International Journal for Research in Engineering Application & Management (IJREAM)
ISSN : 2454-9150 Vol-10, Issue-08, Nov 2024

Artificial Neural Network-Based Short-Term Load Forecasting: *A Case Study of Bauchi State Area of Nigeria.*

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Abstract - This study explores the application of Artificial Neural Networks (ANNs) in Short-Term Load Forecasting (STLF) for efficient energy management. Leveraging historical load data, weather conditions, and other relevant features, the ANN model is trained to predict electricity consumption accurately over short time horizons in Bauchi state, Nigeria. The research focuses on optimizing network architecture, selecting appropriate input features, and fine-tuning model parameters to enhance forecasting precision. Comparative analyses with traditional methods demonstrate the superior predictive capabilities of the proposed ANN-based approach. The findings contribute to the advancement of reliable and responsive energy forecasting systems, supporting effective decision-making in power grid operations and resource planning. Results obtained showed that Trapezoidal membership function with root mean square error (RMSE) of 5.26 performed better than Gaussian, triangular, gbell and sigmoid membership functions with RMSE of 5.32, 11.45,5.34 and 6.33 respectively. Triangular membership function had the worst RMSE with 11.45. Results also showed that the RMSE for the prediction for ANFIS is 3.70 compared with 3.77 for ANFIS. Simulation revealed that ANFIS performed better than ANFIS. The results verify that the short-term load forecasting model using ANN achieves high forecasting accuracy and can provide a new reference for accurate short-term load forecasting.

Keywords:—Artificial, Neural, Network, Load forecasting, Load.

I. INTRODUCTION

Electricity energy is a vital input for technological and socio-economic development of any country. One of the objectives of any commercial electric power company is to provide end users with safe and stable electricity. Electricity energy cannot be stored as it should be generated as soon as it is demanded [1]. Electricity demand pattern has become more complex and it is not easily predictable because people are now using increased number and variety of electric appliances and most of them are environmentally related. This increases the cyclic variation and noise on the demand pattern therefore, electric power load forecasting is a vital process in the planning of electricity industry and the operation of electric power systems [2]. Electric Load forecasting is the operation of predicting what the future consumption will be. Forecasting of the electric load at a future time involves enormous tasks and challenging problems as a result of diversities of uncertainties that surround the study [3]. Accurate models for electric power load forecasting are essential to the operation and planning of a utility company. Load forecasting assists an electric utility to make important decisions such as purchasing and generation of electric power, load switching, and infrastructure development. Load forecasting is extremely important for energy suppliers, independent system operator, financial institutions, and other participants in electric energy generation, transmission, distribution and markets [4]. Accurate forecast also leads to substantial savings in operating and maintenance costs, increased reliability of power supply and delivery system, and correct decisions for future development. Electricity demand is assessed by accumulating

 DOI : 10.35291/2454-9150.2024.0411

the consumption periodically; it is almost considered for hourly, daily, weekly, monthly, and yearly periods. Electric load forecasting is classified in terms of planning horizon and can be divided in to short, medium and long-term forecasting. The major factors affecting load forecasting include time curves [5][6], economics [7][8] and weather [9]. Weather factors include Temperature [10] Humidity, Precipitation, Wind Speed and Wind Chill Index [11].

II. Literature Review

Over the last few decades, a variety of forecasting methods have been developed for short term load forecasting. They can be broadly grouped in to Statistical, Artificial Intelligence, Expert and Hybrid based models [12][13]14]. The statistical models include; similar day approach [15], regression models [16][17] and time series methods [18][19]. The advantages of the mathematical model are their accuracy, simplicity and the use of only weather and load parameters. The artificial intelligence-based methods developed include; Artificial Neural Network [20][21], fuzzy logic [22][23]. Rule based forecasting makes use of rules, which are often heuristic in nature, to do accurate forecasting. Expert systems, incorporates rules and procedures used by human experts in the field of interest into software that is then able to automatically make forecast without human intervention [24]. Implemented expert systems are where knowledge about the load and the factors affecting it are extracted and represented in a parameterized rule base include [25][26][27]. Support vector machines (SVM) have also been used to implement load forecasting schemes. Unlike neural networks, which try to define complex functions of the input feature space, SVMs perform a nonlinear mapping by using so-called kernel functions of the data into a high dimensional feature space [28][29]. Results obtained from using SVM, revealed that SVMs compare favorably against the statistical methods.

Hybrid algorithms combines two or more other algorithms to solve a problem, either choosing one, or switching between them over the course of the algorithm. This is generally done to combine desired features of each so that the overall algorithm is better than the individual component. Learning techniques such as neural networks, genetic algorithm and particle swarm optimization (PSO), SVM, fuzzy logic and others have been successfully hybridized for short-term load forecasting. SVM and ANN was used in [30], a core vector regression optimized by Memetic Algorithm was presented in [31]. A fuzzy autoregressive moving average with exogenous input variables combined fuzzy logic and autoregressive moving average to implement load forecasting [32]. The autoregressive integrated moving average (ARIMA) and SVM was also used as hybrid for load forecast [33]. The accuracy of forecasting is of great significance for the operations and control of a utility company. although many forecasting methods has been developed, none can be generalized for all demand patterns. there is need to develop an enhanced tool that can generalize all demand patterns. This work proposes the use of genetic algorithm to tune an adaptive neuro fuzzy inference system-based model for the short-term load forecasting problem.

III. Materials and Methods

In this section the materials and methods used to carry out the simulation is presented. The ANN, model was implemented in MATLAB 2023 and was run on a personal Laptop HP Intel icore7 with CPU Processor. The main structure of the ANN implantation is described in the following steps:

A. Concept of Artifical Neural Network

Artificial Neural Networks (ANNs) are a fundamental concept in the field of artificial intelligence and machine learning. They are inspired by the structure and functioning of biological neural networks in the human brain. ANNs are a subset of machine learning models that aim to mimic the way the human brain processes information. Neurons are the basic building blocks of artificial neural networks. They are modeled after the neurons in the human brain. Each artificial neuron receives input, processes it using a weighted sum, applies an activation function, and produces an output.

Input Layer:

The input layer is the initial layer of an artificial neural network (ANN) and plays a fundamental role in processing and transmitting input data to the subsequent layers. Its primary function is to receive and distribute the features or variables from the dataset to the neurons in the hidden layers. The configuration of the input layer is determined by the number of input features in the dataset. The number of neurons in the input layer corresponds to the number of features in the input data. Each neuron represents a distinct feature. The input layer processes and transmits the raw input data, which could be numerical, categorical, or a combination of both, depending on the nature of the problem. Neurons in the input layer often do not apply activation functions since they primarily serve as input conduits. However, in certain cases, linear activation functions may be used. Weights are associated with connections between neurons in different layers. In the input layer, weights are typically initialized to accommodate the input data's range and distribution. Before entering the neural network, input data may undergo normalization or standardization to bring all features to a similar scale. This helps improve convergence during training.

 DOI : 10.35291/2454-9150.2024.0411

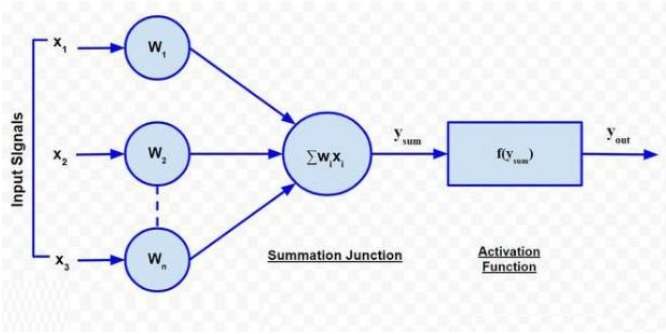

Figure 1. ANN Structure

Hidden Layer

The hidden layer, or layers, of an artificial neural network (ANN) are situated between the input layer and the output layer. These layers play a crucial role in the network's ability to learn complex patterns and representations from the input data. Each hidden layer consists of multiple neurons, and the number of hidden layers, as well as the number of neurons in each hidden layer, can vary based on the architecture of the neural network. The number of neurons in each hidden layer is a hyperparameter chosen during the design of the neural network. Increasing the number of neurons allows the network to capture more complex relationships in the data, but it also increases computational complexity. Neurons in the hidden layer(s) typically apply activation functions to introduce non-linearity into the network. Common activation functions include Rectified Linear Unit (ReLU), sigmoid, hyperbolic tangent (tanh), and others. Weights connecting neurons in the input layer to neurons in the hidden layer and between neurons in hidden layers are initialized to small random values. Proper weight initialization is crucial for efficient training. Each hidden layer may include bias neurons, which contribute a constant value to the weighted sum of inputs, allowing the network to learn translation-invariant patterns. The depth of a neural network refers to the number of hidden layers it contains. Deep neural networks, with multiple hidden layers, are capable of learning hierarchical features and representations. During the forward propagation phase, inputs from the previous layer (either the input layer or a preceding hidden layer) are linearly combined using weights and biases, and the result is passed through an activation function to produce the output of each neuron in the hidden layer. The hidden layers act as feature extractors, learning hierarchical representations of the input data. Each subsequent hidden layer can capture increasingly abstract and complex features. During training, the hidden layers contribute to the error calculation through backpropagation. Gradients are computed with respect to the error, and weights are updated to minimize the error. The hidden layer(s) in an artificial neural network serve as the computational backbone, enabling the network to model intricate relationships within the data. The design and configuration of the hidden layers significantly influence the network's capacity to learn and generalize from the input data, making them a critical component of neural network architectures. The key task is to determine the optimal number of layers and number of neurons in each layer**.**

Output Layer:

The output layer is the final layer in an artificial neural network, producing the network's output or predictions based on the learned patterns and representations from the input data. The structure and characteristics of the output layer depend on the nature of the task the neural network is designed to perform, such as classification, regression, or other specialized tasks. The number of neurons in the output layer is determined by the nature of the task: For binary classification, a single neuron with a sigmoid activation function is often used. For regression tasks, there is typically a single neuron, and the output is directly used as a continuous value. For regression, no activation function or a linear activation function is often used. The output layer produces the final predictions or decisions based on the learned representations from the hidden layers. The predicted class or value is derived from the output neuron(s) with the highest activation.

MATERALS AND METHODS

The hourly load data used in this study came from the Transmission company in Nigeria and is for the period 2015–2023. To ensure more accurate forecast, weather data, such as temperature, were used in addition to the historical data of the loads. Data is separated into training validation and test sets in a ratio of 70% to 150% to 15%. The training validation and test are randomized. The neural networks employed were built using the MATLAB programming language and specifically the neural network functions. The artificial neural network model consists of the following input variables: Hour of the day, day, week, month, year, holiday, temperature and humidity. The architecture of the MLP neural network that was used to predict the hourly value of the load is shown in Figure 1. An input layer, a hidden layer, and an output layer represent the three layers of a neural network. Seven neurons make up the input level. Each neuron is associated with one of the variables listed above. There are between 20 and 50 neurons tested in the hidden layer. The values were chosen experimentally and the best results tabulated. it was found to produce better predictive values by dramatically reducing error. The output layer is composed of a single neuron and refers to the hourly load value for which the prediction is developed.

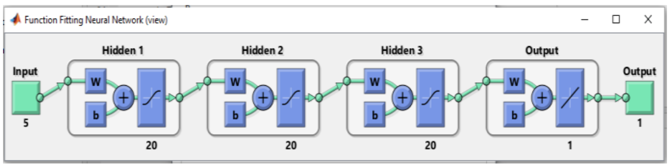

Figure 2. Simple Genetic Algorithm Flow Chart

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IV. Results And Discussions

The ANN model was tested on the Jos Metropolis Distribution System and the best model architecture and training algorithms was determined as presented in Table 1, 2 and 3.

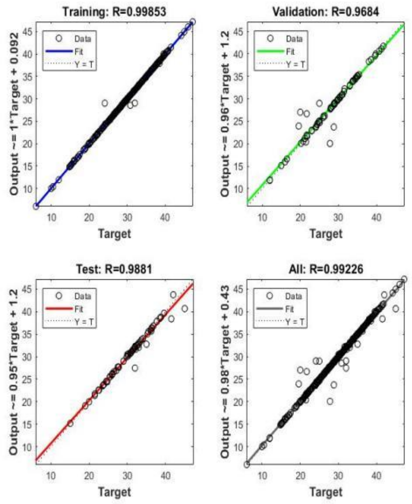

Figure 3. Regression plots for ANN

B. Architecture

The input membership functions tested showed that the Trapezoidal membership function (trapmf) had the lowest mean square error of 5.26 as compared with 11.45, 5.335, 5.322, 6.326 for trimf, gbellmf, dsigmf and gaussmf membership functions respectively as shown in Table 1.

Table 1. Input Layer membership Function

Number of neurons	MSE	RMSE	MAE	MAPE
10	625.5	25.0	0.5032	1.87
20	536.7	23.2	0.4425	1.70
30	687.6	26.2	0.4708	1.78
40	563.5	23.7	0.4522	1.69
50	606.6	24.6	0.5634	2.16

C. Training Algorithm

In the choice of the training algorithm for the model implementation three training algorithms was tested and Table 2 shows the results obtained. Back Propagation, hybrid method and GA training algorithms had an MSE of 5.294, 5.274 and 5.264 respectively. GA had the minimum mean square error. GA training algorithm also had the longest running time of 998 seconds for an epoch of 1000 as compared with 834seconds and 886 seconds for Back propagation and Hybrid respectively. From this result, it can be stated that GA best training algorithm for electrical load forecasting in this research. GA was selected for implementation in the research as the choice of training algorithm because it had the best performance compared the remaining training algorithm tested.

TABLE 2: Choice of Training Algorithm

Number of layers	MSE	RMSE	MAPE
10 10	485.28	22.02	1.40
20 20	474.48	21.78	1.28
20 20 20	478.66	21.87	0.93
20 20 20 20	773.62	27.81	1.71
20 20 20 10	623.67	24.97	2.18

Table 1 shows the performance of the data. The RMSE obtained ANFIS for training, testing and validation is 5.013, 5.339 and 5.324 respectively, while the RMSE obtained for GA-ANFIS for training, testing and validation is 4.987, 5.277 and 5.295 respectively. It can be seen that RMSE obtained for both GA-ANFIS and ANFIS training data was better than that for test data. And the test a data had a better result than the validation for both the GA-ANFIS and ANFIS. It was observed that GA-ANFIS had a better result than ANFIS. The RMSE of training is slightly better than testing because training data had more data than testing. Even though the testing had a better RMSE than the validation, the difference between the two is not significant. This shows that the GA-ANFIS and ANFIS models was able to adequately capture data information.

Table 2 shows results obtained for the overall performance when comparing Adaptive Neuro fuzzy inference system (ANFIS) and GA trained ANFIS (GA-ANFIS). MAPE results obtained ranged from 3.7012 up to 4.7722 for MAPE and 5.10 up to 5.19 for MSE. Results show that the performances were not very far apart but the GA-ANFIS technique had a slightly better performance MAPE of 3.701 as compared with ANFIS. Plots in figure 3 shows the performance of GA-ANFIS alongside ANFIS. This represents a high degree of accuracy in the ability of GA trained ANFIS networks to forecast electric load. The model shows relatively good forecasting performance. As the error becomes smaller, the load model becomes more acceptable for the purposes of load forecasting.

Table 3: Comparison of GA and GA-ANFIS

Training Algorithm	RMSE	MAPE
trainlm	21.87	0.93
trainscg	25.79	2.18
trainbfg	24.19	2.21
trainoss	27.78	2.57
trainrp	22.66	1.81

Table 3 shows the MAPE obtained based on weekdays and the holiday period. For the week days, Wednesday had the highest

 DOI : 10.35291/2454-9150.2024.0411

MAPE of 4.244 while Monday had the lowest MAPE of 3.767. The public holidays had combined error of 4.288. From the results, it can be seen that It shows that the load pattern for holiday periods are not as consistent as the remaining days. Figure 4 shows the 24-hour load forecast against the actual data.

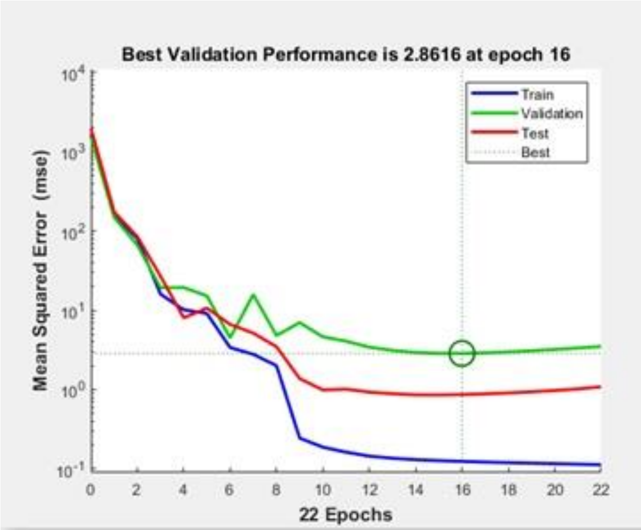

Figure 4. Comparison plot of ANFIS and GA-ANFIS for 1 week.

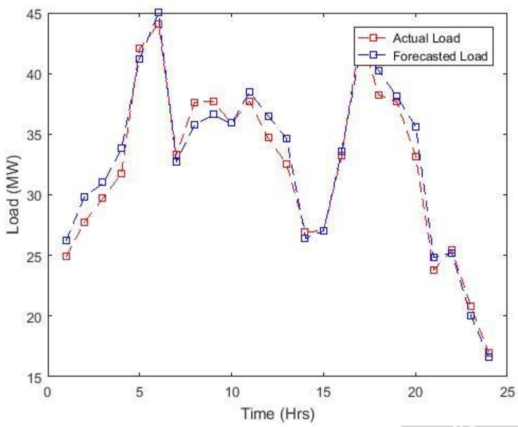

Figure 5. Block Diagram for GA Optimization of ANFIS [1].

V. DISCUSSIONS

The Adaptive Neuro-fuzzy based inference system (GA-ANFIS) is applied to model the next hour load forecast for the Bauchi Metropolis using time of the day, day of the week, next hour temperature, next hour relative humidity, and current hour load as the input variables. A total of twenty-six thousand two hundred and eighty (26280) hourly data for the years 2013, 2014 and 2015 is used for the modelling. 70% was used for training data while, 15% for Testing and 15% for validation. Trapezoidal membership function (trapmf) had the best perfomance compared with other membership functions with mse of 5.26. The overall performance when comparing Adaptive Neuro fuzzy inference system (ANFIS) and GA trained ANFIS (GA-ANFIS). MAPE results obtained ranged from 3.7012 up to 4.7722 for MAPE and 5.10 up to 5.19 for MSE. Results show that the performances were not very far apart but the GA-ANFIS technique had a slightly better performance MAPE of 3.701 as compared with ANFIS. This represents a higher degree of accuracy in the ability of GA trained ANFIS networks to forecast electric load.

VI. CONCLUSION

This paper presents an Artificial Neural Network model system for short term load forecasting for Bauchi State Nigeria. The optimal number of hidden layers and neurons per hidden layer was determined. Five different training algorithms was tested and the best training algorithm was chosen and deployed in the development of the model. Results obtained showed that 3 hidden layers with [30 30 30] neurons produced the best results. Also, of the five tested training algorithms trainlm produced the best results. Therefore, we conclude that ANN model represents a powerful tool for load forecast used by electric power utility companies. This shows that the short-term load forecasting model using ANN can provide a new reference for accurate short-term load forecasting.

Acknowledgement

Authors extend their appreciation to the Department of Electrical and Electronics Engineering Technology, Federal Polytechnic Bauchi, Bauchi, Nigeria.

REFERENCES

1. Eisa, A. & Hassan, S. (2011) A Methodology for Electric Power Load Forecasting, Alexandria Engineering Journal. 50, 137–144.
2. Badri, A., Ameli, Z.& Motie, A. (2012). Application of Artificial Neural Networks and Fuzzy logic Methods for Short-term Load Forecasting. Conference on Advances in Energy Engineering (ICAEE).
3. Volkan S.E. & Huseyin T. (2001). Forecasting the primary energy demand in Turkey and analysis of cyclic patterns, Hacettepe University, Ankara, Turkey.
4. Feinberg, E.A., Hajagos, J. T & Genethliou, D. (2002) Load Pocket Modeling. Proceedings of the 2nd IASTED International Conference: Power and Energy Systems, 50–54, Crete.
5. Feinberg, E.A., Genethliou, D., Chow, J.H., Wu, F.F. & Momoh, J. J., (2005). Load forecasting In Applied Mathematics for Restructered Electric Power Systems: Optimization, Control and Computational Intelligence, Power Electronics and Power Systems. Springer, US, pp. 269–285.
6. Muhammad U. F. & Naeem A. (2014). Factor Affecting Short-term Load Forecasting, Journal of Clean Energy Technologies, Vol. 2, No. 4, October 2014.
7. Khatoon S., Nasiruddin, Ibraheem Singh, Arunesh H. &, Priti I. (2015). Effects of various factors on electric load forecasting: An overview. 10.1109/34084POWERI.2014.7117763.
8. Phuangpornpitak N. & Prommee W. (2016). A Study of Load Demand Forecasting Models in Electric Power System Operation and Planning. GMSARN International Journal 10 (2016) 19 – 24

 DOI : 10.35291/2454-9150.2024.0411

9. Pardo A, Meneu V. & Valor E. (2002). Temperature and seasonality influences on Spanish electricity load. Energy Econ., 24: 55–70.

10. Dudhia, J. & Bresch, J. F. (2002). A Global Version of the PSU-NCAR Mesoscale Model. Monthly Weather Review, 130:2989–3007.

11. Vikas G. & Seema P. (2017). An Overview of Different Types of Load Forecasting Methods and the Factors Affecting the Load Forecasting. International Journal for Research in Applied Science & Engineering Technology (IJRASET). 5(4)729-733.

12. Feinberg, E.A., Hajagos, J.T. & Genethliou, D. (2003). Statistical Load Modeling. Proceedings of the 7th IASTED International Multi-Conference: Power and Energy Systems, 88–91, Palm Springs, CA

13. Mahrufat, D., Olagoke, Ayeni, A, A. & Moshood A. H. (2016). Artificial Intelligence Short-term Electric Load Forecasting using Neural Network and Genetic Algorithm, International Journal of Applied Information Systems Foundation of Computer Science (FCS), NY, USA. 10(4).1-8.

14. [hybrid]

15. Islam, B. (2011). Comparison of Conventional and Modern Load Forecasting Techniques Based on Artificial Intelligence and Expert Systems. International Journal of Computer Science Issues. 8(5)56-63.

16 Dao, H., V., Kashem, M. & Muttaqi, A., P., (2014). Short-term load forecasting using regression based moving windows with adjustable window-sizes Industry Applications Society Annual Meeting, 2014 IEEE, 2014,1-8.

17. Wei Y. (2015). A Review of Data Driven Approach for Prediction and Classification of Building Energy Consumption. Renewable and Sustainable Energy Reviews, 2018. 82. P1027-1-47.

18 Yang, H. T. & Huang, C. M. (1998) A New Short -Term Load Forecasting Approach using Self- Organizing Fuzzy ARMAX Models. IEEE Transactions on Power Systems, 13:217–225

19. Cho, M. Y., Hwang, J.C. & Chen, C. S. (2001) Customer Short-term Load Forecasting by using ARIMA Transfer Function Model. Proceedings of the International Conference on Energy Management and Power Delivery, 1:317–322.

20. Jiarui Z. (2016). Research on Power Load Forecasting Based on the

Improved, Elman Neural Network Chemical Engineering Transactions Vol 51. The Italian Association, of Chemical Engineering. Accessed 13th August 2016, Online at www.aidic.it/cet.

21. Luis, H., Carlos, B., Javier, M., A., Belén, C., Antonio, S. & Jaime, L. (2014). Artificial neural networks for short-term load forecasting in microgrids environment, Energy Journal, 75(1)252–264.

22. Patel P. M. & Ashish, P. S. (2014). Fuzzy Logic Methodology for Short-term Load Forecasting, International Journal of Research in Engineering and Technology. 3(04)322-328.

23 Priti, G. & Monika, G. (2014). Short-term load forecasting using fuzzy logic. International Journal of Engineering Development and Research, pp. 127 – 130.

24. Christiani, N. & Taylor, J.S (2000). An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods. Cambridge University Press, Cambridge.

25. Hyde, O. & Hodnett, P. F. (1997). An Adaptable Automated Procedure for Short-term lectricity Load Forecasting. IEEE Transactions on Power Systems, 12:84–93.

26. Rahman, S. and Hazim, O. (1996). Load Forecasting for Multiple Sites: Development of an Expert System-Based Technique. Electric Power Systems Research, 39:161–169

27. Ho, K. L., Hsu, Y. Y., Chen, F.F., Lee, T.E., Liang, C.C., Lai, T.S. & Chen, K.K. (1990) Short-term Load Forecasting of Taiwan Power System using a Knowledge Based Expert System. IEEE Transactions on Power Systems, 5:1214–1221.

28. Li, Y. & Fang, T. (2003) Wavelet and Support Vector Machines for Short-term Electricl Load Forecasting. Proceedings of International Conference on Wavelet Analysis and its Applications, 1:399–404.

29 Mohandes, M. (2002) Support Vector Machines for Short-term Electrical Load Forecasting International Journal of Energy Research, 26:335–345

30. Mohsen, M., Rasoul, R., Mohammadmehdi, S., Reza, M. & Ebrahim, H. (2016). A hybrid metaheuritic technique developed for hourly load forecasting,Wiley Online Library, 2016 Wiley Periodicals, Inc. Complexity Accessed 13thAugust 2016 from http://onlinelibrary.wiley.com/doi/10.1002/cplx.21766/full..

31. Yuancheng, L., Rong, M., Liqun, Y. & Chen, P. (2016). A Short-term Load Forecasting Model Using Core Vector Regression Optimized by Memetic Algorithm, International Journal of Control and Automation, 9(6)365-378.

32. Yang, H. T. & Huang, C. M. (1998) A New Short -Term Load Forecasting Approach using Self- Organizing Fuzzy ARMAX Models. IEEE Transactions on Power Systems, 13:217–225

33. Hongzhan, N., Guohui, L., Xiaoman, L. & Yong, W. (2012). Hybrid of ARIMA and SVMs for Short- Term Load Forecasting, International Conference on Future Energy, Environment, and Materials, 16, Part C,1455-1460, Energy Procedia.

 DOI : 10.35291/2454-9150.2024.0411