus, this study uses the feature importance of SHAP to demonstrate the impact of each factor on market price.

Using these techniques, this study interprets the performance of machine learning and performs 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

5.1. Results of the machine learning (XGBoost)

The machine learning results by XGBoost are in Fig. 3, and the

Table 3
Correlation coefficients among the variables (April 2016–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				
operatio_ 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

evaluation indices, including Root Mean Squared Error (RMSE), Weighted Absolute Percentage Error (WAPE), and correlation coefficient, are in Table 4. The XGBoost results fit very well during the training period. The accuracy during the verification period from April to November 2020 was also comparatively well, and the model's performance was secured. The magnitude of the price surge to 200 Yen/kWh from December 2020 could not be reproduced, but a price increase trend of about 40 Yen/kWh was captured. Machine learning models output predictions based on data trends over the training period. For this reason, these methods are also used for anomaly detection using the difference between predictions and actuals [59]. Our model failing to fit the December price spike suggests that a unique phenomenon affected the market price during the time (discussed in Section 5.5). Only the training period is used to interpret the model (SHAP and PDP).

The SHAP baseline from April 2016 to March 2020 is 8.96 Yen/kWh, corresponding to the average market price.

Fig. 4 shows feature importance of SHAP. The variable with the largest degree of contribution to *predicted_price* is *demand*, followed by *solar*, *operation_capacity*, and *fuel price*. On average, *demand* contributed approximately 2 Yen/kWh to *predicted_price*, and *solar* was about half 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. Fig. S6 shows examples of changes in SHAP value.

Table 4
Evaluation indices of XGBoost model prediction.

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

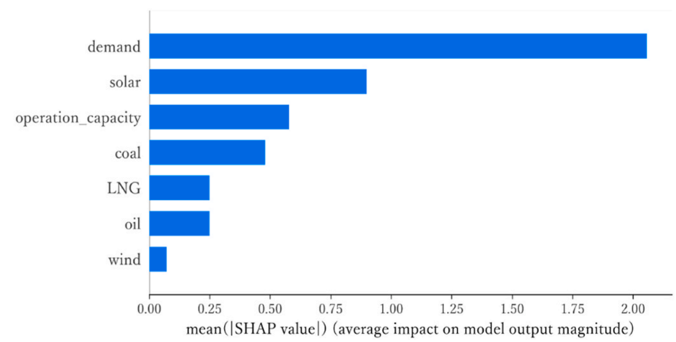

Fig. 4. Feature importance with SHAP.

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

Fig. 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 [60], this study assumes the same and sets the periods accordingly, and March to June are set as spring, and October and November are set as fall.

The effect of *fuels* on *predicted_price* varied with year. For example, the rate of decline in *predicted_price* with *fuel* increased in the winter of FY2019, which complements the decline in fuel price (see Fig. S5).

Demand had increasing effects on *predicted_price* during the day and reducing effects at night. These movements correspond to the increase and decrease in the daily electricity demand. There is seasonal variation in demand. In Japan, air-conditioning systems are widely used with electricity, and demand is higher in summer for cooling and winter for heating (Fig. S5). In spring and autumn, the climate is mild, air-conditioning is unnecessary, and demand is low. In line with this seasonal variation in demand, the SHAP values of *demand* are around 0 Yen/kWh during the day in spring and autumn, whereas it has an increasing effect of 4–6 Yen/kWh in the peak times in summer. In the winter of 2017, the temperature was lower than the year average [61], and in the summer of FY2018, the temperature was a record high [62], so electricity demand increased, and the results of SHAP reflect it.

In contrast, *solar* decreased *predicted_price* during the day and increased at night. From FY2016 to FY2019, *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 daytime *solar* was particularly high at approximately 3 Yen/kWh in FY2019. Additionally, an increasing effect from the baseline on *predicted_price* due to *solar* was observed in summer evening: approximately 2 Yen/kWh during 18:00 in FY2019. This model finds that flexible thermal power generation with high marginal costs, such as LNG, is essential as an adjusting force to rapidly ramp-up to supplement due to the decline in solar generation in the evening, which complements Bushnell and Novan [35]. Although the reducing effect of *predicted_price* caused by *solar* during winter increased from FY2016 to FY2017, there is almost no change after FY2017.

In contrast to solar power generation, because wind generation was small, there was almost no effect of *wind* on *predicted_price*.

We then visualize the effects of VRE by separating the effects of each variable on *predicted_price* using the SHAP value on the market price. This allows for an ex-post time-broad aggregation and a wide range of analyses without pre-treatment or pre-assumption. The effects caused by

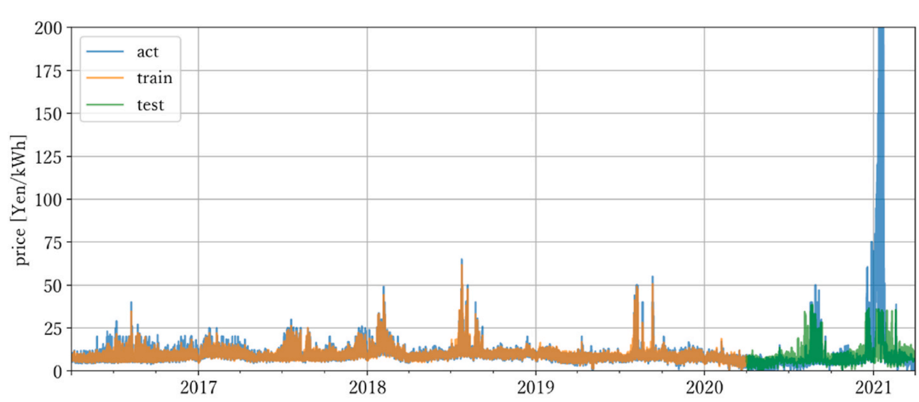

Fig. 3. Results of the XGBoost model (April 2016–March 2020).

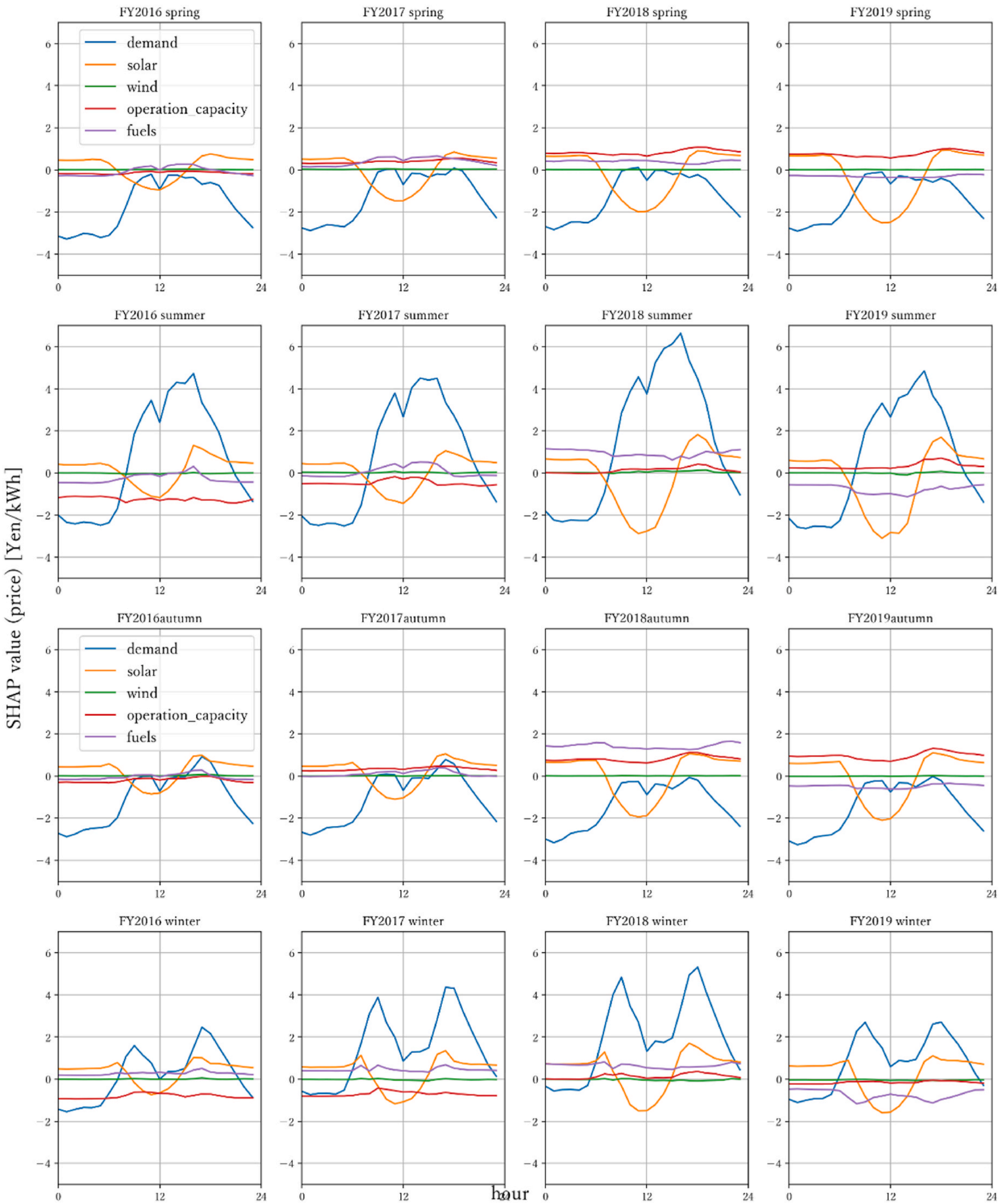

Fig. 5. The effects of each variable on the predicted value for the fiscal year, season, and time of day according to SHAP (Y-axis is the SHAP value (Yen/kWh), and X-axis is the time of day (24-h)).

solar greatly varied according to the time of day and season; the decline in daytime *predicted_price* was high, but increasing effects were also observed during summer evenings. The larger the installation, the larger the MOE by wind power [63], but this analysis not finding any effect of *wind* on market prices is assumed to be the small amount of wind generation.

5.3. Market price change caused by solar power: interaction between solar power and the demand

Fig. 6 illustrates the contribution to *predicted_price* of *solar* and *demand*. Fig. 6a shows that regarding *solar*, *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). Fig. 6b shows that the amount of *demand* increases *predicted_price*. The curvature changed near the *demand* of 125 GWh (90th percentile demand), and the increasing effect on *predicted_price* increased when *demand* was beyond 125 GWh. In addition, when *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.

Fig. S7 shows the degree of contribution to *predicted_price* and

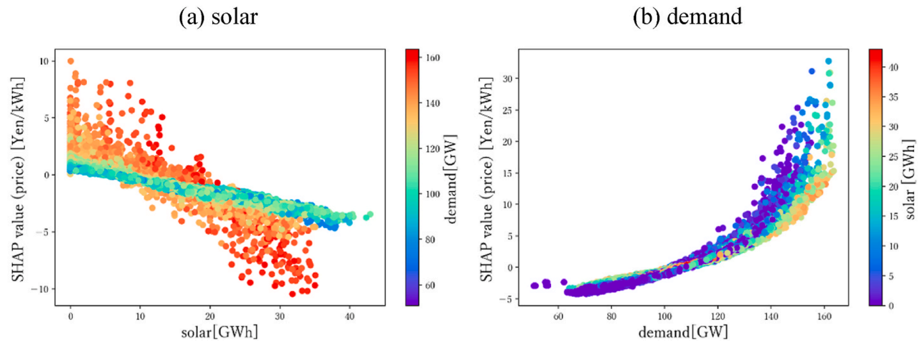

Fig. 6. Contribution to the *predicted_price* of *solar* (a) and *demand* (b); the X-axis represents the amount of solar generation and the demand, and the Y-axis represents the SHAP value (changes of *predicted_price* from baseline). The values of variables whose interactions were large have been colored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

approximate curves of *solar* and *demand*. For *solar* (Fig. 6a and S7a), 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 *predicted_price* per 1 GWh of *solar* ($R^2 = 0.96$). When *demand* was at the upper 10 % (*demand* >125 GWh), although the dispersion was large, in *solar*, for every 1 GWh, there was approximately 0.20 Yen/kWh reducing effect on *predicted_price* ($R^2 = 0.71$). These effects complement Zipp [4] (MOE: 0.103–0.154 €/MWh). The result that the effect of VRE on price varies with the magnitude of demand complements Sirin and Yilmaz [17]. However, when *demand* was high (upper 10 %), and *solar* was small (<10 GWh), *solar* had an increasing effect on *predicted_price*. This is the increasing effect on *predicted_price* in summer evenings (Fig. 5).

Fig. 6b and S7b show that regarding *demand*, there was approximately 0.12 Yen/kWh increasing effect on *predicted_price* per 1 GWh of *demand* when *demand* was below 90th percentile ($R^2 = 0.97$), whereas the effects were different depending on the amount of *solar* when *demand* was at the upper 10 %. When *solar* was within 75th percentile (<10 GWh), there was approximately 0.49 Yen/kWh increasing effect ($R^2 = 0.78$), while when *solar* was 75th percentile (>10 GWh), there was approximately 0.40 Yen/kWh increasing effect on *predicted_price* ($R^2 = 0.81$).

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

Demand is inelastic to price in the short term [63]. However, the result of relationship between solar generation and demand shows that shifting demand to match solar output is essential in increasing solar adoption. Additionally, the introduction of RE in Japan is biased toward solar power, and areas where it is installed are also unevenly distributed, so the periods during which solar power is generated (or not) are also concentrated. This also increases the amount of ramp up required when the output of solar power drops. To further expand RE, diversifying RE and installing them in geographically dispersed locations will be necessary. A clear effect of wind power was not observed, probably because the amount of electricity generated by wind was small.[2]

Through SHAP, the multi-directional interactions between variables were quantitatively and visually demonstrated. The impact of solar on market prices depends on demand, and there is a clear demand threshold; this method has the potential to be used as a pre-processing for conventional methods.

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

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

Solar, *wind*, and *operation_capacity* greatly affected *predicted_price* when *demand* was high (upper 10 %, or >125 GWh). Fig. 7a shows that when *demand* was very high (>140 GWh) and *solar* was low (<30 GWh), the *predicted_prece* increased rapidly, and *solar* reduction effect for *predicted_price* was about 0.2 JPY/kWh for 1 GWh of solar generation. When *demand* was middle to low, the reduction effect by *solar* was low. *Predicted_price* became flat when *solar* generation was very large (>30 GWh), implying that the reducing market price effect declined. This complements Keeley et al. [38], which showed that VRE becomes unresponsive to price once its share in the German electricity market exceeds a particular threshold, suggesting a limitation to the reducing market price effect. For *wind* power, Fig. 7b shows that *predicted_price* declined only when *demand* was high (upper 10 % or >125 GWh). For *operation_capacity*, Fig. 7c reveals that if *demand* is not large, *operation_capacity* will not affect *predicted_price*. However, when *demand* is high (upper 10 %, or >125 GWh), the rate of the increasing effect of *predicted_price* increases as *operation_capacity* decreases. Furthermore, *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 are not by each factor alone but largely different depending on the interaction with *demand*.

5.5. Price surge in the winter of FY2020

In Japan's spot market, the highest price over FY2016–2019 was 75 Yen/kWh but soared up to 251 Yen/kWh in the winter of FY2020. As discussed, the fluctuations in the market price of machine learning results 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 correctly captured. This infers that a phenomenon different from that during the training period occurred. Japan's Ministry of Economy, Trade and Industry (METI) reported that the main factors for this price surge were an increased demand due to sudden cold weather and an LNG stock shortage [64].

Fig. 8 shows a yearly comparison of seven days' average of the daily demand where in FY2020, they were lower than the levels during FY2016–2019 until around November, except during the summer. The declining demand due to COVID-19 may have also affected this. However, the demand increased from December 2020 to January 2021. The

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

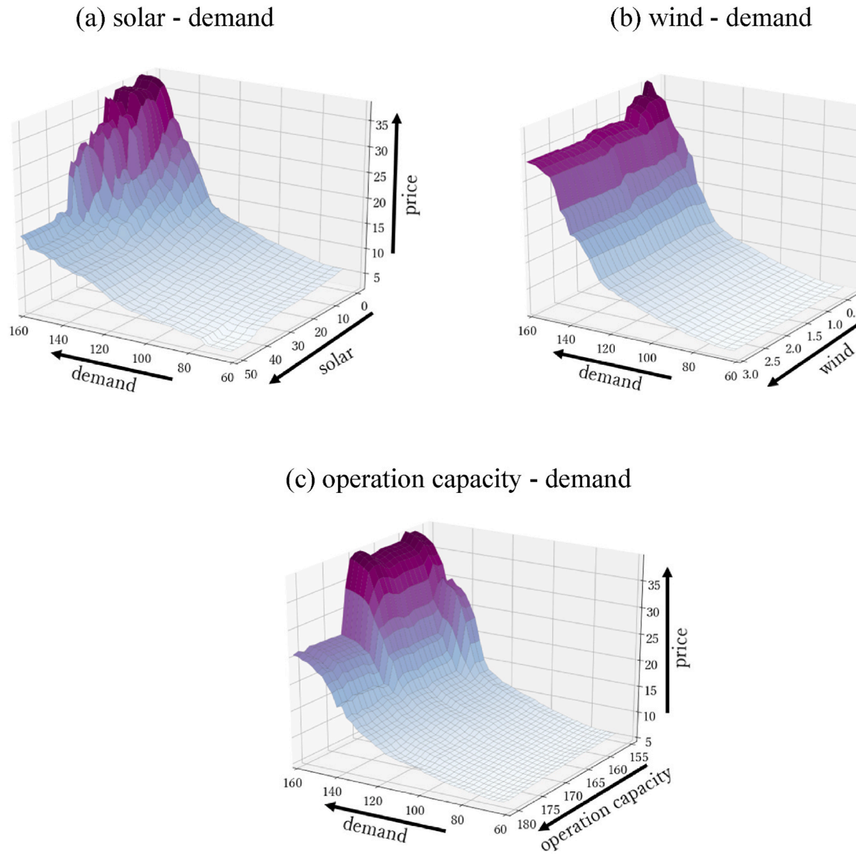

Fig. 7. PDP of *solar* (a), *wind* (b), and *operation_capacity* (c) relationship with *demand*.

demand in early January 2021 was 155 GWh, which exceeded the upper 10 % demand of 125 GWh, where the surge rate of the market price was higher.

The LNG stock of FY2020 at the end of April to July 2020 was higher than that in FY2018 and FY2019, which was approximately 2.5 million tons but decreased to approximately 2 million tons at the end of August [64]. The LNG stock increased when heading into the winter in FY2018 and FY2019 to around 2.5 tons at the end of November, but it remained low in FY2020. Power companies had planned to increase their LNG stock from December, but due to supply problems in gas-producing countries, stocks remained at low levels. Kyushu Electric Power Company, 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 [65]. With demand slump due to COVID-19, the market structure and management environment may have caused some decreases in LNG inventory. The LNG stock was not included in this analysis because of the lack of data.

Fig. 9 shows the relationship between *operation_capacity*, *solar*, and *demand*. The variable *operation_capacity* consistently decreased across FY2016–2020, 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 [66], but until FY2019, the market price was kept low.

In Japan, the capacity market has not started, and there was little appetite for investment in peak-load power plants. Solar power is only generated during daytime and does not supply power during bad weather. The maximum *demand* was about 150 GW, although it varies from year to year. During the price surge, the supply was insufficient because *operation_capacity* and *demand* were at the same level. Fig. 10 shows bid curves at the time of the price surge. For the supply curve with the merit order, the price increased progressively depending on the

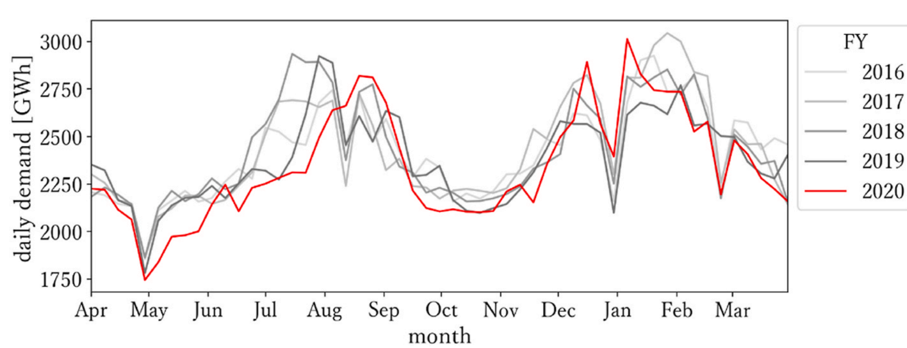

Fig. 8. Seven days' average of daily demand.

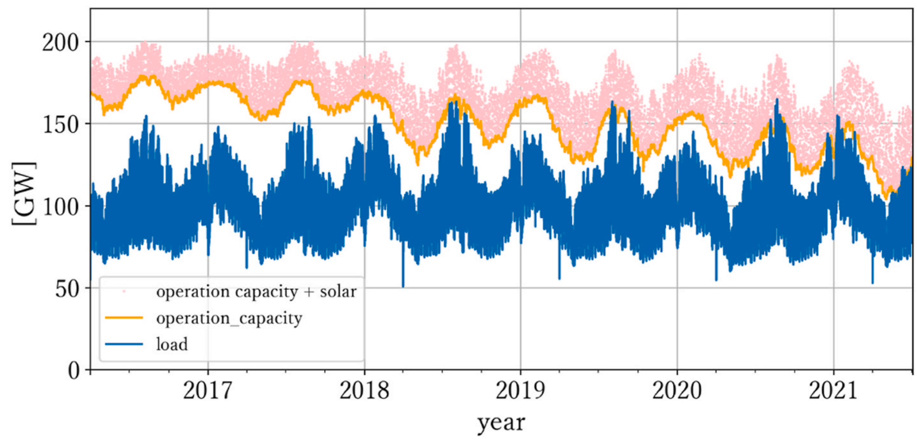

Fig. 9. Relationship between *operation_capacity*, *solar,* and *demand* (Pink dot: Sum of *operation_capacity* and *solar* (hourly value); Orange line: *operation_capacity*; Blue line: *demand*).

power facility type. When the supply becomes insufficient, the curve becomes straight, and the market soars. As shown in Fig. 10, the sell bid was sold out at that time. The PDP of *operation_capacity* (Section 5.4) also depicts this behavior. At the time of the price surge in the winter of FY2020, *operation_capacity* was even smaller than 160 GW, and the price surge was non-linear and sudden. This complements the large increase in the supply curve during the insufficient supply capability in Kolb et al. [14]. Additionally, since such high price data during the price surge were not included in the machine learning training period, the predicted values were greatly deviated.

Furthermore, 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 led to a price hike. Based on these results, the main causes of the price surge in the winter of FY2020 were likely short-term demand increase and LNG shortage. 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 more solar power generation and a decline in operating supply capacity due to the discontinuation or shutdown of existing power plants. Antweiler and Muesgens [66] showed that the MOE is a transitory effect and tends to decline in the long term when capacity is allowed to adjust for RE. The study asserted 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

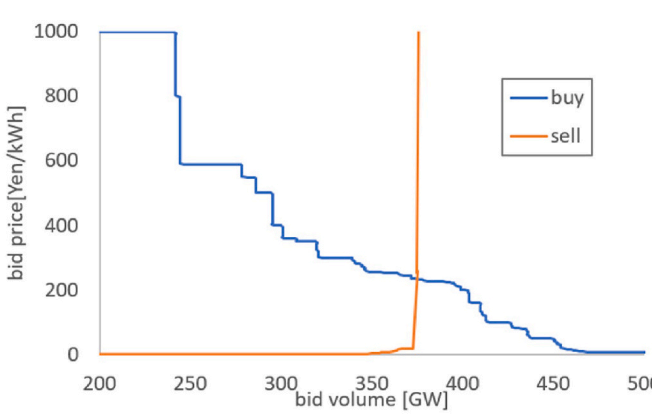

Fig. 10. Bid curve at the time of the price surge in the winter of FY2020 at 16:30, January 15, 2021, and the highest market price of 251 Yen/kWh (Compiled by authors on the JEPX data) [51].

transition, there is a risk of supply capacity shortages. Japanese market price spike in winter 2021 may be a process of this adjustment. Additionally, natural gas is one of the main flexibility to back up VRE nowadays. Due to rising global demand for natural gas, there are risks of price spikes, fuel shortages, and geopolitics. To ensure a stable electricity supply and transition to decarbonization, RE diversification and managing the pace of RE installation and transition of conventional power plants will be important.

5.6. Discussion and future work

In this study, the combination of machine learning and XAI has revealed the previously undisclosed impacts on the electricity market resulting from various variables, including demand, fuel prices, capacity, renewable generation, season, and time. The results of this study are consistent with existing research (approximately 0.11–0.20 Yen/kWh price reduction effect from solar). While this study was conducted for the Japanese electricity market as an example, the methodology is not limited to Japan and can be applied to other regions. The implications for policymakers are to have a clearer understanding of the effects of their policies, such as the consequences of reducing conventional power generation in tandem with the introduction of renewable energy. This study also highlights the importance of flexibility in response to price spikes when renewable generation is low. This highlights the need for demand response and demand-shifting strategies. Furthermore, while the model did not fully capture price surges, it can serve as an anomaly detection tool, alerting stakeholders to unusual phenomena that may have implications for industry and regulators. As RE continues to be introduced into the electricity market, over-reliance on natural gas for VRE backup introduces risks such as price spikes, fuel shortages, and geopolitical concerns. Diversifying RE sources and managing the transition of conventional power plants will be necessary to ensure a stable electricity supply and advance decarbonization.

Amid Japan's rapid expansion of solar power, the operation capacity, with a conventional power capacity of 100 MW or more, continues to decline in Japan. Solar power reduces the daytime market price and may also reduce the operable power facility capacity. Existing studies have shown that the decline in the market price due to MOE can deteriorate the profit of conventional power plants, leading to market price surge [5, 14] and will induce changes in peak-load and base-load capacity [66]. This study has identified that these phenomena have already been observed in Japan. This trend may be a natural part of the transition process toward decarbonization, but depending on the transition pace, there is a risk to the security of electricity supply.

In this study, the limited penetration of wind power in Japan constrained our ability to conduct an in-depth analysis of its impact. Wind power exhibits distinct generation characteristics from solar energy, potentially yielding different effects on the electricity market. Future work may include analysis of different regions and time periods to further improve our understanding of these dynamics. This new approach will contribute to a broader understanding of energy dynamics and price trends.

6. Conclusion

VRE is rapidly advancing globally, and it is important to understand how the electricity market is affected by VRE. This study has developed a new approach using machine learning (XGBoost) and model interpretation (XAI) to better understand fluctuations in the electricity market. This study uses a new approach to research the impact of VRE on Japan's electricity market.

The novelty of this study is that it develops a new method for decomposing electricity market movements into elements and explaining them, including the interactions between the elements. In addition, this study analyzes the Japanese electricity market as a sample, where a large amount of solar power has been introduced. It clarifies that the impact of solar power differs depending on the situation, such as time of day, season, and demand. Through machine learning and XAI, this study demonstrates not only the MOE, average decrease in market prices, and differences of the effect of VRE by period and interactions with other factors without pre-processing or case separation. Our method provides multi-directional analysis and contributes to understanding how the electricity market moves under VRE for market participants and policymakers.

The key findings are that the impact of solar power on market prices is highly volatile and varies greatly depending on time of day, season, and demand. Demand has the largest impact, with prices increasing nonlinearly as demand increases. When demand is large and solar generation is small, prices rise sharply. Operable power facility capacity also interacts with demand to raise prices in stepwise. Fuel prices also contribute to price fluctuations. Wind power had no clear impact on prices, likely due to the small amount of power it generated.

Our estimation results show that solar power lowers market prices during the daytime. However, when demand is high, the increasing effects on the market price were observed when solar generation was small, like on summer evenings. This may reflect that energy sources with high marginal costs, such as natural gas, which can deal with the start-up or sudden fluctuation for evening ramp-up fluctuation, are used during that period. Therefore, solar power affects market price not just during daytime when they generate electricity but also indirectly affects market price during times without generation. Furthermore, this study found that when solar generation is very large, its reducing price effect is limited. The power supply in mainland Japan is divided into nine areas, with each area having interchanging electricity connection lines. However, the capacities of the connection lines are limited. In Kyushu, where the generated share of solar power is the highest, RE electricity is sometimes restricted. To further expand the introduction of RE, it is important to amplify the connection lines, diversify the types of RE, and install them in geographically dispersed locations.

Another important point is how much our model replicates the situation of a price spike occurrence. From December 2020 to January 2021, Japan's electricity market experienced an unprecedented surge. The government attributed this to a shortage of LNG. However, the data on LNG stocks was unavailable. Therefore, this study could not replicate the price spike, but our model could capture the trend of the prices.

The contribution of this research is the development of a new methodology for a comprehensive understanding of electricity market dynamics. Using this method, it became clear that electricity market prices are affected by multiple factors. The result implies that regulations and policies must be designed to take into account the combined effects, such as the reduction of conventional thermal power capacity, instability, the impact of fuel prices on market prices, and electricity shortages. This new analysis method makes it possible to visualize a wide range of impacts, including interactions between elements, without making a priori assumptions.

In the autumn of 2021, Europe's electricity market price soared due to the lack of natural gas [67]. Additionally, the market price had a record high and high volatility in 2022 due to fears of decreased natural gas imports from Russia and gas prices surge [68]. While demand for natural gas has increased globally due to the increasing role of gas power, which is critical for the expansion of VRE and the decarbonization trend, there are risks of price spikes, fuel shortages, and geopolitics. For a smooth transition, policy support would be needed to manage the pace of power plant 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. Our study provides insights into how and when the electricity market changes with VRE and other factors that could be considered.

This research shows that VRE not only has the MOE and may also prompt structural changes in electricity systems dynamically. Beyond MOE, 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.

CRediT authorship contribution statement

Mizue Shimomura: Data curation, Formal analysis, Writing – original draft, Conceptualization. **Alexander Ryota Keeley:** Software, Validation, Writing – original draft, Conceptualization. **Ken'ichi Matsumoto:** Validation, Writing – review & editing. **Kenta Tanaka:** Validation, Writing – review & editing. **Shunsuke Managi:** Supervision, Funding acquisition.

Declaration of competing interest

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

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rser.2023.114037.

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