

GLOBAL JOURNAL OF ENGINEERING SCIENCE AND RESEARCHES AN APPROACH TO ELECTRIC LOAD FORECASTING USING ANN AND MULTIPLE LINEAR REGRESSION WITH SEASONALITY INFLUENCE

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ABSTRACT

Electric load forecasting in summer season is an important task do to avoid any irregularity in the power system .This paper provides a study on the short term load forecasting for summer season. Load Data for the study is collected from Madhya Pradesh Poorva Kshetra Vidyut Vitaran Company Ltd of the summer season i.e. from March2014 –June 2014 and March 2015 –June 2015 Forecasted load is calculated for the 1 July 2016.Different parameters affecting the ELF such as Temperature ,Humidity , hourly load etc. are incorporated in the methods to get a most appropriate model with least error. Also separate study is done by using only certain parameter at each time.An analysis is done with the Artificial Neural Network(ANN) and Regression method using MATLAB 13.0 to get a better model for Short Term Load Forecasting (STLF) .Result shows that ANN gives the result with Mean Absolute Percentage Error (MAPE) 1.267% and MAPE for Regression Analysis is 2.623%. Further the results are compared and shown both graphically and in tabular form

Keywords: Load Forecasting, Artificial Neural Network (ANN), Regression Analysis, BackPropagation Method, MAPE

I. INTRODUCTION

Electricity load forecasting is an essential part of any power system. It is a tool for proper power planning. Load forecasting not only essential for optimal operation of power system but also it is necessary for over all energy consumption patterns that supports an electric utility future system and business operation [1]. Also Load forecasting is very important in the deregulated economy [2]. Load forecasting is the prediction of future power demands by an industry or a particular region. Short term load forecasting (STLF) is a method which is basically used for the predicting the load demand from few hours to a day. In Madhya Pradesh region load forecasting is much important because of large area of the state ,scattered population in many areas, low share of industrial & commercial consumption (around 32.66%),only 67% households are electrified (census, 2011),over 30% of forest area in the State, high distribution losses, previous years arrears of Rs. 5377 Crores[3].

Many algorithms have been proposed in the last few decades for performing accurate load forecasts [4]. Various techniques can be applied to STLF to improve accuracy and efficiency depending upon the availability of the resource such as Load data, weather data, Market Price [5]. This paper includes Multiple Linear Regression techniques [6] and Neural Network algorithms [7] since with the inclusion of many parameters a better model for the load forecasting can be obtained. Certain parameters are included in the study such as Drybulbtemp, dewpoint temperature, Humidity, preweeksamehourload, predaysamehourload to make the model to fit in real time situation. Previous hour average load is not taken as the parameter in the analysis as the study is limited to only summer data so previous hour average load leads to large variation in the MAPE .

II. DATA OBTAINED

For modelling the weather component, data obtained from the local weather forecasting centre Jabalpur, Madhya Pradesh region and Accuweatherwebsite. Load data of the summer season i.e.from March2014 –June 2014 and March 2015 –June 2015 is obtained from Madhya Pradesh Poorva Kshetra Vidyut Vitaran Company Ltd (MPPPKCL) website [8]. Due to wrong measurements and other human errors, some out-of- range values were observed in the historical load data as obtained from the MPPPKVCL. Corrections were made to such outlier values





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by replacing them with the average of both the preceding and succeeding values in the series. Principal Component Analysis (PCA) of the data was then carried out using MATLAB® functions "prepca" and "trapca"[9][10].

III. ARTIFICIAL NEURAL NETWORK ANALYSIS

ANN is a soft technique in mat lab works based on the biological nervous system. The basic concept of ANN is the information processing technique. Similar to biological system ANN also consist of large number of highly interconnected units. Every unit applies an input, activation and an output function to its net input to calculate the output. With advancement in research work load forecasting is mainly based on ANN because ANN includes the best way to deal with uncertainty as well as non linear functionsThe methods for load prediction used in the energy industry in last year's are mainly based on Artificial Intelligence theories because they allow the best way to deal with uncertainty, as well as non-linear functions [11][12][13].

A three-layer feed-forward with sigmoid hidden neurons and linear output neurons can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer. In this project, three-layer feed-forward ANN with one hidden layer. The network will be trained with Gradient Descent with momentum and Adaptive Learning Back Propagation [14] in MATLAB 13.0. First study is done with the consideration of all parameter as discussed above and then study is done with the removal of one parameter from the study at one time. A large variation in result with the removal of humidity and temperature in ANN network is seen which shows their effect on the load demand in the summer times. The results is summarised in Table 1. And the performance of the trained model is given by different plots.



Figure 1: Regression plot to validate the network performance

The number of epochsneeded to reach totally correct classification depends to a large extends on the choice of the error function [15]. In the present analysis the artificial neural network goes through 209 epoch to get ANN model (Figure.1) leading to the MAPE 1.256 % which can be said to be best fit in the present situation of the load forecasting and the regression graph obtained through this model is as per the best performance of the model Figure2.

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Figure 2: Validation performance of Neural Network

The forecasted load through ANN model shows a large variation from actual load at 15HRS .A study for this variation shows that this may be due to large variation of load demand in afternoon during summer due to switch on/off of various cooling appliances in many offices and industry during this leisure time.



Figure3: Plot of Actual load and ANN forecasted load.

IV. REGRESSIONANALYSIS

Multiple Linear Regression Models as said above, if a dependent variable is affected by only one independent variable, and then the time series is a simple linear regression [16]. However, if there are morethan one independent repressorsvariable in a time series, then the regression model is said to be multiple regression model. In general, the dependent variable or response Y may be related to k independent of regressor variables. MLR is a generalised regression function that fits a linear model of an outcome to one or more predictor variables. The term multiple regression applies to linear prediction of one outcome from several predictors.

The load is totally dependent on the temperature, humidity and day type parameters hence regression is used to obtain the relationship between load and these parameters.

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 $\begin{array}{ll} P_{forecasted} = & P_{avg} + & P_1 \\ MAPE = & \sum \left\{ & (P_A \text{-} P_{forecasted}) / P_A \right\} * 100 \end{array}$

Where P_A =Actual power of forecasted power





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 $P_{1} = \{R. \sigma p.(T_{f} - T_{avg}).(H_{f} - H_{avg}).(D_{f} - D_{avg})\}/\{\sigma T.\sigma H.\sigma D\}$

 $P_{\text{forecasted}}$ = forecasted day power, P_{avg} = Average power of the previous year data., R=Coefficient of correlation of load power with temperature, humidity & daytype of the previous year data . σ p, σ T, σ H, σ D = Standard deviation of power, temperature, humidity & daytype of previous year data

 T_f , H_f , D_f = Forecasted day temperature, humidity and daytype

 T_{avg} , H_{avg} , D_{avg} = Average temperature humidity and daytype. This approach is discussed in detail in [17]. In the MLR application, the hourly load is modelled as: (i) taking variation in temperature .

(ii) variation in Humidity (iii) drypoint remains almost constant as the summer has no more effect of dewpoint Intercept component which is assumed constant for different time intervals of the day, (iv) Time of observation which is represent the load characteristic of the day. The data is fit on the MLR regression model with the use of regressmodel in MATLAB 13.0 [18] and the forecasted load is obtained. The variation of actual load and the forecasted load is shown in Fig 4. The forecasting is obtained with a precision MAPE of 2.623 % which is more than MAPE obtained by ANN 1.267%.



Figure4: Plot of actual load and MLR forecasted load

Figure 3 and Figure 4. Both ANN forecasted load and MLR forecasted load is obtained by considering all variable parameter together. This paper also deals with the consideration of one parameter each time and the result is monitored with the view to see the impact of different parameter in the used model.





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Figure 5: Variation of Actual Load, ANN forecasted load and MLR forecasted Load with time.

V. RESULT AND DISCUSSION

From the used MATLAB soft techniques i.e. Artificial neural network and Multiple Linear Regression model, load forecasting model is prepared. Trained model of ANN for one day ahead load forecasting gives MAPE of 1.267% and the result obtained from MLR is 2.623%. The error increases if the forecasting is done without considering humidity and it varies with +- 0.20 %. Analysis shows that ANN is quite better than regressive model for short term load forecasting. Results are tabulated in Table.1

son table between ANN forecasted result and MLR Forecast		
Parameters	ANN Method(M APE%)	Regression Method (MAPE%)
All Parameter Included *	1.267	2.623
Without PreDaySamehour Load	3.302	1.839
Without PreWeeksameHourL oad	2.420	1.975
Without Humidity	2.305	2.735
Without DryBulb Temperature	1.746	2.693
Without DuePoint Temperature	1.315	2.631

 Table 1

 Comparison table between ANN forecasted result and MLR Forecasted result.

all parameter (Drybulbtemp, dewpoint temperature, Humidity, preweeksamehourload, predaysamehourload)

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Study shows that with the result obtained by ANN method without duepoint temperature gives less MAPE 1.315% whereas in Regression the MAPE is 2.631%. This is due to the less influence of duepoint in summer Load demand . And Weather parameter such as Humidity have more influence on the load. Also the result shows that there is less dependency of weather parameter in Regression method as MAPE with all parameter consideration is 2.623% and without humidity MAPE is 2.735%, without drybulb temperature MAPE 2.693%, without duepoint temperature MAPE is 2.631%. It shows there is a very less influence of these parameter on regression analysis.

VI. CONCLUSION

Load forecasting in important for supporting the operation of electric power systemsecurely and economically. Accurateload forecasting method is needed for better synchronisation between load demand and load generation. Load forecasting depends on the variousparameters chosen for the analysis on a large extent. Different load forecasting techniques will give different resultas seen in the present paper. This difference is due to the certain parameters that are taken in the analysis. Some parameters affect the ANN on large extent and some have large effect on MLR. Faulty data may also cause more error in the load forecasting since faulty data because a large variation in the load data included in the study. So proper filtered Load data must be taken for analysis. Further study can be done with the inclusion of wind speed,holidays, precipitation, and large number of previous on load data.

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