Forecasting Power Prices with Artificial Neural Networks

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Abstract- In the restructured power markets, the primary responsibility is setting the price of electricity. Thus, it has become increasingly important to accurately and precisely forecast power prices. An Artificial Neural Network (ANN) that was developed specifically for temporary price prediction in restructured electricity markets is presented in this paper. An input level, two hidden layers, and output layer comprise the four levels of the suggested ANN model, which is a perceptron neural network. Instead of using traditional back propagation for ANN training, using Levenberg-Marquardt retrogression (LMBP) methodology is used to accelerate convergence. The performance and efficacy of the suggested ANN model may be shown by training it on the Ontario power market. MATLAB is used to train the model.

Keywords— *Price forecasting, electricity market, and artificial neural network 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, In recent years, the ANN method has become more and more prominent as a predictive methodology.

Power load planning is crucial for power dispatching organisations. Power companies can develop more realistic strategies for grid construction and obtain a precise assessment of market demand for energy by improving the technical quality of power load forecasting. Many approaches to load forecasting, ranging from traditional computational models to softer computer techniques, have been published in the last few decades. Hybrid strategies have also shown encouraging outcomes. However, load forecasting's inherent stochasticity and uncertainty make the creation of unique strategies involving complex manipulation of a wide variety of factors necessary.

To project future prices, Local electricity supply and demand need to be balanced. The ANN was chosen because of its capacity to identify intricate input-output correlations using supervised training on historical data.

There are many different factors that affect electricity costs, some of that have more significant than others. It makes sense to concentrate only on the most important components and find out how they impact expenses. Numerous variables, such as load designs, bidding patterns, generator outages, and line limitations, affect the price of electricity. Specifically, the way that Generation Companies (Gencos) bid is greatly influenced by the load pattern. Consequently, system load & historical pricing are two important factors influencing price.

The choice of inputs has a significant impact on the ANN approach's success. To estimate power rates, day kind, historical price data, and load quantity were calculated. The primary focus of this work is the immediate forecasting of electricity prices in light of the restructuring power market.

II. 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.

III. PROPOSED CONFIGURATION WORK

- The model is divided into four modules:

1. Choosing Features
2. Feature Extraction
3. GS and cross-validation
4. Using ECNN and ESVR to Predict Prices.

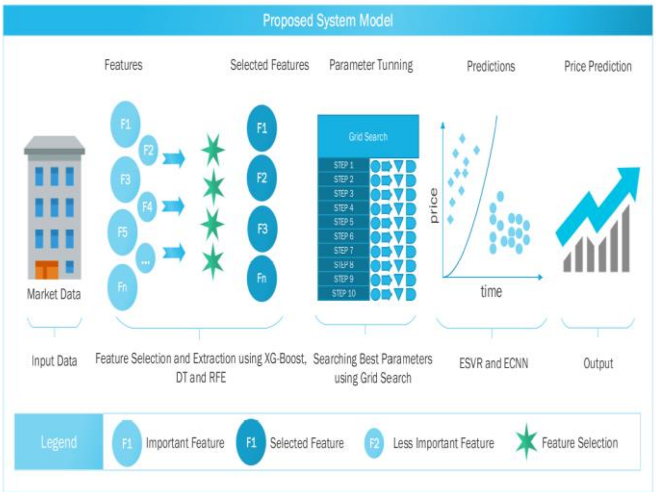

Fig.1. A Model for Predictive Pricing is Suggested

- **Model Overview**

Techniques for the Suggested Model for Predicting Electricity Prices using MATLAB and Artificial Neural Networks (ANN):

- Data Collection and Preprocessing:

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

To maintain data quality and consistency, preprocess the data using methods like data imputation, outlier identification, and normalization to manage missing values, outliers, or inconsistencies.

- Engineering and Feature Selection:

Determine the pertinent factors, like demand, that affect the price of power, 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.

Utilising past power pricing data, train the ANN model by optimising parameters through the use of methods like gradient descent, backpropagation, or metaheuristic algorithms.

To improve model convergence and generalisation, adjust hyperparameters such learning rate, growth, and regularisation.

- Model Evaluation and Validation:

Evaluate the effectiveness of the trained artificial neural network (ANN) model using validation data and metrics such the mean comparative percent error (MAPE), the root average square error (RMSE), and absolute mean error (MAE).

Evaluate the model's capacity for generalisation by utilising out-of-sample testing information to validate its predicted accuracy and resilience.

To determine how input attributes and model parameters affect forecasting performance, do sensitivity analysis.

- 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 model for forecasting with the decision support tools or current energy market systems to help market players make well-informed decisions.

To keep the model accurate and relevant, track its performance over time as well as update it with fresh data on a regular basis.

By applying Artificial Neural Networks using MATLAB in conjunction with this methodology, the suggested model for price of electricity forecasting can successfully capture the intricate dynamics of energy markets, offering insightful information for market decision-making and analysis.

IV. PRICE FORECASTING BY ANN

An artificial brain network (ANN) is a parallel distributed network composed of simple computational units called neurons. These neurons are predisposed to store and make accessible for use experiential knowledge. With the aid of an appropriate learning algorithm, every neural network structure must go through a training stage using easily accessible data and patterns. This learning algorithm's main goal is to systematically modify the network's weights in order to accomplish a certain design objective and increase learning accuracy by lowering mistakes.

An artificial neural network, or ANN, operates in two primary stages: the training phase then the recall and testing phase. The neural network receives both the input pattern and the corresponding target output during the training phase. The input is fed into the network at the input nodes, where it is analysed via the input layer's neurons according to an activation function, and output is produced. The neurons on the next level receive this output after that, and so on, till it reaches the output nodes.

During the training phase of the learning process, the weights the connections across neurons are adjusted to reduce the error between the actual output of the network and the set and pattern of input data. The amount of error reduction depends on the network type, data quality, and learning strategy. Once the error is minimised, the network that has been taught will go through fresh inputs and produce outputs. This is referred to as the testing and recall phase.

Figure 2 depicts the structure of the ANN during the training period. This picture illustrates the important factors to consider while building a robust neural network model voor use in price forecasting, among other applications. In order to ensure that the model forecasts results based on the trained data with the necessary accuracy and efficiency, several modules must be carefully considered in the architecture.

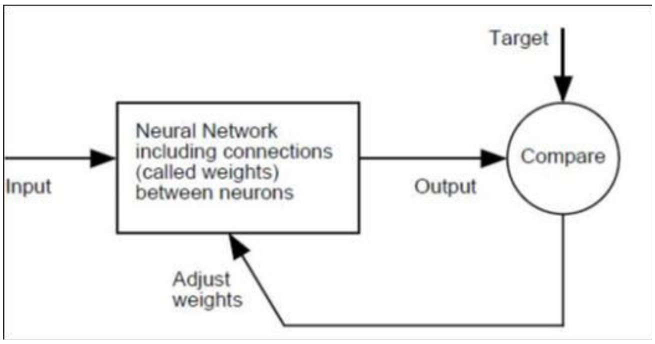

Fig.2. Training of ANN [4].

This outlines the components that need to be taken into account while creating a neural network model that is suitable for price forecasting.

Neural network approach :

Neural networks are intricate networks of linked basic processing units that are intended to replicate the functionality of the human brain in a particular task. Each of those units, which are frequently referred to as neurons, modifies the weighted total of its signals by a fixed quantity known as bias. After that, a transfer function—which could be linear, sigmoid, or hyperbolic tangent—is applied to the total. The internal architecture of the neuron is depicted in Fig. 3. Neural networks with perceptrons that are multilayered are the most popular and commonly used type. Networks that don't form loops are known as feed forward networks. Recurrent non-feed forward networks having one or more loops or links are used in specific application types [8,9]. The arrangement of the units defines the network architecture. Three layers are commonly used to structure units in forward-looking networks: a layer for input, a layer of output, plus a few hidden levels. Even if they aren't linked to one another, the units in every level may share the same inputs. Usually, the elements of the input layer merely relay the pattern of input to all of the nodes in the network.

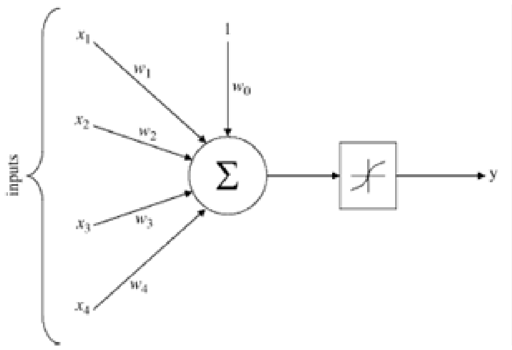

Fig.3. Internal structure of Neuron

The units within the output and hidden layers process the data.

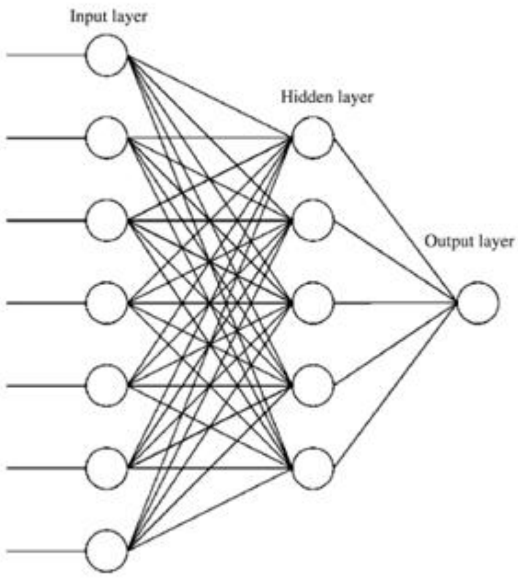

Fig. 4. illustrates the architecture of the typical three-layered feedback neural networks model.

If each unit in the neural network has connectivity to each subsequent unit throughout the network, then the neural network under discussion is fully connected. Determining the ideal network architecture required looking at a lot of combinations. Among the combinations were networks with varying numbers of units in each layer, varying numbers of hidden layers, and varying transfer function types.

A. Input Selection

In the context of an ANN, the input selection process seeks the optimal input parameters. Improving the inputs would provide a more precise, faster-closing, and more compact ANN. Some of the variables influencing power costs are day type (weekday), pricing history, and demand level (system load). Using correlation analysis, the most efficient lags—that is, the prices from the preceding hours—are chosen.

B. Training

A set of samples with appropriate network behavior—that is, network components and target output—is needed for the ANN training process. The ANN's weights and biases are gradually changed during training in order to lower the network effectiveness value. Levenberg-Marquart propagating backwards (LMBP), an ANN train function that modifies weight and bias values in accordance with Levenberg-Marquardt optimisation, will be used to train the new ANN models. To manage the combination of noise in the initial data, this method adds an extra regularisation term to the Gauss-Newton method. LMBP performs better than traditional back propagation methods, which are occasionally too sluggish to be useful. Neurons that output from buried layers or between them have a nonlinear transfer function known as the "tangent sigmoid" (tansig):

$$f(x) = \frac{2}{1+\exp(-2x)} - 1 \qquad (1)$$

A tansig node receives weighted inputs, adds them up, and then repeats the previous steps to get an output. The inputs and outputs of the tansig function should fall within the same range since it produces results that vary from -1 to +1. As a result, limiting the ANN's inputs and goal outputs is necessary. The minimum (min)-maximum (max) standardisation approach was tested, and the mean-standard deviation or min-max method was selected:

$$X_{normalized} = \frac{X_{actual} - X_{\min}}{X_{\max} - X_{\min}} \times 2 - 1 \qquad (2)$$

The advantage of this normalization method is that it may also be used to map the output you want to the non-saturated part of the tansig function. The training or forecasting modes' accuracy is improved by this method.

C. Hidden layers and output

The output layer is present in ANN models. There is only one neuron in the output layer of the price forecasting model as the hourly price is the output. In order to achieve the optimum results, the number and neurons and layers that are hidden in every single one are chosen.

D. Assessment of Performance

We were to contrast the ANN models' forecasts to those of other techniques in order to assess how well they performed. This objective can also be accomplished in other ways. Among these techniques is the Mean Absolute Price forecasting efficacy is frequently assessed using the percentage error (MAPE). This is how the MAPE is defined:

The definition of the Percent Error (PE) is,

$$PE = (X_{forecasted} - X_{actual}) / X_{actual} \quad 100\% \qquad (3)$$

and the APE is:

$$APE = |PE| \qquad (4)$$

then, the MAPE is given as:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} APE_i \qquad (5)$$

Where,

Xforecasted the anticipated price value
Xactual: the price's true value
N: quantity of data that have been trained.

V. ANN MODEL: USING MATLAB FOR PRICE FORECASTING

We introduce an ANN pricing forecasting model in this phase that was trained with Matlab. ANN offers a very efficient way to analyse factors that could impact the cost of power. Using neural networks with artificial intelligence (ANNs), To find the parameters in price projections that will fulfil a given mathematical formula, we use historical data. The developed models are then used to forecast future power prices using actual input data. The input level, two layers that are concealed, and the output layer make up the four levels of the suggested ANN model, which is a perceptron neural network. The system demand, historic pricing information, and attributes that affect the hourly energy price are all contained in the input layer. Since the hourly value is the ANN output, there is just one neural in the final product layer. For ANN training, the traditional forward propagation (BP) method has been replaced with the Levenberg-Mar BP (LMBP) methodology in order to speed up convergence.

Data selection and normalization:

The neural network in this article is trained using historical market data, specifically power prices and hours. Purelin, a purely linear transferring operation, or tantsig, a hyperbolic tangential sigmoid coefficients transmission function with outputs between 1 and 1, are the transfer functions utilised for the concealed to output layers. In this case, the data has been normalised form 0 to 1 for testing and training purposes.

applying an algorithm for neural networks to historical power market data that is based upon the Levenberg-Marquardt approach and the function of radial basis. Testing error for the first approach was found to be less than that of the second. Training outcomes for multiple ANN networks with a learning frequency of (6-10-24, 6-15-24, 6-30-24, and 6-40-24).

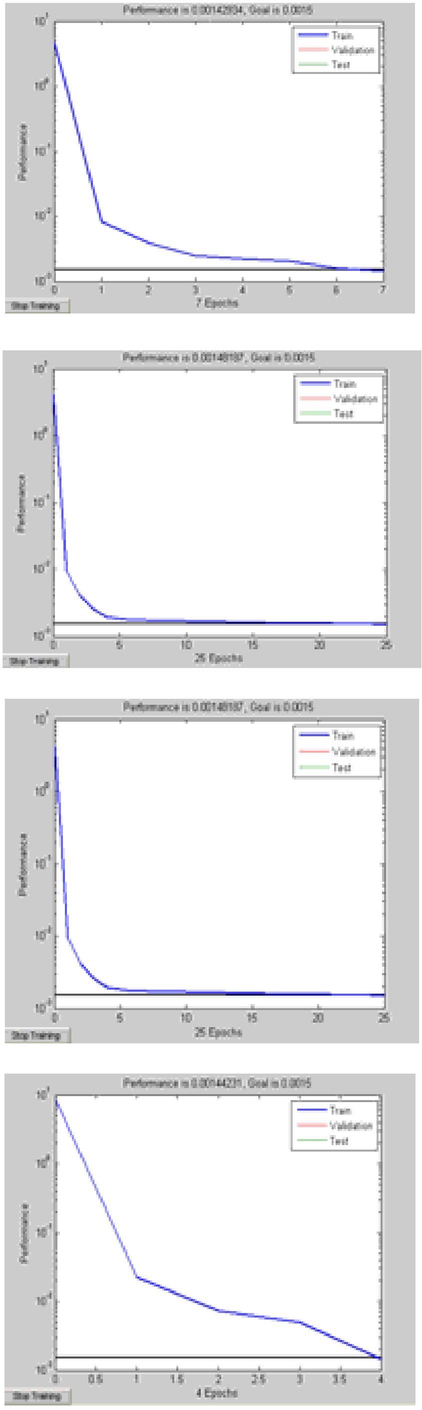

Fig.5. Training results of different ANN Networks

Result from Levenberg_Marquardt Method:

Table 1: Output of Levenberg_Marquardt Method

Training error(RMS value)	Testing error (RMS value)	Average percentage error
0.0349	0.0287	1.78%
0.0347	0.0294	2.01%
0.0348	0.0320	2.33%

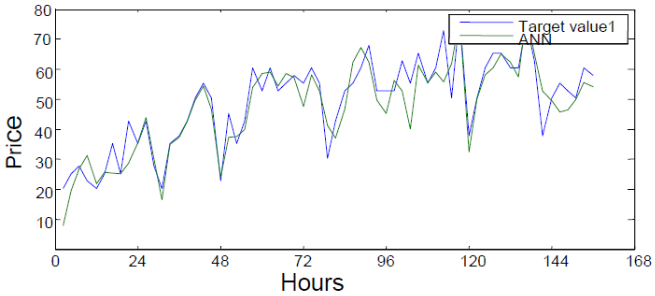

Fig.6. Graphical view of Levenberg_Marquardt Method

Findings using the radial basis functional neural networks technique:

Table 2 : Output obtain from radial basis function neural network

Training error(RMS value)	Testing error (RMS value)	Average percentage error
0.0601	0.0475	3.50%
0.0603	0.0424	3.09%
0.0600	0.0444	3.27%

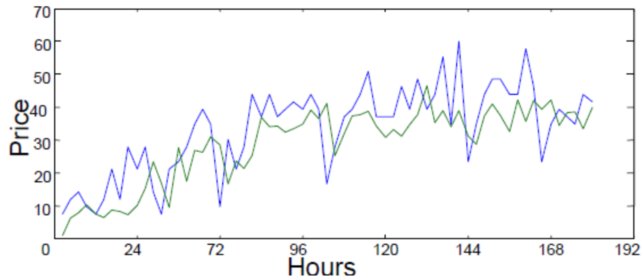

Fig.7. Graphical view of Radial basis function neural network approach

VI. CONCLUSION

Less regulation and more competition in the power market are the results of recent reforms in the electrical business. In these circumstances, figuring out the energy cost is crucial to everything that goes on in the energy market, including generating companies' bid strategies. Thus, this study provides an example of ANN-based rapid power price projections. A pre and post-processing method for price spike data is developed in order to increase the model's accuracy. As a result, performance increased in training and exams. When compared to other simple methods, the results show that the ANN (artificial neural network) model is a useful tool for price forecasting in terms both of accuracy and usability.

ACKNOWLEDGMENT

Our is our opportunity to sincerely appreciate and show our appreciation to the project guide at Tulsiramji Gaikwad College of Engineering in Nagpur, who provided us with guidance and room to do our work.

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