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A Neuro-Fuzzy Logic Based Machine Learning Model for Electrical Load Forecasting

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Abstract: One of the critical aspects of meeting the demands of the energy worldwide is the accurate estimate of electrical loads typically connected to inter connected power systems. However, it is a completely non-trivial challenge as the variables which govern the electrical load are extremely fluctuating in nature with high amount of randomness and non-correlation thereby making the forecasting problem difficult in terms of the accuracy. The work presented in this paper is based on the ANFIS regression process. The essence of the algorithm lies in the fact that the proposed approach uses the errors in each iteration as an exogenous input to the system and hence is used to attains faster convergence with lesser error margin for the system. Moreover, the discrete wavelet transform is used as the decimating and smoothening filter. The performance of the proposed system is evaluated in terms of the accuracy of the system and the percentage error. It has been shown that the proposed work clearly outperforms the baseline approach without the DWT filtering thereby attain a higher degree of accuracy in the forecasting approach.

Keywords:- Machine Learning, ANFIS,, Load Forecasting, Regression Learning, Mean Absolute Percentage Error.

I.Introduction

The continuous and stable supply of electrical energy is the basic prerequisite of an electrical power generation framework. Such frameworks produce the need of meeting the load interest; by examining the set of experiences, conduct, pattern, and factors influencing the load and foreseeing the future interest of load, named as load forecasting. But the load forecasting incurs some challenges today.

Among these difficulties load stream examination, arranging and control of electric energy framework are generally unmistakable. Load Forecasting is likewise quite possibly of the most arising field of exploration for this significant and testing field in most recent couple of years. Load forecasting might be characterized as the proportion of precision of the contrast between the real and anticipated worth of future load interest.

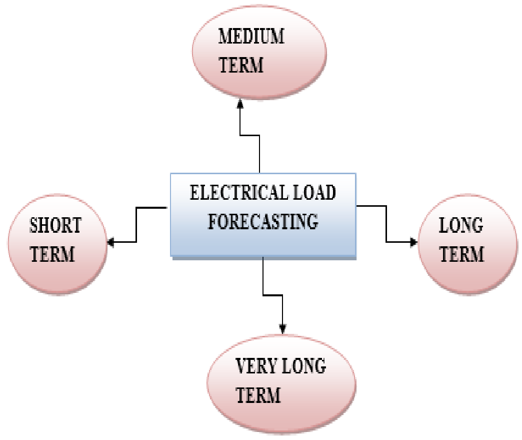

Fig.1 The electrical load forecasting schematic

Forecasting of power request will help in improving the beginning up cost of creating units, and can likewise ready to save the interest in the development of required number of force. It can likewise assist with checking the unsafe activity, fluctuating interest, request of turning store and weakness to load failures. Load forecasting gives the main data for power conveyance and arranging. It additionally assumes a significant part in energy the board framework. Extensively, the load forecasting techniques can be secluded into two classes, for instance, parametric or non parametric systems. The chief hindrance of this methodology is its ability in surprising distinction in such environment or social changes. In any case, this shortcoming is overpowered by applying non-parametric (electronic thinking) based system considering its probability to overall chase. Among these man-made cognizance based approach, artificial neural network has emerged as one of the most obvious method that get significantly more thought of researchers. The ability to address the confounding associations, adaptable control, picture denoising, dynamic under weakness and conjecture plans makes ANN a solid performer than as of late executed methods previously carried out procedures.

II. Methodology

As the load forecasting model needs to be fed with copious amounts of data, hence it becomes mandatory to employ machine learning and deep learning based approaches for the same. Various techniques that were employed in previous works for research in this context involved regression models based methods and also logistic regression based analysis. The precision parameters varied significantly with each of the aforementioned techniques. Therefore artificial intelligence and machine learning backed highly advanced methods have been studied and implemented further for improved accuracy in electrical load forecasting.

Neural Networks:

Artificial Neural networks possess a great ability to extract meaningful information from complicated data; which can applied for extraction of various features from the radical data. Some prominent traits of the ANN comprises of the following:-

1. Adaptive method of learning: An ability to sort out some way to deal with data considering the data given for planning or starting experience.
2. Way of Self-Organization: An ANN can make its own depiction of the information it gets during learning time.
3. Operation in Real Time: ANN estimations may be finished in real time that yields high accuracy and needs lesser amount of time for complex computations.

The output of the neural network can be related to the inputs as:

$$\boldsymbol{output} = \boldsymbol{f}[\textstyle\sum_{i=1}^{n} \boldsymbol{x_i w_i} + \boldsymbol{\theta}] \qquad \textbf{(1)}$$

Here,

Output vector correcsponds to the output vector of the network.

The inputs and weights are represented by x and w respectively.

The additional term of bias termed as θ is added.

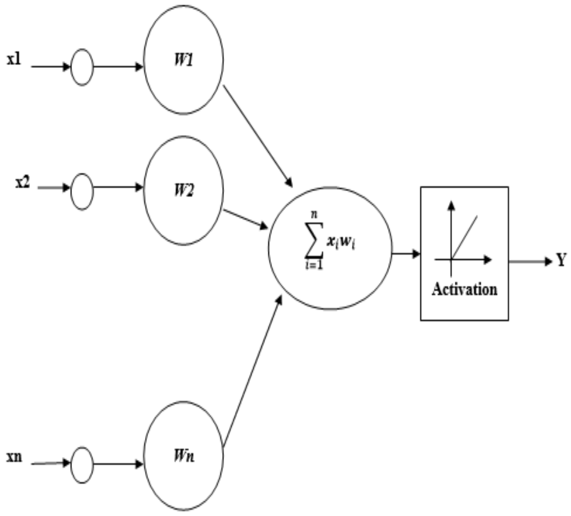

Figure 1. The ANN Model

If the neural network and fuzzy logic networks are combined together, it is called the adaptive neuro fuzzy inference system or ANFIS.

Fuzzy Logic

Another tool that proves to be effective in several prediction problems is fuzzy logic. It is often termed as expert view systems. It is useful for systems where there is no clear boundary among multiple variable groups. The relationship among the inputs and outputs are often expressed as membership functions expressed as [6]:

A membership function for a fuzzy set A on the universe of discourse (Input) X is defined as:

$$\boldsymbol{\mu A}: \boldsymbol{X} \rightarrow [\mathbf{0}, \mathbf{1}] \qquad \textbf{(2)}$$

Here,

each element of X is mapped to a value between 0 and 1. It quantifies the degree of membership of the element in X to the fuzzy set A.

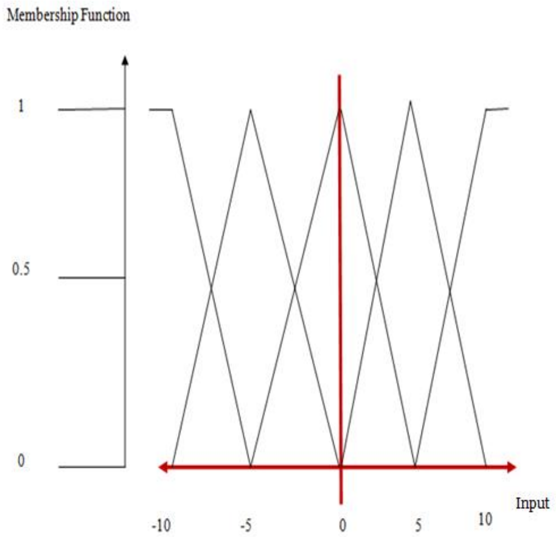

Figure.2 Graphical Representation of Membership Functions

Here,
x axis represents the universe of discourse (Input).
y axis represents the degrees of membership in the [0, 1] interval.
The final category is neuro fuzzy expert systems which governs the defining range of the membership functions.

Adaptive Neuro Fuzzy Inference Systems (ANFIS)
The ANFIS can be thought of as a combination of neural networks and fuzzy logic. In this mechanism, the neural network module decides the membership functions of the fuzzy module. The ANFIS structure is depicted in figure 8.

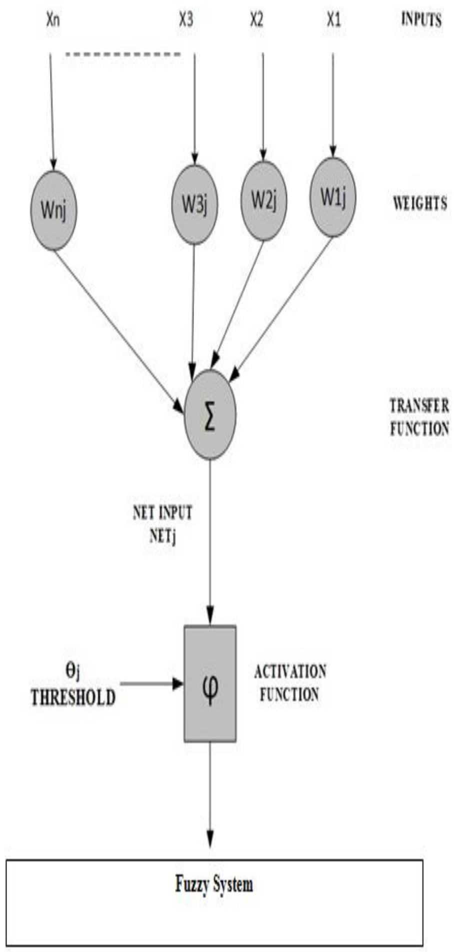

Figure.3 Block Diagram of Neuro-Fuzzy Expert Systems

The data filtration is done through the discrete wavelet transform which is filter which can sense and filter out the fluctuations and local disturbances in the data.

For the purpose, the following algorithm needs to be applied.

Step.1: Load the data in terms of dependent variables and target.

Step.2: Apply the DWT to attain the approximate and detailed co-efficient values.

Step.3: Retain the approximate co-efficient values and discard fluctuations in the detailed co-efficient values.

The performance evaluation parameters are cited as:

1) Mean Absolute Error

$$MAE \;=\frac{1}{N}\sum_{t=1}^{n}|P_i - A_i| \qquad (3)$$

2) Mean Squared Error

$$MSE=\frac{1}{N}\sum_{t=1}^{n}[P_i - A_i]^2 \qquad (4)$$

2) Mean Absolute Percentage Error

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\frac{[P_i - A_i]}{A_i} \qquad (5)$$

Here,

n represents the number of forecasted values

P_i denotes predicted values

A_i denotes actual values

It is always envisaged that the prediction model attains low values of error, and high values of regression and accuracy. The validation of any model stands on the performance comparison with respect to existing baseline techniques.

III. RESULTS

The results obtained through the implementation of the proposed work is depicted in this section.
The results obtained are depicted subsequently.

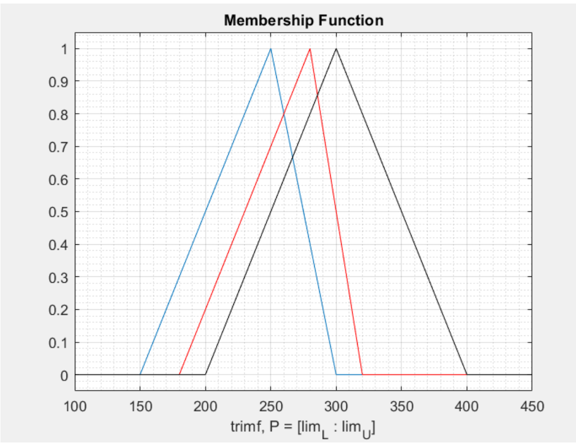

Figure. 4 Block Diagram of Neuro-Fuzzy Expert Systems

Figure 5 ANN design for analysis

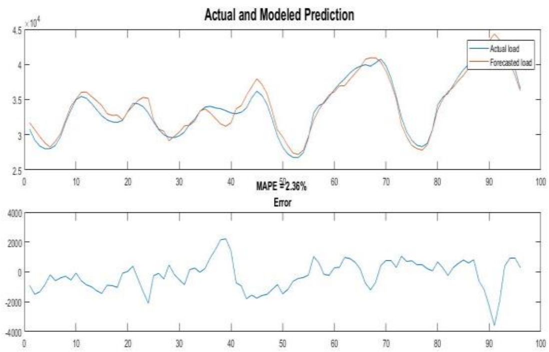

Figure 6 The evaluation of MAPE

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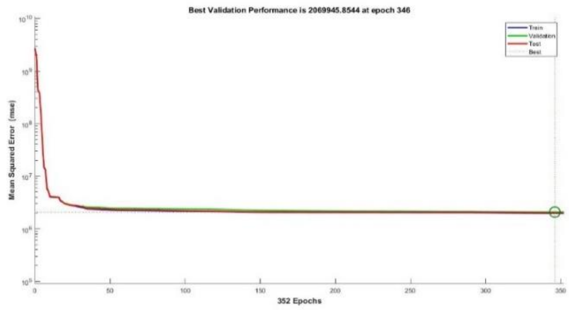

Figure 7 LS optimization based on MSE

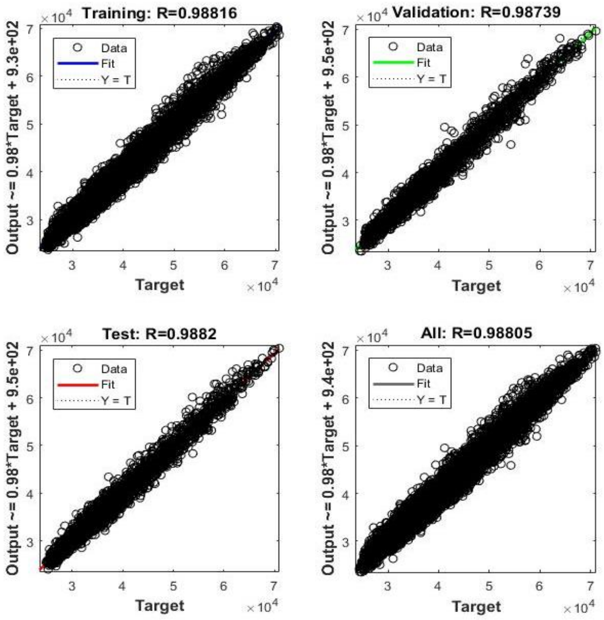

Figure 8 Evaluation of regression for different cases

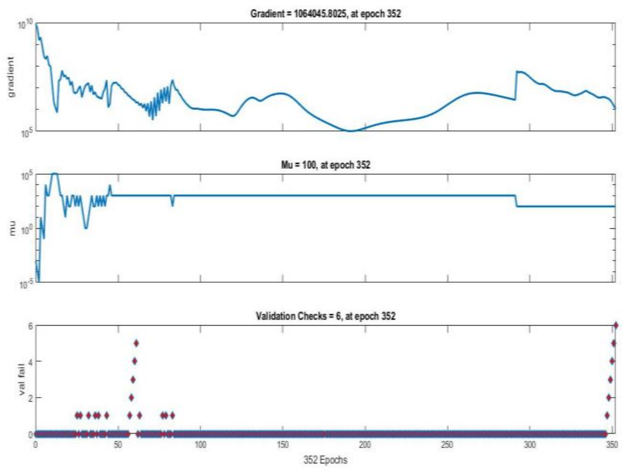

Figure 9 Evaluation of system Training States

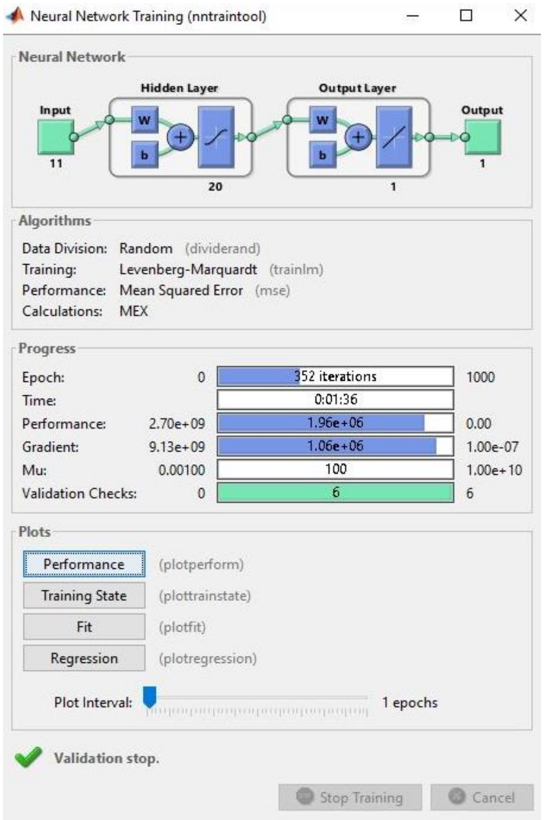

Figure 10 DWT-Filtered ANN

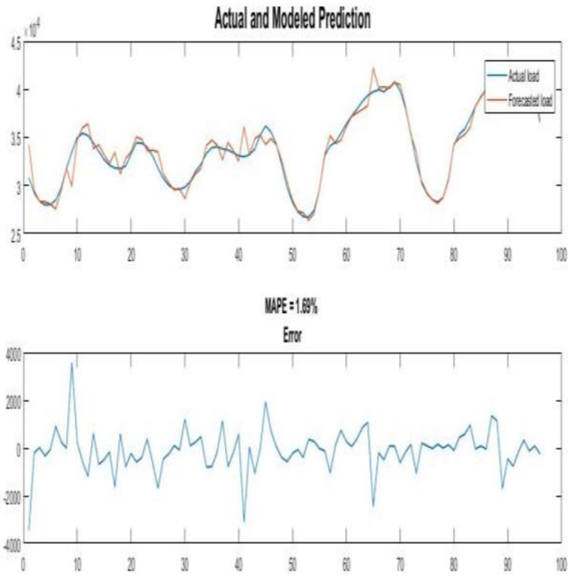

Figure 11 DWT filtered evaluation of MAPE

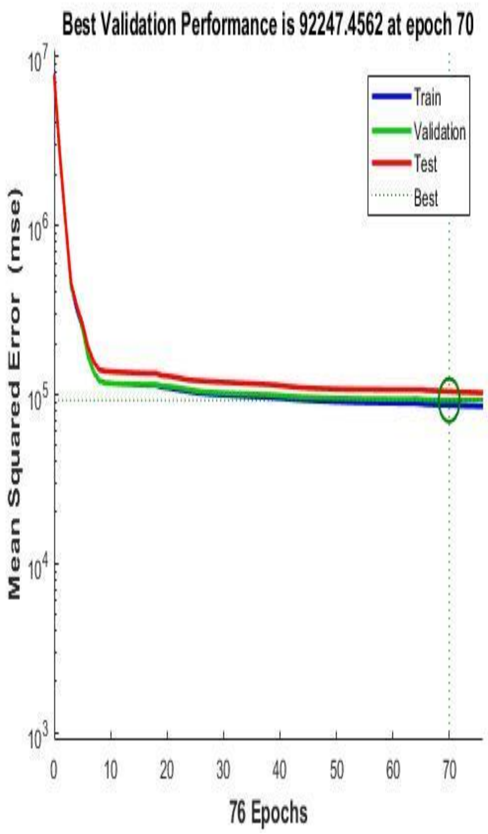

Figure 12 DWT Filtered LS optimization based on MSE

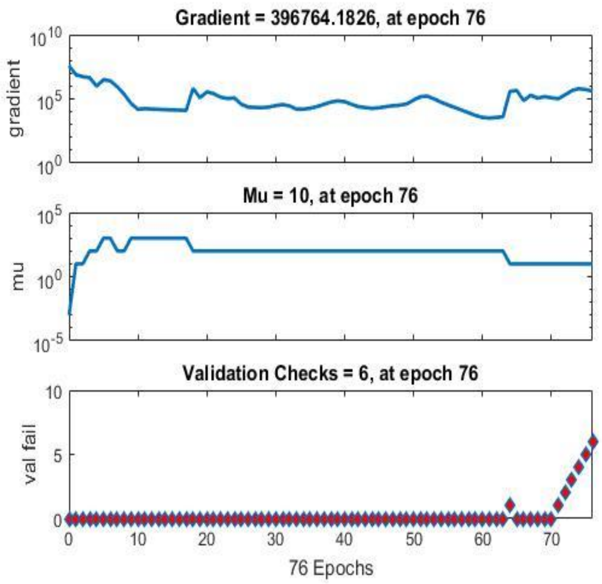

Figure 13 DWT filtered evaluation of system Training States

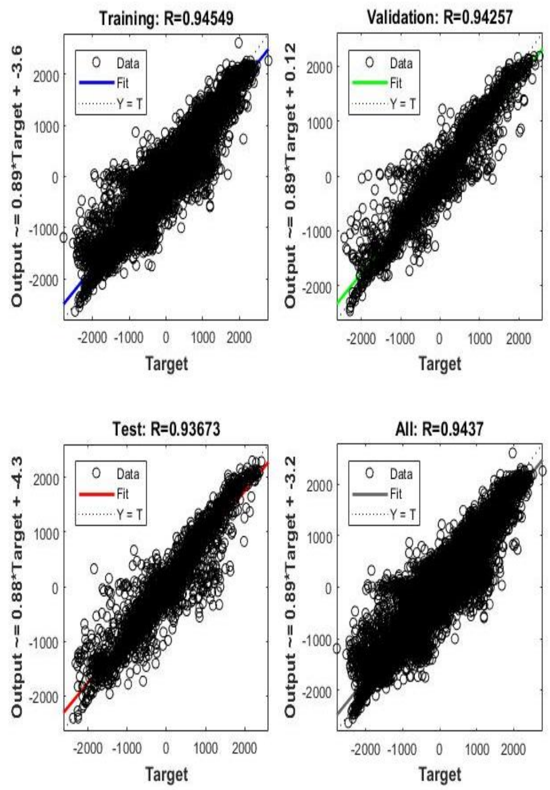

Figure 14 DWT filtered Evaluation of regression for different cases

Conclusion:

The discussions indicate that load forecasting is challenging due to the type and magnitude of uncorrelated data. The work presented in this paper is based on the back propagation based neural network regression process. The essence of the algorithm lies in the fact that the proposed approach uses the errors in each iteration as an exogenous input to the system and hence is used to attains faster convergence with lesser error margin for the system. The salient features of the different techniques have been discussed which paves the path for further research in the domain with the objective to attain higher accuracy of prediction compared to existing techniques. The proposed model employs the gradient descent along with

DWT filtered data to be used for the machine learning model. The discarding process for the detailed co-efficients allows to remove the noisy effects in the raw data. The ANFIS model allows to add an extra degree of freedom to the ML model to be used leading to enhanced training.

References

1. D. Cao et al., "Robust Deep Gaussian Process-based Probabilistic Electrical Load Forecasting against Anomalous Events," in IEEE Transactions on Industrial Informatics, 2022.
2. L. Yin, Z. Sun, F. Gao and H. Liu, "Deep Forest Regression for Short-Term Load Forecasting of Power Systems," in IEEE Access, vol. 8, pp. 49090-49099, 2020.
3. D. Wu, B. Wang, D. Precup and B. Boulet, "Multiple Kernel Learning-Based Transfer Regression for Electric Load Forecasting," in IEEE Transactions on Smart Grid, vol. 11, no. 2, pp. 1183-1192, 2019.
4. N. J. Johannesen, M. Kolhe and M. Goodwin, "Comparison of Regression Tools for Regional Electric Load Forecasting," 2018 3rd International Conference on Smart and Sustainable Technologies (SpliTech), 2018, pp. 1-6.
5. L. Li, K. Ota and M. Dong, "Everything is Image: CNN-based Short-Term Electrical Load Forecasting for Smart Grid," 2017 14th International Symposium on Pervasive Systems, Algorithms and Networks & 2017 11th International Conference on Frontier of Computer Science and Technology & 2017, pp. 344-351.
6. K. P. Warrior, M. Shrenik and N. Soni, "Short-term electrical load forecasting using predictive machine learning models," 2016 IEEE Annual India Conference (INDICON), 2016, pp. 1-6.
7. Hao Quan, Dipti Srinivasan, Abbas Khosravi,"Short-Term Load and Wind Power Forecasting Using Neural Network-Based Prediction Intervals" , IEEE Transactions on Neural Networks and Learning Systems, IEEE, Volume: 25, Issue: 2, pp 303 – 315, 2013.
8. Sharad Kumar, Shashank Mishra, Shashank Gupta, "Short Term Load Forecasting Using ANN and Multiple Linear Regression", Second International Conference on Computational Intelligence & Communication Technology, IEEE, 2016.
9. Kishan Bhushan Sahay, Suneet Sahu, Pragya Singh, "Short-Term Load Forecasting of Toronto Canada by Using Different ANN Algorithms", IEEE 6th International Conference on Power Systems (ICPS), 2016.
10. H.L. Willis. Spatial Electric Load Forecasting. Marcel Dekker, New York, 1996.
11. Renuka Achanta, "Long Term Electric Load Forecasting using Neural Networks and Support Vector Machines", International Journal of Computer Science and Technology, Vol. 3, Issue 1, pp 266-269, 2012.
12. Anand Mohan, "Mid Term Electrical Load Forecasting for State of Himachal Pradesh Using Different Weather Conditions via ANN", Model International Journal of Research in Management, Science & Technology, Vol. 1, No. 2, pp 60-63, 2013.
13. S.S. Somam, H. Zareipour, O. Malik, and P. Mandal, "A Review of Wind Power and Wind Speed Forecasting Methods with Different Time Horizons". North American Power Symposium, Arlington, pp. 26-28, 2010.
14. Wen-Yeau Chang, "A Literature Review of Wind Forecasting Methods", Journal of Power and Energy Engineering, pp. 161-168, 2014.
15. A.D. Papalexopoulos, T.C. Hesterberg, 'A Regression Based Approach to Short Term Load Forecasting', IEEE Transactions on Power Systems, 40 – 45, 1990.
16. N. Amjady, 'Short-term hourly load forecasting using time-series modeling with peak load estimation capability', IEEE Transactions on Power Systems, 498 – 505, 2001.
17. J. Yang, H. Cheng, "Application of SVM to power system short-term load forecast", Power System Automation Equipment China, pp 30 – 32, 2004.
18. W. Christianse, "Short Term Load Forecasting Using General Exponential Smoothing", IEEE Transactions on PAS, 900 – 910, 1971.
19. S.A. Villalba, C.A. Bel, "Hybrid demand model for load estimation and short-term load forecasting in distribution electrical systems", IEEE Transactions on Power Delivery, pp 764 – 769, 2000.

20. David J. Livingstone, “Artificial Neural Networks: Methods and Applications”. IEEE, 22
21. Maria Grazia De Giorgi, Antonio Ficarella, Marco Tarantino, “Error analysis of short term wind power prediction models”. Appl. Energy 88, pp. 1298–1311, 2011.
22. Hyndman, R. and Koehler A. "Another look at measures of forecast accuracy”, International Journal of Forecasting 22, pp. 679 – 688, 2006.
23. D. Marquardt, “An algorithm for least-squares estimation of nonlinear parameters,” SIAM J. Appl. Math., Volume 11, pp. 431–441, 1963.
24. [24] K. Levenberg, “A method for the solution of certain problems in least squares”, Quart. Appl. Mach., Volume 2, pp. 164–168, 1944.
25. Sotirov, “A Method of Accelerating Neural Network Learning”, Neural Processing Letters, Springer, Volume 22, pp. 163–169, 2005.
26. M. T. Hagan and M. B. Menhaj, “Training feedforward networks with the Marquardt algorithm”, IEEE Transactions on Neural Networks, Volume 5, pp. 989–993, 1994.
27. Bogdan M. Wilamowski and Hao Yu, “Improved Computation for Levenberg–Marquardt Training”, IEEE Transactions on Neural Networks, Volume 21, pp. 930 – 937, 2010.
28. http://www.ercot.com/gridinfo/load/load_hist/
29. http://mrcc.isws.illinois.edu/CLIMATE/Hourly/StnHourBTD2.jsp