Artificial Neural Network for short-term load forecasting: An evaluation based on Chhattisgarh State

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Abstract- Load forecasting is a technique of prediction of future occasion, final occasion, final results or trend of load demand based to on historical and probabilistic data. Short term load forecasting has a significant effect at the efficiency of operation. In short term load forecasting, the goal is to estimate the load for the following half an hour up to the next two weeks. In this study artificial neural network (ANN) approach is presented for load forecasting particularly for Chhattisgarh State. A prediction of very next day is shown with different parameters in order to count those parameters which perform well and are able to provide the best results in prediction. The ANN model is trained using an input dataset which consists of previous year data along with a day before data of same date of predicted load as two different features of input dataset. These features further involve both generation and load demand in it. It covers the timeframe from 1 JAN 2022 to 30 NOV 2023 for both training and testing method. After training and testing of model, the result gets evaluated through statistics matrices such as MAPE (mean absolute percentage error) and MAE (mean absolute error) in the end, ensuring accuracy and fitness of the model.

Keywords-Artificial Neural Network, Short term load forecasting, mean absolute percentage error, mean absolute error.

I. INTRODUCTION

Load forecasting is a sort of making plans also it's far stated that "To paintings with a plan is to work with precision". The motive of load forecasting is to create acquiring rules for building capital strength forecasts, which might be had to decide future requirements. For this reason, the key to all making plans is a superb forecast reflecting modern-day and future trends. It also helps to provides power companies with an idea of future electricity consumption and time to reduce the gap between load demand and generation capacity [1]. Depending at the term of interest, a load forecasting manner are categorized into short time period, medium term and long-term techniques. Further, with every study done, there are number of techniques are found to beneficial for prediction of load in advance. Number of machine learning and AI (Artificial Intelligence) related methods has been found such as Artificial Neural Network (ANN), Long-short term load forecasting (LSTM), Gaussian Process Regression (GPR), Time series analysis etc. The purpose of this study is to predict the load demand value with an application of different parameters on Chhattisgarh state, further with the help of statistical matrices/ mathematical calculation, it is then identifying and elect that parameter, which is able to provide the future load demand with the best accuracy possible, and further ensure fitness and efficiency of proposed model.

This paper follows a structure as: Section 2 focuses on a literature review. The utilization of data with its methodology to train and test the data with respective proposed model is presented in Section 3. Application of proposed forecasting model is then presented in Section 4. Result and discussion are shown in Section 5. This section showcases the comparative result in order to ensure the accuracy of prediction. At last Section 6 presents the conclusion for short term load forecasting and further acknowledgement presents in Section 7.

II. LITERATURE REVIEW

The research presented in [2], showcases using non-parametric regression in short time period load forecasting. The networks were trained using three weeks' worth of data and then used to predict loads up to a week ahead. In the end statistical matrices such as root mean squared, and mean absolute gets evaluated in order to ensure accuracy of model.

In [3], a day ahead prediction is performed with the help of five exponentially weighted methods along with a SVD-based exponential smoothing formulation. The dataset utilized for this prediction covers timeframe from 2007 to 2009 for British and French load series respectively. When comparison done in the end, all 5 methods had been outperformed by using the new SVD-based totally exponential smoothing components. In [4] a short-term load prediction method proposed based on deep residual network, where two different datasets were used in order to verify the effectiveness of the proposed model. It is then performed with different test cases for every dataset used. In the end comparison between the proposed model and existing model is presented. The fitness and efficiency of model was estimated with the help of MAPE (mean absolute percentage error).

The study in [5] offers quick-time period load forecasting (STLF) approach based totally at the support vector regression machines (SVR) in conjunction with two distinctive feature choice methods. In order to compare and verify its effectiveness with state-of-the-art algorithms, two different datasets of two different locations (England and North-America) were used with different test cases performed. The result showcases an improvement 20% to 23.4% and from 2.5% to 34.2% two different locations.

In paper [6], framework of three different methods such as similar day selection, wavelet decomposition, and neural networks were used in order to forecast next day load. Further with the help of wavelet decomposition and neural network to identify the load features in both low and high frequencies. The result ensures the accuracy of the method performed.

A CNN-LSTM method proposed for short-term forecasting in [7]. The last five years of load data (e.g., from January 2014 to December 2018) were selected to train the proposed application. On the other hand, the testing process was carried out using data from 2019 (for example, January 2019 - December 2019). Once completed, the results confirmed that CNN-LSTM outperformed other existing algorithms.

In the cited paper [8], short-term load forecasting based on DNN is proposed and implemented in addition to demand-side STLF. The proposed version is then compared with other DNN based STLF strategies which include autoregressive included moving average (ARIMA), shallow neural community (SNN) and double seasonal Holt–Winters (DSHW). The outcome is then evaluated with the help of MAPE and RRMSE, which clearly offer better result for proposed model comparatively.

In paper [9], a model along with convolutional layers and -manner again-propagating recurrent layers LSTM and GRU is offered which were used to predict the weight for the subsequent hour. One-of-a-kind datasets (North-American utility and ISO–NE dataset) had been used to check the performance of the forecasting model. Further the result ensures that the proposed model outperforms the other existing conventional models specifically LSTM and GRU.

A study in [10] showcasing an application of short term load forecasting (STLF) through hierarchical structure. Prediction of root node was first performed by WNNs (wavelet neural network). Other child node presents then forecasted by simple method. In addition to which SPC based switching operation performed in order to count its accuracy. The outcome presented in this paper clearly indicating the high accuracy in prediction method and hence found to be an efficient method in STLF.

In [11], Microsoft excel as data analyzing tool was used to forecast a load demand data. Related to this, the dataset of last 10 days from month Sep 2022 were chosen to perform the prediction of future load demand values. The corresponding error associated with the prediction method was found high.

The study presented in [12], showcase the comparison among the 3 different models such as Gaussian Process Regression, Artificial neuron network and Long short term memory. These models further get trained and tested on selected dataset of Chhattisgarh state varies from the year 2020 to 2021 for input data whereas 2021 to 2022 for target data. In the end of the experiment, LSTM model was found to be the more efficient among the other 2 models.

In [13], the study presented 12 GPR model for 4 Indian cities along with an Australian city, in order to provide an hourly and monthly load demand. Further to distinguish among the proposed model, MAPE was calculated to count the best prediction model. In the end with least error, GPR with "Exponential" kernel function was found to be the best model for prediction.

Load forecasting through GPR approach is presented in [15] with two parameters in it (Ardexponential and constant function), in order to predict a year ahead load data. At last the result confirms its efficiency.

III. METHODOLOGY

A comparative study of different machine learning methods has been proposed for load forecasting [16] along with many AI techniques such as GPR, SVR, RF, ANN etc. Artificial Neural network (ANN), generally grounded on an idea, in which a collection of nodes typically referred to as synthetic/artificial neuron, plays similarly to the biological brain. In ANN, facts are processed by means of neurons the usage of a non-linear mapping technique.

The task of neuron is to receive signals from artificial neurons, process them and send them to different neurons [17]. In machine learning method a commonly known basic architecture of Artificial neural network includes interconnected nodes as Input Nodes, Hidden Nodes and Output Nodes [18], where the output is expressed by (1):

$$Y = f\,[(\sum \boldsymbol{wixi}) + \boldsymbol{\theta}] \ \ldots\ldots\ldots(1)$$

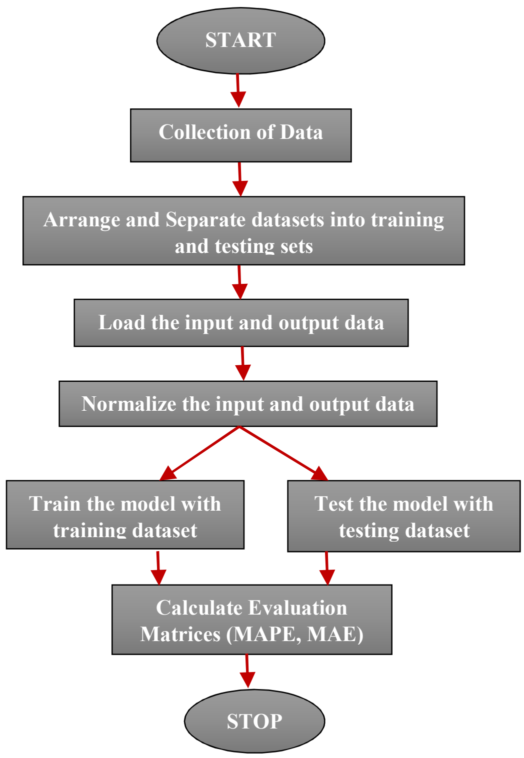

Fig 1 Flowchart of STLF based on ANN model.

Artificial intelligence (AI) techniques mentioned in the literature are expert systems, fuzzy inference, neural networks, fuzzy-neural models. Between various load forecasting techniques, the application of ANN for power system load forecasting has received massive attention in last few years [18]. ANN-based models are experimental in nature, and can provide insights and solution to design problems and situations that can be understood from experimental data [19, 20, 21]. Fig 1 representing a general flowchart for STLF based on ANN model. This experiment is suitable and performed on MATLAB along with some ANN command. In order to have an accurate result in prediction some necessary changes can be done in appropriate manner.

In this paper input data is collected from Chhattisgarh State Load Dispatch Centre. Mainly, 3 varieties of variables are used as inputs to a neural network:

- hourly and very day signs,
- weather-associated inputs, and
- historical loads

On the basis of requirement of power companies, the prediction method consider different variables for input data. It further can also segregate into several other variables depending upon the location, consumption etc. The arrangement of input data can vary as per the need, where every data which are arranged to predict a future data value are known as its historical data. In this paper, previous year data along with the previous day data are counted as historical data. These historical data are then used to evaluate and predict a very next load demand.

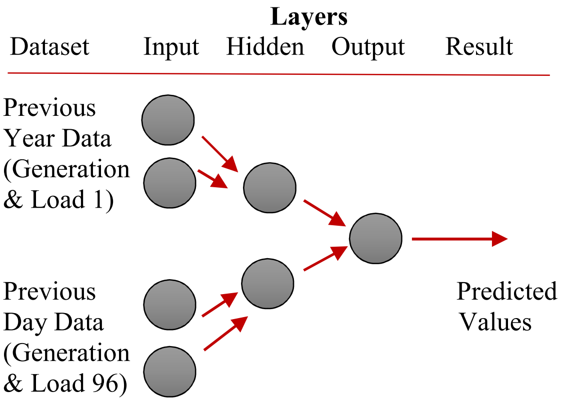

Fig 2: An architecture of ANN for STLF

IV. PROPOSED MODEL

This paper proposed a short-term forecasting method based on artificial neural network (ANN) for future forecasting (next day) in Chhattisgarh.The dataset selected to perform the proposed model involves a previous year data and a day before data in reference to predicted data as their two features. These two features further consist of Generation and Load data in it, which are arranged in hourly and 15 minutes' interval. Fig 2 representing the basic architecture of ANN proposed in this study, where in total input dataset contains four set of data and target dataset contains one set.

The timeframe of input dataset varies from 1 JAN 2022 to 30 NOV 2023, which is then segregated into a ratio of 80:20 i.e. for training and testing separately. For training a dataset, it involves dataset from 1 JAN 2022 to 30 SEP 2023 whereas for the testing process, the dataset varies from 1 OCT 2023 to 30 NOV 2023. In reference to historical data, Generation and load data in it consists of 96 samples each day i.e. it varies from 2880 (96 × 30) to 2976 (96 × 31) number of samples accordingly. The dataset then gets trained and tested with different parameters separately and showcases the comparison among them. For initial two experiments, the input dataset is scaled in the range of -1 to +1. The network configuration is changed in order to train and test the ANN-1 and ANN-2 models. In the first case, the ANN-1 model has 30 neurons in the hidden layer and one neuron in the output layer along with the use 'logsig', 'purelin' activation function in hidden layer and output layer respectively. In the second part, ANN-2 was trained and tested using 50 neurons in the hidden layer and one neuron in the output layer and other transfer function 'tansig', in both the hidden and output layer of ANN-2 network. Further another network ANN-3 with 30 and one neuron in the hidden and output layer with activation function as 'logsig', 'purelin' respectively, with normalised inputs in the range of 0 to 1 are considered.

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n}|Yi-Y'i| \quad \text{........(2)}$$

$$\text{MAPE}=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{Yi-Y'i}{yI}\right| * 100 \quad \text{.......(3)}$$

At last, in order to count the best performed parameter and ensures the fitness of the model, evaluation matrices as MAE (mean absolute error) and MAPE (mean absolute percentage error) are considered and calculated using (2) and (3), where n represents length of dataset and Yi and Yi' are actual and forecasted data respectively.

V. RESULT AND DISCUSSION

This paper follows a brief time period load forecasting technique primarily based on artificial neural network (ANN) to carry out a next day prediction primarily based on its previous records. In this study, previous year and a day before (previous day) data are mainly considered as historical data, arranged in hourly and 15 minutes' interval. Further these previous year and previous day dataset both comprises the values of generation and load demand in MW. The selected dataset of chhattisgarh state covers the timeframe from 1 JAN 2022 TO 30 NOV 2023, which further segregate for both training and testing process i.e. in order to perform training process, the dataset contains dataset from 1 JAN 2022 to 30 SEP 2023 along with considering 30 neurons in the hidden layer. In initial two experiments, the dataset is scaled in the range between -1 to 1. Fig 3 showcase the results of ANN-1 based model represented in form of a graph between actual and predicted data during training process. The graph clearly indicates the fully overlapped of forecasted data over actual, also depicted the corresponding abosulte error values obtained.

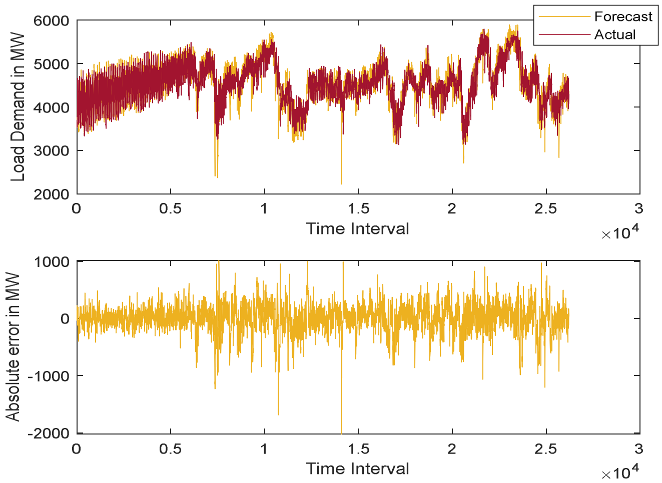

Fig 3 Actual and Forecasted Load along with absolute error observed during training of ANN-1.

Further to test the model, load data from 1 OCT 2023 to 30 NOV 2023 are considered. Fig 4 shows the plot between actual and predicted data during testing process of ANN-1. The testing results show that the predicted load graph is not overlapping with the actual load demand, which also illustrates the corresponding error. Furthermore, the forecasting model performance is also evaluated using statistical matrices such as MAE (mean absolute error) and MAPE (mean absolute percentage error) in order to ensures the fitness of model. The values of respective errors are observed as in 264.07 MW and 2.3745% respectively.

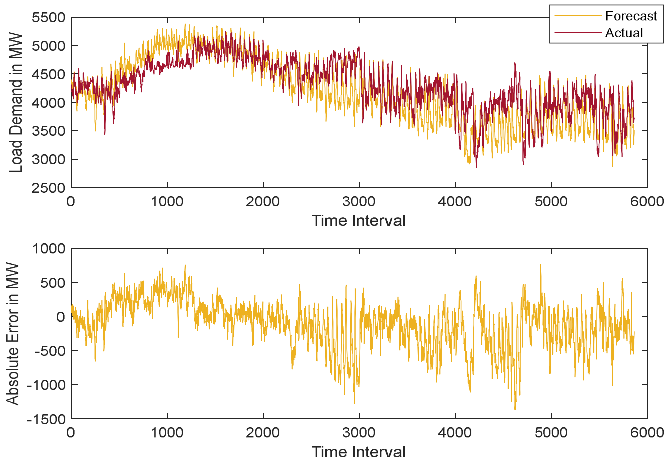

Fig 4 Actual and Forecasted Load along with absolute error observed during testing of ANN-1.

Since the absolute error in Fig.4 is quite high, the second ANN-2 network is trained and tested with 50 neurons in hidden layer in the network with “tansig” function. For Instance, Fig 5 and 6 showcase the plot between actual and forecasted load demand during both training and testing of ANN-2 model along with its corresponding error respectively. Here the MAE and MAPE is observed as 417.79 (MW) and 5.3659 %.

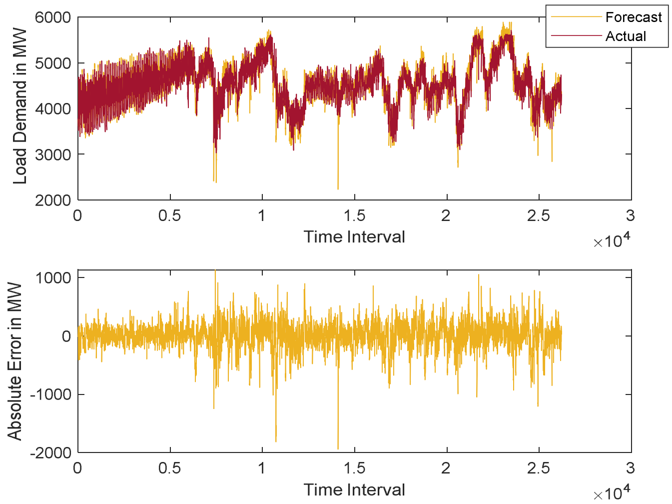

Fig 5 Actual and Forecasted Load along with absolute error observed during training of ANN-2.

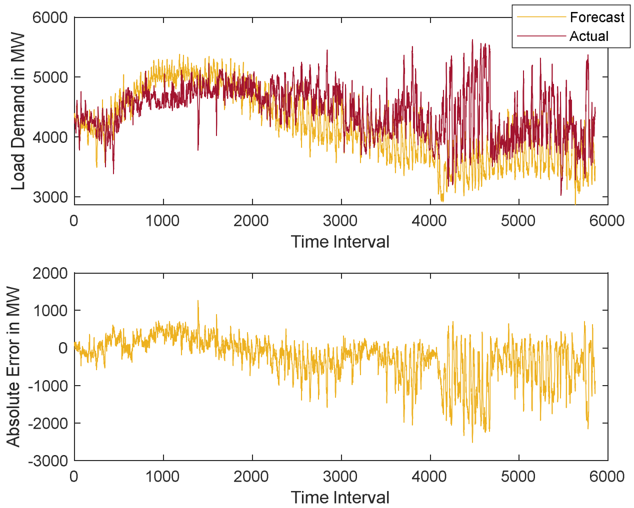

Fig 6 Actual and Forecasted Load along with absolute error observed during testing of ANN-2.

The error observed in experiments of ANN-1 and ANN-2 are high. Since the outcome of tested experiments of ANN-1 and ANN-2 is not accurate according to the needful scenario, thus the default scaling of -1 to 1 is changed into 0 to 1 range as the load demand has always positive values only. Thus, in order to reduce the error and to improve the accuracy of prediction, the ANN-3 model is then trained and tested with different normalized inputs. Further the proposed ANN-3 model performs both training and testing process on selected dataset. Fig 7 and Fig 8 are indicating the graphs between the actual and predicted data during training and testing process of ANN-3 respectively. The graph in Fig 7 clearly indicating the fully overlapping of forecasted data on actual data, which helps to ensures the fitness and efficiency of proposed model. In this final experiment of ANN-3 model, the MAE and MAPE is observed as in 196.98 MW and 0.4981 %, which is the least among the three experiments.

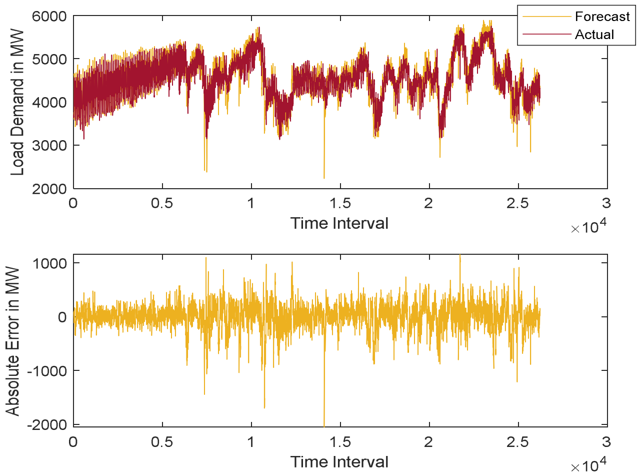

Fig 7 Actual and Forecasted Load along with absolute error observed during training of ANN-3.

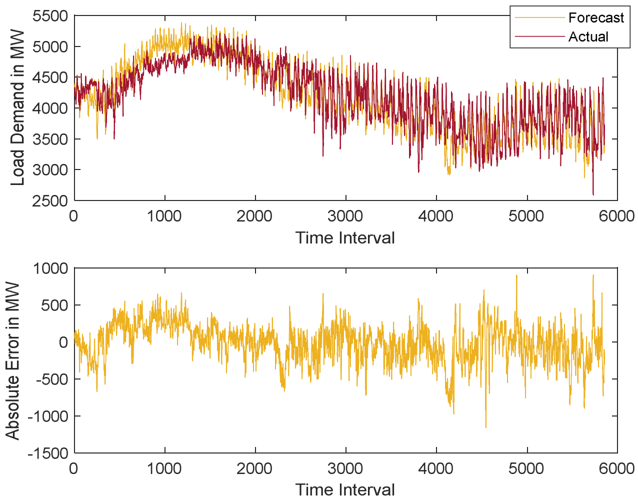

Fig 8 Actual and Forecasted Load along with absolute error observed during testing of ANN-3.

Tabular representation of evaluation matrices observed during training and testing of models ANN-1, ANN-2 and ANN-3 for above experiments are shown in Table I. It is clear from Table I that the ANN-1 and ANN-2 models MAE and MAPE values are large. However, the final proposed model ANN-3 provides the prediction of load demand with least MAE and MAPE values.

TABLE I:
EVALUATION MATRICES

Experiment	MAE (in MW)	MAPE (%)
ANN-1 model, 30 neurons and 1 neuron in hidden and output layers, with "logsig", "purelin" features, scaling range from -1 to 1	264.07	2.3745
ANN-2 model, 50 neurons and 1 neuron in the hidden and output layers, "tansig", "tansig" power, scaling range from -1 to 1	417.79	5.3659
ANN-3 model, 30 neurons and 1 neuron in the hidden and output layers, with "logsig" and "purelin" features, scaling range from 0 to 1	196.98	0.4981

VI. CONCLUSION

In this study, artificial neural network based short term load forecasting for Chhattisgarh state is presented. The model is trained and tested with real data set collected from State Load dispatch center of CG. The timeframe of chosen dataset varies from 1 JAN 2022 to 30 SEP 2023 during training process and from 1 OCT 2023 to 30 NOV 2023 during testing process. The effect of change in different network configuration and different normalization or scaling of dataset in the range of [0 1] and [-1 to 1] is also studied. It is concluded that the Proposed ANN-3 model outperforms over other two model and provides the load prediction with least MAE and MAPE. Hence STLF for real time dataset of CG state through ANN approach is found to be very efficient and applicable for real time filed application.

VII. ACKNOWLEDGEMENT

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