International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 7 Issue 08, August-2018

# Forecasting of Very Short Term Electrical Loads based on Artificial Neural network

Soumyaranjan Ranasingh
PRDCL
Bhubaneswar, India

***Abstract-*** **In this paper few strategic approaches for short term load forecasting has been investigated based on the data collected from the meter dumps of concerned Electrical Substations. The traditional methods of Load Forecasting has been exploited to different sorts of algorithms to perform the forecasting of an existing 11kV Feeder at every fifteen minutes time interval based on the past meter dump data that was made available by the MRT division of the concerned Utility. Three types of the Algorithms namely, the traditional ARIMA Model as Algorithm 1, An Independent Load Frequency Model as Algorithm 2 and an Environment Dependent Independent Load Frequency Model as Algorithm 3 are investigated with equal number of samples from each. Finally based on the obtained errors from these Algorithms a Generalized Conclusion has been drawn.**

***Keywords- ARIMA, Short Term Electrical Loads, ANN, Load Forecasting, Load Modeling***

## 1. INTRODUCTION

The load is a non stationary process which is affected by two main factors: time of the day and weather conditions[1]. The initial works on Short Term Load Forecasting are recorded in 1971. The author, W.R. Christiaanse modeled the Short Term Load as follows in equation-1.

$$X(t) = a\, f(t) + e(t) \quad (1)$$

Where a is a local constant, e(t) is the error and f(t) is considered as the fitting function[2]. The weekly variations in hourly loads are described as a cyclic function of time with a period of one week. It was decided that a Fourier series would be the most appropriate model which meets the requirements for the fitting functions[2]. In 1989, temperature is considered as the dependent variable for the Prediction of Load[3]. The attempt of modeling the behavior of Load temperature variation as a linear relationship in Box Jenkins method can be eliminated and replaced with the ARIMA model for better results[3]. A nonlinear Hammerstein structure for modeling the load-temperature relationship was introduced by Q. C. Lu, W. M. Grady, M. M. Crawford, G. M. Anderson. The paper also models a Linear Transfer Function and Noise Filter[3]. Introduction to a Smoothing Function was evolved which came into picture after being multiplied with a Coefficient Matrix for better prediction of Load[4].
Besides the mathematical modeling, the Research Area of Load Forecasting has also witnessed a drastic change towards implementation of intelligence. The introduction to the intelligent approach steps into the research arena by consideration of several seasonal factors and other consumer behaviors. In 1990 the Paper published by E.H. Barakat, M.A. Qayyum, M.N. Hamed, S.A. Al Rashed which is based on Saudi Consolidated Electric Company considers the effect of Ramadan month as a separate Load Model[5].
The holiday modeling is based on the initial assumption that Loads in the Holidays are generally lower than other loads [6]. The author in the paper [8] has segregated different type of days to different type of data type. It has been experimentally observed that Highest and Lowest Temperature data are more sensitive than the Highest & Lowest Humidity data in the concerned Load Domain. That is the reason why only Temperature data is considered to be the weather data. A Linear Regression based Curve fitting Technique has been adopted to estimate the effect of Load on the Temperature variation. The feature of this Paper [8] is that it has implemented a Knowledge based System. The author have used PROLOG Program for the implementation of the Algorithm which is made flexible with addition of a flow chart that distinguishes the type of data and the type of Analysis to be performed. It distinguishes whether day is a special day, whether Typoon is present in that day or not, whether it’s a new day, holiday etc. A Temperature Humidity Index (THI) has been mentioned in the paper [9] that describes human comfort as a function of warm temperatures and relative humidity.
A formation of the regression model based on the paper [12] uses updating linear polynomial, where the coefficients are estimated by the least squares method with historical exponential weight. The coefficients are updated every day. An optimal structure of the simplified fuzzy inference that minimizes model errors and the number of the membership functions to grasp nonlinear behavior of power system short-term loads has been proposed in [13].
The first glimpse of implementation of Neural Network in the form of Reccurrent Neural Network to the Prediction and Model of Short term Load has been presented by E.C. Botha et. al. in [14]. The inputs to the recurrent neural network can be the weather inputs like the temperature, humidity and wind speed variation at hourly intervals. The hourly peak demands of the Loads can also be predicted by threshold auto regressive model as presented in [15].
A new method, Nonlinear Load Research based Estimation (NLRE), is used in the paper [16] to derive monthly load shapes by subdividing the category of customer class for estimating the peak MW load on substations as a function of total MWh usage by customer class, type of day, and month.
The properties of the load can be described in terms of a multivariate probability density function (PDF) of load and

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 7 Issue 08, August-2018

is presented in [17], time and temperature are possibly other factors.

A new approach to trend removal has been developed in [18] based on optimal smoothing (sometimes referred to as fixed interval smoothing). One hour ahead load forecasts have been calculated for the Shcotland meso-scale system. It is suggested that the best guide to the load value for a particular hour of the day is the value of the load for the same hour and day of the previous week i.e. the hourly mean, 168 hours earlier[18].

Three practical techniques for very short-term load forecasting have been proposed and discussed in the paper [21]. Their performances are evaluated through a simulation study. The preliminary study shows that it is feasible to design a simple, satisfactory dynamic forecaster to predict the very short-term load trends on-line. The performances of FL-based and NN-based forecaster are much superior to the one of AR-based forecaster. In this the researcher has predicted the next 30-minute data.

Based on the recent trends of research of Short term Load Forecasting it can be concluded that the Artificial Intelligence methods like Neural Network outperforms the conventional approach in terms of accuracy, with minimal human intervention[23]. According to the paper [24] it indicates that certain DNN architectures achieve greater accuracy than traditional methods. Besides the Short term forecasting when the results based on DNN for weekdays and weekends were analyzed, we see that DNNs still outperform traditional methods.

## 2. ARIMA MODEL OF LOAD FORECASTING (ALGORITHM 1)

The mathematical model for the prediction of load for a time interval *t* can be represented in the Equation-2.

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_j \varepsilon_j \qquad (2)$$

Where, $y_t$ = the load at time interval t

$y_{t-i}$ = the load at time interval t-i

$\varepsilon_j = y_j - y_{j-1}$, which is nothing but the error term of the load series

p and q are the lengths of load ARIMA & error ARIMA series which are determined based on the formula of auto-correlation function as mentioned in Section 2.1.

$\alpha_0$ = bias of ANN

$\alpha_i$ = coefficient of load series updated by ANN

$\beta_j$ = coefficient of error series updated by ANN

### *2.1.* Determination of lengths of Load & Error Series

We know, Auto-correlation coefficients for a time series $X = [X_1, X_2......X_n]$ with a time lag *k* can be determined using the Equation-3.

$$R(k) = \frac{1}{(n-k)\sigma^2} \sum_{t=1}^{n-k} (X_t - \mu)(X_{t+k} - \mu) \qquad (3)$$

n = length of the series

μ = mean of the time series

σ = Standard Deviation of the time series

Using the above formula of Auto-correlation function *n-1* number of auto-correlation coefficients can be generated for a time series having *n* number of coefficients.

The length of the load ARIMA series (i.e. p) is nothing but the nearest time lag which produces the minimum Auto-correlation coefficient when Auto-correlation coefficients are calculated for the Load Series. Similarly, the length of the error ARIMA series (i.e. q) is nothing but the nearest time lag which produces the minimum Auto-correlation coefficient when Auto-correlation coefficients are calculated for the Error Series.

### *2.2. Determination of Coefficients of Load & Error Series*

The Coefficients of Load & Error Series are determined based on the Approach of Artificial Neural Network Training. Three types of Activation functions namely the Linear Activation function, Unipolar Activation function & Bipolar Activation function are used to update the coefficients.

The Unipolar Activation Function used is of the form as follows:

$$f(x) = \frac{e^{Lx}}{e^{Lx}+1} \qquad (4)$$

The Bipolar Activation Function used is of the form as follows:

$$f(x) = \frac{e^{Lx} - e^{-Lx}}{e^{Lx} + e^{-Lx}} \qquad (5)$$

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 7 Issue 08, August-2018

The values of L & learning parameter C that gives the minimum gross error during training will be used as the L & C values of the Prediction model. The predicted Load based on Algorithm 1 and the Actual Load is plotted in Fig. 1.

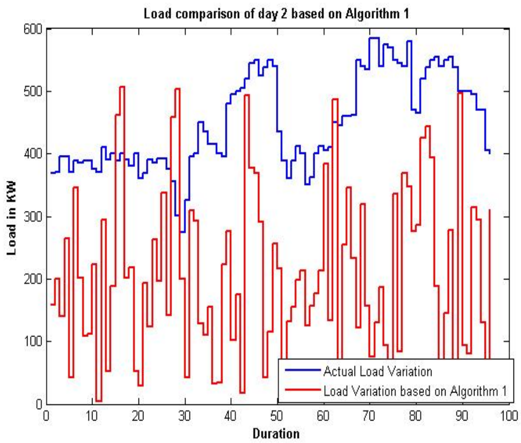


Fig. 1. Load Comparison of a particular day based on Algorithm 1

## 3. ALGORITHM 2

In this algorithm the load of a day is assumed to be Summation of many independent frequency loads of Square wave nature.

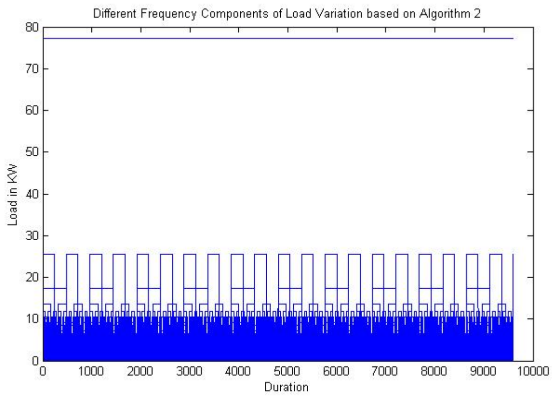


Fig. 2. Different Frequency Components of Load Variation based on Algorithm 2

At the initial stage of this Algorithm the Fast Fourier Transform is performed to analyze the system based on variation of frequency components. A Sample picture of all Independent frequency loads has been presented in Fig. 2.

The mathematical model for the prediction of load for a time interval *t* can be represented in the Equation-6.

$$y_t = \sum_{k=1}^{f} \left[ \sum_{i=1}^{p_k} \alpha_i L_{t-i}(\omega_k) + \sum_{j=1}^{q_k} \beta_j E_j(\omega_k) \right] \qquad (6)$$

$L_{t-i}(\omega_k)$ is the vector of $k^{th}$ frequency component of a particular day *t-i* in the Square wave load amplitude.

$E_j(\omega_k)$ is the error vector of the above load vector

$y_t$ = the load at time interval t

$\alpha_i$ = coefficient of load series updated by ANN

$\beta_j$ = coefficient of error series updated by ANN

$f$ = number of frequency terms

$p_k$ and $q_k$ are the lengths of load ARIMA & error ARIMA series which are determined based on the formula of auto-correlation function as mentioned in Section 2.1.

The coefficients of the load series & the error series are determined in the similar manner as presented in the section 2.2.

The predicted values based on algorithm 2 are compared with the actual values is presented in Fig. 3.

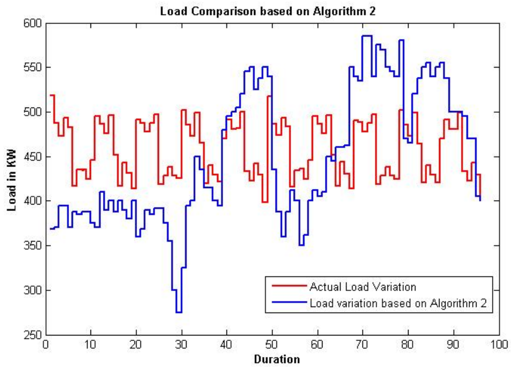


Fig. 3. Load Comparison of a particular day based on Algorithm 2

## 4. ALGORITHM 3

In this algorithm the load of a day is assumed to be an effective summation of effects of Independent Periodic loads of varying frequencies and the environment variables. Among all the environment variables only two are considered here: one is the Temperature and the other is the Humidity.

The mathematical model for the prediction of load for a time interval *t* can be represented in the Equation-7.

$$y_t = \alpha X_2(t) + \beta H(t) + \lambda T(t) \qquad (7)$$

$y_t$ = the load at time interval t

$\alpha$ = Coefficient of load series updated by ANN

$\beta$ = Coefficient of Humidity Neuron Output updated by ANN

$\lambda$ = Coefficient of Temperature Neuron Output updated by ANN

$X_2(t)$ = Predicted load determined by the Algorithm 2

$H(t)=$ Humidity of the locality at the time interval $t$

$T(t)=$ Temperature of the locality at the time interval $t$

The Load Prediction in Algorithm 3 is basically summation of three components: the real load component, temperature component and the Humidity Component. Algorithm 3 utilizes the predicted outputs of Algorithm 2 as its real load prediction. The outputs of the hidden layer are assigned to the vectors which are ultimately fed into the Outer layer. The weights in between the hidden layer and outer layer are initialized based on experimental calculations. Finally, the Load prediction output is calculated based on these three vectors and assigned to a prediction variable.

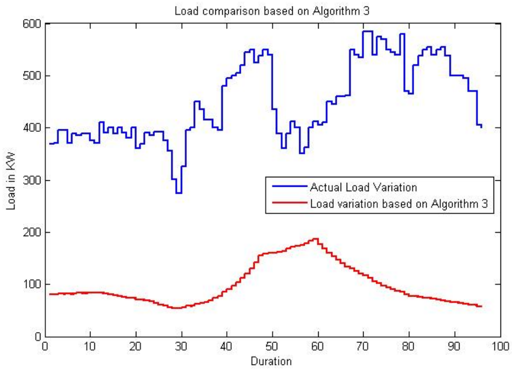


Fig. 4. Load Comparison of a particular day based on Algorithm 3

## 5. CONCLUSIONS

Three different types of Algorithms are investigated and the Average of Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE) & R values for several iterations are presented in the Table I.

Table I**:** Algorithm Comparisons

| Algorithm | RMSE | NRMSE | R |
|---|---|---|---|
| Algorithm 1 | 288.4203 | 0.5649 | 0.5861 |
| Algorithm 2 | 213.4418 | 0.4846 | 0.5679 |
| Algorithm 3 | 235.1597 | 0.5445 | 0.7356 |

From the Comparison following conclusions can be drawn:

i. Short term Load Forecasting with traditional ARIMA model leads to least error with Bipolar Sigmoidal Activation as Training Activation function and Unipolar Sigmoidal Activation as Prediction Activation function at L=0.43 and c=0.53.

ii. Short Term Load Forecasting does not depend significantly on the environment parameter variation which can be concluded from the observations drawn from the Algorithm 3.

iii. The best Method for Short Term Load Forecasting is the method of “independent load Frequency Algorithm” or Algorithm 2 with Bipolar Sigmoidal Activation as Training Activation function and Bipolar Sigmoidal Activation as Prediction Load Activation function. The comparisons of the results of the three types of Algorithms are presented in Fig. 5.

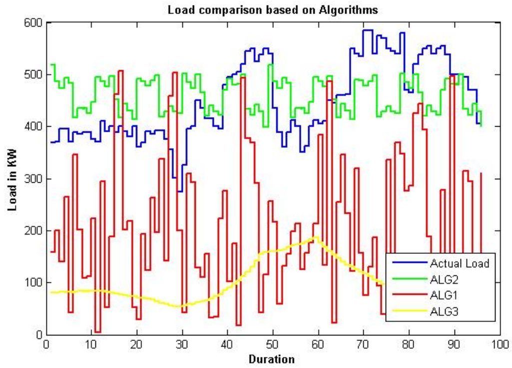


Fig. 5. Load Comparison based on all three Algorithms

## REFERENCES

[1] A.K. Srivastava, Ajay Shekhar Pandey And Devender Singh, “Short Term Load Forecasting Methods: A Review”, International Conference On Emerging Trends In Electrical, Electronics And Sustainable Energy Systems (Iceteeses–16).

[2] W. R. Christiaanse ” Short-Term Load Forecasting Using General Exponential Smoothing”, Ieee Trans On Power Apparatus And Systems, Vol. Pas-90, No. 2, March/April 1971.

[3] Q. C. Lu, W. M. Grady, M. M. Crawford And G. M. Anderson, “An Adaptive Nonlinear Predictor With Orthogonal Escalator Structure For Short-Term Load Forecasting”, Ieee Trans On Power Systems, Vol. 4, No. 1, February 1989.

[4] Lbrahim Moghram And Saifur Rahrnan, “Analysis And Evaluation Of Five Short-Term Load Forecasting Techniques”, Ieee Trans On Power Systems, Vol. 4, No. 4, October 1989.

[5] E.H. Barakat, M.A. Qayyum, M.N. Hamed And S.A. Al Rashed, “Short-Term Peak Demand Forecasting I N Fast Developing Utility With Inherit Dynamic Load Characteristics”, Ieee Trans On Power Systems, Vol. 5, No. 3, August 1990.

[6] Alex D. Papalexopoulos And Timothy C. Hesterberg, “A Recression-Based Approach To Short-Term System Load Forecasting”, Ch2747-4/89/0000-0414s1.00© 1989 Ieee.

[7] Martin T. Hagan And Suzanne M. Behr, “The Time Series Approach To Short Term Load Forecasting”, Ieee Trans On Power Systems, Vol. Pwrs-2, No. 3, August 1987.

[8] Kun-Long Ho, Yuan-Yih Hsu Chuan-Fu Chen, Tzong-En Lee, Chih-Chien Liang And Tau-Shin Lai Kung-Keng Chen, ” Short Term Load Forecasting Of Tawan Power System Using A Knowledge-Base@ Expert System”, Ieee Trans On Power Systems, Vol. 5, No. 4, November 1990.

[9] W. M. Grady, L. A. Groce, T. M. Huebner, Q. C. Lu And M. M. Crawford, “Enhancement, Implementation, And Performance Of An Adaptive Short-Term Load Forecasting Algorithm”, Trans On Power Systems, Vol. 6, No. 4, November 1991.

[10] G. A. N. Mbamalu And M. E. El-Hawary, “Load Forecasting Via Suboptimal Seasonal Autoregressive Models And Iteratively Reweighted Least Squares Estimation”, Ieee Trans On Power Systems, Vol. 8, No. 1, February 1993.

[11] O. Hyde And P.F. Hodnett, “An Adaptable Automated Procedure For Short-Term Electricity Load Forecasting”, Ieee Trans On Power Systems, Vol. 12, No. 1, February 1997.

[12] Takeshi Haida And Shoichi Muto, “Regression Based Peak Load Forecasting Using A Transformation Technique”, Ieee Trans On Power Systems, Vol. 9, No. 4, November 1994.

[13] Hiroyuki Mori And Hidenori Kobayashi, “Optimal Fuzzy Inference For Short-Term Load Forecasting”, 0-7803-2663-6195 $4.00 0 1995 Ieee.

[14] J. Vermaak And E.C. Botha “Recurrent Neural Networks For Short-Term Load Forecasting”, Ieee Trans On Power Systems, Vol. 13, No. 1, February 1998.

[15] S.R. Huang, “Short-Term Load Forecasting Using Threshold Autoregressive Models”, Iee Proc-Gener. Trunsm. Distnb., Vol. 144, No. 5, September 1997.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 7 Issue 08, August-2018

[16] Robert P. Broadwater, Al Sargent, Abdulrahman Yarali And Hesham E. Shaalan, Joanicjusz Nazarko, “Estimating Substation Peaks From Load Research Data”, Ieee Trans On Power Delivery, Vol. 12, No. 1, January 1997.

[17] W. Charytoniuk, M.S. Chen And P. Van Olinda, “Nonparametric Regression Based Short-Term Load Forecasting”, Ieee Trans On Power Systems, Vol. 13, No. 3, August 1998.

[18] D. G. Infield And D. C. Hill, “Optimal Smoothing For Trend Removal In Short Term Electricity Demand Forecasting”, Ieee Trans On Power Systems, Vol. 13, No. 3, August 1998.

[19] J. H. Park, Y. M. Park, Member And K. Y. Lee, ,” Composite Modeling For Adaptive Short-Term Load Forecasting”, Ieee Trans Power Systems,V 01.6, No. 2, May 1 99 1.

[20] J. Y. Fan And J. D. Mcdonald “A Real-Time Implementation Of Short-Term Load Forecasting For Distribution Power Systems”, Ieee Trans On Power Systems, Vol. 9, No. 2, May 1994.

[21] K. Liu S. Sub Bar Ay An R.R. Shoults2 M.T. Manry C. Kwan F. L. Lewis J. Naccarlno, “Comparison Of Very Short-Term Load Forecasting Techniques”, Ieee Trans On Power Systems. Vol. 11. No. 2. May 1996.

[22] G. Juberias, J. Garcia Moreno, R. Yunta And C. Mendivil, “A New Alrima Model For Hourly Load Forecasting”, 0-7803-Ssls-6/99/$10.00 0 1999 Ieee.

[23] Qiniso W. Luthuli And Komla A. Folly, “Short Term Load Forecasting Using Artificial Intelligence”, 2016 Ieee Pes Power Africa Conference

[24] Stefan Hosein And Patrick Hosein, “Load Forecasting Using Deep Neural Networks”, 978-1-5386-2890-4/17/© 2017 Ieee.