Electricity Spot Price Forecasting For Habo Plast

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***Abstract*—Electricity price forecasting is crucial for industrial companies seeking to optimize production costs. This study focuses on predicting hourly electricity prices for Habo Plast, a plastic manufacturing company with high energy consumption. Using historical electricity price data and weather variables from the Swedish Meteorological and Hydrological Institute (SMHI), we evaluated four machine learning models: Random Forest, XGBoost, Artificial Neural Networks (ANN), and Long Short-Term Memory (LSTM) networks.**

Our results indicate that tree-based models (Random Forest and XGBoost) struggle with high volatility, achieving a mean absolute error (MAE) of approximately 29-34 EUR. ANN slightly improved the predictions but remained insufficient for commercial use. LSTM models showed promising results with a significantly lower MAE; however, concerns regarding potential data leakage and overfitting need further investigation.

The weak correlation between electricity prices and weather variables suggests that external factors, such as geopolitical events, power plant maintenance schedules, and market trends, play a crucial role in price fluctuations. Our analysis also reveals that electricity prices peak between 07:00–09:00 and 18:00–20:00, emphasizing the need for strategic production scheduling.

This study highlights the challenges in electricity price forecasting and suggests future improvements by integrating additional data sources and advanced deep learning techniques to enhance predictive accuracy.

I. Introduction

Habo Plast is a company that produces plastic components using heavy machinery, which consumes a significant amount of electricity. To optimize their production process and reduce costs, they aim to plan their manufacturing activities according to fluctuations in the electricity price, thereby avoiding high electricity bills.

The objective of this project is to predict the hourly electricity price for the next week. To achieve this, we used weather data from the Swedish Meteorological and Hydrological Institute (SMHI) along with historical electricity price data provided by the company.

Our approach involved merging and analyzing all available data, followed by a literature review to identify the most commonly used machine learning (ML) techniques for electricity price forecasting. Based on our findings, we selected four ML models for experimentation: Random Forest, XGBoost, Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks.

The ML models provided moderate predictive performance. XGBoost, despite its efficiency in training, yielded a mean absolute error (MAE) of 29. ANN displayed even worst results but with similar RMSE. Finally, LSTM achieved the best overall results, but a concerningly low MAE of 5 over a three-month prediction window suggested a potential data leakage issue, leading to overfitting.

II. Background

A literature review was conducted to identify the most commonly used machine learning techniques for similar tasks. Based on these findings, the following models were selected for evaluation: Random Forest, Extreme Gradient Boosting (XGBoost), Artificial Neural Networks (ANN), and Long Short-Term Memory (LSTM) networks.

A. Electricity Price Forecasting Approaches

Electricity price forecasting is a well-studied problem, commonly approached using four categories of models: statistical models, machine learning models, deep learning models and ensemble methods. Each type offers distinct advantages and limitations. Ensemble methods were not considered in this study due to their limited application in similar contexts and our lack of prior expertise with these techniques.

B. Statistical Models

Statistical models are widely used in electricity load and price forecasting due to their ability to capture temporal dependencies and trends in time-series data. One of the most commonly used techniques is the AutoRegressive Integrated Moving Average (ARIMA) model, which combines autoregressive components, differencing, and moving averages to model stationary time-series data. [2].

C. Machine Learning Models

Machine learning models offer a powerful alternative to traditional statistical methods, particularly for handling nonlinear relationships and complex patterns in electricity price data. Two widely used tree-based ensemble methods are Random Forest and XGBoost.

a) Random Forest: Random Forest is an ensemble learning algorithm that constructs multiple decision trees during training and aggregates their outputs to improve predictive accuracy. Each tree is trained on a random subset of the data, reducing overfitting and enhancing generalization. The final prediction is obtained by averaging the predictions of individual trees for regression tasks or by selecting the majority class for classification tasks.

b) Extreme Gradient Boosting (XGBoost): XGBoost is a gradient boosting algorithm that sequentially trains decision trees, where each tree corrects the errors made by the previous ones. The model optimizes an objective function that includes both a loss function (e.g., mean squared error) and a regularization term to control model complexity and prevent overfitting. Due to its scalability and efficiency, XGBoost is widely used in electricity price forecasting [2].

D. Deep Learning Models

Deep learning models, particularly artificial neural networks (ANN) and recurrent architectures like LSTM, have gained popularity for electricity price forecasting due to their ability to learn complex patterns and temporal dependencies.

a) Artificial Neural Networks (ANN): ANNs consist of multiple layers of interconnected neurons, where each layer transforms the input data through weighted connections and activation functions. They are effective at capturing nonlinear relationships in electricity prices.

b) Long Short-Term Memory (LSTM): LSTMs are a type of recurrent neural network (RNN) specifically designed to handle sequential data. Unlike standard RNNs, LSTMs incorporate memory cells with three key gates: a forget gate, an input gate, and an output gate. These mechanisms allow LSTMs to retain long-term dependencies, making them particularly suitable for time-series forecasting. [2].

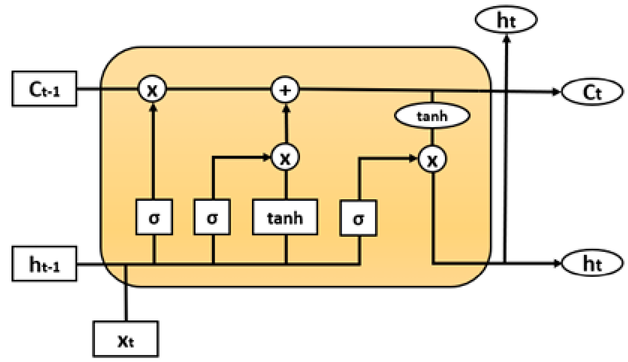

Fig. 1. LSTM cell structure [2]

III. Related Work

A. Time Series Forecasting: A Selective Review

De Gooijer and Hyndman [3] provide a comprehensive review of 25 years of research in time series forecasting, focusing on publications in the International Journal of Forecasting. The paper categorizes forecasting models, including exponential smoothing, ARIMA models, state-space models, nonlinear models, and long-memory processes. Key developments in forecasting accuracy measures and prediction intervals are also discussed. The review highlights both progress and existing gaps in time series forecasting methodologies, concluding with directions for future research.

B. Electricity Spot Price Modeling and Forecasting in European Markets

Tehrani et al. [2] analyze electricity price dynamics across six European countries (France, Germany, Italy, Spain, the UK, and Denmark) using ARIMA and GARCH models. The study explores market volatility, outliers, and asymmetry in price movements. A comparison of out-of-sample forecasts reveals structural differences between markets. The findings emphasize the role of market mechanisms and the impact of country-specific factors on price fluctuations, contributing to the broader understanding of electricity price modeling. This paper initially motivated the exploration of ARIMA modeling. However, after conducting a thorough data analysis and preliminary testing, we determined that it was not suitable and discarded it.

C. State-of-the-Art Electricity Load and Price Forecasting

Laitsos et al. [1] provide a detailed review of recent advancements in electricity load and price forecasting techniques. The study covers statistical models like ARIMA and GARCH, as well as machine learning and deep learning approaches, including neural networks and ensemble learning methods. The paper discusses the impact of renewable energy integration, market regulations, and decentralized energy systems on forecasting accuracy. The review identifies key trends, highlighting the increasing reliance on artificial intelligence models for improved forecasting performance in modern electricity markets. This paper provided valuable insights into the most commonly used models, relevant error metrics, and the underlying mechanisms of electricity pricing.

IV. Method

A. Preprocessing

For data preprocessing, we used a `MinMaxScaler()` to normalize the data. While scaling does not affect tree-based models like Random Forest and XGBoost, it is crucial for deep learning models such as LSTM to ensure stable training.

Additionally, we aggregated daily data to match the hourly format by copying daily values to each corresponding hour.

B. Data Analysis

First, we plotted a correlation matrix (Fig. 2) to assess potential relationships between electricity prices and weather variables. This helped identify features that could be relevant for predictive modeling. This plot revealed small but nonetheless present correlation between the weather and the price especially with the wind speed and the air temperature.

Next, we analyzed the Autocorrelation Function (ACF) (Fig. 3) and Partial Autocorrelation Function (PACF) (Fig. 4) plots. These statistical tools allowed us to determine whether an autoregressive model like ARIMA would be suitable for our dataset by examining dependencies between past and future values. We also assessed the stationarity of the time series using the Dickey-Fuller test, which confirmed that the data was stationary.

The PACF exhibited a sharp drop after a few lags, while the ACF gradually decreased. This pattern is characteristic of an autoregressive (AR) process, indicating that past values of the series influence future values, whereas a moving average (MA) component was not necessary. Given that the series was already stationary, and the observed behavior aligned with an AR model, we determined that an ARIMA model (which includes differencing for stationarity) was not needed in this case.

Additionally, we visualized electricity price trends over time to manually inspect patterns, detect seasonality, and validate the integrity of the data. This step ensured that our dataset was correctly structured before applying machine learning models. We observed the presence of negative prices, and after consulting with the company, we confirmed that this was normal.

C. Machine Learning Models

We experimented with four machine learning models: Random Forest, XGBoost, LSTM, and ANN.

- **Random Forest and XGBoost:** These models were chosen for their simplicity, ease of implementation, and ability to capture non-linear relationships. They served as a baseline to assess whether patterns existed in the data and provided an initial performance benchmark for comparison with deep learning models.
- **ANN:** A fully connected Artificial Neural Network was implemented to model complex relationships in the data. ANNs can learn non-linear patterns effectively and are useful for regression tasks when provided with sufficient training data. The model served as a deep learning benchmark to compare against LSTM and traditional machine learning approaches.
- **LSTM:** This model was selected for its ability to capture temporal dependencies and emphasize recent data points. LSTMs are well-suited for sequential forecasting due to their memory retention capabilities, making them effective for multivariate time series data.

D. Training Strategy

For the tree-based models (Random Forest and XGBoost), we trained on the most recent four weeks of data and predicted one week ahead. This approach was chosen to mitigate the effects of inflation and over-generalization, which negatively impacted model performance when trained on the entire dataset.

For the LSTM model, we trained on the entire dataset up to the training set boundary and predicted the following week. Given its superior performance, we further fine-tuned its hyperparameters.

E. Hyperparameter Tuning

To optimize the LSTM model, we conducted hyperparameter tuning using `GridSearchCV`. The following parameters were fine-tuned:

- **Number of epochs:** Determines the number of training iterations.
- **Number of units:** Controls the dimensionality of the hidden state.
- **Dropout rate:** Helps prevent overfitting by randomly dropping neurons during training.
- **Batch size:** Affects the number of training samples processed before model weight updates.

By systematically optimizing these parameters, we aimed to enhance the LSTM model's generalization ability while minimizing overfitting risks.

V. Experiment Design

In our experiments, we used the following features: *Air Temperature* (°C), *Precipitation Amount* (mm), *Snow Depth* (m), *Sunshine Duration* (s), *Wind Speed* (m/s), *Hour*, *Day of the week*, *Month*, and *Electricity Price* (EUR).

A. Performance Metrics

To evaluate model performance, we used two metrics:

- **Mean Absolute Error (MAE)**: Measures the average absolute difference between predicted and actual prices, expressed in the same unit (EUR), making it intuitive and easy to interpret.
- **Root Mean Squared Error (RMSE)**: Similar to MAE but more sensitive to larger errors, as it squares the deviations before averaging.

B. Experimental Setup

For model validation, we implemented the following strategies:

- **Tree-Based Models (Random Forest and XGBoost)**: We applied moving window cross-validation across the entire dataset. These models were trained on a four-week period and tested on a one-week period, their computational efficiency allowed us to evaluate them across the entire dataset.
- **LSTM Model**: We used time series split validation, testing on a three-month period from 2023 onward and using an 80/20 split for data from 2016 onward.

- **ANN Model**: For ANN we used a hold-out validation, the model was trained in 90% of the set and tested on the last 10%. Training incorporated early stopping to prevent overfitting, with optimization via the Adam algorithm and mean squared error loss.

C. Implementation Details

The project was implemented in Python 3.12.9 using the following libraries:

- `pandas`, `numpy` – data processing
- `sklearn` – Random Forest model, performance metrics and hyperparameter tuning
- `xgboost` – XGBoost models
- `matplotlib` – visualization
- `tensorflow` – LSTM model

D. Computational Resources

Hyperparameter tuning was conducted on a machine running Windows 11, equipped with an AMD Ryzen 7 7700X processor and 32 GB of DDR5 RAM. It was also performed using multithreading; however, we were unable to utilize GPU acceleration.

VI. Results and Analysis

A. Results

The performance of the different models in terms of MAE and RMSE is presented in Table I.

Model	MAE	RMSE
Random Forest	29.70	38.55
XGBoost	29.43	38.08
ANN	34.45	39.52
ANN (1h pred.)	9.215	13.98
LSTM (2016)	5.47	10.90
LSTM (2023)	10.30	15.16

TABLE I
Performance comparison of different models.

B. Analysis

The XGBoost model outperformed Random Forest, which in turn showed better performance than ANN. However, all three models exhibited an MAE around 30, which we consider too high for commercial usability. Tree-based models struggled to forecast electricity prices in periods of high volatility. Additionally, they lacked the ability to use prior predictions, relying solely on weather data for forecasting. ANN performs well for a 1-hour prediction with an MAE of 9, but its accuracy declines too rapidly over time, making it unsuitable for practical use

The LSTM models, in contrast, demonstrated exceptionally low error rates. Their ability to capture temporal dependencies resulted in highly accurate predictions, even for price spikes. However, the results appeared too optimistic, leading us to suspect data leakage. Despite our best efforts, we were unable to pinpoint the exact source of this issue.

VII. Discussion

The analysis of our results indicates that there is little correlation between weather variables and electricity prices. The highest correlations were observed with air temperature and wind speed, with values of only -0.15 and -0.16, respectively. This weak correlation is reflected in the performance of our models. Given that the goal was to predict electricity prices for production planning, we consider a mean absolute error (MAE) of 30 to be insufficient, especially when compared to the average electricity price of 61.66 EUR/MWh from 2020 onward.

While tree-based models and artificial neural networks (ANN) provided moderate performance, the LSTM model demonstrated significantly better results. However, due to the exceptionally low error values obtained, we suspect potential data leakage or overfitting. Further investigation is required to confirm whether the model is truly capturing relevant patterns or if its performance is artificially inflated.

To improve the predictions, future work should explore incorporating additional data sources, both from Sweden and neighboring countries. For instance, analyzing current events, scheduled maintenance of nuclear power plants, and international energy trends could provide valuable insights. The 2022 energy crisis, driven by the war in Ukraine and its impact on gas prices, demonstrated that external geopolitical factors significantly affect electricity prices. Although Sweden does not rely on gas for electricity production, it is interconnected with countries that do, such as Germany, which indirectly influences Swedish electricity prices.

Furthermore, our data analysis revealed that the most expensive hours for electricity are between 07:00–09:00 and 18:00–20:00. Based on this observation, we recommend avoiding production during these peak hours to reduce costs.

Finally, with the recent advancements in large language models (LLMs) and the widespread use of real-time news feeds (e.g., RSS), integrating an energy sentiment score based on news analysis could enhance prediction accuracy. Future models could incorporate this data to better anticipate sudden price fluctuations driven by economic and political events.

VIII. Conclusion

In this study, we explored different machine learning models for predicting electricity prices to optimize production planning at Habo Plast. Using historical electricity prices and weather data, we evaluated the performance of Random Forest, XGBoost, Artificial Neural Networks (ANN), and Long Short-Term Memory (LSTM) networks.

Our results indicate that tree-based models, while easy to train and interpret, struggle to capture price fluctuations, especially in highly volatile periods. ANN showed slightly worst performance making it impractical for precise forecasting. LSTM models produced exceptionally low error values, suggesting strong predictive potential, but also raising concerns about potential data leakage and overfitting.

One key finding is the weak correlation between weather variables and electricity prices, implying that additional data sources—such as power plant maintenance schedules, market trends, and geopolitical events—could improve predictive performance. In particular, the impact of the 2022 energy crisis highlighted the importance of external factors in price variations.

Given that electricity prices peak between 07:00–09:00 and 18:00–20:00, we recommend avoiding production during these hours to reduce costs. Future work should focus on incorporating real-time energy market data, external economic indicators, and sentiment analysis from news sources to enhance forecast accuracy.

While our current models provide a foundation for electricity price prediction, further refinement and additional data integration will be essential to achieving commercially viable accuracy levels for practical industry applications.

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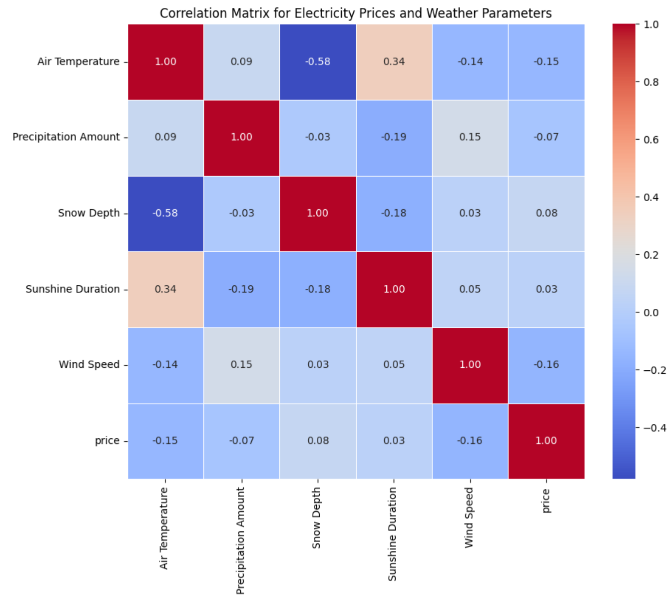

Fig. 2. Correlation matrix.

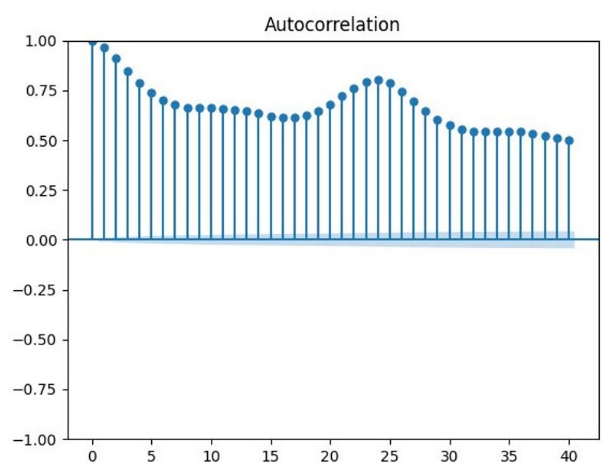

Fig. 3. Autocorrelation function.

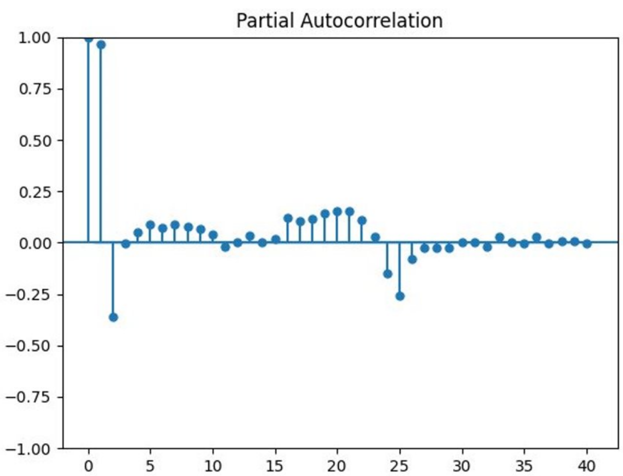

Fig. 4. Partial Autocorrelation Function.

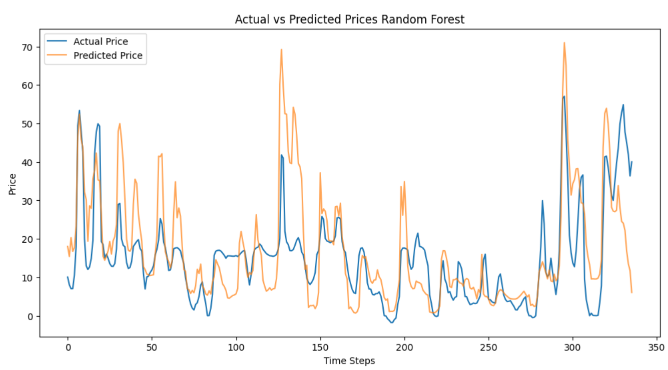

Fig. 5. Random forest prediction, zoom on the last 2 weeks.

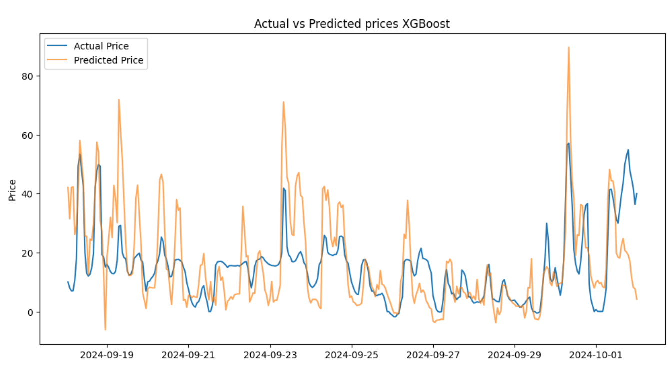

Fig. 6. XGBoost prediction, zoom on th last 2 weeks.

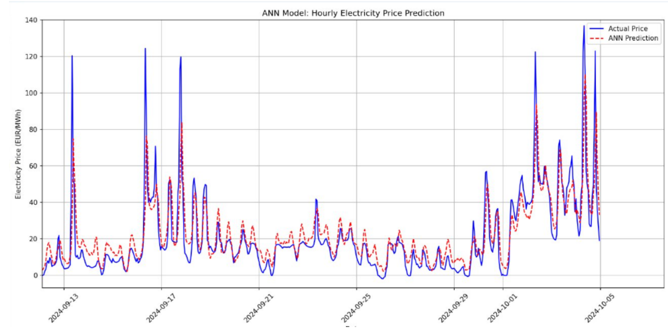

Fig. 7. ANN one hour prediction.

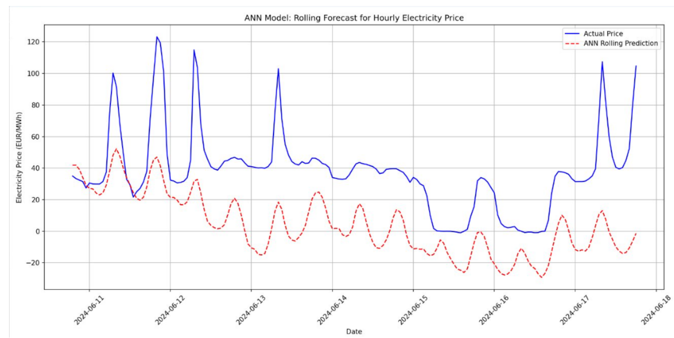

Fig. 8. ANN one week prediction.

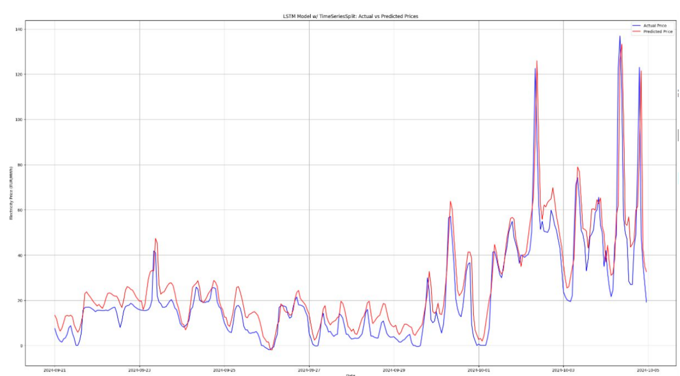

Fig. 9. LSTM 2023 onward, zoom on the last 2 weeks

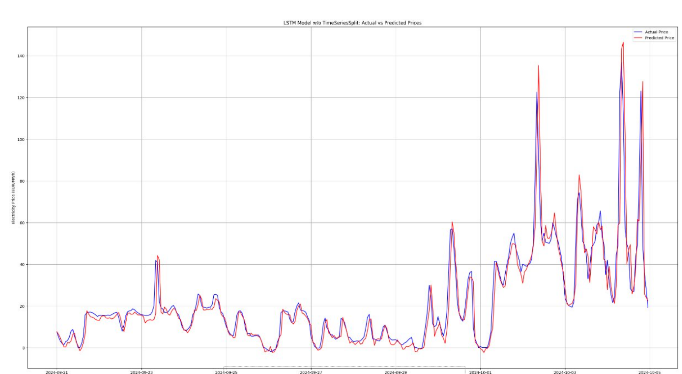

Fig. 10. LSTM 2016 onward, zoom on the last 2 weeks