# IMPROVED CASCADED NEURAL NETWORK FOR ELECTRICITY FORECASTING IN INDIAN WHOLESALE ELECTRICITY MARKET

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***Abstract*- This research paper presents electricity marketing clearing price for Russian wholesale market based on an improved cascaded neural network. In the last decade MCP forecasting is burning issue between researchers. In this research work a novel approach is used that is based on modified back propagation algorithm for training, validation and testing on different month price of electricity. For the implementation of this proposed work MATLAB R 2015a(8.1.0.602)software and simulation are used. In this presented strategy structure a superior technique which can correct the load rate and rectify the MAPE, MSE and RMSE. This proposed method shows minimum MAPE as compare to other recently methods. For the proposed method MAPE value is 1.9%.**

**Keyword:-Day-Ahead Electricity Markets, Electricity Price Forecasting, Time Series Models, Soft Computing Models Neural network, etc...,**

## 1. INTRODUCTION

Electricity has become an essential commodity in a modern society. Our daily lives depend on the use of electricity in various forms. Rapid rise of industrialization in the last century has contributed to a phenomenal growth of electricity consumption and hence the tremendous increase in generation of electrical energy.

The advent of bulk generation of electrical energy required that the electrical energy be transmitted to load centers via elaborate networks of transmission lines. At the load centers, electrical energy is then distributed by a complex web of distribution networks. This basic configuration of generation, transmission and distribution is still in use all over the world.

A part of the electrical energy is lost during its transmission. This puts a physical limit as to the distances of generation centers from the load centers. That is why electrical systems have evolved mainly within their own geo graphical jurisdiction. Although by employing a different technique, called DC transmission, it became feasible to transport electrical energy over longer distance electrical systems predominantly remained bound to their geographical jurisdiction.

### 1.1NATURALMONOPOLYANDREGULATION

A Generation, transmission and distribution of electrical energy require huge capital investment for operation, maintenance and expansion. This type of investment was achieved by awarding monopoly over the entire geographical jurisdiction. In some places, crown corporations were established and given monopoly of generation, transmission and distribution of electrical energy within pre-specified geographical boundaries. A single entity used to run and control all aspects of generation, transmission and distribution within a geographical jurisdiction. The single entity could set its own rate some times with the approval from a regulatory body. A natural monopoly guaranteed a decent return on the huge investment that a single entity or a crown corporation would typically make. However, regulation became part of the electricity industry all over the world. Its chief objective was to protect the consumer, from the inevitable consequences of a monopoly industry.

The regulated electric market is still a natural monopoly industry but carefully watched by the government. Its vertically integrated structure is shown in Figure 1.1. Back in the 1970’s in power distribution system, there was usually a limited number of huge corporations owning and operating few vertically integrated electric systems. Each corporation was an

Independent system. Combined, they controlled more than 90 percent of the total electric market in their country. In a vertically integrated system, local consumers have no other choice for electricity service but the local provider. In a natural monopoly (regulated) electric market, electricity price is high and services are usually limited.

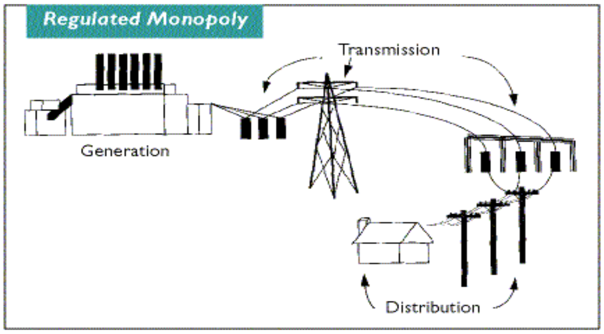



**Fig1.1: Regulated Electric Market**

**DEREGULATEDELECTRICMARKET**

The meaning of deregulation is the reduction or elimination of government control in a particular industry. The purpose of deregulation is to promote more competition within the same industry and same geographical jurisdiction. It is generally believed that fewer and simpler regulation will lead to a raised level of competitiveness and would overall result higher productivity, more efficiency and lower prices.

Deregulation of electrical markets calls for the restructuring of the electricity industry. The traditional vertically integrated system is to break down as three separate businesses; 1) generation company, 2) transmission company and 3) distribution company. These three businesses are to be owned and operated by three different entities. Deregulators advocate that deregulated electric market will bring cheaper electricity and meantime, more choices for the customers.

In a deregulated market, instead of only one generation provider in a local area, there are now several generation providers in the same area. The local regulatory body can no longer set the electricity price. Consumers have more choices about their local electricity providers. They can choose different electricity providers depending on their requirements and demand.

## II. PROPOSEDMETHODOLOGY

This part discuss about the proposed arrangement of electrical market value clearing. There are various strategies accessible foresee MCP and load. In the above chapter talk about the various strategies in writing over view and related issues MCP. The majority of the techniques shows brings about terms MAPE,RMSE and MAE. In this proposed strategy structure a superior technique which can correct the load rate and rectify the MAPE, MSE and RMSE of the proposed technique.

### 2.1DataProcess

This presented work create many features from historical data, proposed work cannot use all generated features since training accuracy depends on the data set different values.

### Feature Extraction

The electricity market data comes in the form of a time series, i.e. (time, value) pairs, and does not provide any specific features for use with ANN. Thus In this proposed method has to create features from the available past data to be used as inputs to the ANN. In this work analyzed the input data using a similar approach to the method and create about different features from the available electricity market data. Hourly data is extracted for 24-hour windows, yielding different features with which in this proposed method seek to forecast the electricity price for the following hour. The best features that give short term trend in the price market are past 24 hour data which has been verified. But this data does not capture the seasonal behaviors and long term trends.

### Feature Selection

For the feature selection implement search algorithms for finding the subset of features in feature space and evaluate the subset using the model or learning algorithm. Each feature subset is evaluated based on the estimated accuracy obtained using the learning algorithm. Estimation of accuracy is done using cross validation. ANN methods are most widely used in the context of supervised learning problems where labels are available. It can also be used for unsupervised learning problems where some other target or objective function which results in better clusters is used instead of classification accuracy. After creating around 20 features that capture long term trends and past 24hour data as features perform feature selection to find the best set of features. Due to large pool of features divide the feature set in to every hour as 24 hourly features in one pool and rest of the features in another pool. As described, past 24 hourly price features capture the current short term trend and selecting only a subset of these features will diminish the accuracy of the proposed ANN model.

### Data Set

The Russian power market remains in a restructuring phase whereby former state-owned vertically integrated monopolies have been unbundled and are partly privatized. However, the network companies, system operator, an dnuclearand

Hydro power plants are still state-owned and the government also has stakes in several territorial and wholesale generation companies through the state-controlled utility, Gazprom. The restructuring is occurring in the two price zones which consume most of the power generated.

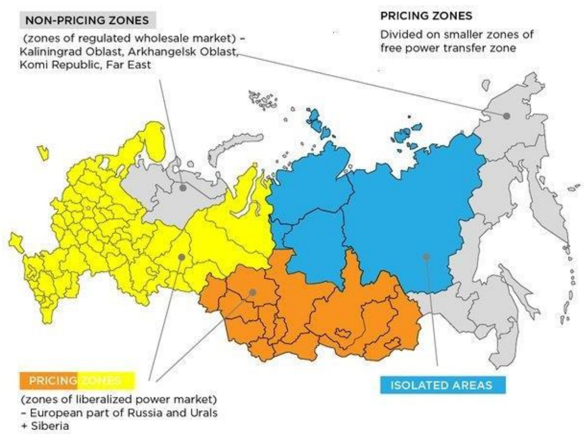



**Fig.2.1:Whole sale Market(Abdurafikov,2009)**

if the spot ER exceeds the maximum tolerable ER. Finally, the forecasted day-ahead real time pricing coming from the integrated model is the desired output in this study.

**Architecture of the proposed Cascaded feed forward network**

Then, the linear behavior of the data is estimated by using the LS fitting model. Afterwards, the GP model is applied in the estimation of the non-linear behavior within the data. After that, the ANN model based error optimization procedure will be determined if it is necessary to be executed on this stage in accordance with the spot error rate (ER) of the initial forecasting result. The ANN model will be executed to improve the specific forecasting accuracy

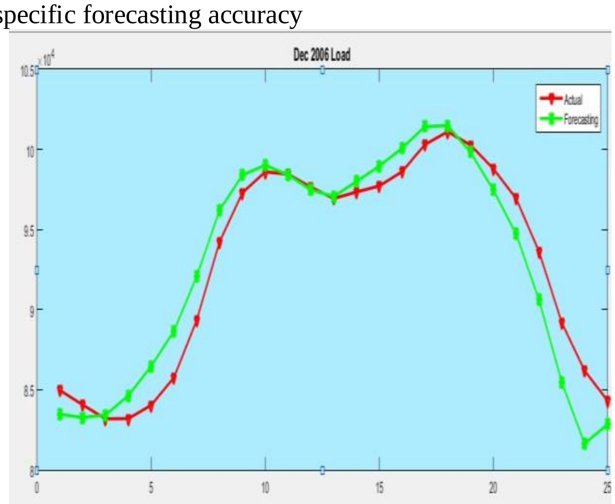
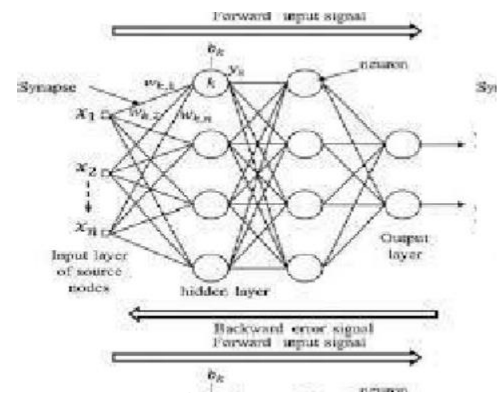



**Fig2.2Historical real time pricing over historical day samples (24 h)**

The process of estimating the model weights W is usually called training. In particular, given a training set –




**2.6 Cascade-Forward Networks**

A feed ahead neural community is a synthetic Cascade-forward networks whereby connections between the nodes do no longer structure a cycle. As such, it is unique from its descendant: recurrent Cascade-forward networks. The Cascade Forward Back-propagation neural network (CFBPNN) is implemented for training the input data. For training the neural network; data should be stored in database initially. The purpose is to find features of the data and it is passed to the network as input. Cascade – forward Back-propagation network consist of layers using the **DOTPROD** weight function, **NETSUM** net input function, and the specified transfer functions. The first layer has a weight coming from the input and each subsequent layer has weight coming from the inputs with all previous layers. The last layer is the network output, called as output layer. Every layer is having biases. Each layers weights and biases are initialized using INITNW function. Adaption is done with TRAINS function and updates weights with the specified learning function. Training is done with the specified training function and corresponding performance is measured according to the specified performance function.

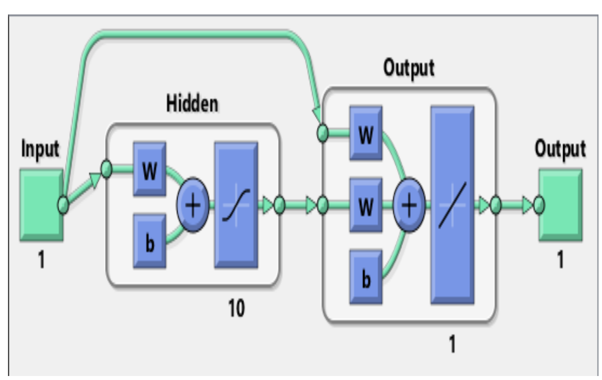



**Fig.2.3Cascade-forwardnetworks**

## III. SIMULATIONANDRESULT

In this section talk about the reenactment model and outcomes of proposed calculation. The proposed strategy is executed utilizing matrix laboratory. matrix laboratory represents Matrix Laboratory is a notable devicefor such sort of calculation usage identified with information examination computation. Matrix laboratory contain a rich capacity of information analysis and machine learning tools.

**Simulation Model Explanation**

A The result of proposed method for development of using machine learning technique for electricity market clearing price shown in this section, simulation of our proposed method and result calculation. For the implementation of proposed work with the help the MATLAB R 2015a (8.1.0.602) software and simulate our whole proposed methodology in data analysis. Figure 3.1 shows software home page window used to

**Result Parameters**

There are different result parameters available in area of electricity market price clearing and load forecasting. There are different parameters available such as mean absolute error (MAE), mean absolute percentage (MAPE),), root mean square error (RMSE). In the shows the definition of these formula -

**A. Mean Absolute Percentage Error(MAPE)**

It is a measure of prediction accuracy of a fore casting method. It is calculated as the average of the unsigned percentage error, as shown in the example below:

$$MAPE=\left(\frac{1}{n}\sum\frac{|Actual-Forecast|}{|Actual|}\right)\times 100 \quad (3.1)$$

**B. Mean Absolute Error(MAE)**

MAE is a measure of errors between paired observations expressing the same phenomenon. MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. It's the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight.

$$MAE=\left(\frac{1}{n}\sum\frac{|Actual-Forecast|}{|Actual|}\right) \quad (3.2)$$

C. **Root Mean Square Error(RMSE)**

RMSE is a quadratic scoring rule that also measures the average magnitude of the error. It's the square root of the average of squared differences between prediction and actual observation.

$$RMSE=\sqrt{\left(\frac{1}{n}\sum_{j=1}^{n}\left((Actual-Forecast)^2\right)\right)} \quad (3.3)$$

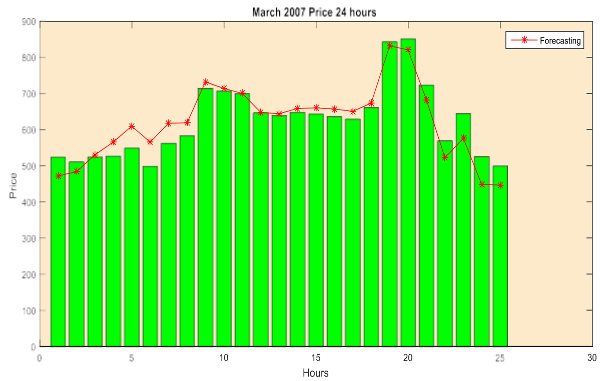



**Fig.3.8(a)Shows the March200724 hours Price forecasting**

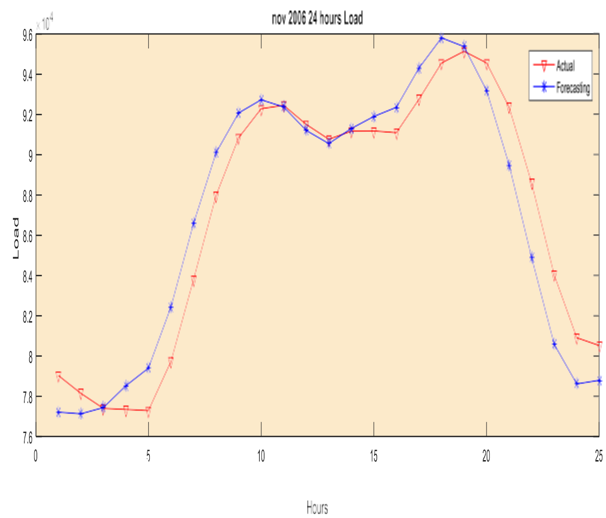



**Fig.3.8(f)Shows the Nov.200624 hours Load forecasting**

In the above figure 3.8 (a) to 5.8 (f) shows the 24 hours price forecasting, in this figure x axis time in hour and Y axis shows the price or load.

LoadMAEandMAPEfor1Sep2006is24hours

**Table3.3ResultOutcomesAverageLoadError**

**MAE and MAPE**

| Load MAE | Load MAPE(%) |
|---|---|
| 1.3186 | 0.0020 |
| 1.4004 | 0.0020 |
| 1.4622 | 0.0017 |

| | |
|---|---|
| 1.5254 | 0.0017 |
| 1.4669 | 0.0018 |
| 1.6042 | 0.0017 |
| 1.5856 | 0.0017 |

It is clearly see that in the graph the value of proposed predicated is most similar to actual value. Its shows that proposed method for MCP and Load prediction work properly. Now discuss the result comparison of proposed method with different previous methods.

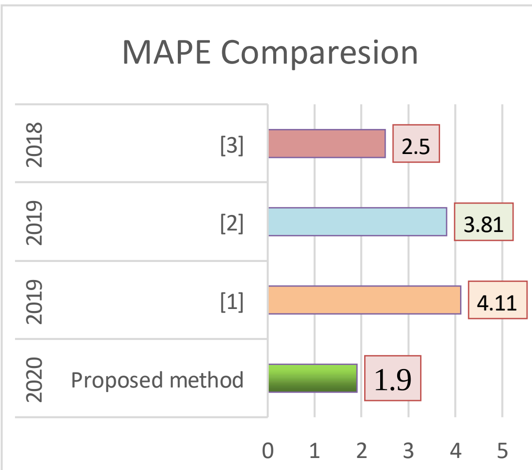



**Fig.3.6ResultComparisoninMAPE**

In the below Fig. 3.6 shows the mean absolute presented error (MPAE), in this figure clearly show the proposed method shows minimum MAPE as compare to other recently methods. For the proposed method MAPE value is 1.9%.

## IV. CONCLUSION

In this presented work focus on feed forward Cascade-forward networks based Electricity load and Market Clearing Price (MCP). The important outcomes of this work are shown in the section of comparative analysis. In this research work observe that the MCP and load forecasting is the major problem in Electricity. The proposed method shows better result as compare to other previous in terms of MAPE that is 1.9%.

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