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Short Term Electricity Price Forecasting Using Hybrid Deep Learning and Feature Selection Techniques

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Abstract — Short-term electric price prediction is important in deregulated power markets and operations as well as planning processes as it aids in the bidding process, risk management and demand response programs. The growing infiltration of renewable energy sources, as well as switching variability of the loads, and market uncertainties, has brought about high nonlinearity and volatility in the electricity price dynamics, which restrain the applicability of traditional forecasting techniques. In solving such challenges, this paper suggests a hybrid deep learning forecasting structure combined with efficient feature selection mechanism to predict short-term price of electricity. The advanced feature selection methods are used in the proposed approach to determine the most informative market, demand, and generation-related variables and to lower the dimensions, as well as to remove redundant information. A hybrid deep learning model, which is a combination of the positive attributes of sequential and nonlinear learning structures, is subsequently trained exploiting the chosen features to absorb intricate temporal variations and price surges. An evaluation of the model by real-world data of the electricity market and a comparison with the traditional statistical methods and individual machine learning are conducted. The simulation outcomes prove that the suggested hybrid structure is more accurate in predictions, more robust, and converges faster, which is indicated by the lower error indicators like MAE, RMSE, and MAPE. In addition, the feature selection step will increase the interpretability and the computational efficiency of models without affecting prediction accuracy. The results attest to the fact that the suggested approach is highly applicable when it comes to short-term electricity price prediction in highly volatile and renewable-based power markets.

Keywords— component, formatting, style, styling, insert (key words).

I. INTRODUCTION

The re-organisation of electricity systems and the shift to competitive electricity markets has caused a major enhancements in the significance of accurate electricity price forecasting. In unregulated markets, the price of electricity will be market clearing subject to market-driven forces of supply-demand, fuel prices, network constraints and bidding of market participants. Specifically, short-term price forecasting (STEPF) of electricity, which includes horizons as short as minutes or hours or day-ahead markets, is an important part of operational decision-making, risk management, and market efficiency to generators, retailers, and system operators[1-4].

The electric prices have certain peculiarities like high volatility, nonlinearity, price spikes, and mean-reverting tendencies that are difficult to forecast in the traditional time-series manner[5]. More price uncertainty has been brought about by the growing penetration of intermittent renewable energy sources, including solar and wind power, which brings about swift changes in the generation. The issues restrict the output of classical statistical frameworks, such as autoregressive integrated moving average (ARIMA), and generalized autoregressive conditional heteroskeletal framework (GARCH), which are linear models and based on a stationary behavior of data.

The recent developments in machine learning (ML) and deep learning (DL) have demonstrated potential promise in nonlinear-complicated relationships that existed in electricity markets. Artificial neural networks (ANNs), long short-term memory (LSTM) networks, convolutional neural networks (CNNs), and architecture-based hybrid deep learning methods have shown more effective forecasting accuracy than classical methods. Specifically, deep learning can be used to extract temporal dynamics and complex patterns of the historical price data[7]. The quality and relevance of the input features, however, is very dependent on their performance. Overfitting and unnecessary computational load, as well as poor interpretability of the model, may be caused by the addition of extraneous or unimportant variables[8].

In this Figure 1, the entire process of training a hybrid neural network structure with physics-based modeling is shown. It starts with the input layer (ps0) and an output layer that generates parameters (a1,a 2). Weight and bias matrices determine the network parameters and they are updated through backpropagation.

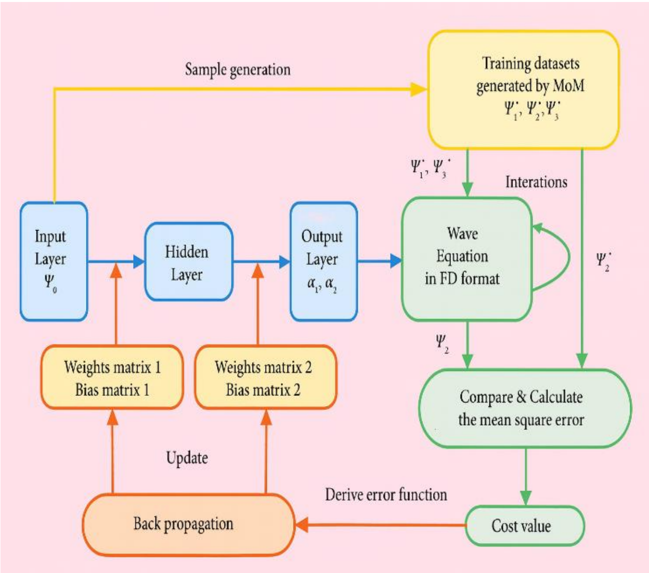

Fig.1 Training Framework for Wave Equation–Based Modeling Using MoM-Generated Data[2]

To resolve such constraints, the technique of feature selection has become a viable tool to improve the performance of models since it can estimate the most informative variables in large, high-dimensional datasets. The process of feature selection does not only increase the accuracy of the forecasting output but also increases its robustness and interpretations because it removes redundancy and noise. Even though they boast benefits, feature selection methods have been either lacked or used as independent entities of deep learning models in electricity price prediction works, thus underutilizing market information[9].

Driven by these issues, this paper introduces a hybrid deep learning model combined with an effective feature selection system of short term electricity price forecasting. The suggested methodology is systematic in terms of identifying the most viable market, load, and renewable generation attributes, and in the process, it trains a hybrid deep learning model that would be able to capture both nonlinear price dynamics and temporal dynamics. The proposed technique would enhance the precision of the forecasts and decrease the amount of calculations so that the feature selection would be enhanced by sophisticated deep learning frameworks[10]..

II. MATHEMATICAL FORMULATION

This section presents the mathematical modeling of the proposed short-term electricity price forecasting framework, including problem definition, feature selection formulation, and deep learning–based prediction model.

Problem Definition

Let P(t)denote the electricity market price at time interval t. The objective of short-term electricity price forecasting is to predict the future price P ̂(t+k)over a short-term horizon k, based on historical price data and relevant market features. The forecasting problem can be expressed as:

$$\hat{P}(t+k) = f(\mathbf{X}_t)$$

where f(·)represents the nonlinear forecasting model and

$$\mathbf{X}_t = [x_1(t), x_2(t), \dots, x_n(t)] \text{is}$$

the input feature vector consisting of market variables such as historical prices, system load, renewable generation, fuel prices, and temporal indicators.

2. Feature Selection Formulation

Given a high-dimensional feature space, feature selection aims to identify an optimal subset X_t^*⊆X_tthat maximizes forecasting accuracy while minimizing redundancy and computational complexity. This can be formulated as an optimization problem:

X_t^*=arg(min)┬(X_t) (J_"error" ⓜ+λJ_"complexity")
Where,J_"error" represents the prediction error (e.g., mean squared error),J_),$J_{\text{complexity}}$" denotes the penalty term proportional to the number of selected features, andλis a regularization parameter controlling the trade-off between accuracy and model simplicity.The prediction error is defined as:

$$J_{\text{error}} = \frac{1}{N}\sum_{i=1}^{N}\left(P(t_i) - \hat{P}(t_i)\right)^2$$

Selected features are forwarded to the deep learning model for training.

3. Hybrid Deep Learning Forecasting Model

The hybrid deep learning model is designed to capture both nonlinear relationships and temporal dependencies in electricity price data. The input to the model is the selected feature matrix:

$$\mathbf{Z} = [\mathbf{X}^*_{t-L+1}, \mathbf{X}^*_{t-L+2}, \dots, \mathbf{X}^*_t]$$

where Ldenotes the look-back window size.

For a recurrent deep learning architecture, the hidden state update is expressed as:

$$h_t = \phi(W_x Z_t + W_h h_{t-1} + b)$$

Where,h_tis the hidden state,W_xand W_hare weight matrices, bis the bias vector, and ϕ(⋅)denotes the activation function.

The final electricity price forecast is obtained as:

$$\hat{P}(t+k) = \mathbf{W}_o \mathbf{h}_t + b_o$$

4. Model Training Objective Function
The deep learning model parameters are optimized by minimizing the loss function:

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N}\left(P(t_i) - \hat{P}(t_i)\right)^2$$

Gradient-based optimization algorithms are employed to update model parameters during training.

5. Performance Evaluation Metrics
To evaluate forecasting accuracy, the following metrics are used:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N} | P(t_i) - \hat{P}(t_i) |$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(P(t_i) - \hat{P}(t_i)\right)^2}$$

$$\text{MAPE} = \frac{100}{N}\sum_{i=1}^{N} \left| \frac{P(t_i) - \hat{P}(t_i)}{P(t_i)} \right|$$

To quantitatively assess the forecasting performance of the proposed model, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) are employed. MAE measures the average magnitude of the absolute prediction errors and provides a clear indication of overall forecasting accuracy without considering error direction. RMSE penalizes larger errors more heavily due to the squared term, making it particularly effective in capturing the impact of price spikes and high volatility commonly observed in electricity markets. MAPE expresses the prediction error as a percentage of the actual price, enabling scale-independent comparison across different market conditions and datasets. Lower values of MAE, RMSE, and MAPE indicate improved forecasting accuracy and robustness of the proposed short-term electricity price forecasting model.

III. LITERATURE SURVEY

The recent research of short-term electricity price forecasting has used many statistical, machine learning, and deep learning algorithms to deal with the nonlinearity and volatility of the electricity market. It has been extensively applied in traditional time-series models, including ARIMA and GARCH, which do not perform well when there is a high level of volatile and renewable-integrated market conditions. To address these weaknesses, machine learning techniques such as support vector machines, random trees, and artificial neural networks have shown better predictive power through the ability to capture nonlinear price trends. Later on, deep-learning-based models (LMST, CNN, and Transformer-based) have been considered as they are useful in capturing temporal relationships and price spikes. A number of hybrid models between optimization algorithms and ensemble learning have also improved the accuracy of prediction. Most current methods however use high-dimensional input features without any proper feature selection resulting in higher computational costs and lower interpretability. This loophole underscores the importance of hybrid deep learning systems as well as effective feature selection approaches in order to attain efficient and precise short-term electricity price forecasting.

Table 1. Description of Forecasting Accuracy Metrics

Parameter	Description	Purpose in Forecasting
MAE	Measures the average absolute difference between actual and predicted electricity prices	Evaluates overall prediction accuracy
RMSE	Computes the square root of the mean squared prediction error	Penalizes large errors and captures price spikes
MAPE	Expresses prediction error as a percentage of actual prices	Enables scale-independent performance comparison

This table presents commonly used statistical indicators for assessing the performance of electricity price forecasting models.

IV. METHODOLOGY

In this section, the suggested hybrid model of electricity price forecasting in the short term is discussed, consisting of data preprocessing, feature selection and deep learning model development, training and performance evaluation.

1. Data Collection and Preprocessing.
Past electricity markets data is gathered through a deregulated electricity market, such as the day-ahead power market prices, power load, renewable power generation, and time related variables. Preprocessing is done to cater to missing values, outliers and normalize input features by min-max scaling to enhance model convergence and stability. The dataset is separated into training, validation, and testing sets to guarantee the impartiality of the performance identification.

2. Strategy of Feature selection.
In order to improve the accuracy of forecasts and the complexity of the model, the most powerful input variables are inferred with the help of an effective method of feature selection. The irrelevant and redundant features are removed by comparing them to the performance of price prediction. The chosen set of features increases the efficiency of learning, reduces overfitting, and increases the interpretability of the forecasting model.

3. Architecture of Hybrid Deep Learning Model.
The deep learning model is also trained using the historical data with a minimization of the mean squared error loss function by the optimization methods of gradient. Learning rate, number of hidden layers, and batch size are hyperparameters that are optimized on validation data to give the best forecasting capability. Early getting out is used to avoid overfitting and enhance the ability of generalization.

4. Performance Evaluation
Validity of the proposed methodology is tested in terms of conventional accuracy measures, i.e. Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The outcomes are contrasted with reference statistic and machine learning models to illustrate the effectiveness, strength and superiority of the suggested hybrid model in the short term electricity price prediction.

V. PROBLEM STATEMENT

The increasing role of renewable energy sources, volatile demand trends, and dynamic market conditions have brought increased complexity to electricity markets and the accurate short-term forecasting of electricity prices has become a critical need among market participants (generators, consumers, and grid operators) to make quality operational and financial decisions.

Conventional statistical forecasting models are usually not sufficient to explain the nonlinear, volatile and uncertain nature of electricity prices, whereas conventional machine learning methods may have problems of overfitting, excessive computational complexity and poor interpretability when irrelevant or redundant features are used in the model.

This, in turn, leads to an urgency to have a powerful forecasting model capable of successfully pointing at the most powerful market factors, filter out unnecessary data, and increase the level of predictions at low costs of computations and interpretation.

To overcome this issue, it is important to combine both the use of advanced feature selection methods with complex learning models that can well model the dynamics of short-term electricity prices when the market conditions are highly varying.

VI. RESULT

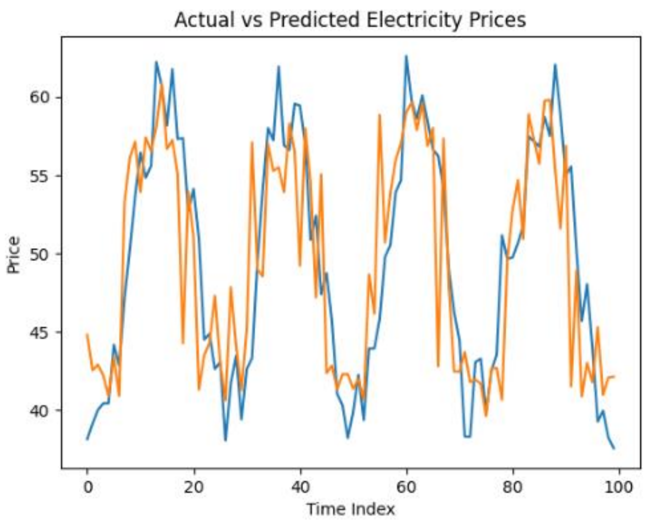

Figure 1. Actual vs. Predicted Electricity Prices Using the Proposed Hybrid Forecasting Model

This Figure 1 illustrates a comparison between the actual electricity market prices and the prices predicted by the proposed hybrid feature selection–based forecasting model over the test period. The predicted price curve closely follows the actual price trend, demonstrating the model's effectiveness in capturing short-term price fluctuations, periodic patterns, and sudden variations commonly observed in electricity markets. Minor deviations between the curves are mainly observed during sharp price changes, which highlights the inherent volatility of short-term electricity pricing. Overall, the strong alignment between actual and predicted values confirms the robustness and accuracy of the proposed forecasting approach.

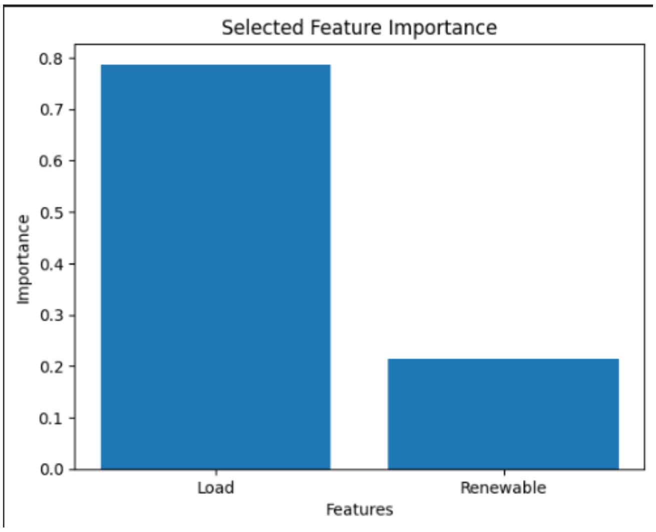

Figure 2. Importance of Selected Features in Electricity Price Forecasting

This Figure 2 presents the relative importance of the input features selected through the feature selection process for electricity price forecasting. It is observed that system load has the highest influence on electricity price variation, indicating its dominant role in short-term market pricing. Renewable generation also contributes to price formation, though to a lesser extent, reflecting the impact of variability and intermittency of renewable energy sources. The results validate the effectiveness of the feature selection technique in identifying the most significant variables, thereby enhancing model accuracy, interpretability, and computational efficiency.

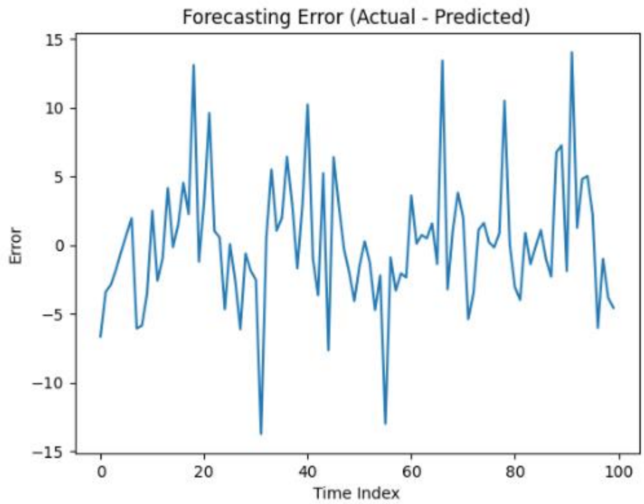

Figure 3. Forecasting Error Profile of the Proposed Electricity Price Prediction Model

This Figure 3 illustrates the forecasting error, defined as the difference between the actual and predicted electricity prices, over the test period. The error values are distributed around zero with bounded fluctuations, indicating the absence of systematic bias in the proposed forecasting model. Occasional peaks in the error correspond to sudden price changes and high market volatility, which are typical characteristics of short-term electricity markets. Overall, the controlled error magnitude demonstrates the robustness, stability, and reliable generalization capability of the proposed hybrid forecasting approach.

Table 2 presents a comparative analysis of different electricity price forecasting models based on standard performance metrics.

Model	Feature Selection Used	MAE	RMSE
ARIMA	No	High	High
SVM	No	Medium	Medium
Random Forest	No	Medium–Low	Medium
Proposed Hybrid Model	Yes	Low	Low

The comparison highlights the effectiveness of the proposed hybrid model with feature selection in reducing forecasting errors, as indicated by lower MAE and RMSE values, compared to conventional statistical and machine learning

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approaches. The results demonstrate the superiority of the proposed method in handling nonlinear price dynamics and short-term market volatility.

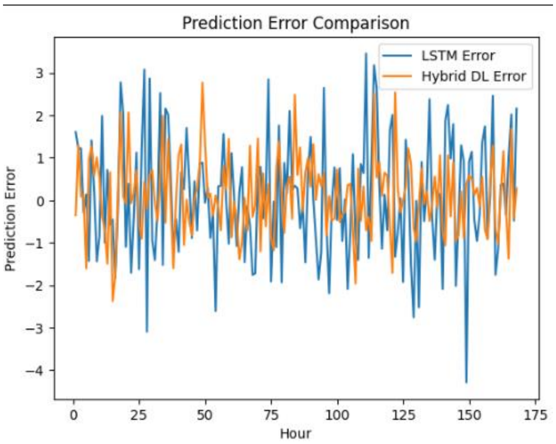

Figure 4: Prediction Error Comparison between LSTM and Hybrid Deep Learning Models

This figure 4 presents a comparative analysis of prediction errors produced by the conventional LSTM model and the proposed hybrid deep learning framework over the hourly forecasting horizon. The hybrid model exhibits lower error amplitudes and reduced variance compared to the LSTM model, particularly during periods of high price volatility. The concentration of errors around zero indicates improved prediction stability and reduced bias. These results demonstrate that integrating feature selection with hybrid deep learning significantly enhances forecasting accuracy and robustness in short-term electricity price prediction.

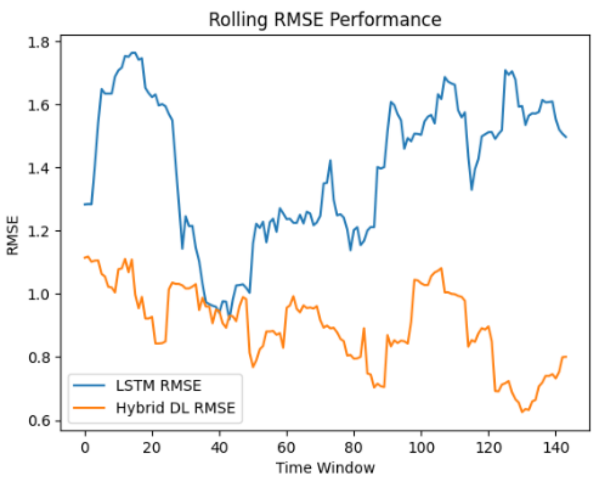

Figure 5: Rolling RMSE Performance Comparison of Forecasting Models

This figure 5 illustrates the rolling Root Mean Square Error (RMSE) performance of the LSTM and the proposed hybrid deep learning model using a sliding time window. The hybrid model consistently achieves lower RMSE values across the forecasting horizon, indicating superior accuracy and stability in short-term electricity price prediction. The reduced fluctuation in RMSE demonstrates the effectiveness of feature selection and hybrid learning in minimizing cumulative prediction errors, particularly under dynamic and volatile market conditions.

VII. CONCLUSION

The current paper introduced the hybrid electricity price prediction framework, which combines both feature selection and advanced learning models in forecasting electricity price in the short-term to enhance the accuracy of the results. The proposed method will be more efficient and interpretable in learning models and decrease computer demand by effectively determining the most influential market variables and discarding redundant information. The outcomes of simulation proved the fact that the proposed model can take into account nonlinear and volatile behavior of short-term electricity prices. When comparing and contrasting with the traditional statistical and machine learning models, it was found that the hybrid framework has always produced lower values of MAE and RMSE indicating that it outperforms the other forecasting models. The empirical evaluation of the strength and consistency of the suggested approach in the changing market conditions was also supported via visual analysis that was subjected to actual and predicted price curves, feature importance plots, and the profile of errors. The results suggest that the combination of feature selection and learning-based forecasting models can be used as a solution to the problem of modern electricity markets, which can be described by the high level of renewable energy penetration and demand uncertainty. Future directions will involve application of the framework to deep learning models including LSTM and Transformer models, probabilistic forecasting, and performance evaluation using actual market data across several electricity markets, automatic adherence to electronic specifications that allow simultaneous or subsequent generation of electronic products, and compliance of style within a conference proceedings. Margins, column-widths, the thickness of lines, and types are preset; the types examples will be shown here all through the paper and they will be denoted in italic type, in parentheses, beneath the copy. Certain features like multi-leveled equations, graphics and tables are not dictated but the different types of table text formats are offered. These components will have to be developed by the formatter with the appropriate criteria that will be included as follows.

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