



Electrical Load Forecasting For 33/11kv Substation Manewada Mesedcl

¹Prof. Sagar Bhaisare, ²Sagar Shelke, ³Prathamesh Dhamankar, ⁴Rishika sahare

¹Assistant Professor, Department of Electrical Engineering, KDK College of Engineering, Nagpur,
Maharashtra,

^{2,3,4}UG Student, Electrical Engineering, KDK College of Engineering, Nagpur, India

Abstract: Electrical load forecasting plays a crucial role in the efficient operation, planning, and management of power distribution systems. This project focuses on forecasting the electrical load for a 33/11 kV substation using an Artificial Neural Network (ANN). Traditional load forecasting methods often struggle with complex, non-linear relationships in power consumption patterns. ANN, with its ability to learn and adapt, provides an effective solution for accurate short-term and long-term load prediction. The proposed model is trained using historical load data, weather conditions, seasonal variations, and other influencing factors. By leveraging machine learning techniques, the ANN model captures intricate patterns in power demand, enhancing prediction accuracy. This improved forecasting helps in reducing energy wastage, optimizing power distribution, and ensuring reliable power supply. The results of this project demonstrate the effectiveness of ANN in predicting load demand with high precision, thereby assisting power utilities in efficient decision-making, load management, and infrastructure planning. This study highlights the potential of artificial intelligence in modern power systems, providing a data-driven approach to enhance the reliability and efficiency of electrical networks.

Keywords: Artificial neural networks ,Electric power load forecasting, Machine learning, Mean square error, Mean absolute percentage error.

I. INTRODUCTION

Electrical load forecasting is a crucial aspect of modern power systems, enabling utilities to predict and manage the demand for electricity efficiently. Accurate load forecasting allows power grid operators to optimize energy generation, reduce operational costs, and improve system reliability, especially in high-demand situations. In the context of a 33/11 kV substation, which acts as a critical node in the distribution of electricity from the high-voltage transmission network to the lower-voltage distribution system, precise load forecasting plays a pivotal role in maintaining system stability and avoiding overloads. With the rapid advancements in computational techniques, Artificial Neural Networks (ANNs) have emerged as a powerful tool for forecasting electrical loads due to their ability to model complex, non-linear relationships between input variables such as time of day, weather conditions, historical load data, and seasonal trends. ANNs, inspired by the structure of the

human brain, can adaptively learn patterns in data and provide highly accurate predictions even in the face of dynamic and unpredictable load fluctuations. By leveraging ANNs, utilities can improve their short-term and long-term load forecasts for 33/11 kV substations, thereby ensuring the optimal operation of the power grid, minimizing the risk of blackouts, and enhancing the efficiency of energy distribution. This research aims to

explore the application of ANNs in electrical load forecasting for 33/11 kV substations, highlighting their effectiveness in addressing the challenges associated with load prediction and system management.

In order to supply electricity to the customers in a reliable and economic manner, an electric utility has very complex tasks in operation and control of the power system. The short term load forecasts (days to a few weeks ahead) is used in planning the level and mix of generating capacity that will be needed to supply the actual demand. The medium term load forecasts (month to a few years ahead) are used to predict capacity needs. Operating costs may be reduced using more accurate load predictions, as fewer generating units will need to be started up and kept as reserve. The need for accurate load forecasts will increase in the future because of the dramatic changes occurring in the structure of the utility industry due to deregulation and competition. This environment compels the utilities to operate at the highest possible efficiency, which, as indicated above, requires accurate load forecasts. For decades the problem of improving the accuracy of load forecasts has been an important topic of research. Various types of load forecasting methodologies as reported in have their own advantages. Load forecasting can be performed using many techniques such as regression analysis, statistical methods, artificial neural networks, genetic algorithm, fuzzy logic etc. Short Term load Forecaster studies began at early 1960s with one of the first studies done by Heinemann et al. in 1966 which dealt with the relationship between temperature and load . In 1971, a load forecasting system was developed by Lijesen and Rosing which used statistical approach. In 1987, Hagan and Behr forecasted load using a time series model . The time series approach assumes that the load of at any time depends mainly on previous load patterns. Like the autoregressive-moving average models and spectral expansion technique , the regression method utilizes the tendency that the load pattern has a strong correlation to weather pattern. The weather sensitive portion of the load is arbitrarily extracted and modeled by a predetermined functional relationship with weather variables. The statistical methods, such as autoregressive moving average, linear regression, stochastic time series, and general exponential smoothing involves the use of hard computing techniques based on the exact model of the system and utilize linear analysis. However, they have limited ability to capture non-linear and non stationary characteristics of the hourly load series and are not adaptive to rapid load variations.

II. BLOCK DIAGRAM OF THE PROJECT

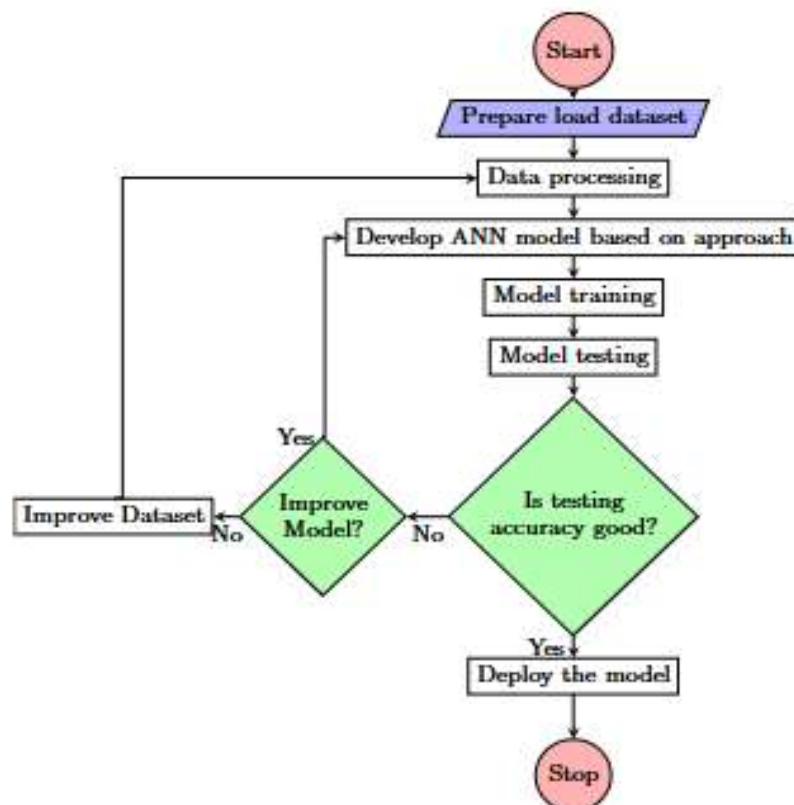


FIG 1: BLOCK DIAGRAM OF THE PROJECT

III. PERFORMANCE OF ANN MODEL

ANN architecture was developed in MATLAB by considering different numbers of hidden neurons in the hidden layer. The performance of the network was observed at different hidden neurons in terms of MSE and R. The architecture which has better performance, i.e. one with low MSE and high R was considered to predict the load. The performance of the network at different number of hidden neurons is presented.

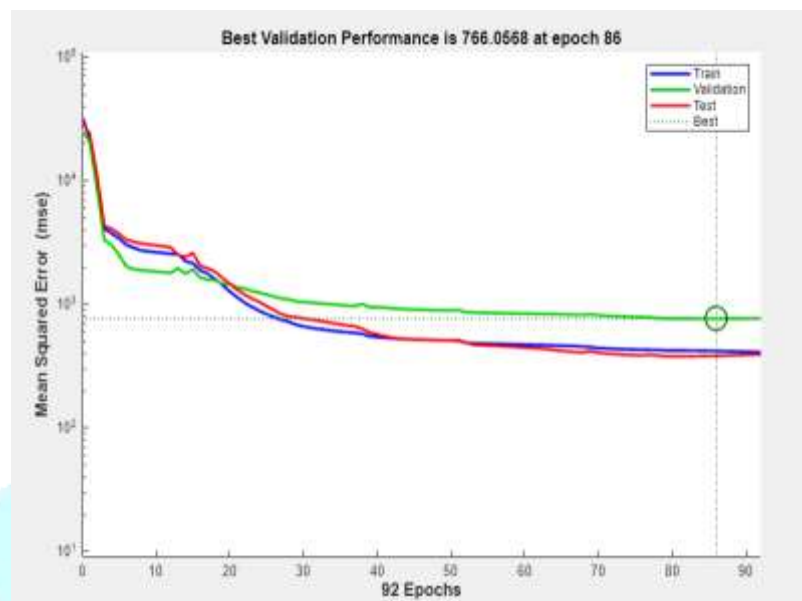


Fig 2: ANN Model performance plot

In this paper, an architecture with 11 hidden neurons, low MSE and high R is considered as optimal model. The performance of the optimal model with 11 hidden neurons is observed based on MSE. The performance plot of the model at each level (Training, Validation and Testing) is presented in Fig. 2. Regression plot with training, validation and testing data is presented in Fig. 3. The values of regression coefficients for training, validation and testing are 0.97, 0.94 and 0.9 respectively and these are acceptable as these values are near to one.

Error histogram plot with training, validation and testing data is presented in Fig. 4 and it is observed that all the errors show normal distribution. After successfully training the network, deployable ANN model is generated with SIMULINK as shown in Fig. 5. Actually deployable model provides output in terms of normalized values. So actual predicted load was observed after de-normalizing the output of ANN. This is incorporated as shown in Fig. 5.

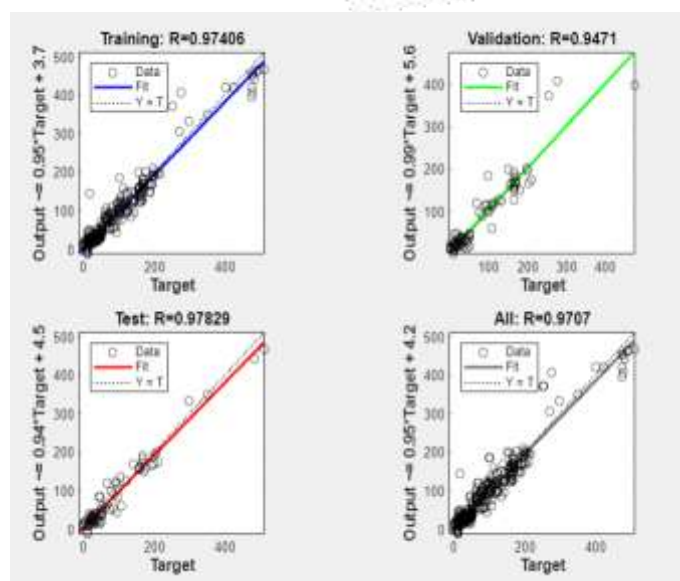


Fig 3: Regression plot with training data

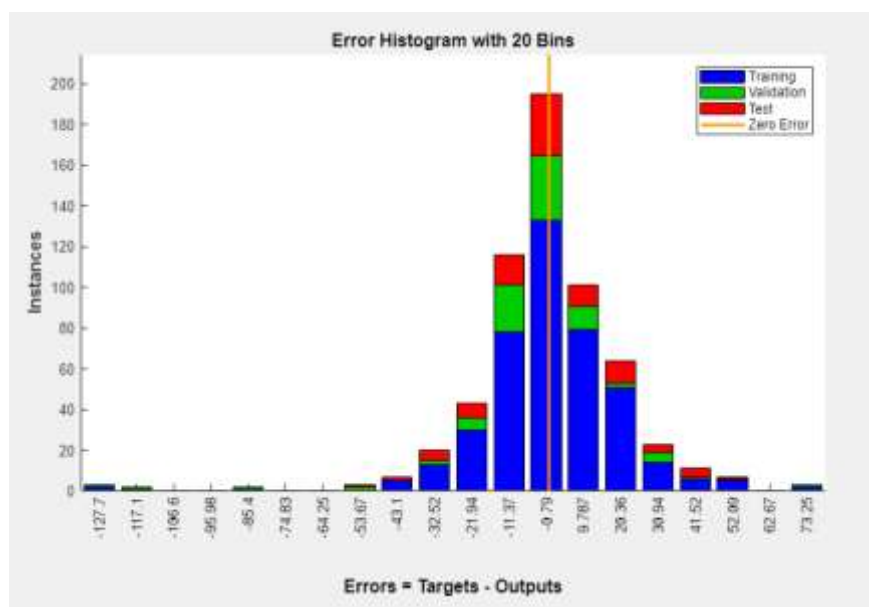


Fig 4: Error histogram plot

IV. PREDICTION OF LOAD USING ANN MODEL

12 month load on 33/11kv electrical substation manewada msedcl is predicted using trained ANN model. The comparison of both actual load and predicted load for the time horizon 12 month is presented in Fig. 6 to 11. Based on the analysis it has been observed that predicted load was almost following the actual load. Based on the predicted values, testing performance of the model was measured in terms of mean absolute percentage error and its value was 5.87%.

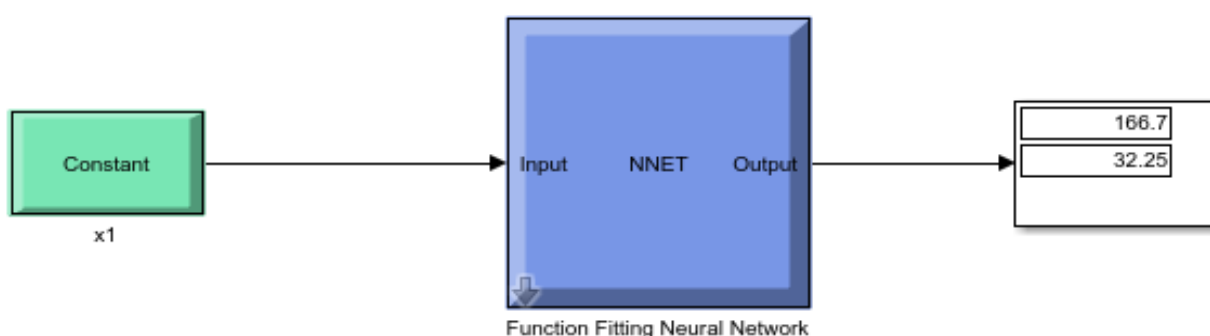


Fig 5 : Deployed ANN Model

FOR THE MONTH OF AUGUST 2024

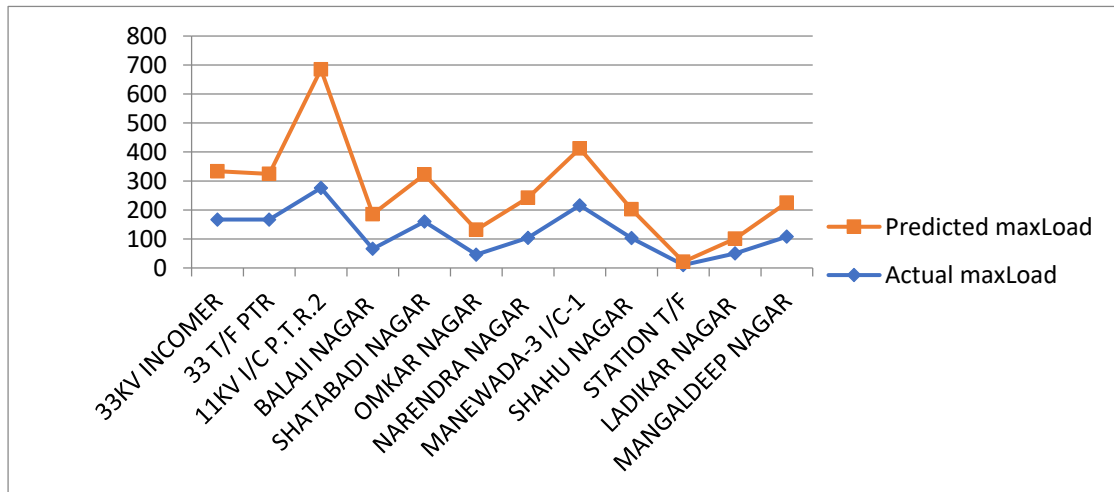


Fig 6: Comparison of predicted and actual max load

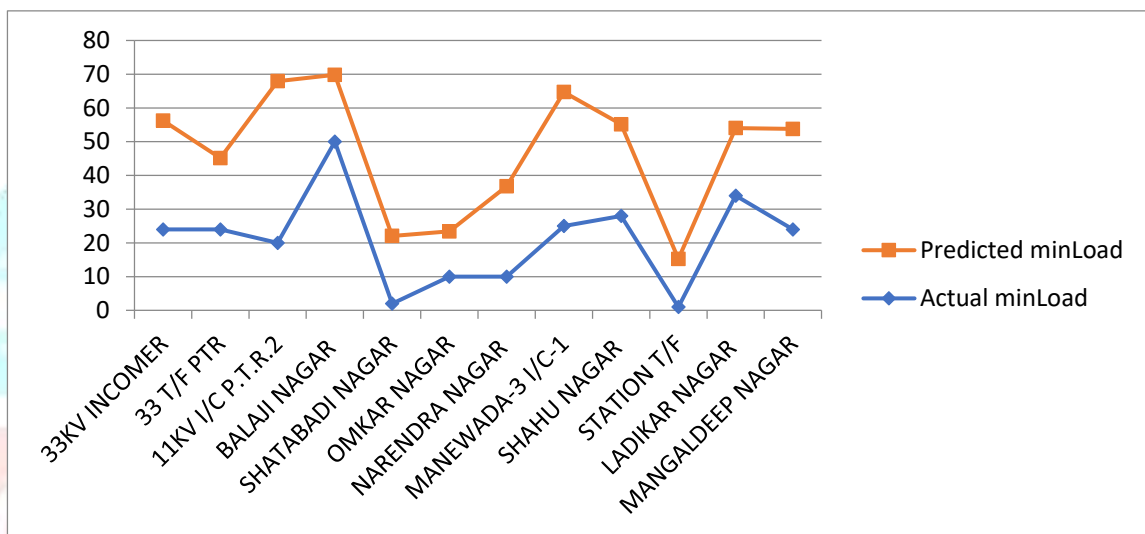


Fig 7: Comparison of predicted and actual min load

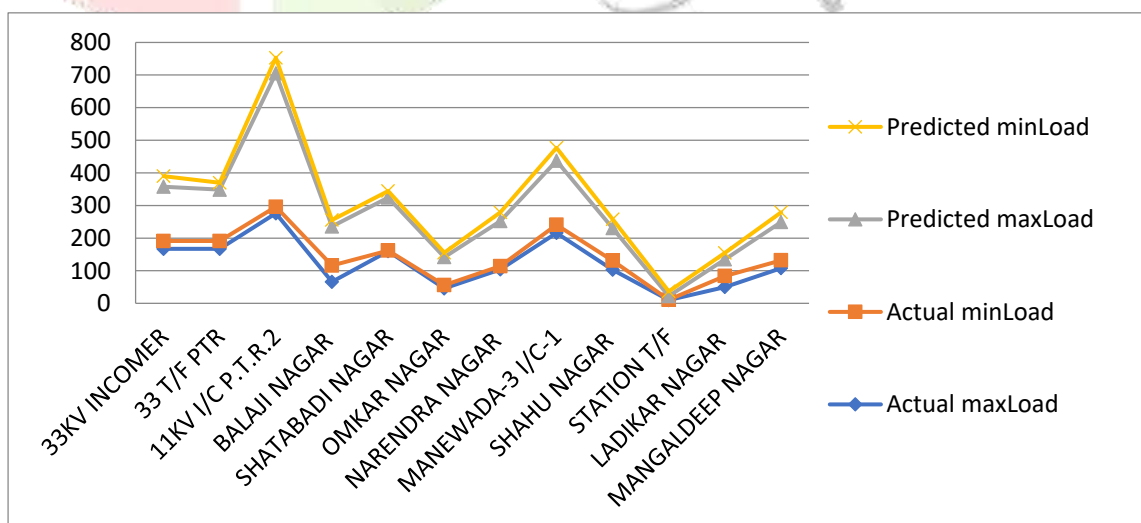


Fig 8: Comparison of predicted and actual max and min load

FOR THE 33KV INCOMER

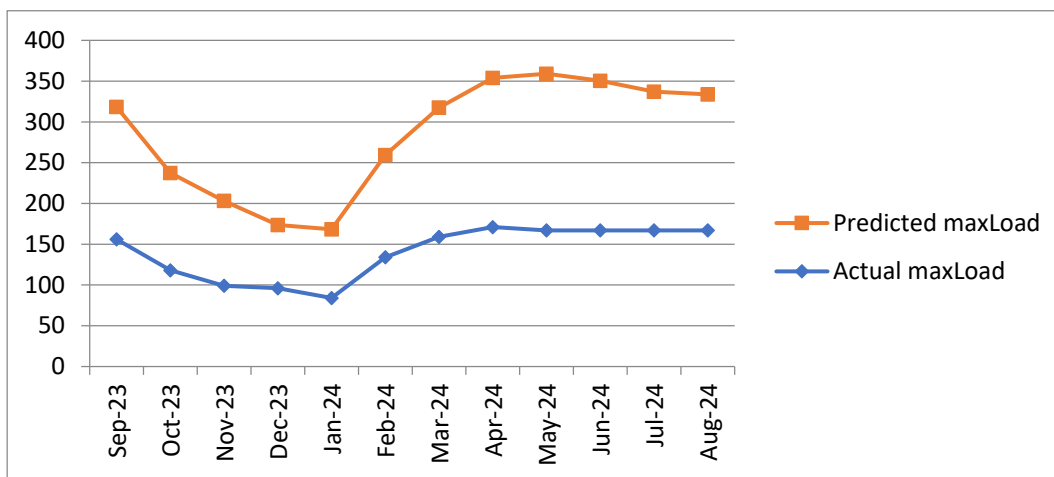


Fig 9: comparision of predicted and actual max load

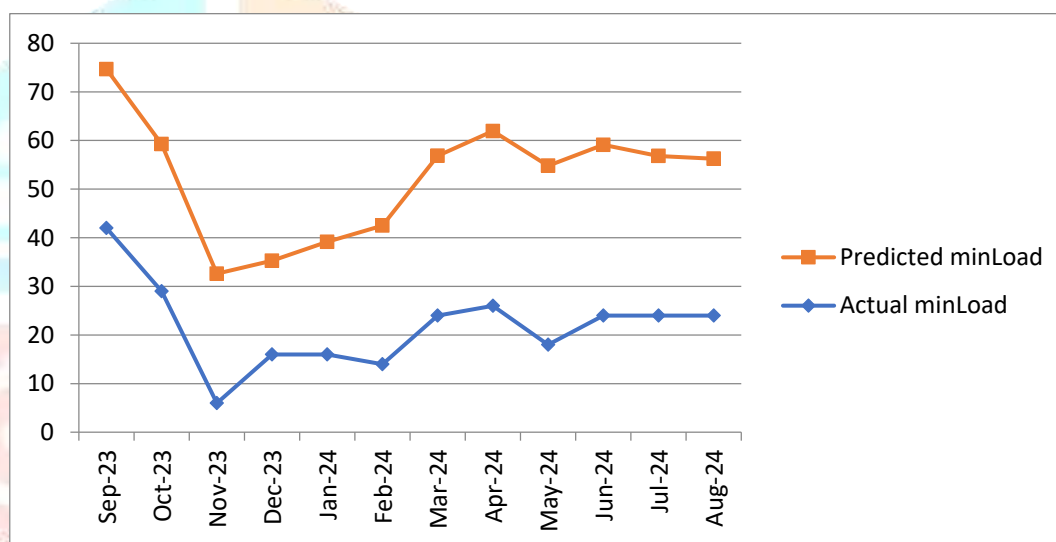


Fig 10: comparision of predicted and actual min load

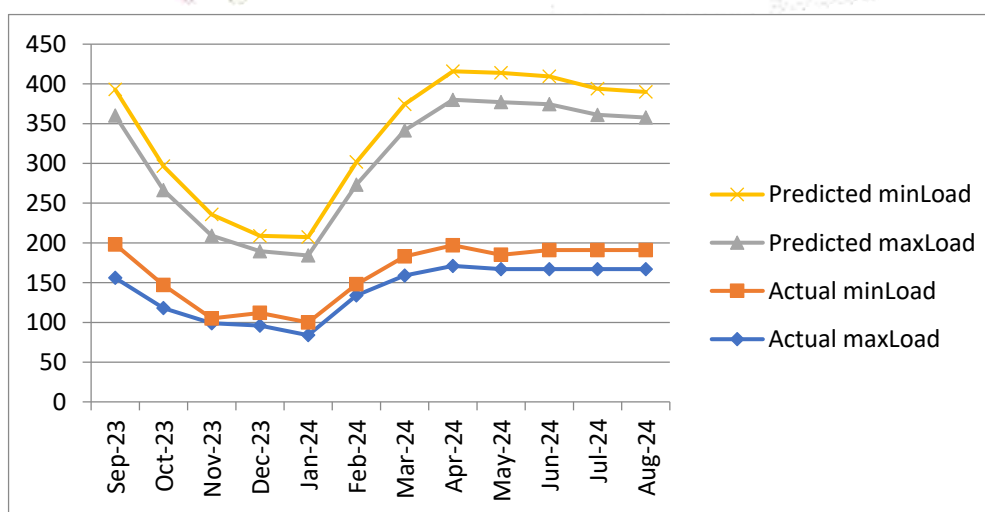


Fig 11: comparision of predicted and actual max and min load

V. CONCLUSION

Medium term load forecasting is one of the key issues in energy trading markets. Distribution companies and industries are able to predict and quote reasonable amount of power in energy exchange. The proposed model can be helpful to distribution companies and industries to predict actual load with reasonable accuracy. Real time load data was collected and processed such that no NaN values exist, making data follows normal distribution. last 12 month load data Artificial neural network topology was developed to predict the load based on the proposed approach. Levenberg Marquardt based back propagation algorithm was used to train the proposed ANN model. The proposed ANN model has been implemented and tested in MATLAB environment.

The ANN model developed predicts the load with good accuracy. The proposed ANN model had training MSE

of 419.3968 and validation MSE of 766.0568. Testing accuracy was measured in terms of MAPE which was equal to 5.87%. The developed model was compared with models available in literature in terms of regression coefficient. The performance of the model in terms of uncertainty in error and regression was observed and compared with existing models. The approach to predict the load using ANN model can be used in other research areas in power systems like LMP computation, effective trading in energy market, power system deregulation, etc. This work to predict load can be further extended by considering the sequential networks and by considering week days and weekend.

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