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Artificial Neural Network Model for Hourly Peak Load Forecast

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ABSTRACT

Artificial Neural Network (ANN) model for short-term demand forecast of hourly peak load is proposed in this paper. For learning of the ANN model Levenberg-Marquardt algorithm is adopted because of its ability to handle the large number of non-linear load data. The training of network is done by using hourly peak load data of preceding 5 years from the period of forecast and the temperature data. The validation of the developed ANN model is tested with historical load data of Bangalore Electricity Supply Company Limited power system. The comparison of conventional methods and ANN model with respect to percentage error is evaluated, from the results it has been found that the proposed ANN model with optimal number of hidden layer neurons gives accurate predictions.

Keywords: Artificial Neural Network, Normalization, Forecasting
JEL Classifications: C8, Q470

1. INTRODUCTION

Electricity is one of the most important sources of energy utilized by human in everyday life. It is essential in almost all the fields such as residential, commercial, agriculture, industrial, transportation, medical, etc. Though, India is currently the third largest power producer and fourth largest consumer of electricity and has the installed capacity of 326.848 GW as on 31-03-2017. It has 0.7% peak energy shortage and 1.6% peak power shortage during the financial year 2016-17 and similarly in Karnataka the total installed capacity is 21.316 GW and has 0.5% peak energy shortage and 0.2% peak power shortage (Load Generation Balance Report, 2016-17). The shortage of power is mainly because of lack of generation due to shortage of resources, unscheduled maintenances, outages and faults. The difference in demand and generation can be minimized to some extent by reducing Transmission and Distribution losses and using energy efficient lighting system and machineries. Primarily increasing the generation is the most effective way to meet the demand. To achieve this, information regarding the requirement of future load is essential. Therefore, load forecast plays an important role in estimating the load requirements of the future. The development of an accurate, fast and robust electrical load forecasting methodology is of importance to both the electric utility and its customers. A forecast that is too low or too high can result in revenue loss (Damitha et al., 1997).

Based on the time horizon, load forecasting is classified as short term, medium term and long term forecast (IEEE Committee Report, 1980). Short-term load forecast is an hourly forecasting with time lead of 1 h to several days and are useful in operational decisions such as committing units, load dispatch, automatic generation control, reserve margin, load management, energy transactions, system security monitoring and control. Medium-term load forecast is daily forecasting, varying from several weeks to several months ahead, are required for power system operation, maintenance scheduling, scheduled power purchase and scheduling of fuel purchases. Long-term load forecast is monthly or seasonal forecasting, covering from 1 year to several years ahead, is used for maintenance scheduling and up gradation of existing systems and/or installation of new generating station, transmission and distribution systems.

Numerous methods have been suggested for demand forecast in the literature, most of them are classified under the following categories: Conventional or classical methods such as Regression methods, Time series analysis, Exponential smoothing, weighted least squares, box and Jenkins model, Kalman filtering and state space. Artificial intelligence (AI) techniques such as expert system, fuzzy logic, neural networks, support vector machine (SVM), particle swarm optimization and genetic algorithm. Other category such as hybrid technique is a combination of more than one techniques i.e., mostly either the combination of classical and AI techniques or the combination of different AI techniques (Ramesh and Dixit, 2013).

Tomonobu et al. (2002) forecasted the demand by incorporating load and temperature deviation data as the correction factor, as the temperature and load power are interrelated and the forecasted error increases with change in temperature. James and Roberto (2002) used weather ensemble predictions in the Artificial Neural Network (ANN) technique with load along with three weather variables (temperature, wind speed and cloud cover) as inputs. Vitor and Alexandre (2007) predicted the load by Bayesian and SVM technique with load, temperature and prices of electricity as input. Hinojosa and Hoese (2010) applied fuzzy inductive reasoning and simulated rebounding algorithm techniques using load and temperature data as input parameters. Yang et al. (2011) forecasted the load by using time-series and SVM technique. The input was load, temperature and humidity data. Ni et al. (2016) used generalized ANN model, the inputs were cost function (minimization) and temperature data in addition to actual load data. Yizheng and Jovica. (2016) applied ANN and Monte Carlo Simulations technique, with load, temperature, humidity and wind speed as input parameters. Rodrigues et al. (2014) employs ANN with Levenberg-Marquardt algorithm to forecast hourly and daily forecast for only for house hold consumption. Singh and Kumar (2016) uses load data in his ANN techniques with Levenberg-Marquardt algorithm with ten hidden layers in his ANN model which is very complex model.

Tomonobu et al. (2002), James and Roberto (2002), Vitor and Alexandre (2007), Hinojosa and Hoese (2010), Yang et al. (2011), Ni et al. (2016), Yizheng and Jovica (2016), utilizes either hybrid techniques or requires more than two inputs resulting in complexity and Rodrigues et al. (2014), Singh and Kumar (2016), though uses ANN with Levenberg-Marquardt algorithm but does not give the exact details about the number of neurons in the hidden layer(s) which decides the actual ANN model. Hence, the present work proposes an ANN model that uses only load and temperature data to predict future load demand with optimal number of hidden layer neurons and is validated on Bangalore Electricity Supply Company Limited (BESCOM) power system.

2. CONVENTIONAL TECHNIQUES

Among the conventional techniques, curve fitting method is the simplest techniques that are employed in load forecasting. Let x be any particular hour in a day, an independent variable and y be the demand to be forecasted that depends on x such that $y = f(x)$. If the function $f(x)$ is known, then for any hours of $x = x_1, x_2.x_{24}$, the corresponding load $y = y_1, y_2 \ldots y_{24}$ can be found and thereby determine the pair of values $(x_1, y_1), (x_2, y_2)\ldots(x_{24}, y_{24})$. These pairs of values of hour and load determines 24 points for a day on the curve . In practical, it is not possible to find the actual curve that passes through these values. Hence, an attempt to find a curve that serves as best approximate to the curve $y = f(x)$ that passes through these values. Such a curve is called as curve of best fit. The process of determining a curve of best fit is known as curve fitting, and they generally employ the method of least squares. The curve fitting can be either interpolation where the curve is fitted exactly to only available data or extrapolation where it is fitted beyond the available data to certain range. Some of the curve fitting techniques used in electrical load forecasting are:

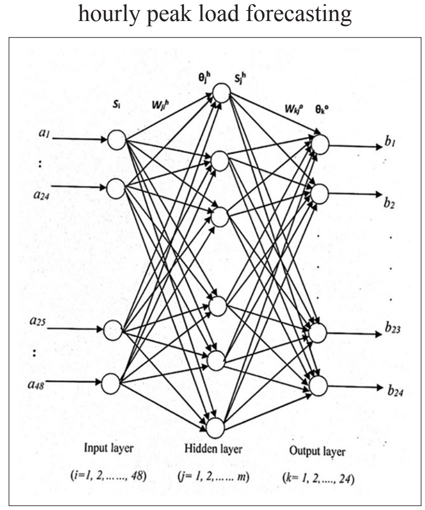
- Linear: $y = Ax + B$
- Exponential: $y = Ae^{Bx}$
- Logarithmic: $y = A\ln(x) + B$
- Polynomial: $y = Ax^2 + Bx + C$
- Power: $y = Ax^B$.

Where A, B and C are constant given by least square method. In present work, the approximated interpolation curve fitting is done for linear fit and second order polynomial fit.

3. ANN TECHNIQUES

A multilayer feed-forward ANN model with supervised learning will be implemented to predict the hourly peak load demand for any particular day. Figure 1 shows the neural network architecture consists of number of neurons that are connected in forward through weighted links and are organized in multilayer that is input layer, output layer and middle hidden layer. The 48 nodes in the input layer represents two input parameters consisting of hourly patterns, $a_1, a_2, \ldots, a_{24}$ represents normalized hourly peak load growth data and $a_{25}, a_{26}, \ldots, a_{48}$ normalized hourly peak temperature data. The 24 nodes in the output layer represent hourly peak demand predictions. The proposed ANN model has single hidden layer, the repetition in convergence with minimum percentage forecast error is obtained by varying the number of hidden layer neurons. The resultant outputs of the input layer S_i, for $i = 1, 2, \ldots, 48$ in response to the normalized input load and temperature is given by Eq. (1).

Figure 1: Multilayer fed-forward Artificial Neural Network model for hourly peak load forecasting



$$S_i = \alpha_i \quad (1)$$

The hidden layer neurons output s_j^h, for $j = 1, 2,\ldots, m$ and the output layer neurons output b_k, for $k = 1, 2,\ldots, 24$ are governed by Eq. (2) and (3) respectively.

$$s_j^h = f\left\{\sum_{i=1}^{48} W_{ji}^h s_i - \theta_j^h\right\} \quad (2)$$

$$b_k = f\left\{\sum_{j=1}^{m} W_{kj}^o s_j^h - \theta_k^o\right\} \quad (3)$$

Where W_{ji}^h represents connection weights from input nodes to hidden layer nodes and W_{kj}^0 from hidden layers nodes to output layer nodes, θ_j^h and θ_k^0 are the respective hidden layer and output layer bias terms. The outputs $b_1, b_2,\ldots, b_{24}$ of the neural network represents hourly peak demand forecast of any required day.

4. INPUT DATA SELECTION

In the present work, the hourly peak load data for more than 5 years i.e., from January-2012 to March-2017 is collected from Bangalore Electricity Supply Company (https://www.bescom.org) and the hourly peak temperature data for the same period is collected from Meteorological Centre, Bengaluru. Using the load data from 2012 to 2016, the average load data for 2017 is calculated to fitting the curves in conventional method. For ANN technique, the load growth data for 2017 is estimated, with the load growth data and the temperature data, the hourly peak load as per the requirements can also be forecasted ahead.

The value of historical load and temperature data lies in wide range. Since the proposed neural network model activation function is sigmoid, during learning process the actual value of input data may create convergence problem. Therefore, the input load and temperature data are normalized using Eq. (4), in order to scale the input to a range between 0 and 1.

$$L_{nor} = \frac{L_{(p,q)}}{L_{q_{max}}} \quad (4)$$

Where, L_{nor} is the normalized inputs to the network, $L_{(p,q)}$ is the growth load/temperature, $p = 1$ to n (no of days), $n = 1, 2 \ldots 31$ and $q = 1$ to m (no of hours), $m = 1, 2\ldots 24$ and L_{qmax} is the maximum load/temperature of that particular hour.

5. TRAINING THE NETWORK

The proposed ANN model is trained with historical load and temperature data. For this purpose, the analysis of percentage growth in load for more than 5 years from hour to hour, month to month and year to year is carried out. Based on the estimation of average percentage load growth, the training file has been prepared and used to train the proposed model to forecast the load demand ahead. The size of the training file for entire month will be in the order of 31 × 48 and testing file size can be same as that of training file or subset of training file as per the demand to be forecasted.

Levenberg-Marquardt training algorithm is employed to train the proposed ANN model for 2500 epochs and mean square training error is fixed to a value of 0.0001. Also to improve the convergence characteristics, the learning rate parameter (η) and momentum coefficient (α) are initially set to 0.1 and 0.9 respectively (Dixit and Gopal, 2004). Initially the training of the network is carried by varying the numbers of hidden layer neurons. For the proposed neural net structure with $48N_i$, $38N_h$ and $24N_o$ in input layer, hidden layer and output layer respectively, the minimum sum of mean square error of 10^{-5} was obtained. The training error curve with respect to number of epochs having 38 hidden layer neurons for 31st March 2017 is shown in Figure 2.

6. RESULTS AND DISCUSSIONS

6.1. Demand Forecasting Using Conventional Methods

In conventional method, the linear and second order polynomial curve is fitted to the calculated average load data of any particular day of the month. The fitted curve for 31st March 2017 is shown in Figure 3 and the corresponding equations obtained for linear and polynomial fit is given by the equation (5a) and (5b) respectively. The accuracy of the forecast is mainly depends on the goodness of fit (R^2). The result is more accurate with the goodness of fit tending towards 1.

$$Y=2.140x+3698 \text{ MW} \quad (5a)$$

$$Y=-1.193x^2+31.97x+3569 \text{ MW} \quad (5b)$$

Figure 2: Training error curve for 31st March-2017

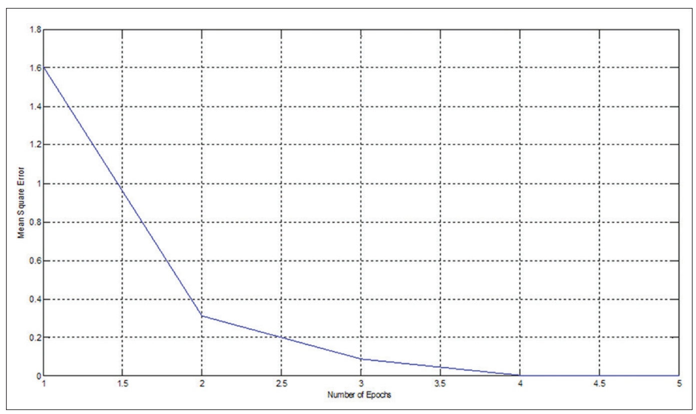
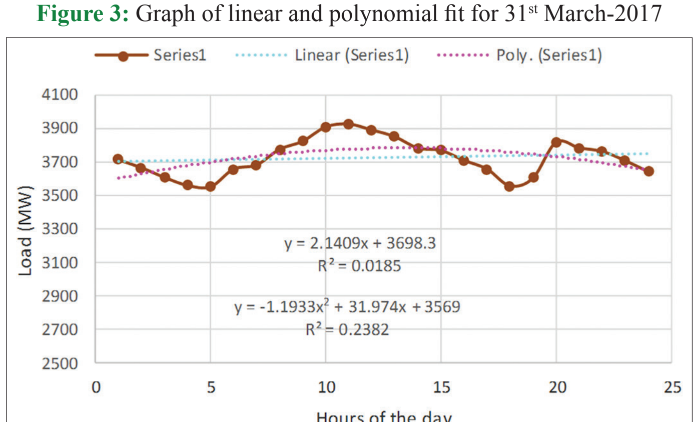


Figure 3: Graph of linear and polynomial fit for 31st March-2017



Where, Y is electrical load in MW and x is the hour of the day.

Using the above equations, the forecasted load is calculated and shown in Table 1. The percentage error is calculated using Eq. (6). The maximum percentage error in prediction of linear method is 18.94% and the minimum error is about 7.96%. Similarly for polynomial method the maximum percentage error is 18.98% and minimum error is about 7.79% of actual demand. The comparison of actual load and forecasted demand for linear and polynomial fit is shown in Figure 4a and b respectively. This method requires one equation for a day and 365 equations for a year and the process becomes complex and tedious. Further the number of equations required can be reduced to 12 i.e., one equation for a month by taking hourly average of the calculated average load data. As the number of equations reduces, it is found the percentage error increases drastically.

$$\%Error = \left| \frac{Load_{Actual} - Load_{Forecasted}}{Load_{Actual}} \right| \times 100 \tag{6}$$

6.2. Demand Forecasting Using Developed ANN Model

The validation of the proposed ANN model has been tested for March 2017, by varying the number of hidden layer neurons. The variation of hidden layer neuron is done during the training and testing of the ANN model till repeatability of convergence is achieved. The results are tabulated in Table 2, and it is found that the developed model predicts more accurately with 38 neurons in its hidden layer. The forecasted load without and with temperature factor for 31st March 2017 along with actual demand is represented in Figure 5. Using equation (6), the percentage error is calculated and tabulated in Table 1. The ANN forecast of hourly peak demand results show that the proposed model predicts more accurately with a maximum percentage error of about −5.87% and minimum of −0.17%, with the inclusion of temperature factor it gave a maximum percentage error of about −4.84% and minimum of −0.02% in comparison with the actual load. The result shows that the temperature has influence on the load demand. The comparison of conventional methods and ANN model without and with temperature factor considered is shown in Figure 6. As compared to the conventional method, the ANN model gives minimum percentage error and also has the advantage of simplicity and large number of non-linear load data handling capability, since the same ANN model can be used to predict hourly demand of any day in a year with the only changing of training file.

Table 1: Hourly demand forecast results for 31st March 2017

Hour	Actual load (MW)	Linear forecasted load (MW)	% Error	Polynomial forecasted load (MW)	% Error	ANN forecasted load (MW)			
						Without temperature	% Error	With temperature	% Error
1	4136	3700	10.54	3600	12.96	4210	−1.78	4208	−1.73
2	4134	3702	10.44	3628	12.24	4283	−3.59	4235	−2.43
3	4098	3704	9.60	3654	10.83	4264	−4.06	4214	−2.83
4	4112	3707	9.86	3678	10.56	4188	−1.85	4187	−1.82
5	4089	3709	9.30	3699	9.54	4329	−5.87	4265	−4.31
6	4219	3711	12.04	3718	11.88	4385	−3.93	4347	−3.03
7	4131	3713	10.12	3734	9.60	4364	−5.65	4310	−4.34
8	4266	3715	12.91	3748	12.13	4356	−2.11	4284	−0.43
9	4288	3717	13.31	3760	12.31	4421	−3.10	4339	−1.20
10	4367	3719	14.83	3769	13.68	4511	−3.31	4494	−2.91
11	4507	3722	17.43	3776	16.21	4654	−3.26	4615	−2.40
12	4594	3724	18.94	3781	17.70	4602	−0.17	4595	−0.02
13	4478	3726	16.80	3783	15.52	4515	−0.82	4512	−0.77
14	4332	3728	13.94	3783	12.68	4507	−4.04	4502	−3.93
15	4193	3730	11.04	3780	9.85	4421	−5.43	4396	−4.84
16	4248	3732	12.14	3775	11.13	4450	−4.76	4446	−4.67
17	4301	3734	13.17	3768	12.40	4432	−3.04	4383	−1.91
18	4308	3737	13.27	3758	12.77	4379	−1.66	4369	−1.42
19	4062	3739	7.96	3746	7.79	4214	−3.74	4202	−3.45
20	4605	3741	18.77	3731	18.98	4457	3.22	4480	2.71
21	4534	3743	17.45	3714	18.08	4405	2.85	4429	2.31
22	4311	3745	13.13	3695	14.29	4379	−1.58	4339	−0.65
23	4277	3747	12.39	3673	14.12	4333	−1.32	4332	−1.30
24	4459	3749	15.91	3649	18.16	4440	0.43	4452	0.16

ANN: Artificial neural network

Table 2: Maximum percentage error for different neural network structure

Neural network structure			Maximum % error
No of input layer neurons (N_i)	Number of hidden layers neurons (N_h)	Number of output layer neurons (N_o)	
48	37	24	−5.65
48	38	24	−4.84
48	39	24	−5.61

Figure 4: (a) Comparison of actual and forecasted load curve of linear fit for 31st March-2017. (b) Comparison of actual and forecasted load curve of polynomial fit for 31st March-2017

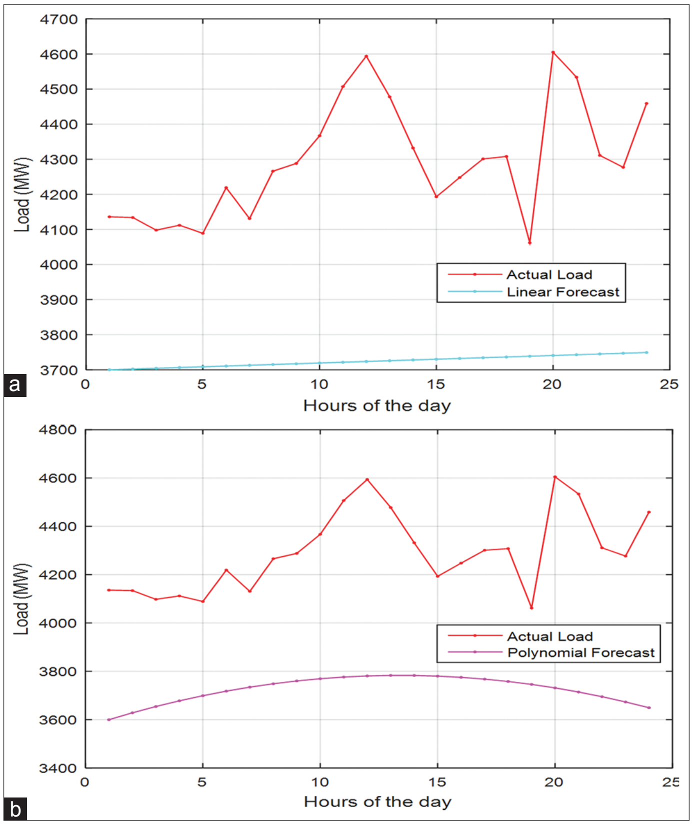
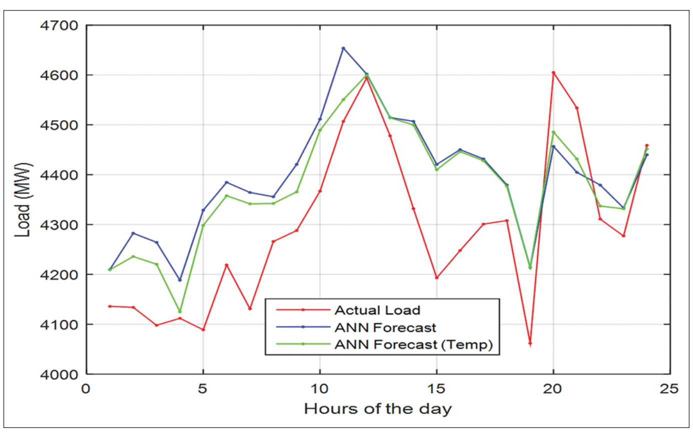


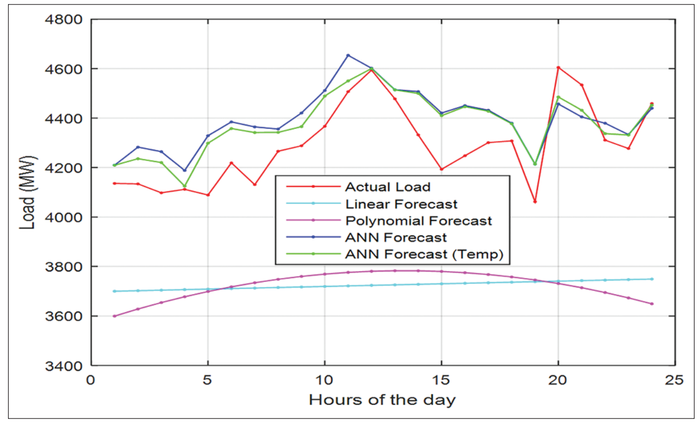
Figure 5: Comparison of actual and forecasted load curve of Artificial Neural Network model for 31st March-2017



7. CONCLUSIONS

The conventional and ANN technique has been implemented for hourly peak load forecasting. The conventional linear and second order polynomial method gives higher value of percentage error, since most of the electrical loads are non-linear. The proposed ANN model has been trained and tested with normalized load and temperature by varying the hidden layer neurons. The training has been carried out to forecast the hourly peak demand accurately with the optimal number of hidden layer neurons. From the results, it can be observed that ANN forecast is more accurate as compared to actual demand. Hence the proposed ANN model gives better results in comparison with conventional methods.

Figure 6: Comparison of conventional and Artificial Neural Network method for 31st March-2017



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REFERENCES

Damitha, K.R., George, G.K., Richard, G.F. (1997), Economic impact analysis of load forecasting. IEEE Transactions on Power Systems, 12(3), 1388-1392.

Dixit, P.K., Gopal, H.G. (2004), ANN Based Three Stage Classification of Arc Gradient of Contaminated Porcelain Insulators. Toulouse, France: International Conference on Solid Dielectrics. p427-430.

Hinojosa, V.H., Hoese, A. (2010), Short-term load forecasting using fuzzy inductive reasoning and evolutionary algorithms. IEEE Transactions on Power Systems, 25(1), 565-574.

IEEE Committee Report. (1980), Load forecasting bibliography. IEEE Transactions on Power Apparatus Systems, 99, 53-58.

James, W.T., Roberto, B. (2002), Neural network load forecasting with weather ensemble predictions. IEEE Transactions on Power Systems, 17(3), 626-632.

Load Generation Balance Report. (2016-17), Central Electricity Authority. Government of India, Ministry of Power.

Ni, D., Clementine, B., Guillaume, F., Yvon, B., Frederic, W. (2016). Neural network-based model design for short-term load forecast in distribution systems. IEEE Transactions on Power Systems, 31(1), 72-81.

Ramesh, K.V., Dixit, P. (2013), One Day Ahead Electrical Load Forecasting using Artificial Neural Network. 2nd International Conference on Information & Communication Engineering (IRD India). Bangalore: India, 9-12.

Rodrigues, F., Cardeira, C., Calado, J.M.F. (2014), The daily and hourly energy consumption and load forecasting using artificial neural network method: A case study using a set of 93 households in Portugal. Energy Procedia, 62, 220-229.

Singh, A., Kumar, T.V. (2016), Load forecasting using multi-layer perceptron neural network. International Journal of Engineering Science and Computing, 6(5), 5463-5466. Available from: https://www.bescom.org

Tomonobu, S., Hitoshi, T., Katsumi, U., Toshihisa, F. (2002). One-hour-ahead load forecasting using neural network. IEEE Transactions on Power Systems, 17(1), 113-118.

Vitor, H.F., Alexandre, P.A.S. (2007), Toward estimating autonomous neural network-based electric load forecasters. IEEE Transactions on Power Systems, 22(4), 1554-1562.

Yang, W., Qing, X., Chongqing, K. (2011), Secondary forecasting based on deviation analysis for short-term load forecasting. IEEE Transactions on Power Systems, 26(2), 500-507.

Yizheng, X., Jovica, V.M. (2016), Day-ahead prediction and shaping of dynamic response of demand at bulk supply points. IEEE Transactions on Power Systems, 31(4), 3100-3108.