Predicting Day-Ahead Electricity Prices in Western Denmark (Dk1) Using Bayesian Deep Learning: Robust Intervals and The Role of Renewable Energy

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Published in:
CIGRE 2025 International Symposium

Publication date:
2026

Document Version
Accepted author manuscript, peer reviewed version

CIGRE 2025 International Symposium
Palais des Congrès de Montréal, Québec, Canada
September 29 to October 3, 2025

10274
C5 ELECTRICITY MARKETS & REGULATION
Application of Technologies, Information Technology (It) and Artificial Intelligence (Ai)

PREDICTING DAY-AHEAD ELECTRICITY PRICES IN WESTERN DENMARK (DK1) USING BAYESIAN DEEP LEARNING: ROBUST INTERVALS AND THE ROLE OF RENEWABLE ENERGY

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SUMMARY

In the competitive electricity market, accurate prediction of electricity price is crucial for market participants to develop optimal bidding and offering strategies. However, due to the influence of various factors, electricity price prediction remains a challenging task. In addition, the increasing integration of renewable energy sources over the past two decades has significantly amplified price variability. Hence, to address this challenge, this study proposes a Bayesian-optimized hybrid forecasting model combining Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN). Indeed, the LSTM model is employed to capture long-term dependencies in electricity price patterns, while the CNN model is used to extract significant features and detect sudden price fluctuations. To enhance model accuracy, Bayesian Optimization (BO) is utilized for hyperparameter tuning, improving the model's efficiency and performance. Additionally, the Bayesian technique is applied to quantify the uncertainty of predictions and determine robust prediction intervals with confidence levels of 90%, 80%, and 65%. A key contribution of this study is the customized forecasting model designed for electricity price prediction in the western region of Denmark (DK1). In this model, amounts of total load, solar power, onshore and offshore wind power are used as independent variables.

Moreover, the CNN layer in the multivariate model is designed with a dilated structure, which enhances the model's ability to capture dependencies between variables and their long-term effects in the time dimension. The model is evaluated using various error metrics and the Diebold-Mariano (DM) test. Furthermore, Bayesian uncertainty analysis is used to determine the uncertainty in the results obtained with the forecasting models in different intervals. The results indicate that the Bayesian-optimized hybrid model outperforms traditional forecasting models and provides more reliable and accurate electricity price predictions. Additionally, the study highlights the significant impact of renewable energy generation on forecasting accuracy and reliability, demonstrating that incorporating renewable energy data into the model improves price prediction performance.

KEYWORDS

Energy Market, Forecast, Deep Learning, Electricity Price, Multivariate, LSTM, CNN

1 Introduction

In the competitive electricity market environment, electricity price forecasting is a critical factor for market players to develop optimal bidding/offering strategies to maximize their revenues. However, accurate prediction of electricity price is questionable due to impact of various factors on its exact value [1]. Therefore, it is necessary to predict a robust interval for the electricity price on the next day with a certain level of confidence.

There are subjective and objective factors that contribute to electricity price fluctuations. However, in the last two decades, uncertainty in electricity price has increased significantly due to the widespread integration of renewable energy sources. to deal with the temporal patterns of electricity price, long short-term memory (LSTM) based forecasting methods have been introduced in electricity price forecasting due to its ability to learn time dependencies and model long-term dependencies [2]. Memarzadeh and Keynia have proposed the LSTM method for load and price forecasting in the Pennsylvania-New Jersey-Maryland and Spain electricity markets in [3]. In the same study, load forecasting was also performed for the Iran electricity market. At the end of the study, they obtained successful results with the method they applied wavelet transform (WT) and feature selection (FS). Moreover, the convolutional neural network (CNN) method, which has the ability to extract important features and reduce scales to identify price fluctuations and sudden changes, is used in combination with LSTM [4] [5]. Heidarpanah et al. have employed the CNN-LSTM method for daily electricity price forecasting in the Iranian market in [6]. The study aimed to predict the maximum daily electricity price (MDEP) and average daily electricity price (ADEP). The proposed method's results were compared with multivariate linear regression (MLR), support vector machine (SVM), adaptive neural fuzzy inference system (ANFIS), artificial neural network (ANN), and hybrid ANN-genetic algorithm model (ANN-GA), revealing that the CNN-LSTM model achieved higher accuracy than the alternative approaches. Likewise, a hybrid CNN-LSTM model is used for day-ahead electricity price forecasting in the Indian power market in [7]. In addition, exponential smoothing is used in the proposed model. The results showed that the proposed method outperforms the LSTM and CNN-LSTM methods. Bozlak and Yaşar have used LSTM and CNN-LSTM models for day-ahead electricity price forecasting in the German electricity market and have compared the results in [8]. To capture accurate electricity price predictions, multivariate models are used in addition to univariate studies that only use past electricity prices. In this study, CNN-LSTM was a multivariate model, whereas the LSTM method was a univariate model. The study analysed three different cases, revealing that while the CNN-LSTM model performed best in 2019 and 2020, the LSTM model provided the most accurate forecasts in 2021. At the conclusion of the study, the results were statistically analysed using the Diebold–Mariano (DM) test, along with various error metrics. Micu et al. have utilized a multivariate CNN-LSTM model for electricity price forecasting in the United Kingdom (UK) in [9]. They have used power demand, generation mix (wind, solar, storage, gas, fossil fuels) and weather data as inputs for their forecasting model. The CNN-LSTM model proposed in this study has illustrated a successful performance. As deep learning methods have developed rapidly following neural network methods, hyperparameter optimization of the models has also gained importance. In order to ensure better prediction of the proposed hybrid method, the hyperparameter adjustments of the hybrid deep learning model were made with Bayesian optimization (BO) [10]. The study emphasized that the proper tuning of the hyperparameters is critical for the stability and accuracy of the model. Likewise, Dao et al. have employed BO to optimize the hyperparameters of the CNN-LSTM model in [11]. Based on the results, the CNN-LSTM model optimized with BO has enhanced the prediction accuracy.

This study aims to develop a customized forecasting model for electricity price prediction in the western region of Denmark (DK1). To achieve this, a day-ahead electricity price forecasting model based on a CNN-LSTM hybrid framework is proposed. In the forecasting phase, a multivariate model is designed to incorporate the influence of renewable energy data on electricity prices. In addition, the model utilizes a dilated CNN structure to capture long-range dependencies effectively. To optimize the hyperparameters of the prediction model, the Bayesian Optimization (BO) algorithm is employed, as it is widely used for parameter optimization in deep learning models. Finally, an uncertainty analysis of the forecasting results is conducted using the Bayesian Framework, evaluating different uncertainty intervals to enhance the model's reliability. The organization of the paper is as follows: the methodology for the electricity price forecasting is discussed in Section 2, the evaluation of the proposed model is done in Section 3 and finally, the last section sums up the findings.

2 Methods

LSTM is a type of RNN introduced by Hochreiter & Schmidhuber in 1997 as an advanced deep learning method [12]. While RNNs can capture short-term dependencies due to cyclic connections in their hidden layers, they struggle with learning long-term dependencies. LSTM was designed to address this limitation by overcoming the vanishing gradient problem in RNNs. LSTMs incorporate a memory unit and a gate mechanism, enabling them to retain relevant information while discarding unnecessary details. This capability allows them to effectively learn long-term dependencies. The key components of an LSTM network include: forget gate, input gate and output gate. This model optimizes memory cells by providing information flow on the network using these gates.

CNNs (Convolutional Neural Networks) are part of the Artificial Neural Network (ANN) family and were proposed by Lecun et al. in 1998 [13]. CNN models have the ability to process input data directly, so no additional feature extraction step is used in the early stages. The receptive field of the filter kernel (the region it covers in the input data) significantly impacts the performance of the CNN network model. To enable CNN networks to capture larger regions, their perceptual area must be expanded. In traditional networks, pooling and stride-based convolution methods are commonly used to achieve this; however, these approaches can lead to loss of important features in some cases. To address this issue, the dilated convolution method has been introduced. In classical convolution, filters are applied to adjacent elements in the input data to generate an output feature map [14]. In dilated convolution this process involves sampling values at specific intervals, leaving gaps determined by the dilation rate. This approach allows the model to capture a broader context without reducing the resolution of the feature map.

2.1 Hybrid Structure

In this study, a new prediction structure is developed by using CNN and LSTM models in a hybrid structure. CNN structure is used to extract the high features of the dataset and reduce the data size. Then, taking these extracted features, LSTM is used to learn the long-term dependencies in the time series. In the proposed model, the first convolutional layer of the CNN stage is dilated-CNN followed by two convolutional layers of classical CNN and then, an LSTM layer is added. The schematic architecture of the proposed prediction model is given in Figure 1.

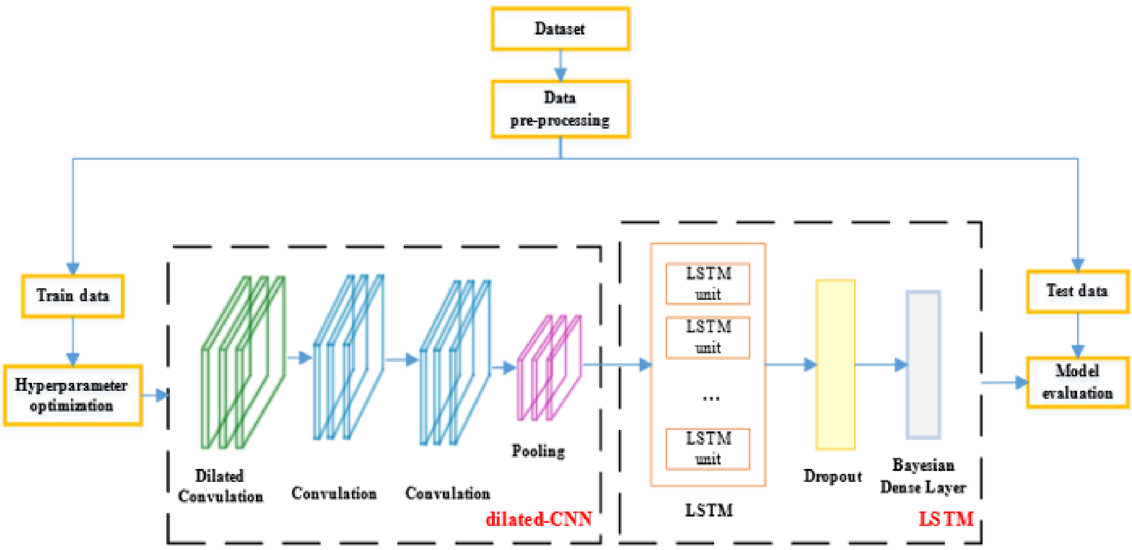

Figure 1 – The framework of the proposed forecasting model

2.2 Hyperparameter Tuning

The drawback of complex deep learning models, including ANN-based methods, is determining the optimal hyperparameters. These models require training to effectively fit the given problem. The goal of the optimization process is to identify the best set of parameters within the search space of possible parameter combinations. Even a small change in hyperparameters can significantly impact the model's performance, making hyperparameter selection a crucial optimization problem. In this study, Bayesian optimization method is chosen for this purpose. Since the objective is to achieve the lowest error rather than simply running the model, the optimization problem can be formulated as follow:

$$P^* = \underset{P \epsilon S}{argmin} f(P) \tag{1}$$

where P denotes the set of hyperparameters in the search space and $f(P)$ denotes the objective function. S is the search space of possible hyperparameter candidates.

3 Results

In this paper, an improved hybrid deep learning approach combining CNN and LSTM layers is presented for electricity price prediction. First, CNN layers are employed to capture the temporal patterns and relationships within the input data. Additionally, these layers help suppress noise in the time series and mitigate the impact of unstable components. In this step, the CNN layer is used in a dilated structure. Subsequently, the LSTM layer is utilized to learn the long-term nonlinear dependencies among the outputs of the CNN unit, resulting in more accurate prediction outcomes. In this regard. the hyper parameters of the deep learning models were determined using Bayesian optimization algorithm. Finally, in the stage of the forecasting model, a Bayesian dense layer is used to analyse the uncertainty.

The proposed forecasting model has been evaluated based on the hourly data for the western region of Denmark (DK1), covering the period from 01/05/2023 00:00:00 to 01/06/2024 00:00:00. Data taken from Energi Data Service [www.energidataservice.dk]. To compare the forecasting performance of the multivariate forecasting model, the study examines both univariate and multivariate forecasting models: the univariate model relies on the price dataset for the specified period and the multivariate model incorporates amount of the total load and renewable energy sources (amounts of solar power, wind power onshore and wind power offshore data) in addition to price data. In this study, missing data in the dataset were filled by averaging the values from the preceding and following time steps. For training the forecasting models, approximately 90% of the dataset (01/05/2023 - 30/04/2024) was used, while the remaining 10% (01/05/2024 - 31/05/2024) was used for testing phase.

RMSE (%), sMAPE (%), MAE, and R^2 were used as performance metrics to measure the prediction models. RMSE (%) quantifies the average magnitude of the error between actual and predicted values. sMAPE (%) measures the symmetric percentage error, providing a scale-independent evaluation of forecasting accuracy. MAE represents the mean absolute difference between predicted and actual values and R^2, which indicates the proportion of variance in the dependent variable explained by the independent variables, was used to assess the model's explanatory power and predictive accuracy. The aforementioned metrics can be formulated using Eqs. (2) - (5):

$$RMSE = \sqrt{\frac{1}{N}\sum_{n \in N}(y_{actual} - y_{estimated})^2} \tag{2}$$

$$sMAPE = \frac{1}{N}\sum_{n\in N}\left|\frac{y_{actual} - y_{estimated}}{(|y_{actual}| + |y_{estimated}|)/_2}\right| \quad (3)$$

$$MAE = \frac{1}{N}\sum_{n\in N}|y_{actual} - y_{estimated}| \quad (4)$$

$$R^2 = 1 - \frac{\sum_{n\in N}(y_{actual} - y_{estimated})^2}{\frac{1}{N}\sum_{n\in N}(y_{actual} - y'_{actual})^2} \quad (5)$$

where N is the amount of data. y_{actual} and $y_{estimated}$ are observed and predicted results of the prediction models, respectively. y'_{actual} is the mean of actual values. The criteria in Eqs. (2) - (4) are based on the error rate between predicted and actual values, where lower values indicate higher prediction accuracy. Since R^2 measures the fit between the predicted and actual results, a higher R^2 value signifies a stronger alignment between them, indicating better model performance. The evaluation of the results obtained from univariate and multivariate forecasting models based on error criteria is presented in Figure 2.

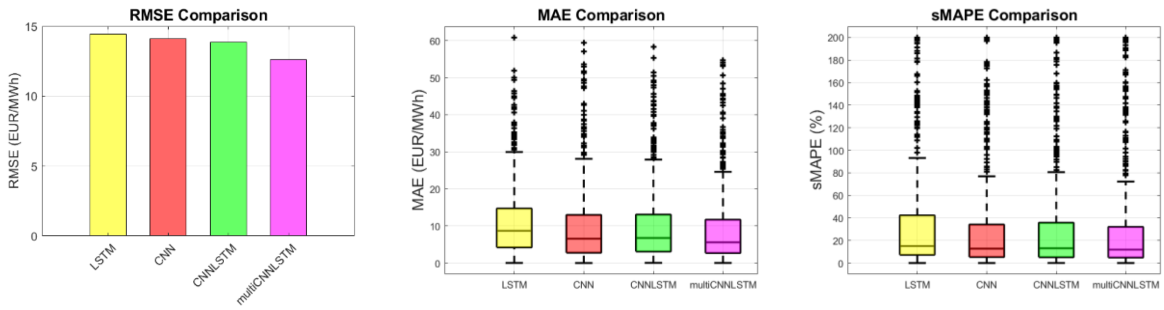

Figure 2 – One-month prediction results

As depicted in Figure 2, the proposed model outperforms all other models. In addition to obtain the lowest RMSE (12.59), sMAPE (39.05) and MAE (8.64), it provides the strongest explanatory power with the highest R^2 value (0.901). The findings show that the proposed multi-CNN-LSTM model provides the most accurate predictions with the lowest error and the highest explanatory power. In contrast, the LSTM model exhibits the highest RMSE (14.44) and sMAPE (42.31), indicating that it has relatively lower prediction accuracy. Although the CNN model provides an improvement over the LSTM, especially in terms of MAE (9.80), it lags behind the multi-CNN-LSTM. Similarly, the CNN-LSTM model offers some improvements compared to CNN with lower RMSE (13.85) and MAE (9.86) values, but it fails to reach the level of multi-CNN-LSTM. When examining the dispersion and outliers in the RMSE and MAPE results, the LSTM and CNN models exhibit more outliers, suggesting that they occasionally produce large prediction errors. In contrast, the multi-CNN-LSTM and CNN-

LSTM models have fewer outliers, indicating a more consistent and stable prediction performance.

As illustrated in Figure 3, the Bayesian dense layer is utilized in the final step to quantify the uncertainty of the prediction model. This figure presents the uncertainty levels of different prediction models, highlighting the 90%, 80%, and 65% uncertainty intervals, respectively. Additionally, Table 1 provides a detailed comparison of the uncertainty analysis results across different models. A high confidence interval reflects the model's reliability and accuracy in uncertainty estimation. Analysing the results across different confidence intervals reveals that the proposed method achieves the highest values in all intervals, indicating the widest confidence interval coverage. The CNN model ranks second, demonstrating better uncertainty management than CNN-LSTM and LSTM method while maintaining high accuracy.

The results of the uncertainty analysis for different forecast models are given in Figure 3. The provided subfigures illustrate the comparison between predicted and actual values. Additionally, the results of the uncertainty analysis at 90%, 80%, and 65% confidence levels are visually presented, highlighting the respective uncertainty ranges. The 90% confidence interval provides a broader range for analysis, while the 65% confidence interval offers a more constrained perspective. Additionally, each forecast result graph includes a zoomed-in view showing the prediction results for May 15th. Among the evaluated models, the proposed model produces the most reliable prediction results, demonstrating superior uncertainty management.

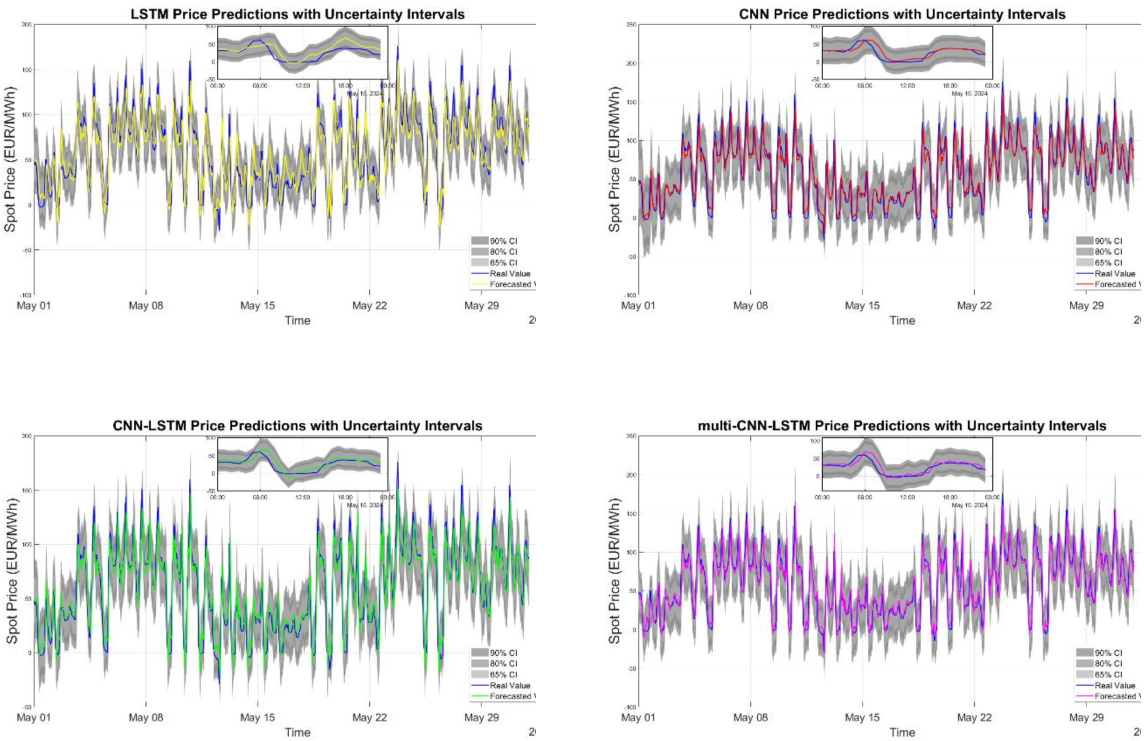

Figure 3 – Forecasting performance with 90%, 80%, and 65% confidence intervals

The DM test was implemented to compare the prediction errors of the developed model and the benchmarked prediction model and to determine whether there is a statistically significant difference. Results have been provided in Table 2. If the result of the DM test is positive, it means that the second forecast model is successful when the null hypothesis can be rejected, while a negative result means that the first forecast model is more successful. The DM test values for LSTM, CNN, and CNN-LSTM highlight the differences in their prediction accuracy. According to the MSE criterion, the p-values for LSTM, CNN, and CNN-LSTM are 2.57E-05, 2.05E-08, and 3.5E-07, respectively. Similarly, based on the MAE criterion, the p-values are 1.28E-11, 2.59E-09, and 6.2E-10. These values are all below the 0.01 significance level, leading to the rejection of the null hypothesis, indicating a statistically significant difference in forecast accuracy among the models. This indicates that the proposed model performs statistically significantly better than the other forecasting models. The rejection of the null hypothesis in all comparisons confirms that the observed performance differences are statistically significant.

Table 1 – Uncertainty analysis results

Models	90% confidence interval	80% confidence interval	65% confidence interval	R^2 (%)
LSTM	96.10	91.40	83.74	0.870
CNN	97.31	95.43	90.46	0.876
CNN-LSTM	96.24	92.74	84.01	0.880
proposed model	97.98	96.37	93.15	0.901

Table 2 – DM test results: interpretation of test statistics, p-values, and significance levels

Testing the proposed model with other prediction models				
Model	DM Test Value	p-value	Significance Level (%)	Accept/Reject
MSE				
LSTM	4.23	2,57E-05	1	Reject
CNN	5.67	2,05E-08	1	Reject
CNN-LSTM	5.14	3,5E-07	1	Reject
MAE				
LSTM	6.88	1,28E-11	1	Reject
CNN	6.03	2,59E-09	1	Reject
CNN-LSTM	6.27	6,2E-10	1	Reject

To enhance comprehensibility, the 1-day forecast results are presented in Figure 4. Among all methods, proposed model produces the closest predictions to the actual values. While other models can capture the overall trend of the curve, the proposed method achieves the most accurate results. Additionally, this figure displays RMSE values for the forecasts made on May 1, 2024, further confirming that the developed model outperforms the others in prediction accuracy.

Within the scope of this study, electricity price forecasts were generated using four different models. As shown in Figure 3, the observed values align more closely with the predictions made by proposed, demonstrating its superior performance. This is further supported by the prediction results in Figure 2, where different error criteria confirm its accuracy. Additionally, the DM test applied to the prediction results indicates that the developed model is statistically significantly different from the other methods.

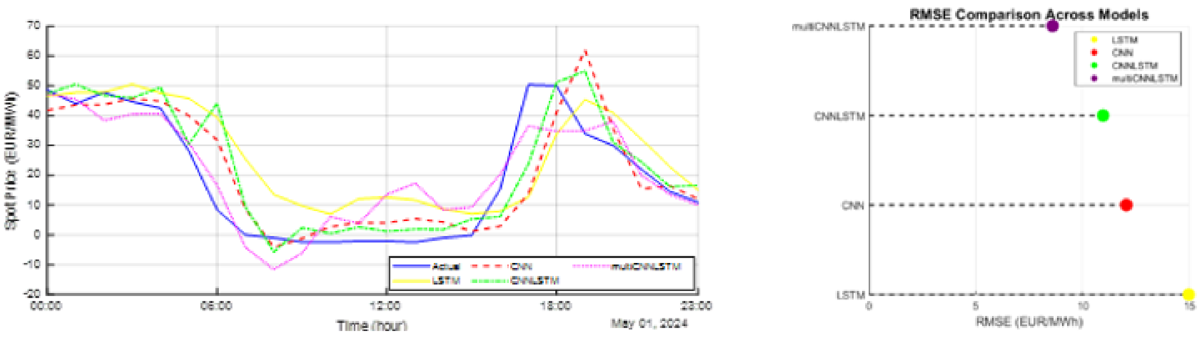

Figure 4 – One-day prediction results

Figures 3 and 4 present the forecasting results for May, which corresponds to the spring season. The distribution of electricity prices varies across different seasons, which in turn affects forecasting accuracy. To address the impact of seasonal variations, the monthly forecasting results obtained using the proposed method across the other three seasons are presented in Figure 5.

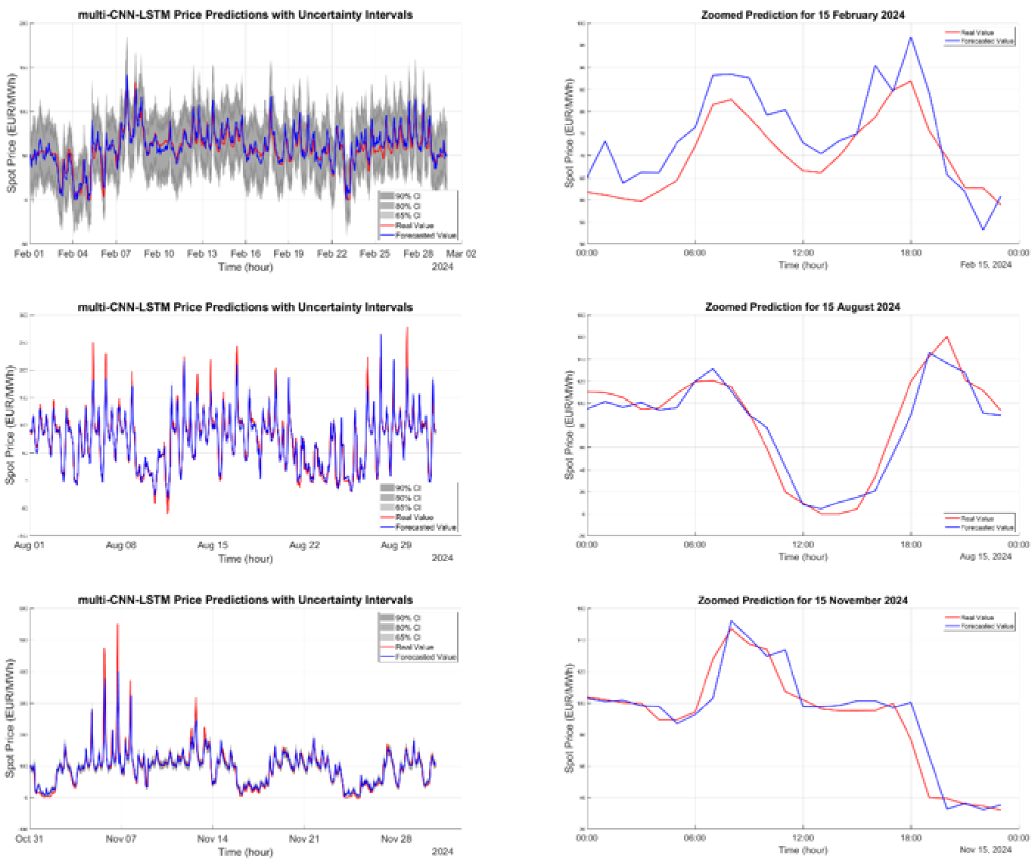

Figure 5– Prediction performance across different seasons

Figure 5 presents the predicted electricity prices along with their corresponding confidence intervals, offering insights into the model's uncertainty. Additionally, zoomed-in forecasts for the 15th day of each selected month are provided to enable a detailed assessment of the proposed model's daily prediction performance. The RMSE value for February is 8.09, whereas it increases to 14.97 in August and 19.52 in November. This variation can be attributed to the absence of sudden price fluctuations in the February, while the August and November exhibit more volatile price behaviours. The numerical and graphical results indicate that the proposed approach performs successfully in forecasting electricity prices.

4 Conclusion

In this paper, a deep learning-based CNN-LSTM hybrid model is proposed for day-ahead electricity price prediction in electricity markets. Dilated convolution structure was preferred for CNN networks to capture larger regions. The impact of renewable energy sources on electricity prices was also considered in this study. In this regard, the prediction method is developed in a multivariate structure and amounts of total load, solar power, onshore and offshore wind power data are used as independent variables. The hyperparameters of the proposed deep learning method were optimally tuned using Bayesian optimization method. The obtained results were compared with the univariate LSTM, CNN and CNN-LSTM methods according to different error criteria. RMSE values of the univariate hybrid model were 10.96, compared to 14.98 and 12.05 for LSTM and CNN, respectively. The multivariate model achieved an improved RMSE of 8.59. The DM test applied to the results also statistically demonstrated the success of the proposed method. The time series data of electricity price in the energy market has a complex structure and usually contains components of different frequencies. Therefore, in future studies, a comprehensive study of this time series will be aimed using decomposition techniques.

5 Acknowledgments

İnayet Özge Aksu acknowledges support from the Scientific and Technological Research Council of Türkiye (TÜBİTAK) BIDEB-2219 Postdoctoral Research Fellowship Program. Amjad Anvari-Moghaddam and Sina Ghaemi also acknowledge the support of MARGIN project funded by Danida Fellowship Center and Ministry of Foreign Affairs of Denmark under the grant no. 21-M06-AAU and the EFFORT project granted by El-Forsk grant no. ELF221-496872.

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