Efficient Neural Network-Based Electricity Price Prediction with Minimal Parameter Design: A Case Study of the Indian Energy Exchange

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***Abstract*:**
Accurate electricity price forecasting is crucial for managing and optimizing power generation in the vertically unbundled electricity market. This study introduces a novel method for predicting electricity prices using the generalized regression neural network (GRNN) framework with a single design parameter. Partial autocorrelation is applied to time series data to select appropriate input values, and historical price data is sourced from the Indian energy exchange. The proposed model is evaluated against other contemporary forecasting techniques, including artificial neural networks (ANN), ANN-ANN combined with particle swarm optimization (PSO), Wavelet-based ANN, and Wavelet-based ANN-ANN-PSO. Results demonstrate that GRNN outperforms these methods in forecasting accuracy, including approaches mentioned above. The proposed method is straightforward and enhances forecast precision, making the GRNN model a reliable tool for predicting market clearing prices in energy exchanges.

Keywords: **Generalized Regression Neural Network Deregulated Electricity Market, Soft Computing, Electricity Price Forecasting.**

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I. INTRODUCTION

Electricity price forecasting has become a critical task for energy producers, consumers, and regulators, especially in deregulated markets [1]. Accurate price predictions enable efficient market participation, strategic planning, and financial decision-making [2-3]. In India, where the energy market operates through platforms such as the Indian Energy Exchange (IEX), the increasing volatility and demand-supply fluctuations have heightened the need for robust and accurate forecasting models.

Historically, price forecasting has predominantly utilized statistical and econometric methods, including time series models, autoregressive integrated moving averages (ARIMA), GARCH, WT-ARIMA, GIGARCH, and multiple linear regression. While these methods have provided useful insights, they often struggle to capture the non-linear patterns and complex interactions present in electricity prices, especially in markets like the IEX, where factors such as demand surges, renewable energy integration, and policy changes add layers of complexity. As a result, machine learning models, particularly neural networks, have gained popularity due to their ability to handle large volumes of data and model intricate, non-linear relationships [4-5].

Neural networks (NN) have been widely adopted for forecasting purposes, with various models viz. recurrent neural networks (RNN) and long short-term memory (LSTM) being implemented to model time-sensitive’s in time series data. However, one common issue with neural network models is the need for fine-tuning multiple design parameters, such as the number of hidden layers, learning rate, and the neurons in the layer, which often complicates model implementation and increases computational cost [6-7].

Numerous studies have been published on energy price forecasting using various computational techniques such as support vector machines, RNN, fuzzy NN, and ANN [8-15]. The majority of these studies concentrate on day-ahead price forecasting, where price data from the current day (nth day) is used to predict prices for the following day (n+1). This approach is based on the strong linear and nonlinear relationships between consecutive days' prices. For instance, Monday's price profile is used to predict Tuesday's price.

However, deregulation has also introduced new challenges in the energy market. Unlike other commodities, electricity cannot be stored, requiring continuous adjustments in supply and demand. In competitive markets, power prices are influenced both directly and indirectly by a range of interconnected factors, including dynamic variables such as load, weather conditions, market dynamics, and bidding strategies. This makes price forecasting increasingly complex. Accurate electricity price prediction is crucial for market participants, and its importance differs from other commodities due to the unique dynamics of the power market. Forecasting electricity prices is essential for supporting the entire energy market, and through competition, deregulation aims to improve generation efficiency and availability. In these recent studies [19-26], for improving electricity price forecasting in highly volatile markets, demonstrating that machine learning techniques are well-suited to capturing complex price movements.

This paper proposes a NN-based electricity price forecasting tool that simplifies the design process by using a single design parameter. The approach aims to streamline the model structure while maintaining high prediction accuracy. The single design parameter method significantly reduces the complexity associated with hyperparameter tuning, making the tool simple to implement in real-world scenarios such as the Indian Energy Exchange.

In this study, we evaluate the performance of the GRNN tool on historical price statistics from the IEX. The results are compared with traditional models to demonstrate the effectiveness of the single design parameter approach in predicting electricity prices with high accuracy, while reducing the computational overhead typically associated with neural network architectures.

The paper is detailed into four sections: Section 2 details the GRNN modeling methodology, Section 3 presents experimental results and discussions, and Section 4 concludes the study.

II. METHODOLOGY

This section discusses the data source, input feature selection for GRNN, and fundamentals of the GRNN approach used in the proposed work.

A. *Data Source*

The proposed research uses data taken from the Indian energy exchange market clearing price (MCP) [27].

B. *Input Feature Selection Through Correlation Analysis*

Selecting the most appropriate variables is a crucial first step in system modeling, especially for neural networks (NNs), which are powerful computational tools. In time series modeling, input features often include lagged variables (representing memory). As the number of variables rises, the complexity of the tool also rises, making it more difficult for the system to learn and resulting in poor convergence. By reducing the number of irrelevant variables, the network can focus more effectively on establishing meaningful relationships. The challenge lies in selecting a subset of input features from all available data that will lead to a better tool. If multiple time series are involved, it's also necessary to determine the significant lags for each series that influence the output.

Correlation measures the degree of linear relationship between two variables, indicating how strongly they are related. This is determined by the correlation coefficient, which ranges between −1 and 1. Nearer to 1 indicates a positive correlation, and −1 indicates a negative correlation, and 0 implies no correlation.

Correlation analysis is a commonly employed method for selecting input features and identifying the optimal number of lags. Several researchers [28-30] have applied correlation analysis to select inputs for price forecasting. In this study, the lagged prices (from previous hours) for the Indian energy market are used as input features for different time periods:

- For a week in June: {1, 2, 8, 22, 23, 24, 25, 34, 35, 36, 47, 49, 52, 62, 63, 70, 72, 77, 79, 81, 83, 84, 87, 89, 91, 94}
- For a week in September: {1, 2, 8, 19, 20, 21, 22, 23, 24, 25, 40, 45, 46, 48, 52, 58, 64, 65, 68, 74, 76, 77, 80, 83, 88, 102, 103, 107, 111, 112, 113, 115, 122}
- For the first week of October: {1, 2, 4, 14, 18, 24, 25, 39, 54, 59, 67, 72, 86, 89}
- For the second week of October: {1, 2, 16, 20, 21, 23, 24, 52, 59, 61, 67, 80, 81, 82, 83, 90, 92, 95, 96, 98, 108, 116, 118, 119, 129, 136}

These input features were selected based on the results of the correlation analysis and demonstrate the influence of trends, daily periodicity, and weekly cycles. The selected variables were applied to the Indian power market in this study to develop the forecasting model..

C. Generalized Regression Neural Network Modeling

With the knowledge that feed-forward neural network (FFNN) systems have a few deficiencies (e.g., enormous input parameters, more learning time and having local minima) that result in erroneous prediction performance, in this research, a single input parameter GRNNs are developed which are an exceptional kind of neural systems. GRNN has just a single input parameter and is straightforward and quick in learning, which are the attributes that are appealing to researchers in automated forecasting. This paper centers on constructing a forecasting scheme to exploit these desirable GRNN properties.

The GRNN [31] (1991) is an FFNN based on layers, the input, pattern, summation, and output layers. The architecture of GRNN is presented in Fig. 1.

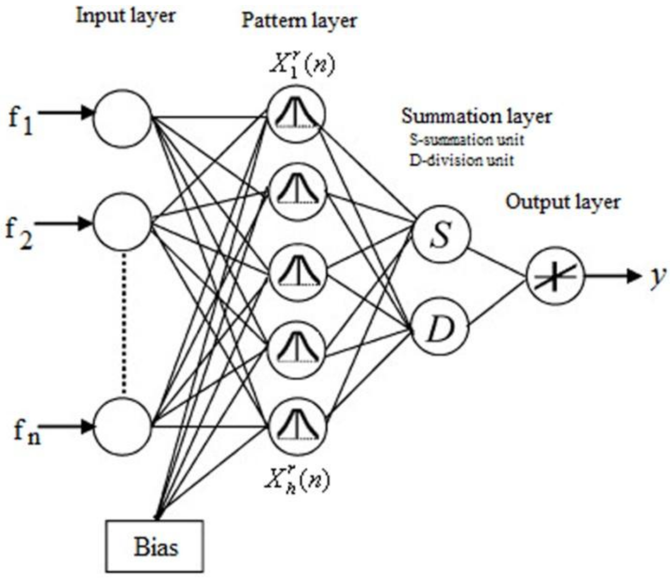

Fig. 1. Implementation of GRNN for the Indian energy exchange electricity price forecasting

The GRNN details are explained in [33] and [34]. Equations that are used in the GRNN model are shown in [33] and [34].

Output Activation Calculation Process:

1. Input Activation: The activation of the input units is determined by the data sample presented to the network.
2. Pattern Unit Transfer: Each pattern unit computes its transfer function using the radial basis function, typically Gaussian, based on the distance between the input vector and the center vector.
3. Summation Unit Transfer: Each summation unit calculates the weighted sum of contributions received from the pattern layer.
4. Output Unit Transfer: The output unit's activation is computed by dividing the summation unit's output by the output of the division unit, ensuring proper normalization.

D. Evolution of Prediction Performance

The more detailed discussions on mean absolute percentage error (MAPE), readers can refer to [9].

III. Numerical Results

This section discusses the data source, input feature selection for GRNN, and fundamentals of the GRNN approach used in the proposed work.

A. Case Studies

The energy market of the IEX is used as a real-world case study in this research. In this market, the electricity price fluctuates due to the strategic actions of dominant players, making it difficult to predict. As shown in Figures 2–5 (representing June, September, and two weeks of October), the data series exhibit an unstable mean and variance. This volatility increases the complexity of forecasting, highlighting the challenges of predicting prices in the Indian power market. Due to its high unpredictability, the Indian energy market is frequently used by researchers as a benchmark for testing predictive models.

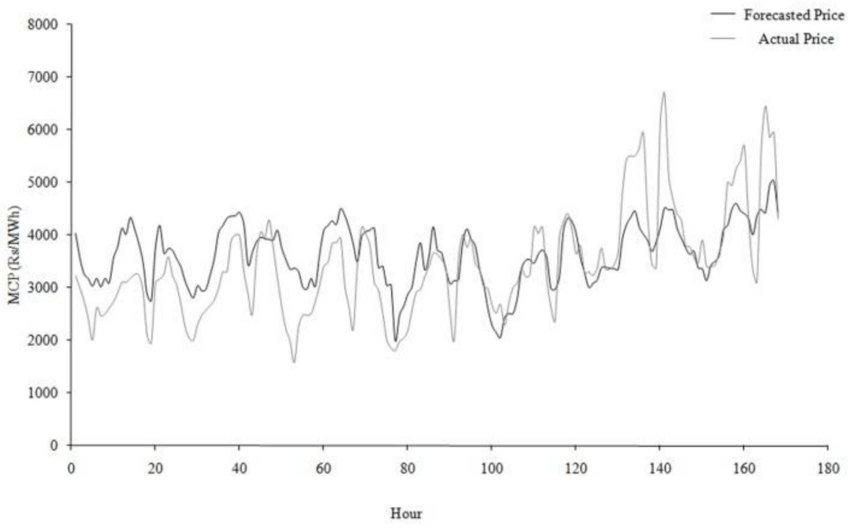

Fig. 2. Qualitative Analysis of Week 1 Forecasted Price

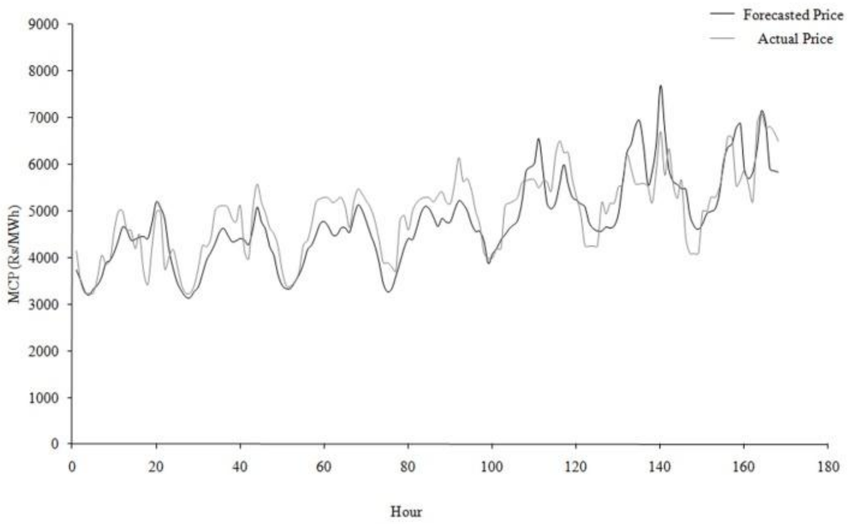

Fig. 3. Qualitative Analysis of Week 2 Forecasted Price

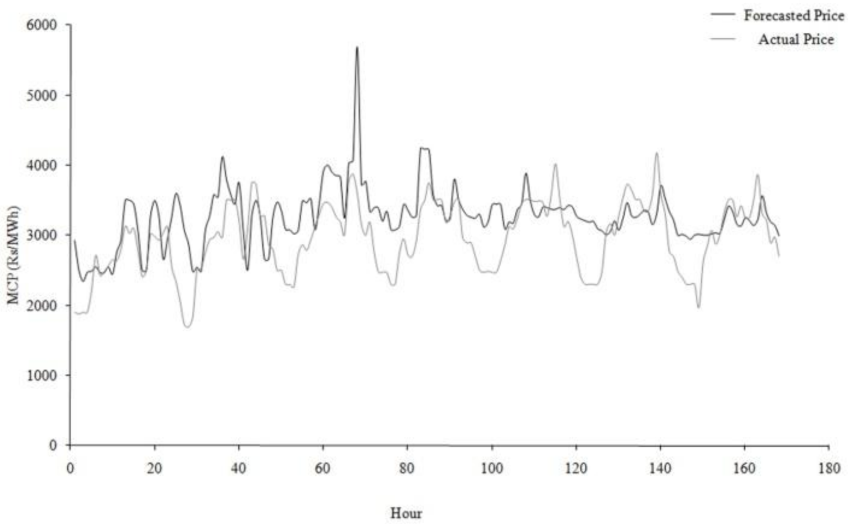

Fig. 4. Qualitative Analysis of Week 3 Forecasted Price

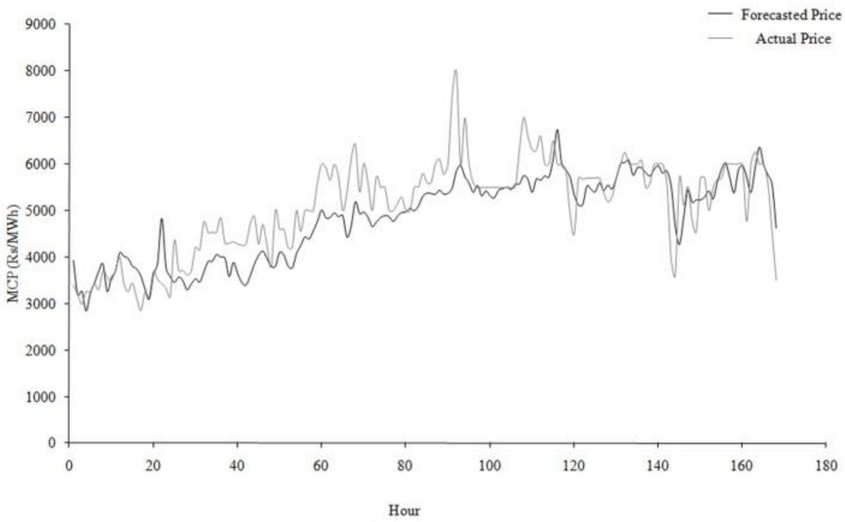

Fig. 5. Qualitative Analysis of Week 4 Forecasted Price

In this study, day-ahead energy market data from the IEX for the year 2014 is utilized to forecast electricity prices. For the correlation analysis, months with stable prices are excluded; instead, weeks with the highest price volatility are specifically selected to assess the model's robustness.

To build the forecasting model for each selected week, the available data includes hourly prices from the 42 days preceding the week for which predictions are being made. To avoid over fitting during the learning process, large training datasets are intentionally avoided. Testing over more than 42 days did not yield better accuracy and increased redundancy when training the GRNN. Therefore, the past 42 days are used for training, and predictions are made for the subsequent 7 days.

For testing purposes, the selected periods are based on [32], with the corresponding past 42 days used for training. These datasets are used to predict prices for the respective weeks.

B. *Comparison with Other Approaches*

Different forecasting methods were applied to the Indian Energy Exchange market, and their results were compared. Table 1 presents a comparison of the proposed GRNN model's accuracy in forecasting energy prices, with the MAPE used as the evaluation metric. The first column of the table represents the deregulated power market, the second column shows the week during which prices were predicted, and the third column lists the MAPE values. The proposed GRNN model achieved an average MAPE of 13.4129%, demonstrating its effectiveness in forecasting energy prices in the Indian market.

TABLE I. QUANTITATIVE ANALYSIS FOR THE FOUR WEEKS USING GRNN

Market	Forecast Week	MAPE
Indian (2014)	June	19.3043
	September	08.5808
	First October	16.1116
	Second October	09.6550
	Average, %	13.4129

Table 2 provides a comparative assessment between the GRNN tool and four other hybrid tools. The GRNN model stands out as a singular, non-hybridized approach, delivering competitive performance without integrating multiple processing techniques, unlike the hybrid models.

Despite being a simpler and more conservative model, the GRNN achieves impressive forecasting accuracy close to the state-of-the-art techniques. Additionally, it requires less computation time, making it a robust yet efficient solution. On the other hand, the hybrid models tend to involve more complex combinations of soft computing models, but the GRNN manages to perform nearly as well without the added computational complexity.

This comparison highlights the GRNN model’s balance of simplicity, accuracy, and efficiency, making it a powerful alternative to more complex hybrid models.

TABLE II. COMPARATIVE MAPE RESULTS BETWEEN THE VARIOUS MODELS

Method	June	September	First October	Second October	Average
ANN [32]	24.3832	13.0963	10.1464	14.7888	15.6036
ANN-ANN-PSO [32]	24.3855	12.9346	09.9469	14.7534	15.5051
Wavelet-based ANN [32]	24.3809	13.0329	10.0097	14.1191	15.3856
Wavelet-based ANN-ANN-PSO [32]	24.3802	12.8764	09.2523	14.0773	15.1465
GRNN	19.3043	08.5808	16.1116	09.6550	13.4129

The total execution time of the tool, including preprocessing (standardization), testing the GRNN, and postprocessing (denormalization), was approximately 55 milliseconds on an AMD processor with a 2 GHz clock speed and 1 GB of RAM. After the learning phase, the average prediction (testing) time for the GRNN was about 50 milliseconds. This makes the approach well-suited for real-time applications in deregulated power markets, where fast price forecasting is essential.

The GRNN strikes an ideal balance between forecasting accuracy and computational efficiency, while also reducing modeling complexity. This is particularly valuable for real-time applications in deregulated power markets, where timely and precise price predictions are crucial for effective decision-making in dynamic market conditions.

IV. CONCLUSION

Accurate power price predictions are vital for market participants. In this research, input determination by correlation investigation of crude information by evacuating repetitive segments encourages the neural system to learn better. Forecast aftereffects of ongoing power market of Indian energy exchange for the month of June, September and October for the year 2014 were represented, yielding a normal week after week MAPE close to 13.4129%, while the normal calculation time is under 50 ms and better capacity than upgrade the issue of predicting value spikes. The GRNN demonstrates a unique and superior neural network structure. It outperforms other forecasting methods, such as ANN, ANN-ANN-PSO, Wavelet-based ANN, Wavelet-based ANN-ANN-PSO, and Wavelet-based ANN-PSO (with random initialization), in accurately predicting market prices. The process is straightforward, and it has been observed that this approach enhances forecasting precision. Consequently, the proposed GRNN tool can be implemented within the IEX for accurate and rapid market-clearing price forecasts.

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