CNN-LSTM とアンサンブル学習を用いた電力スポット市場価格の予測及び予測信頼区間推定に関する研究

Research on Day-Ahead Electricity Price Forecasting Using CNN-LSTM and Ensemble Learning with Insights on Prediction Confidence Interval Estimation

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Abstract

Electricity price forecasting (EPF) is critical in energy markets, particularly with the rise of renewable energy sources (RES) in Japan, which can cause day-ahead spot prices to drop to nearly zero JPY/kWh, impacting retailer profitability. This study demonstrates that the Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) model outperforms the LSTM model in both prediction accuracy and computational efficiency in Japan's electricity spot market. A novel ensemble learning strategy enhances both the robustness and accuracy of the EPF model is proposed. Novel multimodal explanatory variables, including electricity spot price, system price, actual power generation, actual solar power generation, meteorological forecasts and calendar forecasts, alongside the rolling features of spot prices, are utilized and verified. Furthermore, a "policy-versus-policy" approach addresses the zero-inflated regression issue of the zero price prediction is proposed. Our model, with a comprehensive feature integration, achieves an RMSE of 5.66 JPY/kWh and an R^2 of 0.729 during the test range from 2022.01.01 to 2022.12.31. The paper also implies a novel method for estimating confidence intervals using ensemble learning.

Keywords : electricity price forecasting (EPF), renewable energy sources (RES), CNN-LSTM, ensemble learning, confidence interval

1. Introduction

In recent years, the growing integration of renewable energy sources (RES), especially wind and solar, has led to a novel occurrence in the electricity markets of the US and EU: negative spot prices [1,2]. In contrast, Japan's experience tells a different story. The substantial addition of solar and wind power to the Japanese grid has resulted in wholesale spot market prices nearing zero, recorded lowest at 0.01 JPY/kWh. These occurrences will be referred to as zero prices throughout this paper. The electricity spot prices in Kyushu region, Japan, is depicted in Fig. 1(a). Fig. 1(b) offers a zooming-in observation of the intermittent zero prices. Fig. 1(a) shows that the significant occurrence of zero prices started around 2020, primarily due to the swift adoption of RES. In this shifting energy environment, day-ahead electricity price forecasting (EPF) in spot markets has become critically important [3]. Various statistical methods, including the Autoregressive Moving Average (ARMA) [4,5] and the Autoregressive Integrated Moving Average (ARIMA) [6–8], have been extensively utilized in EPF research. Although these models offer a solid foundation, their linear nature can present limitations. The growing penetration of RES, coupled with demand variability, leads to non-linear patterns and abrupt price fluctuations that traditional statistical models might not accurately capture.

Additionally, as depicted in Fig. 1(b), the significant periods of zero prices in the target variable introduce a zero-inflated regression challenge in machine learning after data normalization. Nonetheless, most machine learning algorithms, such as Random Forest (RF), Support Vector Regression (SVR), and neural networks, usually fail to predict consistent zero values.

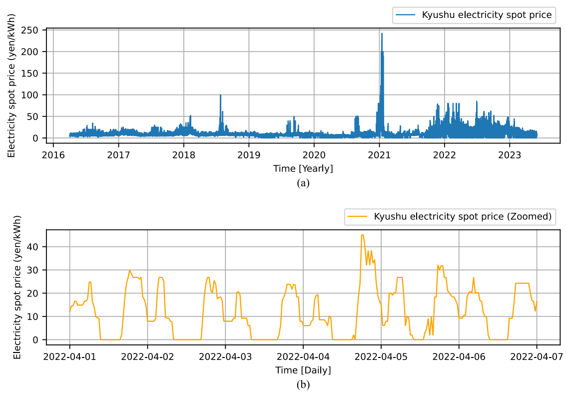

Fig. 1 Kyushu electricity spot price [JPY/kWh] (a) and zooming-in zero inflated prices (b).

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Conventional approaches to address zero-inflated regression typically require a dual-model setup: one classification model to detect zero values and a separate regression model for non-zero values. This approach effectively doubles the training time and associated costs.

To tackle the aforementioned challenges, this paper aims to improve EPF in the Kyushu region of Japan by employing multimodal data as novel features, utilizing LSTM and CNN-LSTM prediction models. Additionally, a new ensemble learning approach is applied to enhance the prediction accuracy of LSTM and CNN-LSTM models, addressing their inherent uncertainties. The performance of LSTM and CNN-LSTM in EPF is evaluated based on prediction accuracy and computation time. To address the zero-inflated problem in the Japan Electric Power eXchange (JEPX) spot market, a novel "policy-versus-policy" strategy is introduced, which forecasts zero prices and halves the computation time compared to the traditional dual-model method. Furthermore, a natural logarithm transformation is used to improve the Skewness and Kurtosis of the spot prices, thereby enhancing prediction accuracy. This paper also introduces a new method for extracting meteorological forecast data using Google Maps. Finally, a novel method for estimating the confidence interval of EPF is demonstrated.

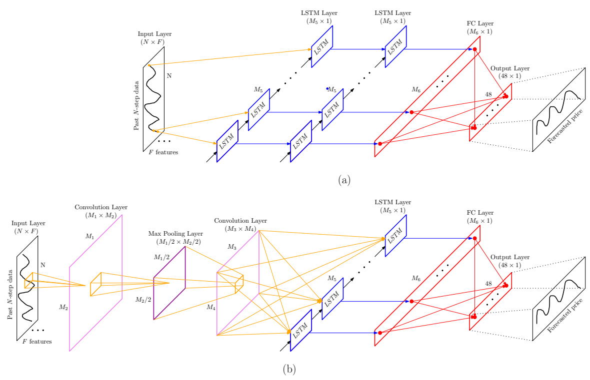


Fig. 2 Schematic of the architectures of the (a) LSTM and (b) CNN-LSTM models.

2. Methodology

2.1 LSTM and CNN-LSTM forecasting models

An LSTM model and a CNN-LSTM model were developed and utilized for EPF, with a comparative analysis conducted using the Python TensorFlow Keras library. The architectures of these models are illustrated in Fig. 2, and the hyperparameters were chosen empirically to achieve optimal performance.

2.2 Ensemble learning strategy

Due to the inherent variability of neural network models, which arises from their sensitivity to initial conditions and the stochastic nature of their training processes, training the same neural network multiple times and averaging the resulting predictions can help mitigate individual model errors. This approach leads to improved prediction performance, as different models will not produce identical errors on the test set [9,10]. Based on this principle, an ensemble learning approach was adopted. The CNN-LSTM and LSTM models were trained multiple times, and the individual predictions were then combined using an averaging method to form the final ensemble prediction.

2.3 "Policy-versus-policy" zero prices forecasting strategy

This study presents an innovative approach to address the zero-inflated regression issue in EPF within the JEPX spot market. The solution starts with an analysis of broader trends in global electricity spot markets. According to Seel et al. [1], an overabundance of RES can result in negative electricity spot prices in the US and EU. From this, we can deduce that negative pricing is a natural outcome of high RES penetration. In Japan, however, regulations stipulate that electricity spot prices cannot fall below 0.01 JPY/kWh, preventing negative prices. Assuming similar factors that lead to negative prices in the US and EU are present in Japan, it is logical to assume that the explanatory variables in these contexts would show similar patterns. When these Japanese variables are input into a machine learning regression model, the model would predict negative prices since it is not limited by Japan's minimum pricing regulation. Therefore, by using this logic, zero prices can be forecasted by converting any model negative outputs to zeros. This method operates as a "policy-versus-policy" forecasting strategy, mirroring actual market conditions.

3. Data Preparation

This study leverages multimodal data to improve EPF, incorporating actual total power generation, actual solar power generation, rolling features of spot prices (minimum, maximum, mean, and standard deviation), system spot price, meteorological forecast data, and calendar forecast data. The comprehensive data architecture and associated time frame are depicted in Fig. 3. The Kyushu area meteorological data were downloaded from the Japan Meteorological Business Support Center (JMBSC) and were obtained by using OpenCV to identify the land area on the map, as is shown in Fig. 4. The input data are divided into three green blocks based on their temporal delay. To ensure consistency with the JEPX spot price data, all inputs were linearly interpolated to a 30-min time resolution. A 7-day-long moving window was applied to the input data before being input into the CNN-LSTM and LSTM models. In the JEPX spot market, all transactions must be finalized by the 10:00 JST bidding deadline. To ensure a thorough and precise prediction process, sufficient time is

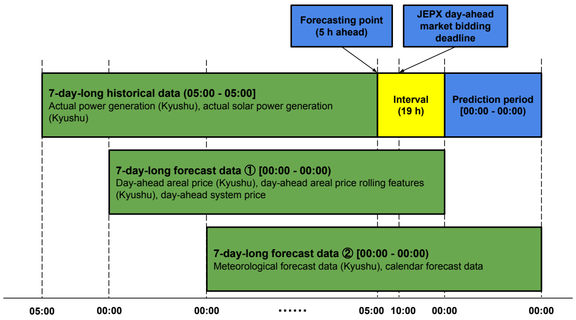
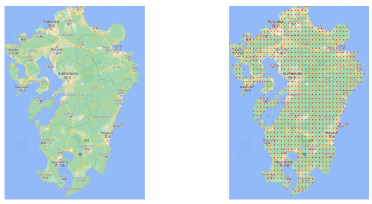


Fig. 3 Illustration of the data architecture with a 30-min time interval, highlighting the time delays among different data.

allocated for the execution and refinement of neural network calculations. Considering the computational demands and the complexities involved, a 5-hour buffer before the deadline is established. The forecasting time is set to 05:00 JST, covering the entire following day from 00:00 JST to 23:30 JST, encompassing a total of 48 time frames.



(a) (b)

Fig. 4 Kyushu area map (a) and the identified land areas (b). Map data: ©2024 Google, TMap Mobility.

In this study, photovoltaic (PV) power is the primary RES in the Kyushu region due to its significantly higher installed capacity compared to wind power. Consequently, features related to wind power are not included in this investigation.

4. Results and Discussion

4.1 Ensemble learning results

An ensemble learning technique was applied to each feature set to generate ensemble predictions. Table 1 presents the prediction accuracy and the computation time of the proposed LSTM and CNN-LSTM models. According to Table 1, the CNN-LSTM only has half the computation time of the LSTM for same training times of ensemble learning, while still boasts higher prediction accuracy over the LSTM using less computation time.

Table 1 Prediction accuracy and computation time comparison.

Model	Computation time	Ensemble times	R^2	RMSE
LSTM	59 min	15	0.5782	7.062 JPY/kWh
LSTM	120 min	30	0.5821	7.028 JPY/kWh
CNN-LSTM	**60 min**	**30**	**0.5825**	**7.027 JPY/kWh**
CNN-LSTM	40 min	20	0.5824	7.031 JPY/kWh

The results of the predictions using all features in the day-by-day prediction method are illustrated in Fig. 5. It is evident from Fig. 5 that each training iteration generates a distinct prediction on the test set, highlighting the inherent uncertainty in the neural network training process. The ensemble learning method we proposed effectively minimizes the variability present in individual model predictions. While some predictions may

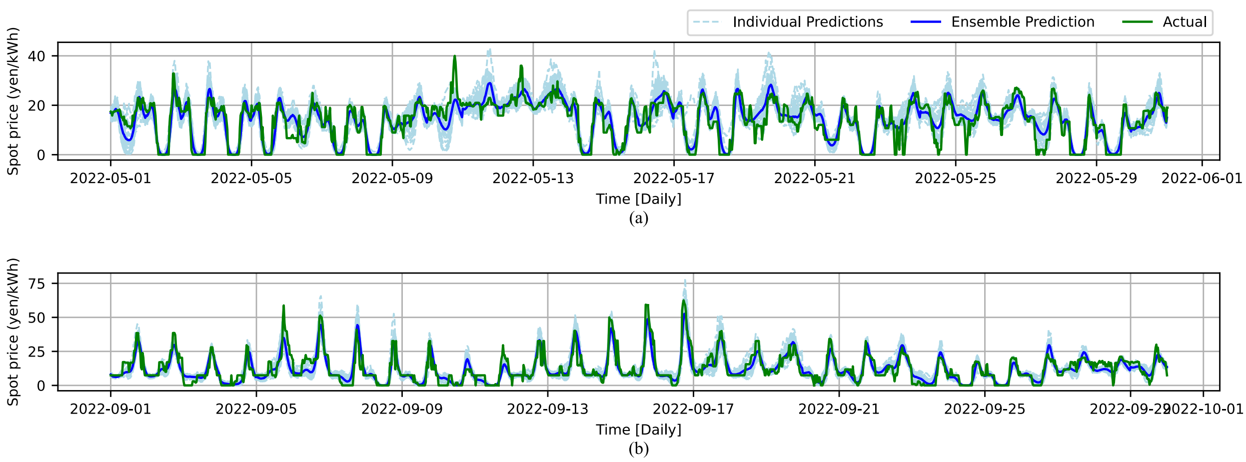


Fig. 5 Individual and ensemble predictions for the test range of May and September in 2022, using all the proposed features and day-by-day prediction approach.

significantly deviate from the actual electricity spot prices, the ensemble approach, averages these forecasts to yield a more accurate final prediction. The model's capability to predict zero prices validates the "policy-versus-policy" zero prices forecasting strategy. The performance metrics of the ensemble learning for the day-by-day prediction method using all features are presented in Table 2. This day-by-day prediction approach significantly enhances prediction accuracy compared to the one-time prediction method.

Table 2 Ensemble learning metrics for the day-by-day prediction approach using all proposed features.

Metrics	
RMSE	R^2
5.66 JPY/kWh	0.729

4.2 Implications for EPF's confidence interval

In Fig. 5, it is noteworthy that when the ensemble learning prediction accuracy is high, the 30 individual predictions tend to highly overlap each other and also demonstrate high prediction accuracy, as shown for the period 2022.05.09-2022.05.14 in Fig. 5(b). Conversely, when the ensemble learning fails to predict the actual value accurately, the 30 individual predictions tend to diverge from each other without overlapping. The standard deviation of the 30 individual predictions at the same time point is calculated and used to compute the Person correlation efficient with the ensemble learning prediction error at the same time point. The correlation efficient value is 0.462, indicating a moderate correlation. By utilizing the above-mentioned phenomenon, a novel confidence interval estimation method for EPF can be developed in our future work.

5. Conclusions and Future Work

This study has proposed an innovative EPF framework that utilizes multimodal data augmented by an ensemble learning technique. The CNN-LSTM model is superior over the LSTM model in both prediction accuracy and computation time. The logarithm transform of the pre-processing for the electricity spot price data has been shown crucial for EPF in the Japan electricity spot market. A "policy-versus-policy" strategy has been proposed to solve the zero-inflated regression problem, which halfs the computation time compared with traditional two-stage method. By using the day-by-day prediction approach, the ensemble learning method achieved a RMSE and R^2 of 5.66 JPY/kWh and 0.728 over the test range of the full year 2022. An implication for a novel estimation method of the EPF's confidence interval using the ensemble learning approach has been proposed.

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