International Journal of LNCT
Volume-4 Issue-18 June -2020
ISSN: (Online):2456-9895

A BIRD EYEVIEW ON A ROBUST APPROACH FOR MULTI-STEP ELECTRICITY MARKET PRICE FORECASTING FOR ELECTRICITY MARKET PRICE MANAGEMENT USING ANN

Archana kumari, Ms.Sudeshna Ghosh
[1]Research Scholar,[2]Assistant Professor,
Department of Electrical & Electronics Engineering
Lakshmi Narain College of Technology Excellence (L.N.C.T.E) Bhopal (M.P), India,
archanaku10494@gmail.com

***Abstract*—Electricity markets, price forecasting is gaining importance between various market players in the power in order to adjust their bids in the day-ahead electricity markets and maximize their profits. In this research work present electricity price forecasting problem and its soft computing based solutions. An accurate price forecasting method is an important factor for the market players as it enables them to decide their bidding strategy to maximize profits. There are different models are available for electricity price forecasting such as time series models and simulation models The presented work summarizes the influencing factors that affect the price behavior and various established forecasting models based on time series and other simulation based models.**

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

1. INTRODUCTION

1.1 Background

Since the early 1990s, the process of deregulation and the introduction of competitive electricity markets have been reshaping the landscape of the traditionally monopolistic and government-controlled power sectors. Throughout Europe, North America and Australia, electricity is now traded under market rules using spot and derivative contracts. However, electricity is a very special commodity: it is economically non-storable and power system stability requires a constant balance between production and consumption. At the same time, electricity demand depends on whether (temperature, wind speed, precipitation, etc.) and the intensity of business and everyday activities (on-peak vs. off-peak hours, weekdays vs. weekends, holidays, etc.). These unique characteristics lead to price dynamics not observed in any other market, exhibiting daily, weekly and often annual seasonality and abrupt, short-lived and generally unanticipated price spikes.

Extreme price volatility, which can be up to two orders of magnitude higher than that of any other commodity or financial asset, has forced market participants to hedge not only volume but also price risk. Price forecasts from a few hours to a few months ahead have become of particular interest to power portfolio managers. A power market company able to forecast the volatile wholesale prices with a reasonable level of accuracy can adjust its bidding strategy and its own production or consumption schedule in order to reduce the risk or maximize the profits in day-ahead trading. A ballpark estimate of savings from a 1% reduction in the mean absolute percentage error (MAPE) of short-term price forecasts is $300,000 per year for a utility with 1GW peak load.

1.2 Classification of Modeling Approaches

In the below figure 1.1 shows the different classification approaches in electricity market price prediction**.**

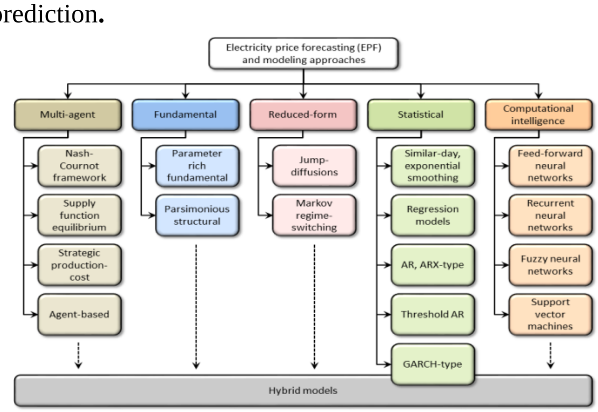

Fig 1.1 A taxonomy of electricity price forecasting (EPF)

A variety of methods and ideas have been tried for EPF over the last 15 years, with varying degrees of success. They can be broadly classified into six groups.

1.2.1 Multi-Agent Models

Multi-agent (multi-agent simulation, equilibrium, game theoretic) models simulate the operation of a system of heterogeneous agents (generating units, companies) interacting with each other, and build the price process by matching the demand and supply in the market. This class includes cost-based models (or production-cost models, PCM), equilibrium or game theoretic approaches and agent-based models.

Multi-agent models generally focus on qualitative issues rather than quantitative results. They may provide insights as to whether or not prices will be above marginal costs, and how this might influence the players' outcomes. However, they pose problems if more quantitative conclusions have to be drawn, particularly if electricity prices have to be predicted with a high level of precision.

1.2.2 Statistical Models

Statistical (econometric, technical analysis) methods forecast the current price by using a mathematical combination of the previous prices and/or previous or current values of exogenous factors, typically consumption and production figures, or weather variables. The two most important categories are additive and multiplicative models. They differ in whether the predicted price is the sum (additive) of a number of components or the product (multiplicative) of a number of factors. The former are far more popular, but the two are closely related - a multiplicative model for prices can be transformed into an additive model for log-prices. Statistical models are attractive because some physical interpretation may be attached to their components, thus allowing engineers and system operators to understand their behavior. They are often criticized for their limited ability to model the (usually) nonlinear behavior of electricity prices and related fundamental variables. However, in practical applications, their performances are not worse than those of the non-linear computational intelligence methods (see below). For instance, in the load forecasting track of the attracting hundreds of participants worldwide, the top four winning entries used regression-type models.

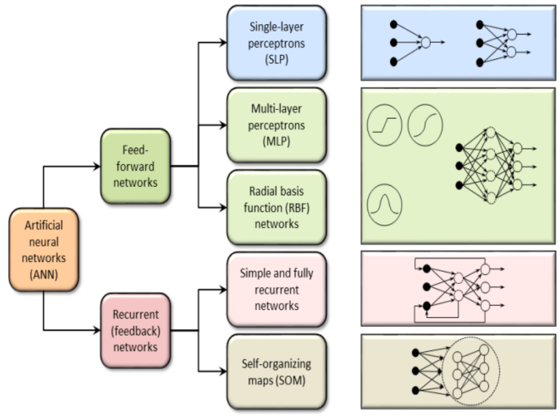

Fig 1.2 Activation Functions for RBF Networks

Input nodes are denoted by filled circles, output nodes by empty circles, and nodes in the hidden layer by empty circles with a dashed outline. The activation functions for RBF networks are radial basis functions, whereas multi-layer perceptions (MLP) typically use piecewise linear or sigmoid activation functions (illustrated in circles).

Statistical models constitute a very rich class which includes:

- Similar-day and exponential smoothing methods.
- Regression models.
- Time series models without (AR, ARMA, ARIMA, Fractional ARIMA - FARIMA, Seasonal ARIMA - SARIMA, Threshold AR - TAR) and with exogenous variables (ARX, ARMAX, ARIMAX, SARIMAX, TARX).

1.2 Fundamental Price Drivers And Input Variables

A key point in electricity spot price modeling and forecasting is the appropriate treatment of seasonality. The electricity price exhibits seasonality at three levels: the daily and weekly, and to some extent - the annual. In short-term forecasting, the annual or long-term seasonality is usually ignored, but the daily and weekly patterns (including a separate treatment of holidays) are of prime importance. This, however, may not be the right approach. As Now otarski and Weron have recently shown, decomposing a series of electricity prices into a long-term seasonal and a stochastic component, modeling them independently and combining their forecasts can bring - contrary to a common belief - an accuracy gain compared to an approach in which a given model is calibrated to the prices themselves.

1.3 Multivariate Factor Models

The literature on forecasting daily electricity prices has concentrated largely on models that use only information at the aggregated (i.e., daily) level. On the other hand, the very rich body of literature on forecasting intra-day prices has used disaggregated data (i.e., hourly or half-hourly), but generally has not explored the complex dependence structure of the multivariate price series. If In this proposed method want to explore the structure of intra-day electricity prices, In this proposed method need to use dimension reduction methods; for instance, factor models with factors estimated as principal components (PC).

II. LITERATURE SURVEY

Angamuthu Chinnathambi, R., Mukherjee, A., Campion, M., Salehfar, H., Hansen, T. M., Lin, J., & Ranganathan, P. (2019) - In this presented authors investigated a novel two-stage approach that combined the ARIMA model in Stage-1 and the resulting residuals as input to another forecasting method in Stage-2. The datasets used were drawn from the Iberian electricity markets. The results indicated a promising insight into the need for a focus on the residual improvement and training for forecasting the price markets. For the shorter duration of the dataset, ARIMA-SVM combinations outperformed other hybrid models. While, for a longer duration of the datasets, ARIMA-GLM performed better than the other models such as **ARIMA, ARIMA-SVM, ARIMA-RF and ARIMA-LOWESS.** Future work using our presented model will include testing and validating the results with larger data sets and investigation of the impacts on the MAPE values. **[01]**

Zhang, Q., Lu, J., Yang, Z., & Tu, M. (2019) - In this research work explore the relationship between electricity market and short-term load forecasting, and discuss different machine learning model for load forecasting. The influence features have been found and proved by experiment. Finally, the results show that the presented model can accurately forecast the daily load and the real-time load in the power spot market. Such short-term load forecasting can not only the extract features in the historical data, but also use the current time data to correct the load forecast at the next period. This model can apply to regional-wide node load forecasting, and in the future can assist the power retailer's quotation strategy and the power operator's node price setting. Obviously, with the reform of the electricity market, the integration of electric vehicles and renewable power generation, the uncertainty of power load will continue to increase. In the future work, these uncertain factors can be specifically analyzed and integrated into the neural network.**[02]**

Yang, W., Wang, J., Niu, T., & Du, P. (2019) - In this research work authors discuss, an adaptive deterministic and probabilistic interval forecasting system is presented for electricity price multi-step forecasting in this study, which is not required to follow the assumption that future values in preprocessing will not affect the results of the model and will be a novel forecasting technique with high management practical value. Furthermore, the developed system can self-adjust at the data preprocessing stage and forecasting stage as long as future electricity price information is available, which successfully improves the forecasting performance in management practice. To prove its performance in electricity price forecasting, some experiments are also presented in this paper. The results reveal that the presented system has the best forecasting performance among all benchmark models**.[03]**

Singh, A. K., & Parida, S. K. (2018) - In this work researchers presented , an attempted to **review** the existing works on integration of DGs, an area that has seen tremendous research activity in the last few years. Several possible ways of classifying the works depends on different parameters and operating conditions with DGs have been discussed, and based on this, a classification of hierarchy has been investigated. The traditional industry dominated by large monopolistic and vertically integrated utilities has now given way to a healthy competitive environment in which a number of generation and distribution companies can trade freely and have a nondiscriminatory access to the transmission network. Because of rapid growth of population along with proportionate industrial development, the healthy competitive environment deteriorates with a gap in generation and demand. This can be counteracted by integrating DGs at sub-transmission or distribution level, which adds value to the system with proper planning. Review of the various DG allocation techniques for power flow analysis has been presented in this work. Proper allocation of DGs will be beneficial to environment and economically beneficial for utility and consumers. The passive distribution or sub-transmission network becomes active, when DGs are integrated into the system and hence, leading to some technical and economic issues. This survey is a step to identify the current state of the art in the area and some of the interesting research challenges**. [05]**

Monteiro, R. V., Guimarães, G. C., Moura, F. A., Albertini, M. R., & Albertini, M. K. (2017) - In this research work authors was to compare the widespread and used ANN training algorithms for the temporal estimation of data. Then following on with a comparison using two data prediction methods, which are becoming more widely used, the SVM and KF. For a relatively large quantity of data as that used in the neural network analyzed in this paper, the NARX network architecture, the training algorithm that obtained the best performance from among all those analyzed was the Bayesian Regularization. The Levenberg–Marquardt algorithm, although obtaining the second best performance, needed less training and preparation time for the neural network. If time is a limiting factor then is

International Journal of LNCT
Volume-4 Issue-18 June -2020
ISSN: (Online):2456-9895

recommended the use of LM training algorithm. In terms of prediction accuracy, by comparing the performance of the two best training algorithms from the ANN with the performance of the SVM, it was noted that for the estimation of diversified data, the ANN model significantly outperformed the SVM-based model. This is due to the fact that the Kernel function has an intrinsic limitation when data samples with heavy noise or which are non-linear are included in the data set and this can therefore lead to a bad performance of the SVM. Moreover ANN has better ability of capturing nonlinear and time-varying nature ofthe data than the SVM model does However, the SVM technique showed to respond very well for the problem analyzed, as one can see by means of its statistics results. In addition, the SVM model achieved a better performance than the Kalmam Filter model, which is largely due to the good generalization ability of SVM. The KF showed the worst results among all the verified techniques, but in general responded with very good accuracy too.**[06]**

Peesapati, V. R., & Kumar, N. (2017) - In this research work authors presented the wide-area controllers have been developed and applied on Australian power system. The control algorithms are designed based on energy function and employ the kinetic energy and critical angles to improve the first swing stability and damp the post-fault oscillations of the system. The developed wide-area control system employs a non-linear Kalman estimator using PMU measurements across the system to estimate the aggregated system states to obtain the angles and velocities of the critical areas. The approach has been evaluated through simulations on simplified and full models of the Australian national grid by adding the wide-area controllers as the supplementary controllers to the available SVCs in the system. The results have demonstrated the capabilities of the developed wide-area controllers in improving the system security and efficiency by increasing the utilization of available assets in the network. It has been shown that the wide area control of major elements in the network such as generators, SVCs and other FACTS devices can significantly improve the effectiveness of the controllers in the system.**[07]**

III. PROPOSED METHODOLOGY

In this chapter discuss the proposed solution of electrical market price clearing. There are different methods available predict MCP and load. In the above chapter discuss the different methods in literature survey and related problems. Most of the methods shows results in terms MAPE ,RMS and MAE. In this proposed method design a better method which can rectify the error rate and improve the accuracy of the proposed method.

3.1 Data Processing

In 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.

3.2 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 hours as 24 hourly m 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.

3.3 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.

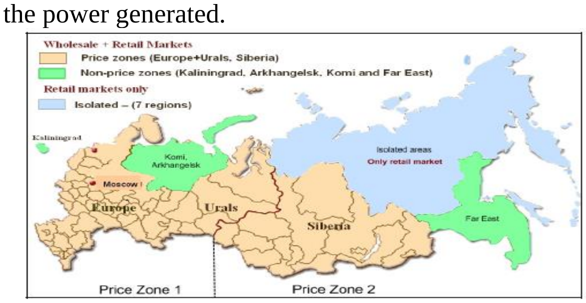

Fig. 3.1: Wholesale Market (Abdurafikov, 2009).

The Europe-Urals zone includes six hubs and the Siberian zone includes two (Figure 3.1). In addition there is an isolated area and non-price zones (regulated market).

3.4 Proposed Algorithm

During the last decade, the field of neural networks has gone through some major innovations that have lead to now a days is known as deep learning. Specially, the term deep refers to the fact that, thanks to the novel developments of recent years, In this proposed method can now train deferent neural network configurations whose depth is not just limited to a single hidden layer (as in the traditional multilayer perception), and which have systemically showed better generalization capabilities.

3.4.1 Architecture of the proposed Model

Considering time scales, the real time pricing forecasting is classified into ultra-short term, short term, medium term and long term. The Ultra-short term is from several minutes to 1 h ahead forecasting. The short term means the forecasting values from 1 h to several hours. From a few hours to 1 week ahead forecasting is defined as the medium term and beyond that it is the long term forecasting. However, we focus on the day (24 h) ahead real time pricing forecasting with a resolution of 0.5 h in this work, which belongs to the short term forecasting. The time series dynamic electricity prices vary dependent on load demand at different time periods. Based on the variations of historical real time pricing samples in figure 3.2, electricity prices exhibit a prominent regularity apparently and it consists of linear and non-linear information along with the prices varying. According to these, the characteristics of the linear and non-liner properties of time series data have to be incorporated into the forecasting model. Therefore, the proposed forecasting model can be formulated as:

$$P_t = L_t + N_t + E_t^* \qquad (3.1)$$

where *Pt* is the forecasting real time pricing at time *t*. *Lt* and *Nt* represent the estimations of linear behavior and non-linear behavior, respectively, of the input data. Additionally, *E∗t* which is an optional forecasting component, denotes the error optimization procedure. In order to present the architecture of the proposed hybrid forecasting model, Fig. 2 illustrates the flow chart of forecasting day-ahead real-time electricity prices based on several days' historical real time pricing data. Specifically, the historical data is input as the basis to establish the model. Then, the linear behavior of the data are 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

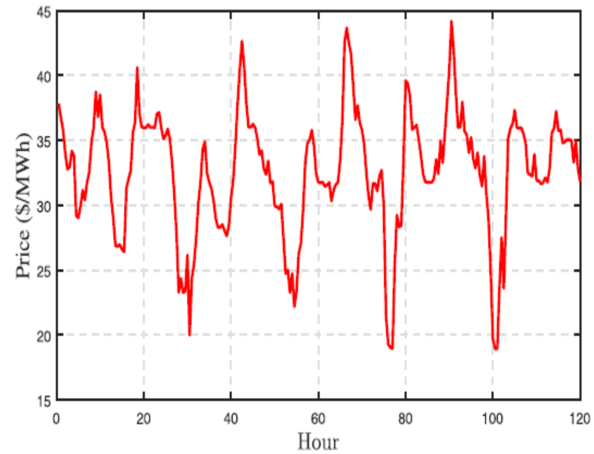

Fig 3.2 Historical real time pricing over 5 historical day samples (120 h)

In next subsections, the specific descriptions of the relevant forecasting components in the hybrid model are introduced in details.

3.4.2. Training

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

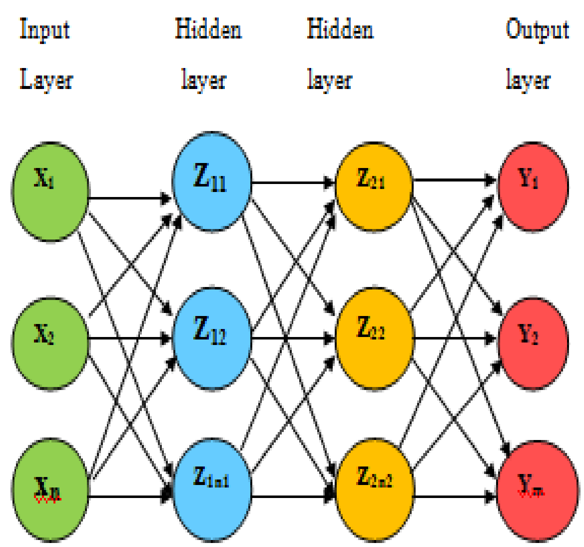

Fig 3.3 Example of a DNN

It is important to note that is an approximation of the real problem In this proposed method wish to minimize. Particularly, in an ideal situation, In this proposed method would minimize the cost function w.r.t. to the underlying data distribution; however, as the distribution is unknown, the problem has to be approximated by minimizing the cost function over the training set.

3.4.4 Method

This section introduces the methodology which includes the architecture of the proposed forecast strategy and the specific description of the proposed hybrid forecasting model in this work. The Feature creation and selection is the first step in classification or regression (i.e., forecasting in our context). It is a widely used process in machine learning and involves either the creation of new features or the selection of an optimal subset from a pool of existing features. The selected subset will contain key features which contribute to the accuracy of the forecasts and also help reduce over-fitting of the model. Our approach towards creation and selection of features as well as training and updating the ANN model.

Back Propagation is used to calculate the Jacobian jX of performance perf with respect to the weight and bias variables X. Each variable is adjusted according to Levenberg-Marquardt,

jj = jX * jX (3.2)
je = jX * E (3.3)
dX = -(jj+I*mu) \ je (3.4)

Where E is all errors and I is the identity matrix.
The adaptive value mu is increased by mu_inc until the change above results in a reduced performance value. The change is then made to the network and mu is decreased by mu_dec.

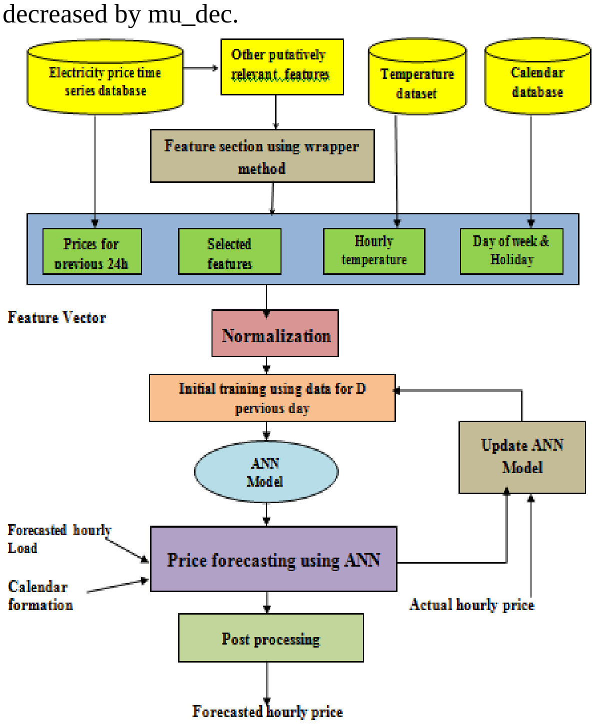

Fig. 3.4. Overview of the proposed price forecasting scheme.

3.4.5 Feed Forward Neural Network

A feed ahead neural community is an synthetic neural network whereby connections between the nodes do no longer structure a cycle. As such, it is unique from its descendant: recurrent neural networks. The feed forward neural community was once the first and easiest kind of synthetic neural community devised. In this network, the statistics strikes in solely one direction, forward, from the enter nodes, thru the hidden nodes and to the output nodes. There are no cycles or loops in the community

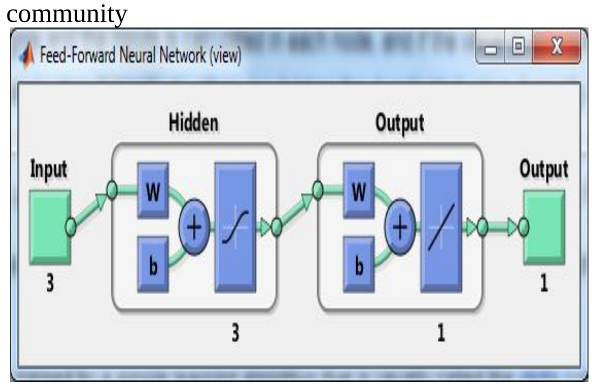

Fig. 3.5 Feed Forward NN

Assume the input data set *H* consisting of *n* = *N* days' historical real time pricing data, *H* can be formulated as:

H = {*D*1,*D*2, ...,*Dn*} (4.5)

However, the historical real time pricing of a day can be treated as a number of discrete values wit an interval. In this study, a time interval of 0.5 h is adopted, which means *t* = 48 fixed values are included in an individual day sample. Hence, *Dn* is represented as:

Dn =[*yn*,1, *yn*,2, ..., *yn*,*t*] (3.6)

In addition, the fitting function *L(t)* is taken to model the main stream variation in the linear behavior estimation. However, the general formats of the fitting function include Fourier, Gaussian, polynomial, sum of sine, etc. and they can be formulated in Eqs. (7) - (10), respectively, as follows.

Gaussian format

$$:f(x) = \sum_{i=1}^{d} \mathrm{aj} \, . \, \mathrm{e} \left(-\left(\frac{\mathrm{x} - \mathrm{bj}}{\in \mathrm{i}}\right)^{2} \right) \quad (3.7)$$

Fouries format: $f(x) \sum_{i=l}^{d} aj \, . \, cos(i \, . \, \omega . \, x) + bj \, . \, sin(i \, . \, \omega . \, x)$ (4.8)

Polynomial format : $f(x) \sum_{i=0}^{d} Pi \, . \, xi$ (3.9)

Sum of sine format

: $f(x) \sum_{i=l}^{d} ai \, . \, \sin{(bi \, . \, x + ci)}$ (3.10)

where *d* ∈*N*+ is the degree of the adopted function. Additionally, *ai*, *bi*, *ci*, *ωi* and *pi* are undetermined constant parameters in model. Although all the proposed fitting function formats are effective in modeling the linear behavior within the data, the Fourier format is adopted in this study due to its better fitting performance. Therefore, the objective function on this stage can be formulated as determining a group of appropriate parameters (*ai*, *bi* and *ωi*) to minimize the total square errors *J*. The objective function is presented.

IV. SIMULATION AND EXPERIMENTAL RESULT

4.1 Introduction

In this chapter discuss the simulation model and result of proposed algorithm. For the implementation of proposed algorithm use Matrix laboratory. Matrix laboratory is a well-known tool for such kind of algorithm implementation related to data analysis calculation. MATLAB contain a rich function family of data analysis.

4.2 Simulation Tool and Hardware Requirement

The result of proposed method for development of middle ware 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. Basic configuration of our system is: Processor: Intel (R) Quad Core (VM) i3 – 3110 Central Processing unit @, 2.40 GHz with 4GB RAM: System type: 64-bit Operating System. Figure 4.1 shows software home page window used to design and simulate of proposed method.

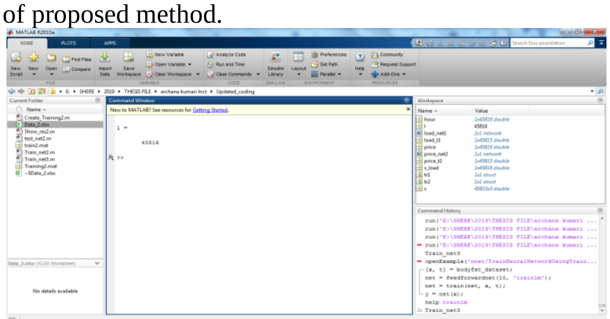

Fig. 4.1 Shows MATLAB Software Home Page

4.3 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 (MPAE),), root mean square error (RMSE). In the shows the definition of these formula -

5.3.1 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:

$$MAPE\ \left(\frac{1}{n}\sum\frac{|Actual-Forecast|}{|Actual\ |}\right)\times 100 \qquad (4.1)$$

4.3.1 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.

$$MAE = \left(\frac{1}{n}\sum\frac{|Actual - Forecast|}{|Actual\ |}\right) \qquad (4.2)$$

4.3.2 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.

$$RMSE = \sqrt{\left(\frac{1}{n}\sum_{j=1}^{n}((Actual - Forecast)^2)\right)} \qquad (4.3)$$

4.3.3 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.

$$MSE = \left(\frac{1}{n}\sum_{j=1}^{n}((Actual - Forecast)^2)\right) \qquad (4.4)$$

3.4 Data Sets

There are different moth MCP and Load data set are taken for performing analysis proposed work. First discuss about the russian power market Dataset. This dataset is originally from the wholesale electricity market.

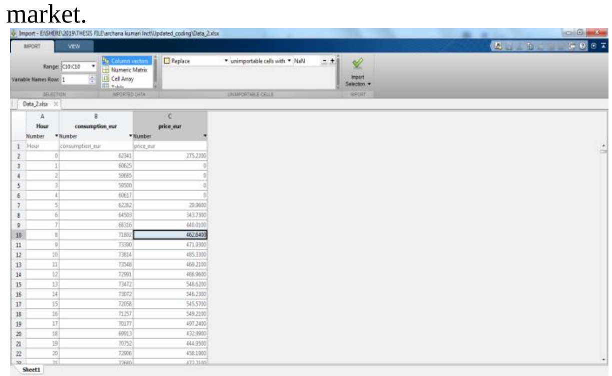

Fig. 4.2 Shows the MCP database in MATLAB

4.5 Result of Proposed Feed Forward based ANN

Feed forward networks consist of a series of layers. The first layer has a connection from the network input. Each subsequent layer has a connection from the previous layer. The final layer produces the network's output. Feed forward networks can be used for any kind of input to output mapping. A feed forward network with one hidden layer and enough neurons in the hidden layers, can fit any finite input-output mapping problem. In the below figure 4.2 shows the feed forward network

International Journal of LNCT
Volume-4 Issue-18 June -2020
ISSN: (Online):2456-9895

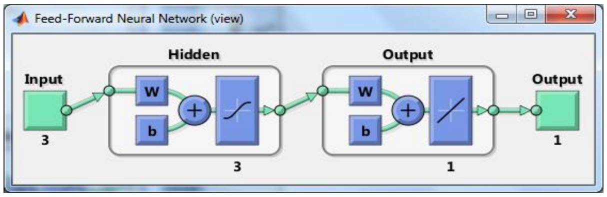

Fig. 5.3 Shows Feed Forward Network

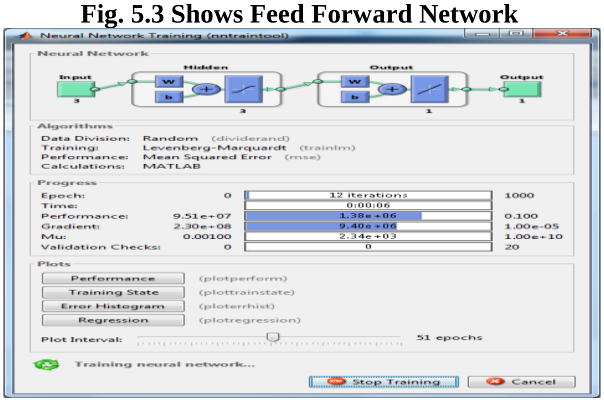

Fig. 4.4 Shows the Training of Neural Network

In the above figure 4.3 shows the training of neural network. For the training of the neural network use Levenberg-Marquardt backpropagation. 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 figure 5.4.

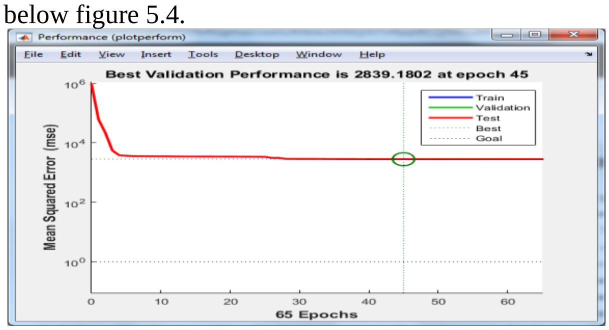

Fig. 4.5 Shows the Performance output in terms of MSE

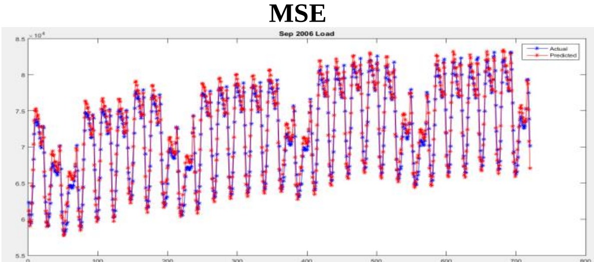

Fig. 4.5.1 Shows the Performance output in September 2006 Load

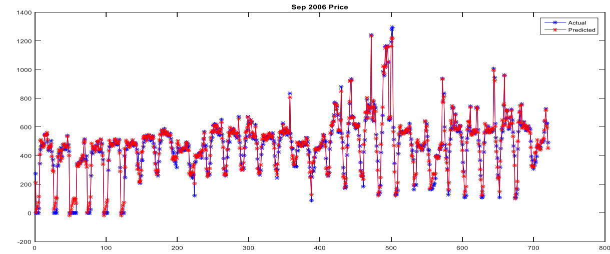

Fig. 4.5.2 Shows the Performance output in September 2006 Price

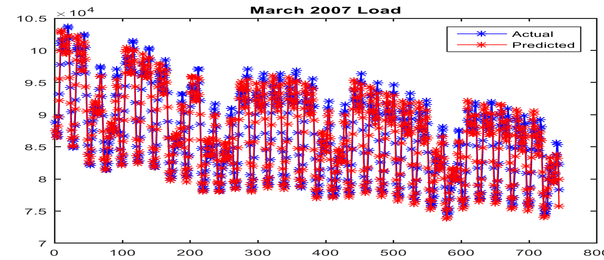

Fig. 4.5.3 Shows the Performance output in March 2007 Load

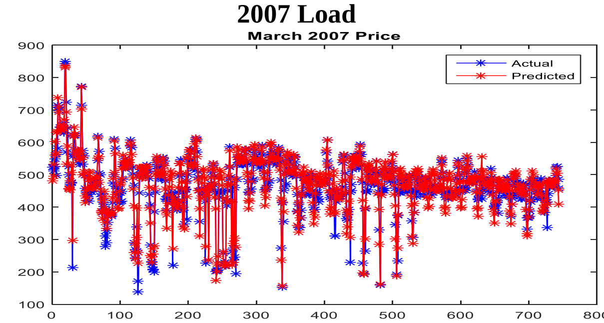

Fig. 4.5.4 Shows the Performance output in March 2007 Price

In the below figure 5.6 shows the mean absolute presented error (MPAE), in this figure clearly show the proposed method shows minimum MAPE as compare to other recently methods. Proposed method MAPE value 1.9%.

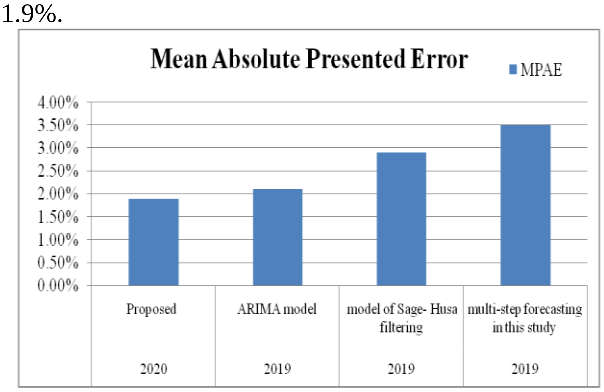

Fig. 4.6 Result Comparison in MPAE

V. CONCLUSION

In this presented work focus on feed forward nureal network 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 shows better result as compare to other previous in terms of MAPE that is 1.9%.

REFRENCES

[1] Angamuthu Chinnathambi, Radhakrishnan, et al. "A multi-stage price forecasting model for day-ahead electricity markets." *Forecasting* 1.1 (2019): 26-46.

[2] Chinmoy, Lakshmi, S. Iniyan, and Ranko Goic. "Modeling wind power investments, policies and social benefits for deregulated electricity market–A review." *Applied Energy* 242 (2019): 364-377.

[3] Zhang, Qipei, et al. "A Deep Learning Based Real-time Load Forecasting Method in Electricity Spot Market." *Journal of Physics: Conference Series*. Vol. 1176. No. 6. IOP Publishing, 2019.

[4] Hudson, Robert, Viktor Manahov, and Andrew Urquhart. "High-frequency trading from an evolutionary perspective: Financial markets as adaptive systems." (2018).

[5] Singh, A. K., and S. K. Parida. "A review on distributed generation allocation and planning in deregulated electricity market." *Renewable and Sustainable Energy Reviews* 82 (2018): 4132-4141

[6] Monteiro, Raul VA, et al. "Estimating photovoltaic power generation: performance analysis of artificial neural networks, Support Vector Machine and Kalman filter." *Electric Power Systems Research* 143 (2017): 643-656.

[7] Peesapati, VV Rajagopal, and Niranjan Kumar. "Electricity point price evaluation using hybrid algorithm." *Power Research* 13.2 (2017): 269-276.

[8] Tahmasebifar, Reza, Mohammad Kazem Sheikh-El-Eslami, and Reza Kheirollahi. "Point and interval forecasting of real-time and day-ahead electricity prices by a novel hybrid approach." *IET Generation, Transmission & Distribution* 11.9 (2017): 2173-2183.

[9] Aien, Morteza, and Aahmud Fotuhi-Firuzabad. "Probabilistic GENCOs bidding strategy in restructured two-side auction power markets." *International Journal of Smart Electrical Engineering* 6.03 (2017): 109-117.

[10] Panapakidis, Ioannis P., and Athanasios S. Dagoumas. "Day-ahead electricity price forecasting via the application of artificial neural network based models." *Applied Energy* 172 (2016): 132-151

[11] Exizidis, Lazaros, et al. "Incentive-compatibility in a two-stage stochastic electricity market with high wind power penetration." IEEE Transactions on Power Systems 34.4 (2019): 2846-2858.

[12] Deng, Lirong, et al. "Generalized locational marginal pricing in a heat-and-electricity-integrated market." *IEEE Transactions on Smart Grid* 10.6 (2019): 6414-6425.

[13] Tosatto, Andrea, Tilman Weckesser, and Spyros Chatzivasileiadis. "Market Integration of HVDC Lines: internalizing HVDC losses in market clearing." IEEE Transactions on Power Systems 35.1 (2019): 451-461.

[14] Xu, Shuai, et al. "Bi-level Optimization Model for the Biding of Retail Electricity Market Under Pay as Bid and Marginal Pricing." 2019 IEEE Sustainable Power and Energy Conference (iSPEC). IEEE, 2019.

[15] Wang, Jinran, et al. "Two-stage integrated electricity and heat market clearing with energy stations." IEEE Access 7 (2019): 44928-44938.

[16] Dvorkin, Yury. "A chance-constrained stochastic electricity market." *IEEE Transactions on Power Systems* (2019).

[17] Chen, Ruidi, et al. "Learning from past bids to participate strategically in day-ahead electricity markets." IEEE Transactions on Smart Grid 10.5 (2019): 5794-5806.

[18] Ahmadian, Saeed, et al. "Modelling cyber attacks on electricity market using mathematical programming with equilibrium constraints." IEEE Access 7 (2019): 27376-27388.

[19] Tosatto, Andrea, Tilman Weckesser, and Spyros Chatzivasileiadis. "A modified version of the IEEE 3-area RTS'96 Test Case for time series analysis." arXiv preprint arXiv:1906.00055 (2019).

[20] Xuan, Peizheng, et al. "Research on the Electricity Market Clearing Model and Price Fluctuation with Wind Power." 2019 IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia). IEEE, 2019.

[21] Zhao, Jinye, Tongxin Zheng, and Eugene Litvinov. "A multi-period market design for markets with intertemporal constraints." IEEE Transactions on Power Systems (2019).

[22] Ding, Liang, and Quanbo Ge. "Electricity Market Clearing Price Forecast Based on Adaptive Kalman Filter." *2018 International Conference on Control, Automation and Information Sciences (ICCAIS)*. IEEE, 2018.

[23] Khorasany, Mohsen, Yateendra Mishra, and Gerard Ledwich. "Distributed market clearing approach for local energy trading in transactive market." 2018 IEEE Power & Energy Society General Meeting (PESGM). IEEE, 2018.

[24] Li, Rui, et al. "Participation of an energy hub in electricity and heat distribution markets: An MPEC approach." IEEE Transactions on Smart Grid 10.4 (2018): 3641-3653.

[25] Jiang, Sifan, et al. "Distributed photovoltaic generation in the electricity market: status, mode and strategy." CSEE Journal of Power and Energy Systems 4.3 (2018): 263-272.

[26] Zalzar, Shaghayegh, and Ettore Bompard. "A day-ahead joint energy and uncertainty reserve market clearing model to manage VRE uncertainty." 2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe). IEEE, 2018.

[27] Wang, Cheng, et al. "Equilibrium of interdependent gas and electricity markets with marginal price based bilateral energy trading." IEEE Transactions on Power Systems 33.5 (2018): 4854-4867.

[28] Kuang, Xiaolong, et al. "Pricing chance constraints in electricity markets." IEEE Transactions on Power Systems 33.4 (2018): 4634-4636.

[29] Chen, Tao, et al. "Graph based platform for electricity market study, education and training." 2018 IEEE Power & Energy Society General Meeting (PESGM). IEEE, 2018.

[30] Saranya, A., and K. Shanti Swarup. "Offering strategy for a photovoltaic power plant in electricity market." 2018 IEEE Power and Energy Conference at Illinois (PECI). IEEE, 2018.

[31] Yadav, Pranay. "Color image noise removal by modified adaptive threshold median filter for RVIN." *2015 International Conference on Electronic Design, Computer Networks & Automated Verification (EDCAV)*. IEEE, 2015.

[32] Sharma, Bharti, et al. "ANN based short-term traffic flow forecasting in undivided two lane highway." *Journal of Big Data* 5.1 (2018): 48.

[33] Singh, Jagendra, et al. "Fuzzy logic hybrid model with semantic filtering approach for pseudo relevance feedback-based query expansion." *2017 IEEE Symposium Series on Computational Intelligence (SSCI)*. Ieee, 2017.

[34] Singh, Jagendra, et al. "Fuzzy logic hybrid model with semantic filtering approach for pseudo relevance feedback-based query expansion." *2017 IEEE Symposium Series on Computational Intelligence (SSCI)*. Ieee, 2017.

[35] Sharma, Shachi, and Pranay Yadav. "Removal of fixed valued impulse noise by improved Trimmed Mean Median filter." *2014 IEEE International Conference on Computational Intelligence and Computing Research*. IEEE, 2014.

[36] Gupta, Vikas, Dilip Kumar Gandhi, and Pranay Yadav. "Removal of fixed value impulse noise using improved mean filter for image enhancement." *2013 Nirma University International Conference on Engineering (NUiCONE)*. IEEE, 2013.

[37] Yadav, Pranay, and Parool Singh. "Color impulse noise removal by modified alpha trimmed median mean filter for FVIN." *2014 IEEE International Conference on Computational Intelligence and Computing Research*. IEEE, 2014.

[38] Yadav, Pranay, et al. "Image De-Noising For Salt and Pepper Noise by Introducing New Enhanced Filter." *International Conference on Innovations in Engineering and Technology (ICIET'2013) Dec*. 2013.

[39] Yadav, Pranay, et al. "Multi-Band Rectangular Zig-Zag-Shaped Microstrip Patch Antenna for Wireless Applications." *Design and Optimization of Sensors and Antennas for Wearable Devices: Emerging Research and Opportunities*. IGI Global, 2020. 66-86.

[40] Choudhary, Ekta, Shilpi Sharma, and Pranay Yadav. "A Modified Wideband Bow-Tie Antenna with DGS for Wireless Fidelity Range." *2018 International Conference on Advanced Computation and Telecommunication (ICACAT)*. IEEE, 2018.

[41] Yadav, Pranay, and Shachi Sharma. "Double Element Ultra Wideband Monopole Radiating Antenna Array with Coplanar-Ground Plane." *IEEE*. 2018.

[42] Yadav, Pranay, and Parool Singh. "Color impulse noise removal by modified alpha trimmed median mean filter for FVIN." *2014 IEEE International Conference on Computational Intelligence and Computing Research*. IEEE, 2014.

[43] Prasad, Mukesh, et al. "Fusion based En-FEC transfer learning approach for automobile parts recognition system." *2018 IEEE Symposium Series on Computational Intelligence (SSCI)*. IEEE,

[44] Sangwan, Munesh, Gopal Panda, and Pranay Yadav. "A Literature Survey on Different MIMO Patch Antenna." *2020 International Conference on Inventive Computation Technologies (ICICT)*. IEEE, 2020.

[45] Sangwan, Munesh, Gopal Panda, and Pranay Yadav. "A Design and Analysis of P Cut MIMO Patch Antenna for Reduce of Mutual Coupling in Wireless Range." *2020 International Conference on Inventive Computation Technologies (ICICT)*. IEEE, 2020.

[46] Rohan, Abhijeet, et al. "A Robust Printed Dipole L-Shape Patch with Triangular Cut for Wireless Fidelity Devices." *2020 International*

ISSN: (Online):2456-9895

Conference on Inventive Computation Technologies (ICICT). IEEE, 2020.

[47] Yadav, Pranay, et al. "Image De-Noising For Salt and Pepper Noise by Introducing New Enhanced Filter." *International Conference on Innovations in Engineering and Technology (ICIET'2013) Dec*. 2013.

[48] Sharma, Vikalp, and Pranay Yadav. "Web Service Discovery Approach Among Available WSDL/WADL Web Component." *Recent Findings in Intelligent Computing Techniques*. Springer, Singapore, 2019. 339-344.

[49] Maurya, Sweta, Shilpi Sharma, and Pranay Yadav. "Internet of Things based Air Pollution Penetrating System using GSM and GPRS." *2018 International Conference on Advanced Computation and Telecommunication (ICACAT)*. IEEE, 2018.