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# DEMAND FORECASTING BY USING GENERALIZED REGRESSION NEURAL NETWORK

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***Abstract:*** **With the increases in competitive business environment, forecasting of demand is directly linked up with the portfolio of the generating companies and considered as an important parameter of power system regulation. To take decisions like bidding of the power blocks in a pool market, trade decisions, generation schedules, dispatch and unit commitment operations require precise knowledge of the system demand. It is also essential to consider an accuracy of load forecasting to maintain balance in power system regulation. In this paper we propose sensitivity analysis with an application of adaptive supervised learning technique "Generalized Regression Neural Network" (GRNN) to know the effect of the change in parameters in forecasting engine performance. Different inputs are changed uniformly and fair comparison is carried out on the basis of standard error index Mean Absolute Percentage Error (MAPE).**

***Keywords*** *– Load Forecasting, Power system regulation, Sensitivity Analysis, GRNN, MAPE*

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## I INTRODUCTION

With the rapid development and growth in technology, the demands of electric energy highly increase, correspondingly the load forecasting becomes more and more important and close attention is increasingly paid to continuous power supply by both electric industry and consumers. The major duty of any electrical utility is to supply reliable power to its customers. The prediction of future active loads at various load buses in power system is known as load forecasting [1].The main objective of load forecasting is to provide the load prediction for generation scheduling, power system security, generation reserve of the system, and proper market operation. For a restructured power system, Generation Company would have to forecast the system demand to make a suitable market decision. To satisfy the load demand it is necessary to predict the load for future [2]. Accurate load determination is necessary for application like automatic generation control [3], contingency ranking [4], stability assessment [5] and price forecasting [6]

Load forecasting can be classified in three categories depending upon the time span used for forecasting. The long term forecasting is done for more than one year, medium term (intermediate) forecast is done for few weeks to one year and short term load forecasting belongs to an hour to few days. The important factors which are to be considered mainly are time, weather parameters and categorized consumer classes [7].

Figure 1 shows the general model architecture of load forecasting. It is shown in the figure that various numbers of input parameters are considered for prediction of the load. Evaluation of these input parameters is very time consuming and as well as cost effecting for load forecasting. Sometimes large no of parameters are not much responsible for precise load forecasting. By avoiding such parameters, we can also do a good load forecasting. It is essential to know the effect of each input parameter on load forecasting. The process to know the effect of these parameters on load forecasting is known as sensitivity analysis. The main object of sensitivity analysis is to study the impact of different input factors on the proposed architecture for load forecasting. The sensitivity analysis is also performed to identify the significant inputs. Electrical load is highly sensitive to the weather conditions such as temperature, humidity, wind cover, sunshine, etc in which temperature ,wind speed and humidity are the most significant but other parameters shall also be considered which depends upon the geographical conditions of the forecasting region [8]. There is a functional relationship between electrical load and temperature. As saturation level and per capita consumption increases, to reflect the wide- spread use of weather-sensitive devices, it is necessary to include weather effects in forecasting future load requirements [9].

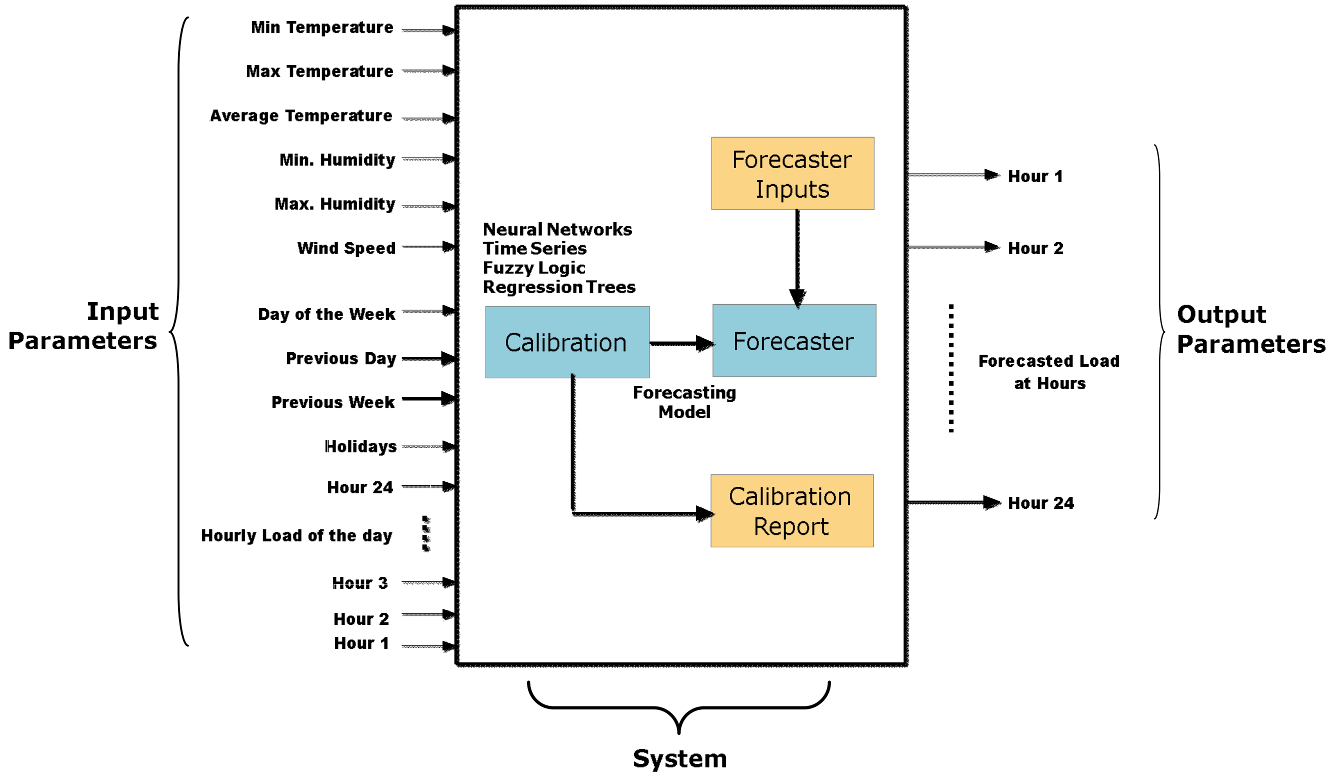


*Figure 1 Model Architecture of Load Forecasting*

## II FORECAST TECHNIQUES

There are several traditional methods like wavelets, neural networks; grey theory, genetic algorithm prediction etc are used for prediction the load. Some of them are:

- ❖ Time series and regression techniques
- ❖ Intelligent methods like Neural network approach and fuzzy systems
- ❖ Hybrid structures with neural and fuzzy systems, neural networks and genetic algorithms etc.

These deterministic methods are conventional model of load and input variables. Curve fitting, data extrapolation and smoothing methods are including in these methods [10-15].

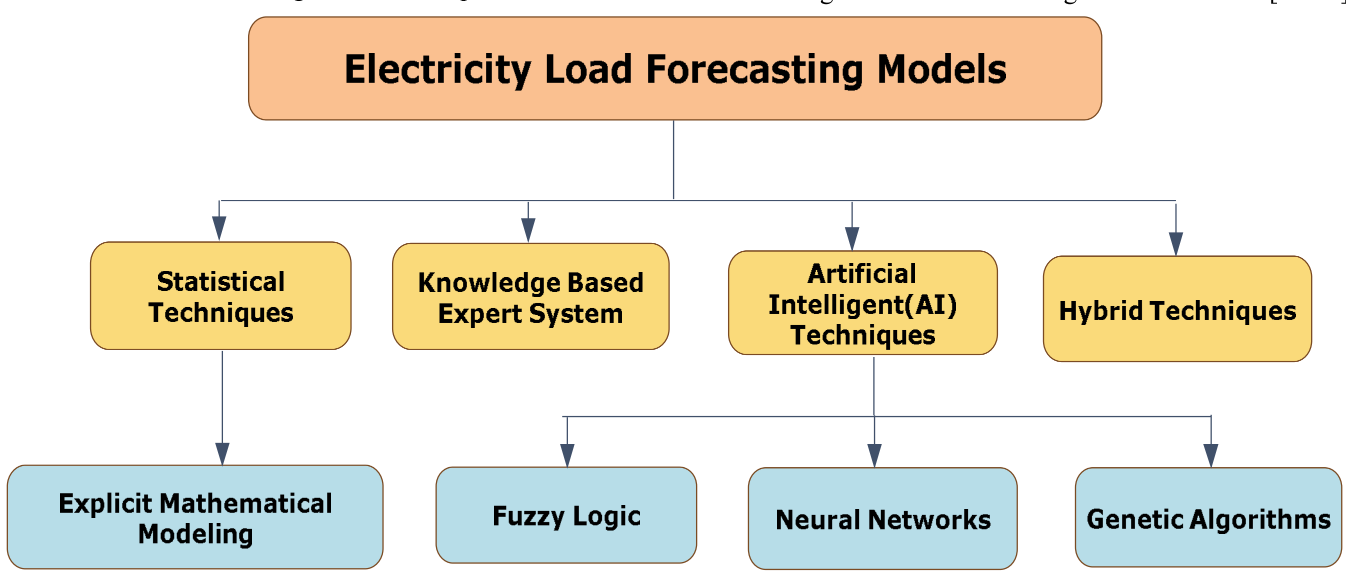


*Figure 2 Classification of Different Electricity Load Forecasting Methods*

Figure 2 shows the classification of different electricity load forecasting methods. Although these methods are used to forecasting the load from the years, yet they cannot satisfy the requirement of forecast precision. So the new researchers put forward some methods according to the inaccuracy of these traditional methods.

Different forecasting methods have been employed in power systems for achieving forecasting accuracy. Some of the models are regression, statistical and state-space methods. [16].Jihang et.al. [17] proposed the support vector machine (SVM) optimized by improved fruit fly algorithm and the similar day method used for optimize and auto select parameters of SVM, in the meantime, a similar day method (SDM) was used to reduce the number of training samples, boost training speed and increased the forecast precision. Nikita et.al.[18] suggested an application of statistical forecasting method for predicting the demand of similar days. It also presents a comparison of different statistical load forecasting methods namely trend analysis, decomposition and moving average method. A.Hemlatha et.al. [19] worked on sensitivity analysis of load forecasting by using a mixed model of artificial neural networks and fuzzy logicto know the effect of changes in input variables on system outputs. Among the models are regression, statistical and state-space methods. In addition, artificial intelligence-based algorithms have been introduced based on expert system, evolutionary programming, fuzzy system, artificial neural network (ANN), and a combination of these algorithms. Among these algorithms, ANN has received more attention because of its clear model, easy implementation, and good performance. One of the keys to a good architecture in ANN is choosing appropriate input variables.

## III ARTIFICIAL NEURAL NETWORKS

An ANN is a method to perform non-linear modeling and adaptation which is based on training the system with past load data as input and current load data as target. The ANN learns from experience and generalizes from previous examples to new ones [20].There are three types of learning strategies are used supervised,unsupervised and reinforced learning.The number of hidden layers,number of iterations to perform neural network and learning rate are the key factors which is used to consider for accurate load foreacsting. The modification of the weights and biases of a neural network can be done by learning rule.The main purpose of these learning rules is to train the network to perform some task. The supervised learning provided a set of training data of proper network behavior[21].

## IV ALGORITHM OF GRNN

The generalized regression neural network is a new method which is used to overcome the limitations of the other methods used for short term load. The GRNN gives the higher accuracy and stability as compared to other neural networks. It is the nonlinear regression analysis.

The regression analysis of the non- independent variable Y with respect to the independent variable x is to calculate the maximum probability value of y. So the joint probability density function of random vector x and random variable y is $f(x, y)$, the conditional mean value is given by [22]

$$\hat{Y}(X) = E[y/X] = \frac{\int_{-\infty}^{\infty} y f(X,y)dy}{\int_{-\infty}^{\infty} f(X,y)dy} \tag{1}$$

Where the observed value of x is X, the Y is relative to the regression of X.

Specht scholars pointed out that the continuous probability density function can be estimated from the observation

$$\hat{f}(X,Y) = \frac{1}{(2\pi)^{\frac{p+1}{2}}\sigma^{(p+1)}} \bullet \frac{1}{k} \bullet \sum_{i=1}^{k} \exp\left[-\frac{(X-X_i)(X-X_i)}{2\sigma^2}\right]\exp\left[-\frac{(Y-Y_i)^2}{2\sigma^2}\right] \tag{2}$$

where $X_i$ and $Y_i$ are the i sample observation value of random variable x and y, is the smoothing parameter, p is the dimension of random variable x, k is the sample number.

Use $\hat{f}(x,y)$ instead of $f(x,y)$ the conditional mean value can be obtained by

$$\hat{Y}(X) = \frac{\sum_{i=1}^{k} Y_i \exp\left(-\frac{D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^{k} \exp\left(-\frac{D_i^2}{2\sigma^2}\right)} \tag{3}$$

Where $\hat{Y}(X)$ is the weighted average of all observation value $Y_i$ , $D_i^2$ is the Euclidean distance , $D_i^2 = (X - X_i)^T (X - X_i)$ .The structure of GRNN is shown in the figure 3.It is composed of four layers, the input layer, the pattern layer, the summation layer and the output layer. Corresponding network input is X =[$x_1$, $x_2$,…,$x_m$], its output is Y=[$y_1$,$y_2$,…, $y_m$].

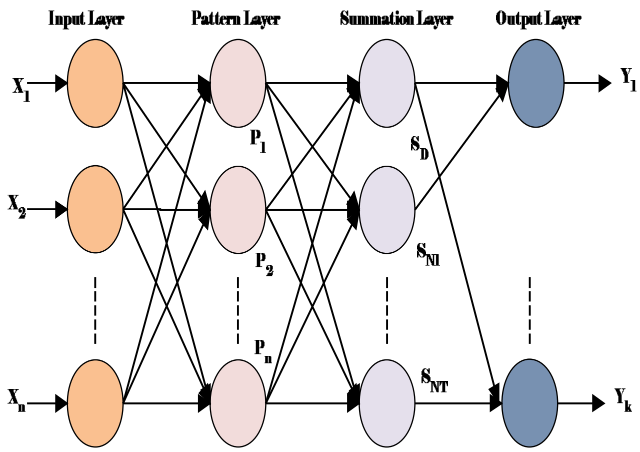


*Figure 3 General structure of GRNN*

## V SENSITIVITY ANALYSIS

For the prediction of accurate load it is very essential to know the effect of various input parameters on it. The process to know the effect of these parameters on load forecasting is known as sensitivity analysis. The main motive of sensitivity analysis is to study the impact of different input factors on the proposed architecture for load forecasting. The "$\varepsilon-\delta$" method is used to calculate sensitivity analysis .The main purpose of the use of "$\varepsilon-\delta$" method is to analyze the sensitivity of ANN by perturb the ANN input with a small amount ($\varepsilon$).The analysis of sensitivity of ANN represents the input–output mapping, to the input by checking the variation of the output ($\delta$ ).

## VI PROBLEM FORMULATION

For STLF the inputs can be classified in time, weather and historical load. From these inputs weather and historical load are much responsible for accuracy of prediction the load. To continue and satisfy the load demand, it is required to know the effect of input parameters on load forecasting so that the important input parameters can be considered instead of least input parameters. To analysis the impact of each input parameter on load forecasting, sensitivity analysis will be applied on each input. Sometimes it is also dependent on customer behavior. Customer load demand does vary because of human activities follow daily, weekly, and monthly cycles. The load demand is generally high during the day time and lower in the late evening and early morning .Similarly load demand does also vary in weekdays, weekends and some special days (holidays) because of the human activities are different in these days. The inputs used for prediction of load demand is also non linear in behavior.

With the all consideration of above, sensitivity analysis is done in this work. The input data is collected from Australia Electricity Market [23] of year 2006 to 2009 of which is segregated into three folds namely week days, weekends and special days. From Monday to Friday, the five days of week are considered as weekdays and the two days Saturday and Sunday are considered as weekends. The four days also considered as special days for load prediction as the load demand is fluctuated differently in these days, are:

- New Year day (1st January)
- Good Friday
- Christmas day (25th December)
- New Year eve (31st December)

Thus the whole data is divided in eleven days i.e. seven weekdays and four special days. The input parameters are humidity, temperature (Wet bulb measurement, Dry bulb measurement, Dew point measurement) and electrical price. The system load is considered as target. For forecasting the load ANN is used because of the ability to handle the nonlinear relationships between load and the factors affecting it directly from historical data. Among the all ANN methods generalized regression analysis model is used as our inputs are nonlinear in nature.

The data of each year is from 2006 to 2009 divided in two parts as training and validation (test data) sets.By using GRNN topology training would be easier and results will be more accurate. To analysis the impact of each input parameter on load forecasting, sensitivity analysis will also be applied in which the each input parameter is changed by 1 percent. By applying the sensitivity analysis it would be easier to find the impact of each input. The sensitivity of each input parameter is decided with the calculating of Mean Absolute Percentage Error (MAPE) of each changed one percent input of each day. The formula of MAPE is:

$$M = \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| * 100 \tag{4}$$

Where $A_t$ is the actual system load and $F_t$ is the forecast load.

## VII SIMULATION RESULTS

To analyze the sensitivity GRNN is constructed for the data of 11 days: 5 week days, 2 weekend days and 4 special days i.e. holidays of year 2006 to 2009 of Australian Electricity Market. Six models are designed for all 11 days by changing 1 % increment in each input parameter. The strategy of designing of models are shown in figure 4 in which first block shows the forecaster model with actual inputs and the other five blocks from 2-6 are designed with changed inputs. Thus total 66 models are designed in this work. All these changed input parameters along with the model which is designed with original inputs. The output (Forecasting Load) calculated from the trained network for a particular day is the result obtained for the same day of 2010.Model 1 is considered with the modification of 1 % humidity, model 2 is considered with the modification of 1 %

dry bulb, model 3 is considered with the modification of 1 % dew point, model 4 is considered with the modification of 1 % price and model 5 is considered with the modification of 1 % wet bulb. MAPE is also calculated for each model.

The Average value of MAPE is also calculated of all six models for the proposed technology for the Weekdays and Weekends. The comparative table is shown given below.

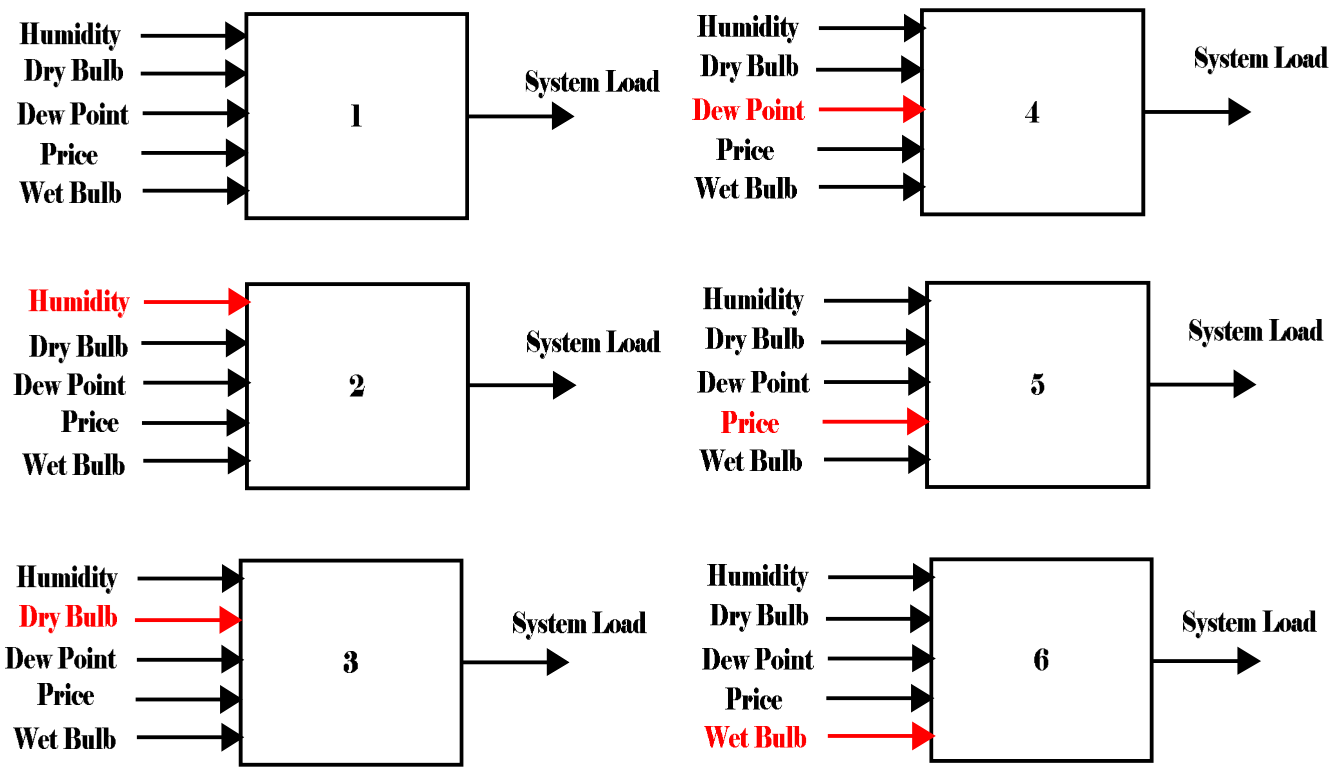


*Figure 4 Block diagram representation of Modified Inputs*

Table 1 shows the average value of MAPE of a week of all six models of GRNN topology. The sensitivity of inputs are judged by the average value of MAPE of each input of a week. The highest value of MAPE is obtained from modified humidity, than from price, dew point, than wet bulb and last from dry bulb respectively. These results show the sensitivity in decreasing order i.e. humidity, price, dew point, wet bulb and dry bulb.

***Table 1 COMPARATIVE TABLE OF AVERAGE VALUE OF "MEAN ABSOLUTE PERCENTAGE ERROR" OF ALL SIX MODELS FOR PROPOSED TOPOLOGY***

| DAY | MAPE | MAPE 1 | MAPE 2 | MAPE 3 | MAPE 4 | MAPE 5 |
|---|---|---|---|---|---|---|
| Mon | 2.1230911 | 2.211551388 | 1.81718758 | 1.895731183 | 2.177464244 | 1.8817679 |
| Tue | 2.0128147 | 1.772956673 | 2.132758097 | 2.110542164 | 2.261857503 | 2.120140406 |
| Wed | 3.695034 | 10.25996535 | 9.434128921 | 9.452754777 | 8.862831601 | 9.442574139 |
| Thurs | 14.442984 | 13.534555 | 13.2112925 | 13.49883121 | 14.1924164 | 13.50413132 |
| Fri | 12.673576 | 13.87304651 | 12.66469713 | 12.73065143 | 12.80067618 | 12.70768947 |
| Sat | 0.3749587 | 1.377791969 | 0.2880462 | 0.339379598 | 0.032281411 | 0.321990583 |
| Sun | 3.7784226 | 3.668926327 | 3.921658857 | 3.855951841 | 4.130956795 | 3.867603274 |
| **Avg.Value** | **5.5858401** | **6.671256173** | **6.209967041** | **6.269120315** | **6.35121202** | **6.263699584** |

Table 2 shows the average value of MAPE of a four special days of all six models of GRNN topology. Sensitivity is also calculated from average value of MAPE .Again the sequence of highest sensitivity to lowest sensitivity is obtained from humidity, than from price, than dew point, than wet bulb and last from dry bulb. Thus the sensitivity in this case also obtained in decreasing order i.e. humidity, price, dew point, wet bulb and dry bulb.

*Table 2 COMPARATIVE TABLE OF AVERAGE VALUE OF "MEAN ABSOLUTE PERCENTAGE ERROR" OF ALL SIX MODELS FOR PROPOSED TOPOLOGY*

| DAY | MAPE | MAPE 1 | MAPE 2 | MAPE 3 | MAPE 4 | MAPE 5 |
|---|---|---|---|---|---|---|
| NEW YEAR DAY | 0.5737838 | 4.75144133 | 4.692351643 | 4.720640695 | 4.735451578 | 4.707852318 |
| GOOD FRIDAY | 6.8635285 | 6.764852716 | 6.881620728 | 6.874389542 | 6.733765573 | 6.87673782 |
| CHRISTMAS DAY | 2.2794703 | 2.937224463 | 2.243045669 | 2.281229245 | 2.537960143 | 2.271319886 |
| NEW YEAR EVE | 3.5793093 | 4.099104745 | 3.813264291 | 3.778184416 | 3.947549631 | 3.784108665 |
| **Avg.Value** | **3.324023** | **4.638155813** | **4.407570583** | **4.413610975** | **4.488681731** | **4.410004672** |

## VIII CONCLUSION

For the continuous and smooth operation of electrical industry precise load forecasting is essential. In this paper an application of ANN, GRNN is used for prediction the load estimation with sensitivity analysis. From the proposed topology, the following results are concluded of:

a) The Mean Absolute Percentage Error (MAPE) is minimized when there is no change in input data i.e. the actual data.

b) Then the each input data is erroneous by 1%, MAPE is increased. The minimum value of MAPE is obtained by changing in Dry bulb measurement.

c) The Maximum value of MAPE is increased from changing in humidity.

From this analysis it can be concluded that Dry bulb measurement method of temperature measurement is a least sensitive variable as the MAPE obtained in model is low and the variation of the MAPE from the original values are very low. On the other hand, it can be concluded that the values of MAPE is higher as compared to the original values when the humidity is varied with 1%. From this finding we can suggest that humidity is a sensitive parameter in load forecasting.

Sensitivity analysis can become most accurate with changing input parameters by 2 % to 5% .

## REFERENCES

[1]*M.Amirthavalli, "Fuzzy Logic and Neural Networks", SCITECH Publications, 2004.*

[2]Moh.Shahidehpour, HatimYamin, Zuyi Li, *"Market OperationinElectric Power Systems: Forecasting, Scheduling and Risk management"* IEEE, New York, Wiley Interscience, 2002.

[3]. Gupta, Esha, and Akash Saxena. *"Grey wolf optimizer based regulator design for automatic generation control of interconnected power system."* Cogent Engineering 3.1 (2016): 1151612.

[4] Soni, Bhanu Pratap, Akash Saxena, and Vikas Gupta. *"A least square support vector machine-based approach for contingency classification and ranking in a large power system."* Cogent Engineering 3.1 (2016): 1137201.

[5] Saxena, Akash, and Ankit Kumar Sharma. *"Assessment of Global Voltage Stability Margin through Radial Basis Function Neural Network."* Advances in Electrical Engineering 2016 (2016).

[6]. Saini, Deepak, and Akash Saxena. *"Electric Price Forecast using Interbreed Approach of Linear Regression and SVM."* Indonesian Journal of Electrical Engineering and Computer Science 2.3 (2016): 537-544.

[7]H. K. Alfares, M. Nazeeruddin, *"Electric load forecasting: literature survey and classification of methods",*International Journal of Systems Science, 33(2002), pp. 23-34.

[8]A.Hemalatha, G.Moulika, E.Harika, Hemachandra, "Sensitivity Analysis in Load forecasting using Computational Intelligence", Helix Vol. 7(5), 1 September, 2017, PP No. 2086-2089.

[9] Nahid-Al-Masood , Mehdi Z. Sadi , Shohana Rahman Deeba and Faeza Hafiz,"*Temperature Sensitivity Analysis of Bangladesh Electrical Load*: A Linear Regression Based Approach.*"*2009

[10] Mittal, Nikita, and Akash Saxena. *"Layer Recurrent Neural Network Based Power System Load Forecasting"* Indonesian Journal of Electrical Engineering and Computer Science 16.3 (2015): 423-430.

[11] M. T. Hagen and S. M. Behr, *"The time series approach to time series load forecasting"*, IEEE Trans.,1987, PRWS-2(3), pp. 785-791.

[12] S. R. Haung, *"Short Term Load Forecasting using Thresold Autoregressive Models"*, IEE Proc. Gener. Trans. Distrib., Vol. 144, No.5, Sept.1997, pp.477-481.

[13] D. Singh, S. P. Singh and O. P. Malik, *"Numerical Taxonomy Short Term Load Forecasting using general exponential smoothing Network for Short-Term Load Forecasting"*, Jour. Electric Power Components and Systems, No. 30, 2002, pp. 443-456.

[14] W. R. Christiaanse, "*Short Term Load Forecasting using general exponential smoothing"*, IEEE Trans. On Power Appar. Syst, 1988, PAS-3, pp 900-911.

[15] A. D. Papalexopoulos, T. Hasterberg, "*A Regression based Approach to Short Term System Load Forecast*", IEEE Trans. On Power Systems. Vol.5, No.4, Nov. 1990, pp 1535-1544.

[16] Yi Yang, Jie Wu, Yanhua Chen, and Caihong Li, "*A New Strategy for Short-Term Load Forecasting*", Abstract and Applied Analysis, vol. 2013, Article ID 208964, 9 pages, 2013.

[17] A. h. Jiang and N. x. Liang, "*Short-term load forecasting using support vector machine optimized by the improved fruit fly algorithm and the similar day method*", *2014 China International Conference on Electricity Distribution (CICED)*, Shenzhen, 2014, pp. 1466-1471.

[18]Nikita Mittal and Akash Saxena, "*Short Term Load Forecasting By Statistical Time Series Methods*", Journal of Automation & Systems Engineering, vol.10 no.2,pp 99-111,June 2016.

[19]A.Hemalatha, G.Moulika, E.Harika, Hemachandra, "*Sensitivity Analysis in Load forecasting using Computational Intelligence*", Helix "The scientific explorer" Vol. 7(5), page no.2086-2089.

[20]D. K. Chaturvedi, Sinha AnandPremdayal, Ashish Chandiok, "*Short-term load forecasting using soft computing techniques, Scientific research*" , Int. J. Communications, Network and System Sciences, 2010, 3, 273- 279.

[21]H. Yoo and R. L. Pimmel, "*Short term load forecasting using a self-supervised adaptive neural network*", in *IEEE Transactions on Power Systems*, vol. 14, no. 2, pp. 779-784, May 1999.

[22] Guang-ya BAI, Yong LI, "*Application of Generalized Regression Neural Network in Short-term Load Forecasting*", International Conference on Material Science and Civil Engineering , Pages 424 -430 .

[23] http://www.aemo.com.au/