Review On Design and Simulation of Electricity Price Forecasting Using Artificial Neural Network

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Abstract- Setting the price for electricity is the main task in the reorganized power markets. Forecasting power costs well and precisely has therefore become more crucial. An ANN (Artificial Neural Network) model specifically designed for short-term forecasting of prices in restructuring electricity markets is presented in this research. The input layer, two layers that are concealed, and output layer make up the four layers of the suggested ANN model, which is a perceptron neural network. In place of traditional back propagation, the Levenberg-Marquardt back propagation (LMBP) technique is used for ANN training in order to accelerate convergence. The suggested ANN model is trained using MATLAB, and its effectiveness and performance are shown through a use in the Ontario energy market.

Keywords— *Fuel cell electric vehicle, high voltage gain IBC, PEMFC, MPPT, RBFN etc.*

I. INTRODUCTION

The electrical markets in a number of nations have recently undergone reforms that have made the energy industry less controlled and more competitive. The cost of energy has taken on a central role in all power market operations under this new arrangement.

Reliable precision in price forecasting helps electricity suppliers make logical short-term offers. ANNs and fuzzy logic are examples of contemporary methodologies, whereas classical models comprise the majority of forecasting models.

Regression analysis and time series are two components of conventional price forecasting models. However, artificial intelligence techniques—in particular, the ANN method—have grown in popularity and potency as predicting techniques in recent years.

For power dispatching agencies, power load prediction is essential. Improving power load forecasting's technical quality helps power firms create more realistic plans for grid building while also providing an accurate estimate of the demand for energy in the market. Over the past few decades, a variety of load forecasting methods—from conventional mathematical models to softer computing methods—have been published. Promising results have also been observed with hybrid approaches. But stochasticity and uncertainty are hallmarks of load forecasting, necessitating the development of novel approaches with sophisticated handling of a wide range of variables.

It is necessary to balance local power supply and demand in order to forecast future pricing. The ANN was chosen because of its capacity to discover intricate input-output correlations via supervised training on historical data.

Electricity costs are influenced by a wide range of factors, some of which are more important than others. It seems sense to focus just on the most crucial elements and research how they affect costs. Electricity costs are influenced by several factors, including generator outages, load patterns, bidding patterns, and line limits. In particular, the load pattern has a big impact on how Generating Companies (Gencos) bid. As a result, two crucial variables affecting price are system load and historical pricing.

The choice of inputs for the ANN technique has a significant impact on how well it performs. For the purpose of projecting electricity prices, day type, historical pricing data, and load quantity have been determined. The short-term forecasting of the prices of electricity in the light of the reorganised power market is the main emphasis of this study.

II. OBJECTIVE

The principal goals of using MATLAB and artificial neural networks (ANNs) for electricity price prediction are as follows:

1. Use artificial neural networks (ANNs) to create a forecasting model for power prices that is accurate and dependable.
2. To increase model performance, optimize data preparation methods to clean and normalize power pricing data.
3. To guarantee quick convergence and reliable model optimization, put ANN training methods into practice and optimize them.
4. Use the proper metrics and validation procedures to analyze the accuracy and dependability of the forecasting model.
5. Investigate methods for improving the interpretability and transparency of models to aid in energy market decision-making.

III. Literature survey

K. Wang, D. Hu et. al. 2019 , In this study, Wang et al.'s paper suggests a unique method for predicting power prices by fusing the Gravitational Searching Algorithm (GSA) with Artificial Neural Networks (ANNs). The goal of the article is to increase the prediction accuracy of power prices by optimizing the ANN model variables through the application of GSA. The authors want to improve the efficacy of power price forecasting models and aid in energy market decision-making by using cutting-edge optimization techniques.

M. E. Khodayar et. al. 2018, In this paper, ANNs, or artificial neural networks, optimized by an Integrated Particle Storm Optimization (IPSO) algorithm are used in this technique for forecasting power prices. The importance of optimization strategies in improving the precision of power price forecasts is emphasized in the article. The authors show increases in predicting ability by combining ANN models with IPSO, which helps energy markets make better decisions.

J. Kim et. al. 2017, In this paper, a hybrid method that combines neural networks (ANNs) with ensemble averaging and local optimization strategies to anticipate short-term power prices. The study emphasizes the value of ensemble approaches, which combine predictions from several models to increase forecasting accuracy. The authors want to improve the flexibility of ANN models for capturing intricate pricing dynamics by implementing local optimization approaches, which would provide energy market players useful information.

C. Huang et. al. 2016, This paper, provide an innovative method of predicting power prices by combining genetic algorithm (GA) optimization with artificial neural networks (ANNs). In order to improve forecasting accuracy, the study focuses on optimizing the ANN model's architecture and parameters using GA. The authors exhibit improvements in electricity price forecasting ability by utilizing GA's evolutionary capabilities, which offers important new information for energy market evaluation and choice-making.

M. E. H. Golshan et. al. 2015, This research proposes a novel method of power price forecasting by using Modified Harmony Search Algorithm (MHSA)-optimized Artificial Neural Networks (ANNs). The significance of algorithmic optimization in enhancing the precision and resilience of ANN-based models for forecasting is emphasized in the research. The authors show improved effectiveness in capturing fluctuations in prices and volatility by adding MHSA, offering stakeholders in the energy market insightful information.

S. A. Abbaspour et. al. 2014, This paper, suggest merging Artificial Neural Networks (ANNs) with Wavelet Transform (WT) decomposition to anticipate power prices in a hybrid manner. The study demonstrates how well wavelet-based feature extraction can uncover multiscale patterns from data on power prices. The authors show increased forecasting accuracy and resilience by combining ANN models with WT, enabling more informed decision-making in the energy markets.

A. Mohammadi et. al. 2013, This paper, provide a method for predicting power prices using neural networks that have been optimized via particle swarm optimization (PSO). In order to enhance the convergence and efficiency of ANN models, the research highlights the significance of optimization strategies. The authors show improved accuracy and dependability in power price prediction by combining PSO with ANN-based forecasting models, offering insightful information for energy market research and planning.

IV. Existing Configuration

Electricity price forecasting is vital for energy market operations, enabling informed decisions on energy production, consumption, and trading. Traditional methods often struggle with the complex and nonlinear relationships in price dynamics. Artificial Neural Networks (ANNs) offer a promising solution to enhance forecasting accuracy. However, several key issues need addressing:

Data Preprocessing: Raw electricity price data may contain noise, outliers, and missing values, affecting ANN model performance. Proper preprocessing techniques are necessary to clean and normalize the data.

Feature Selection: Selecting relevant input variables is crucial for capturing patterns in price data. Careful feature engineering enhances forecasting accuracy.

Model Architecture: Designing an effective ANN model requires choosing appropriate layers, nodes, and activation functions to capture nonlinear relationships without overfitting.

Training Algorithm: Efficient training algorithms are essential for quick convergence and avoiding local minima during parameter optimization.

Model Evaluation: Evaluating ANN performance using metrics like MAE, RMSE, and MAPE ensures accuracy and robustness. Cross-validation techniques enhance generalization capability.

Computational Complexity: ANN models can be resource-intensive, necessitating efficient implementation strategies for scalability.

Interpretability: Despite high predictive performance, ANN models often lack interpretability. Techniques like feature importance analysis can enhance transparency.

Addressing these challenges is crucial for developing effective ANN-based electricity price forecasting models. Overcoming these obstacles can provide valuable insights for decision-making in energy markets.

V. Proposed Configuration work

- The model is divided into four modules:

1. Feature Selection
2. Feature Extraction
3. GS and cross-validation
4. Price Prediction using ESVR and ECNN.

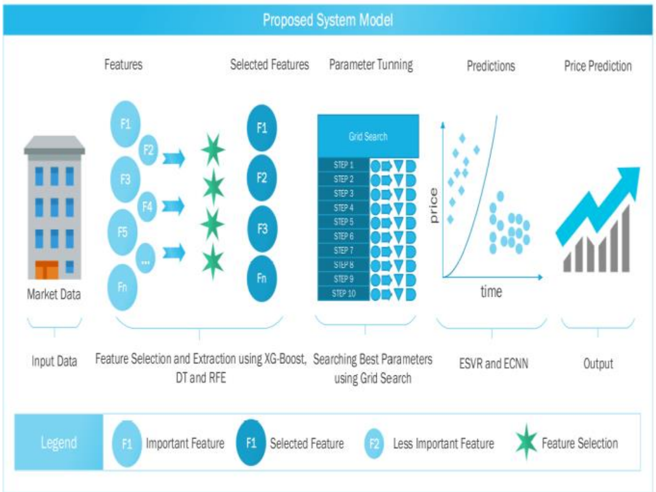

Fig.1. Proposed Model for Price Prediction

- **Model Overview**

Methodology for Proposed Model for Electricity Price Forecasting Using Artificial Neural Network (ANN) with MATLAB:

- Data Collection and Preprocessing:

Gather historical electricity price data from reliable sources like energy market databases or regulatory agencies.

Preprocess the data to handle missing values, outliers, and inconsistencies by employing techniques such as data imputation, outlier detection, and normalization to ensure data quality and consistency.

- Feature Selection and Engineering:

Identify relevant features influencing electricity prices, such as demand, weather conditions, market trends, and historical price patterns.

Engineer additional features or transformations to enhance predictive power, such as lagged variables, moving averages, or seasonal indicators.

- Model Design and Architecture:

Design the architecture of the ANN model, specifying the number of layers, neurons, and activation functions.

Choose appropriate input features and output targets based on the forecasting horizon (e.g., hourly, daily, weekly).

- Training and Optimization:

Split the preprocessed data into training, validation, and testing sets to evaluate model performance.

Train the ANN model using historical electricity price data, optimizing parameters using techniques like backpropagation, gradient descent, or metaheuristic algorithms.

Tune hyperparameters such as learning rate, momentum, and regularization to enhance model convergence and generalization.

- Model Evaluation and Validation:

Evaluate the trained ANN model's performance using validation data and metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE).

Validate the model's predictive accuracy and robustness using out-of-sample testing data to assess its generalization capability.

Conduct sensitivity analysis to understand the impact of input features and model parameters on forecasting performance.

- Forecasting and Visualization:

Utilize the trained ANN model to generate electricity price forecasts for future time periods based on input features.

Visualize forecasted electricity prices alongside historical data to identify trends, patterns, and potential deviations.

Generate performance reports and visualizations to communicate forecast accuracy and provide insights for energy market stakeholders.

- Model Deployment and Integration:

Deploy the trained ANN model in production environments for real-time or batch forecasting applications.

Integrate the forecasting model with existing energy market systems or decision support tools to facilitate informed decision-making by market participants.

Monitor model performance over time and update the model periodically with new data to maintain accuracy and relevance.

By following this methodology, the proposed model for electricity price forecasting using Artificial Neural Networks with MATLAB can effectively capture the complex dynamics of energy markets, providing valuable insights for market analysis and decision-making.

VI. CONCLUSION

The energy market is now less regulated as well as more competitive as a result of recent developments in the electrical sector. In these circumstances, estimating the price of energy is crucial to all power market operations, including creating producing firms' bid plans. As a result, this study offers a model for ANN-based short-term power price predictions. A data pre-processing & post-processing technique for price spikes is developed in order to increase the model's accuracy. As a result, performance on tests and in training both improved. The findings demonstrate that, in terms of both accuracy and ease of use, the ANN model is a strong instrument for price forecasting when compared to other straightforward techniques.

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