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A Machine Learning based Load Forecast Analysis for Power Grid and Electricity Market Regularization using Modified Soft Computing Technique

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Abstract*— In this research work focus on electricity market clearing prices are important for market participants as they determine the price of electricity at which the market is cleared. Accurate prediction of these prices is essential for energy traders, producers, and consumers to make informed decisions about energy production, consumption, and trading. In this study, different machine learning models such as linear regression, decision trees, random forests, artificial neural networks, and support vector machines are evaluated for their effectiveness in predicting electricity market clearing prices. The data used for analysis is obtained from the electricity market, and various statistical measures such as mean absolute error, root mean squared error, and coefficient of determination are used to compare the performance of the different models. As part of the strategy framework, we provide an improved approach that can reduce the load time while also reducing the MAPE, MSE, and RMSE. The proposed method's end goal is to forecast the energy market clearing price. The MAPE of our proposed technique is the smallest of all that have been reported in the literature. The calculated MAPE for the proposed strategy is 1.9%. The proposed method may be used in a number of different types of electric boards to provide clean, stable electricity.

***Keywords*— Electricity Marketing; Machine Learning; Clearing Price Prediction.**

I. INTRODUCTION

In In the modern world, electricity is a basic need. In many respects, our everyday lives would be impossible without the usage of electricity in some form or another.. The last century's rapid industrialization has led to spectacular increases in power use and, consequently, electrical energy production. Electrical energy had to be transferred to load centers via complex networks of transmission lines when bulk electrical energy generation began. An intricate system of distribution networks is then used at the load centers to disperse the electrical energy. All around the world, this fundamental setup of power generation, transmission, and distribution is still in use.

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 geographical 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.

A. History of Electricity Market

P.W. Fleury & Co. performed the first official lighting demonstration in Kolkata (formerly Calcutta) on July 24, 1879. On January 15, 1897, the Indian Electric Co. was established in London, and on January 7, 1897, Kilburn & Co [41]., in their capacity as agents, were authorised to install electric lights in Calcutta. The corporation changed its name to the Calcutta Electric Supply Corporation about a month after selecting its initial name. It wasn't until 1970 that the company's headquarters were moved from London to Calcutta. After the success of bringing power to Calcutta, it was expanded to neighboring Bombay (now Mumbai). Mumbai's Crawford Market hosted the city's first electric lighting demonstration in 1882, and the Bombay Electric Supply & Tramways Company (BEST) constructed a generating station that powered the tram network in the city in 1905. At a tea estate in Sidrapong, the Darjeeling Municipality constructed India's first hydroelectric plant in 1897.The first electrical street light in Asia was switched on on August 5, 1905, in Bangalore, India. On February 3, 1925, the first electrical train in the country travelled over the Harbour Line from Bombay's Victoria Terminus to Kurla. The Government Engineering College in Jabalpur was the first organization to establish a high-voltage laboratory in India in 1947. [21] When a new solar facility was inaugurated on August 18, Cochin International Airport in India became the first airport in the world to be totally powered by solar energy.

II. LITERATURE SURVEY

Sajawal ur Rehman Khan, et. al. (2024)- In this research study, The main objective of the efficient and effective electric-load prediction for big data is successfully achieved using our proposed ECNN and ESVM forecasting models. Furthermore, our proposed forecasting models helped decrease computational complexity of the forecasting model by eliminating less-important features using modern feature-selection and extraction methods. The numbers of layers of our proposed ECNN are increased and the hyper parameters of the proposed techniques ECNN and ESVM are dynamically adjusted. Simulation results of our proposed techniques are compared with conventional CNN and SVM techniques using four performance error estimators, The performance metrics proved that our proposed ECNN and ESVM electric-load forecasting models have the lowest error rates. Due to the growing worldwide interest in reliable and sustainable energy supply, incorporating more renewable and alternative energy sources reduces stress on existing electric transmission systems. The proposed schemes should be helpful in finding the exact power generation from distributed sources and power consumption that helps in smooth working of the smart grid. The same infrastructure can be implemented for industrial power-management systems and will also be effective for smart agriculture systems [01].

Jiahui Wu, et. al. (2022) - The electricity market will tend to be diverse and competitive to realize Carbon Neutrality goals under Energy Internet. Moreover, bidding strategies and methods are essential for the stable and benign operation of the electricity market. With the development of artificial intelligence and computer simulation technology, multi-agent simulation has gradually become a significant method for electricity market bidding. Among them, Multi-Agent Reinforcement Learning (MARL) can help agents adapt to changing environments. In contrast, Multi-Agent Transfer Learning (MATL) can help agents learn from not only the target task but also other similar tasks [02].

Dakhaz Mustafa Abdullah, et.al. (2021) – In this research work presented, we present three LSTM-based hybrid architectures for the EPF. This study puts emphasis on the influence of feature selection methods in the proposed hybrid models. In particular, we compare the prediction performance of the two-step feature selection, the autoencoder, and two-stage feature selection models based on the empirical study on the Nord Pool day-ahead system price. In addition, we employ a SHAP method to evaluate the importance and impact of the features on predicting this price. The main findings are the following: (1) We conclude that the different feature selection methods will lead to different feature selections. As input, diverse features will have a comparably significant impact on the performance of LSTM-based predictive models. (2) Compared to CNN-LSTM and ConvLSTM, LSTM-LSTM is a better autoencoder structure for EPF. (3) The two-stage models can improve the forecasting accuracy of two-step models to some extent. The superior feature selection from the RFE-SVR model [03].

Haq, M. R., & Ni, Z, et.al (2019) - Forecasting electricity demand is crucial today to further reduce the cost of the energy market for the day ahead. Utility operators can benefit from load forecasting for effective administration of a demand response programmed. Utility managers can create appropriate operational plans for generating units with the aid of more accurate and efficient forecasting of the power load demand. But resolving the load forecasting issue is a difficult undertaking given that the current load, various exogenous external elements (such as weather variables, social variables, working day or holiday), time of day, and season of the year all have an impact on the current load [04].

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III. PROPOSED METHODOLOGY

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 overview and related issues MCP. The majority of the techniques shows 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.

A. Data Process

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.

B. Feature Extraction

The electricity market data comes in the form of a time series, i.e. as (time, value) pairs, and does not provide any specific features for use with ANN. Thus In this proposed method have 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.

In price forecasting, it is important to take into account both short and long term trends and also seasonal patterns. Sudden changes in the price might be caused by seasonal behaviors and other factors. In order to capture this behavior proposed create putatively relevant features based on historical data which lasts for longer period. In this work create features such as last year same day same hour data, last year same day same hour price fluctuation, last week same day same hour price, last week same hour price fluctuation etc. To achieve higher forecasting accuracy, over-fitting and over training of ANN should be avoided. In order to select the best features In this proposed method use feature selection techniques as described in the next section.

C. 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 24 hour data as features perform feature selection to find the best set of features. Due to large pool of features divide the feature set into 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.

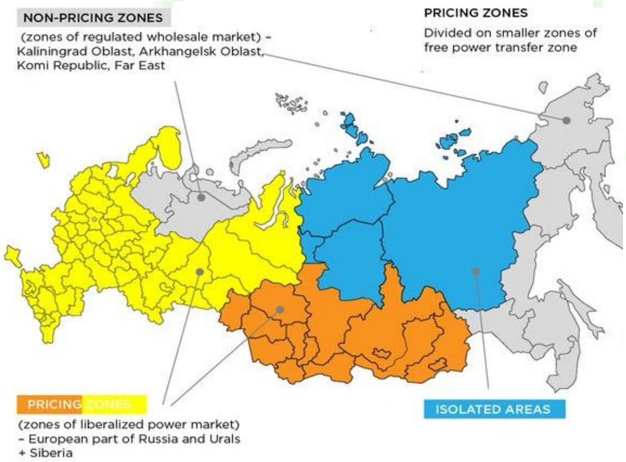

Fig. 1: Wholesale Market (Abdurafikov, 2009).

D. 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, and nuclear and hydropower plants are still state-owned and the government also have 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

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IV. RESULT AND DISCUSSION

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 device for such sort of calculation usage identified with information examination computation. Matrix laboratory contain a rich capacity of information analysis and machine leaning tools. 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 4.1 shows software home page window used to design and simulate of proposed method.

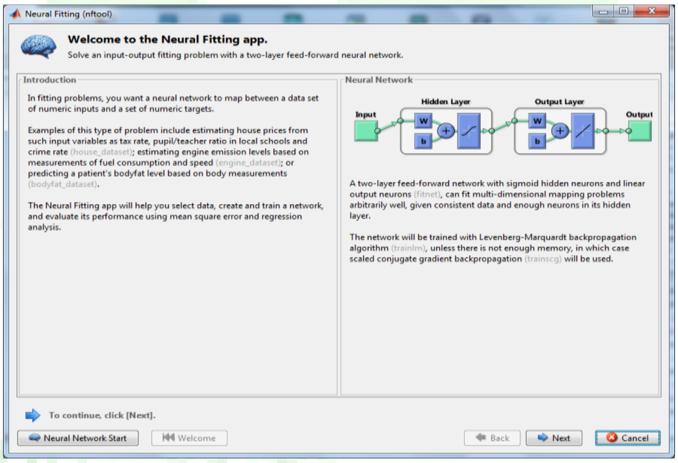

Fig 2 Shows Neural fitting Software

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 (MPAE), root mean square error (RMSE).

A. Mean Absolute Percentage Error (MAPE)

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

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

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

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

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.

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

D. Mean Square Error (MSE)

MSE 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

$$\mathrm{MSE} = \left(\frac{1}{\mathrm{n}}\sum_{\mathrm{j}=1}^{\mathrm{n}}((\mathrm{Actual} - \mathrm{Forecast})^2)\right)$$

Proposed Cascade-forward networks

Cascade-forward networks consist of a series of layers. Cascade-forward networks are similar to feed-forward networks, but include a connection from the input and every previous layer to following layers. As with feed-forward networks, a two-or more layer cascade-network can learn any finite input-output relationship arbitrarily well given enough hidden neurons, can fit any finite input-output mapping problem. In the below Fig. 3 shows the feed forward network

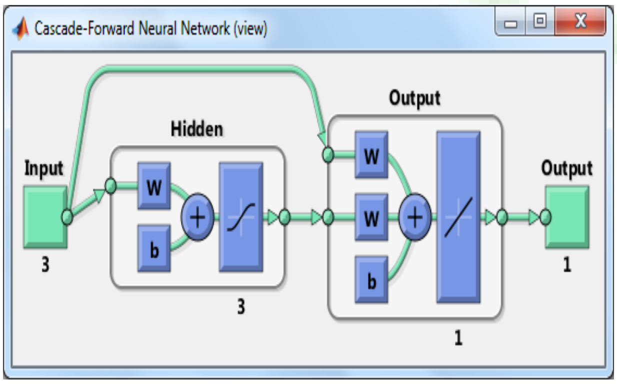

Fig 3 Shows Feed Forward Network

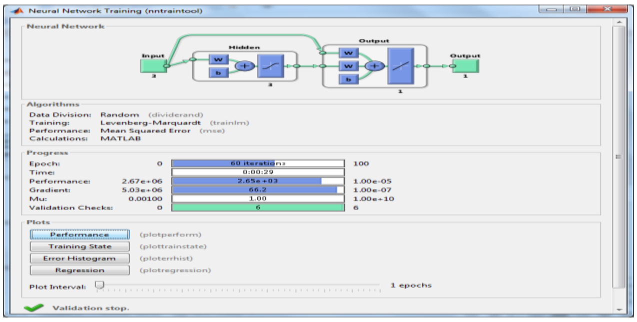

Fig 4 Shows the Training of Cascade-forward networks

In the above Fig. 4 shows the training of Cascade-forward networks. For training of Cascade-forward networks use Levenberg-Marquardt back propagation. This training function works based on updates weight and bias values according to Levenberg-Marquardt optimization. This training function is often the fastest back propagation algorithm, and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms. The outcome of the Levenberg-Marquardt is shown in the below Fig. 5

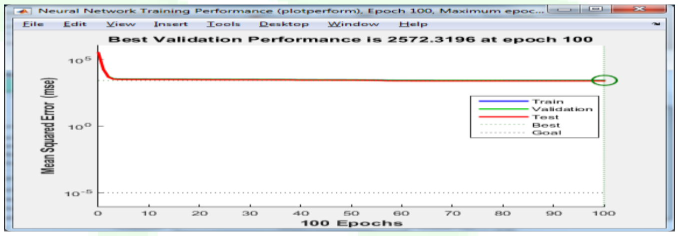

Fig 5 Shows the Performance output in terms of MSE

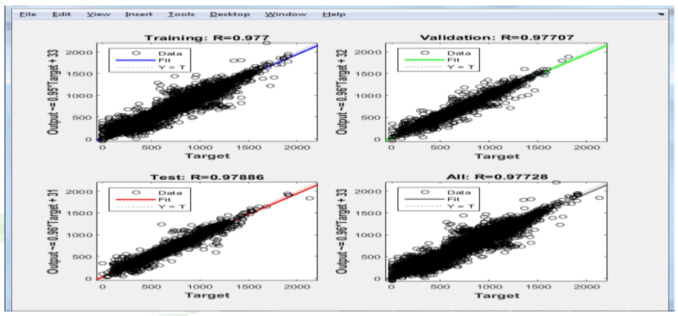

Fig 6 Shows the Performance output in terms of Regression

The mean square error of proposed method shows in the above Fig.6 The error training is observe in terms of mean square error MSE that is shown in the y axis and in the x axis shows the number of epochs that is used to calculate the optimum result of the purposed method for electricity market price clearing.

A. Resultant Outcome of Proposed Method

In the below figure 6 shows the average price prediction of the proposed Cascade-forward networks method.

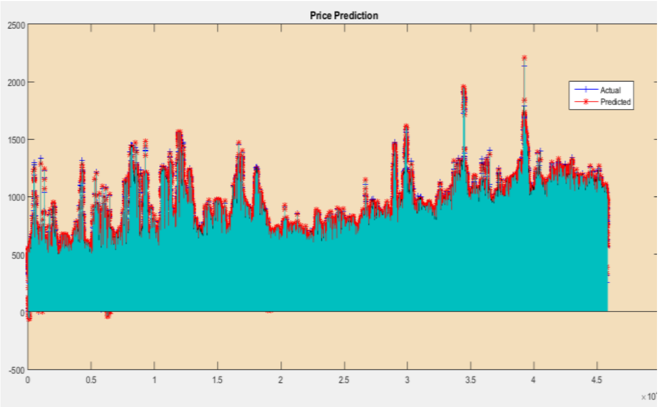

Fig 6: Shows the overall Price predation of complete data set

In the below figure 6 shows the average load prediction of the proposed Cascade-forward networks method. The proposed network fallow similar load prediction.

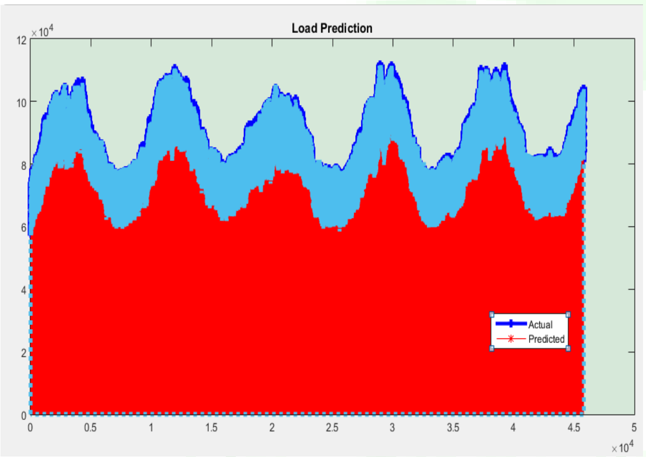

Fig 7: Shows the load prediction of Data set

In the below section shows the different resultant value obtain in matlab..That is discuss in the below table 5.2 discussed parameters are MAE_load ,MAE_price , MAPE_Price, MAPE_load, MSE_load and MSE_price

Table 1 Result Outcomes

MAE_load	681.6736	MSE_load	7.3145e+05
MAE_load	0.8364	MSE_prie	2.5697e+03
MAE_load	29.7809	MSE_load	1.0010e+03
MAE_load	105.1729	MSE_load	1.2069
MAE_load	29.7872	MSE_prie	106.8627

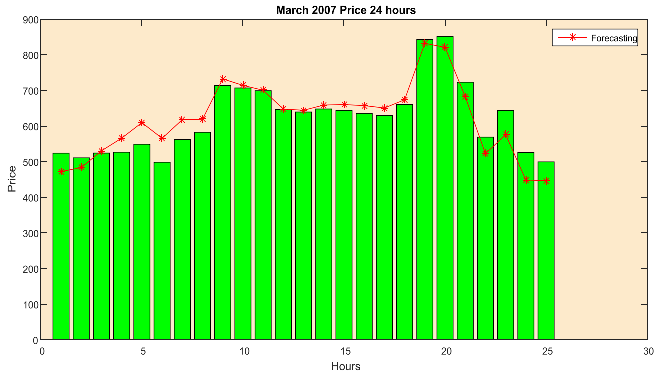

Fig 8 Shows the March 2007 24 hours Price forecasting

In the above figure 8 24 hours price forecasting, in this figure x axis time in hour and Yaxis shows the price. In this graph green bars shows the actual price in march 1 days 24 hours requirement, and red line shows proposed forecast of 24 hours.

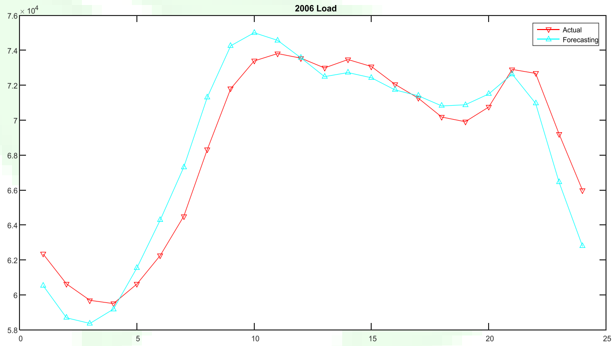

Fig 9 Shows March 2006 24 Hours Load

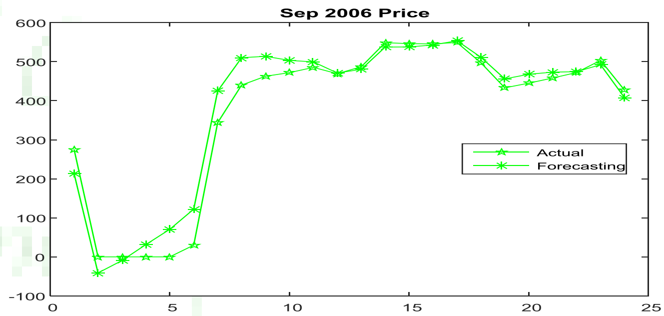

Fig 11 Shows the Sep. 2006 24 hours Price forecasting

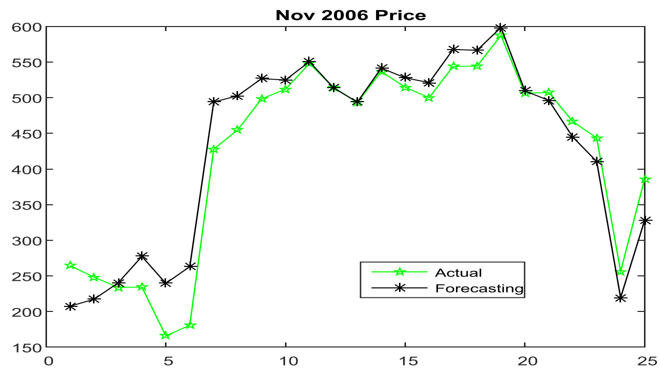

Fig 12 Shows the Nov. 2006 24 hours Price forecasting

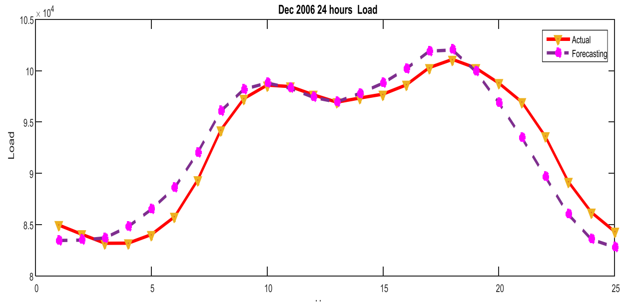

Fig 13 Shows the Dec. 2006 24 hours Load forecasting

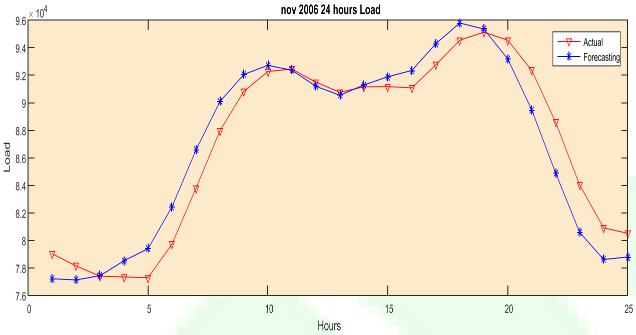

Fig 14 Shows the Nov. 2006 24 hours Load forecasting

In the above figure 8 to 14 shows the 24 hours price forecasting, in this figure x axis time in hour and Y axis shows the price or load. Load MAE and MAPE for 1 Sep 2006 is 24 hours

Table 2 Result Outcomes Average Load Error 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

Avarage MAE of Load = 1.480474e+03
Avarage MAPE of Load = 1.783831e+00
Price Parameter----- 1 Sep 2006 to 31 -March 2007 is 24 hours

Table 3 Result Outcomes Average MSE and RMSE

MSE_Load	7.3145e+05
MSE_Price	2.5697e+03
RMSE_load	2.7707e+07
RMSE_price	1.6423e+06

The different months Load and different month price forecasting or can said MCP and Load. In all figure x-axis shows the number of hours and y- axis shows load. In this figure clearly see that red color in graph shows the predicated value of load and price and blue shows the actual value of load and price 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.

V.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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