Electric power load forecasting on a 33/11 kV substation using artificial neural networks

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Abstract

Estimation of electric power load on electric power substation is an essential task for system operator in order to operate the system in a reliable and optimal manner. In this paper, machine learning with artificial neural network is used for forecasting the load at a particular hour of the day on an electric power substation. Historical load data at each hour of the day for the period from September-2018 to November-2018 is taken from 33/11 kV substation near Kakatiya University in Warangal. A new artificial neural network architecture is developed based on the approach used to forecast the load. The developed model is simulated in MATLAB with available historical data to forecast the load on 33/11 kV electric power substation. Based on the analysis it is observed that the proposed architecture forecasts the load with better accuracy.

Keywords Artificial neural networks · Electric power load forecasting · Machine learning · Mean square error · Mean absolute percentage error

List of symbols

$L(D, t)$	Load at D th day and t th hour
$L(D, t - 1)$	Load at D th day and $(t - 1)$ th hour
$L(D, t - 2)$	Load at D th day and $(t - 2)$ th hour
$L(D, t - 3)$	Load at D th day and $(t - 3)$ th hour
$L(t, D - 1)$	Load at $(D - 1)$ th day and t th hour
$L(t, D - 2)$	Load at $(D - 2)$ th day and t th hour
$L(t, D - 3)$	Load at $(D - 3)$ th day and t th hour
$L(t, D - 4)$	Load at $(D - 4)$ th day and t th hour
MAPE	Mean absolute percentage error
MSE	Mean square error
y_i^{Target}	Actual output
$y_i^{Predicted}$	Predicted output
m	Number of samples
R	Regression coefficient

1 Introduction

In order to maintain the balance between load demand and supply, electric power companies estimate the load. Electric power load forecasting becomes one of the core processes for planning periodical operations and expanding facilities by power companies [1]. Active power load forecasting on a substation is classified into three categories based on time horizon like short term, medium term and long term load forecasting [2, 3]. Details of each type of load forecasting are presented in Table 1.

Short term electric power load forecasting is a very critical issue for proper operation and dispatch of power system in order to prevent frequent power failures. It is an important prerequisite for economic dispatch of generation units in power plants [4]. The short term active power load forecasting technique must be more accurate so that it helps users to select more optimal power consumption

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Table 1 Classification of load forecasting

Type of load forecasting	Time horizon	Purpose
Short term	Few hours to days	Schedule the electricity generation and transmission
Medium term	Few weeks to months	Schedule the purchase of fuels
Long term	1–10 years	Develop the generation, transmission and distribution systems

scheme, to minimize production cost and to optimize resources of power system [5].

Artificial intelligence (AI) has become an integral part in many fields like waste generation [6, 7], automobiles, international business, educational institution [8], civil engineering applications [9, 10], medical [11], image processing [12] and also, electrical power system applications [13]. AI analyze the system and make prediction based on previous available data.

AI techniques can be helpful to power system operator to trade electricity with maximum profit by predicting electric load and electricity price. AI techniques are also used to predict day-ahead electricity price. In [14], the authors predicted electricity price using various ANN models by considering input features like day type, hour indicator, holiday indicator, electric load, renewable energy generation and natural gas price. Probabilistic methodology for predicting the hourly electric price is presented in [15]. In this the authors have used bootstrapping technique to implement uncertainty as this method takes very little computation time. A bi-level decision making framework is developed in [16] to estimate the electricity price so that power plant operator can trade electricity with maximum profit. A hybrid methodology by combining the wavelet transform, self-adapting PSO based kernel extreme learning machine (KELM) and auto regressive moving average (ARMA) is proposed in [17] to predict electricity price. A two stage programming is developed in [18] to address issues like distasteful congestion and locational marginal price. A game theoretical approach is developed in [19] to maintain the competition between micro-grid aggregators and distribution system operator such that profit among all players will be maximized. All these works provide good contribution towards trading in electricity market in the form of electricity price by various stakeholders of power sector like electric power distribution companies, large customers, generation companies and retailers. However, there is no contribution from these methods to predict the electric power load so that stakeholders will trade electric energy successfully in the energy market.

Many researchers have been working on active power load forecasting with different predictions methods and models. Prediction methods of load forecasting may be categorized into two categories as conventional

prediction methods like regression analysis, time series methods and grey prediction methods, and novel artificial intelligence based prediction methods like artificial neural networks (ANN) and expert systems. In [20], authors have developed an ANN topology to estimate the electric load at a particular hour of the day using load data of last 4 h. A new ANN topology was developed in [21, 22] to predict the load at a particular hour of the day based on load data for last 4 h and load data at same hour for the last 2 days. A support vector regression model was developed in [23] to predict load; however, in this methodology, the authors did not consider the load on weekends.

In this paper ANN was used to forecast the load at a particular hour of the day, as ANN turned out to be the most accepted and essential model for clustering and forecasting in various applications. LevenbergMarquardt algorithm has been used to train the ANN. The proposed topology with learning algorithm is validated by comparing it with models developed in [20, 21].

The main objectives of this paper are as follows:

- Predict the load on a 33/11 kV substation with good accuracy
- Observe the uncertainty of the model in statistical framework

The main contributions in this work are as follows:

- New ANN topology is developed to predict the load with good accuracy comparing to existing models
- Real time load data is collected and processed such that no NaN values exist, making the data follow normal distribution.
- Performance of the model observed in stochastic framework is based on error uncertainty.
- Electric power load at particular time of the day $L(D, t)$ has been forecast based on last 3 h load data ($L(D, t-1)$, $L(D, t-2)$, $L(D, t-3)$) and load at same hour for the last 4 days ($L(D-1, t)$, $L(D-2, t)$, $L(D-3, t)$, $L(D-4, t)$)
- Optimal model that can be deployed is identified by tuning the number of hidden neurons in ANN model.

- The performance of model in terms of uncertainty in error and regression was observed and compared with a few existing models.
- The predicted load over 24 h time horizon with different models including with the proposed is correlated with actual load in time horizon; the predicted load with the proposed model has more correlation coefficient compared to predicted load with other models.

The remaining of the paper has been organized as follows. Section 2 deliberates on the ANN architecture design to forecast the load on substation. Section 3 presents result analysis using the proposed model and load data on 33/11 kV substation in Warangal, and conclusions of this paper are described in Sect. 4.

2 Methodology

2.1 ANN architecture design

A new approach has been developed to forecast load at particular hour of the day. The approach is the load at particular hour of the day is estimated based on last 3 h load data and load data at the same hour for the last 4 days. Block diagram and ANN topology of the proposed model are presented in Figs. 1 and 2 respectively.

The proposed ANN model has a total of seven neurons in the input layer because load at a particular hour of the day is predicted based on seven features like load on last 3 h and load on the same hour but for the last 4 days. The main goal is prediction of load at particular hour of the day and so the output layer consists of only one neuron. The number of neurons in the hidden layer is equal to 11 which is randomly considered.

Performance of the neural network during training and testing is observed based on metric like mean square error (MSE) and mean absolute percentage error (MAPE) [24] as shown in Eqs. (1) and (2) respectively. Globally used statistical techniques were used for evaluating forecast/

Fig. 1 Block diagram for proposed approach

Fig. 2 ANN topology for the proposed approach

prediction result such as mean square error (MSE) to measure the performance, final decision, and best model structure [7]. The non-linear activation used in each neuron in hidden and output layers is sigmoid activation [25].

$$MSE = \frac{1}{m} \sum_{i=1}^m \left(y_i^{Target} - y_i^{Predicted} \right)^2 \quad (1)$$

$$MAPE = \frac{1}{m} \sum_{i=1}^m \frac{y_i^{Target} - y_i^{Predicted}}{y_i^{Target}} \times 100 \quad (2)$$

In this model sigmoid activation function is used as there exist simple relationship between the value of the function and derivative value at any point. This reduces the computational complexity of the network [26]. The mathematical modeling of sigmoid activation is shown in Eq. (3).

$$f(x) = \frac{1}{1 + e^{-x}} \quad (3)$$

Any machine learning model using ANN can be developed with a sequence of steps like data collection, data processing, development of ANN architecture, training and testing the model to deploy it. Steps that are followed to develop optimal ANN model for this work are presented in Fig. 3.

3 Result analysis

Historical load data at each hour of the day for the period from September-2018 to November-2018 was taken from 33/11 kV substation near Kakatiya University in Warangal. This load data was used as a data-set to train and test the ANN. The time series data-set consists of a total 2184

Fig. 3 Process to develop ANN model

samples which have been captured at sample rate of 1 h. Out of 2184 samples, 1444 samples were used for training, 310 samples for validation and the remaining 310 samples for testing. LevenbergMarquardt based back propagation algorithm was used to train the proposed ANN model. The proposed ANN model has been implemented and tested in MATLAB [27] environment on i3 processor computing machine which has a processing speed of 3.65 GHz and RAM of 4 GB. It took less than one second to implement it.

3.1 Statistical information of load data

The time series load data of the period referred to the training and testing set is presented in Fig. 4. It has been observed that the load at each hour the day for given period is vary greatly. Statistical information of load data is presented in Table 2.

Figure 5 shows the distribution of load data in the specified time period from 01.09.2018 to 30.11.2018. It shows how many number of times a particular value of load is occurring over a specified period. Frequency refers to the number of instances the load value is appearing in the specified time period. It has been observed that load data distribution follows normal distribution with a mean value of 6028 kW and standard deviation of 1066 kW. Out of 2184 load samples in the specified time period, 95% of data points were falling between 5983 and 6072 kW.

Load data which was collected over a period from September-2018 to November-2018 was rearranged

Fig. 4 Time series load data over 3 months from 01.09.2018 to 30.11.2018 on 33/11 kV substation

Fig. 5 Distribution of load over 3 months from 01.09.2018 to 30.11.2018

Table 2 Statistical description of load data

Statistical information	
Count	2184
Mean	6028.125
SD	1066.399
min	3377.92
25%	5258.768
50%	5935.91
75%	6738.692
max	8841.669

on a hourly basis. Statistical information of load at each hour of the day over the above mentioned time horizon is presented in Table 3.

Table 3 Statistical information of load at each hour of the day

Time	0:00	1:00	2:00	3:00	4:00	5:00
Count	91	91	91	91	91	91
Mean	5810.451	5698.608	5738.325	5941.613	5907.223	5822.543
SD	651.1365	607.5749	639.101	1028.879	1048.045	863.3072
min	4315.538	3945.635	4451.933	3926.617	3788.508	4207.513
25%	5395.63	5309.663	5221.902	5199.377	5158.225	5075.063
50%	5673.408	5654.235	5744.178	5864.206	5709.884	5725.94
75%	6088.829	6059.289	6136.684	6675.093	6815.619	6544.154
max	7647.473	7115.922	7611.932	7769.059	8024.702	8053.696
Time	6:00	7:00	8:00	9:00	10:00	11:00
Count	91	91	91	91	91	91
Mean	5915.042	6225.603	6136.922	6171.44	6546.838	6369.245
SD	871.0938	993.53	929.3087	837.9327	882.4954	982.5019
min	4298.703	3839.948	4155.137	3907.912	3466.148	3613.922
25%	5147.158	5400.93	5306.935	5587.83	5991.092	5794.917
50%	5831.159	6471.202	6354.604	6252.659	6464.344	6389.833
75%	6657.167	6883.895	6761.919	6687.252	7245.536	6980.704
max	8087.678	8325.551	7993.838	8401.932	8487.666	8755.156
Time	12:00	13:00	14:00	15:00	16:00	17:00
Count	91	91	91	91	91	91
Mean	6244.033	6127.326	6326.9	6363.584	6253.365	6053.945
SD	991.6653	1093.987	1229.21	1573.495	1600.583	1541.331
min	4048.827	3581.655	3515.094	3377.92	3377.92	3446.507
25%	5614.486	5338.266	5471.692	5176.463	5046.303	4749.586
50%	6263.57	6258.582	6494.584	6075.579	5969.425	5586.739
75%	6824.193	6856.46	7252.473	7978.406	7981.68	7681.455
max	8504.813	8665.369	8841.669	8824.367	8754.377	8648.378
Time	18:00	19:00	20:00	21:00	22:00	23:00
Count	91	91	91	91	91	91
Mean	5963.614	5867.746	5877.603	5805.716	5671.137	5836.185
SD	1388.287	1199.225	1052.943	886.4026	503.9632	663.7953
min	3583.681	4051.321	3381.193	4269.553	4655.824	3910.406
25%	4875.147	4839.918	5074.985	5118.554	5294.62	5407.165
50%	5429.612	5604.198	5830.38	5692.582	5722.043	5744.49
75%	7373.124	6903.769	6669.638	6282.821	5994.132	6282.977
max	8710.574	8410.505	8045.746	8701.533	6746.331	7699.693

3.2 Performance of the 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 in Table 4. In this paper, an

Table 4 Performance of the ANN

Hidden neurons	MSE	R
9	0.24	0.87
10	0.26	0.87
11	0.2	0.89
12	0.24	0.87
13	0.23	0.88

Fig. 6 ANN model performance plot

architecture with 11 hidden neurons, low MSE (0.2) and high R (0.89) is considered as optimal model.

The performance of the optimal model with 11 hidden neurons is observed based on MSE. Training MSE of the model is 0.2 and validation MSE is 0.26. The performance plot of the model at each level (Training, Validation and Testing) is presented in Fig. 6. Regression plot with training, validation and testing data is presented in Fig. 7. The values of regression coefficients for training, validation and testing are 0.89, 0.85 and 0.8 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. 8 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

Fig. 7 Regression plot with training data

Fig. 8 Error histogram plot

observed after de-normalizing the output of ANN. This is incorporated as shown in Fig. 9.

3.3 Prediction of load using ANN model

24 h load on Kakatiya University in Warangal is predicted using trained ANN model. The comparison of both actual load and predicted load for the time horizon 24 h is presented in Fig. 10. 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 9.21%.

3.4 Comparative analysis

In order to validate the proposed model with Levenberg-Marquardt based back propagation algorithm, the proposed model was compared with the approach proposed in [20] for load forecasting. Based on the analysis it was observed that the proposed method predicts the load which is more correlated to actual load when compared to the approach proposed in [20]. The correlation coefficient of predicted data with the proposed model is 0.6237, whereas correlation coefficient of predicted load data with the model proposed in [20] is 0.3852. The predicted load pattern for 24 h time horizon with the proposed method is compared with actual load, and the load predicted with the approach proposed in [20], and this comparison is presented in Fig. 11.

The developed optimal model is again compared with the model proposed in [21] where authors have estimated the load at particular hour of the day based on last 3 h load data and load data at same time but for the last 4 days. The predicted load pattern for 24 h time horizon with the proposed method is compared with actual load, and the load predicted with approach proposed in [21], and this comparison is presented in Fig. 12.

The proposed model is again compared with models developed in [20, 21] in terms of MSE and R (Regression Coefficient) as presented in Table 5. From Table 5, it has been observed that the proposed model is performing better than existing models [20, 21].

The performance of the proposed model is also observed in stochastic environment in terms of MSE and R. To achieve this, the proposed model and existing models were also trained and tested 8 times with the same

Fig. 9 Deployed ANN with de-normalization

Fig. 10 Comparison of predicted load with actual load

Fig. 11 Comparison of proposed model with model proposed in [20]

load data and uncertainty in MSE and R was observed. The model with weights at best MSE and R values was used for testing, and the best MSE and R values of each model are presented in Table 5.

Uncertainty in regression coefficient (R) over 8 executions is measured in terms of statistical parameters like mean and standard deviation, and is presented in Table 6. The proposed model has the best mean value in comparison with both models proposed in [20, 21]. However

standard deviation of R values from its mean value is almost same in all the models.

Uncertainty in mean square error (MSE) over 8 executions is measured in terms of statistical parameters such as mean and standard deviation, and is presented in Table 7. The proposed model has best mean value i.e. 0.225 in comparison with both models proposed in [20, 21] which have 0.25 and 0.297, respectively. However standard deviation of MSE values from the mean value for the proposed

Fig. 12 Comparison of proposed model with model proposed in [21] **Table 5** Comparison in terms of MSE and R

Model	MSE		R
	Training	Testing	
Proposed model	0.2	0.32	0.89
[21]	0.23	0.44	0.87
[20]	0.29	1.59	0.84

Table 6 Statistical validation of proposed model in terms of regression coefficient (R)

Parameter	Proposed	[21]	[20]
Count	8	8	8
Mean	0.87625	0.8675	0.83875
SD	0.01	0.01	0.011
min	0.86	0.86	0.82
25%	0.875	0.86	0.83
50%	0.88	0.87	0.84
75%	0.88	0.87	0.85
max	0.89	0.88	0.85

model is same when compared to [21], and lower in comparison with [20].

4 Conclusion

Short term load forecasting is one of the key issues in energy trading markets. Distribution companies and industries are able to predict and quote reasonable

Table 7 Statistical validation of proposed model in terms of MSE

Parameter	Proposed	[21]	[20]
Count	8	8	8
Mean	0.225	0.25	0.2975
SD	0.01	0.01	0.02
min	0.2	0.24	0.28
25%	0.2175	0.2475	0.28
50%	0.22	0.25	0.295
75%	0.235	0.2525	0.305
max	0.25	0.26	0.33

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.

A new approach was developed to predict load based on last 3 h load data and load data at same hour for the last 4 days. Artificial neural network topology was developed to predict the load based on the proposed approach. LevenbergMarquardt 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 0.2 and validation MSE of 0.26. Testing accuracy was measured in terms of MAPE which was equal to 9.21%. The developed model was compared with models available in literature in terms of regression coefficient. The proposed

model had regression coefficient of 0.6237 whereas the model proposed in the literature had regression coefficient 0.3852. 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 weekends.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

References

- Almeshaie E, Soltan H (2011) A methodology for electric power load forecasting. *Alex Eng J* 50(2):137
- Alfares HK, Nazeeruddin M (2002) Electric load forecasting: literature survey and classification of methods. *Int J Syst Sci* 33(1):23
- Su P, Tian X, Wang Y, Deng S, Zhao J, An Q, Wang Y (2017) Recent trends in load forecasting technology for the operation optimization of distributed energy system. *Energies* 10(9):1303
- Mi J, Fan L, Duan X, Qiu Y (2018) Short-term power load forecasting method based on improved exponential smoothing grey model. *Math Probl Eng* 2018:11
- Hu R, Wen S, Zeng Z, Huang T (2017) A short-term power load forecasting model based on the generalized regression neural network with decreasing step fruit fly optimization algorithm. *Neurocomputing* 221:24
- Soni U, Roy A, Verma A, Jain V (2019) Forecasting municipal solid waste generation using artificial intelligence models—a case study in India. *SN Appl Sci* 1(2):162
- Ali SA, Ahmad A (2019) Forecasting MSW generation using artificial neural network time series model: a study from metropolitan city. *SN Appl Sci* 1(11):1338
- Lau E, Sun L, Yang Q (2019) Modelling, prediction and classification of student academic performance using artificial neural networks. *SN Appl Sci* 1(9):982
- Kumar BA, Sangeetha G, Srinivas A, Awoyera P, Gobinath R, Ramana VV (2020) Models for predictions of mechanical properties of low-density self-compacting concrete prepared from mineral admixtures and pumice stone. In: Das KN, Bansal JC, Deep K, Nagar AK, Pathipooranam P, Naidu RC (eds) *Soft computing for problem solving*. Springer, Berlin, pp 677–690
- Awoyera P, Akinmusuru J, Krishna AS, Gobinath R, Arunkumar B, Sangeetha G (2020) Model development for strength properties of laterized concrete using artificial neural network principles. In: Das KN, Bansal JC, Deep K, Nagar AK, Pathipooranam P, Naidu RC (eds) *Soft computing for problem solving*. Springer, Berlin, pp 197–207
- Kumar SN, Kumar PP, Sandeep C, Shwetha S (2018) Opportunities for applying deep learning networks to tumour classification. *Indian J Public Health Res Dev* 9(11):742
- Dhandapani K, Venugopal K, Kumar JV (2019) Ecofriendly and green synthesis of carbon nanoparticles from rice bran: characterization and identification using image processing technique. *Int J Plast Technol* 23:1–11
- Noureldeen O, Hamdan I, Hassanin B (2019) Design of advanced artificial intelligence protection technique based on low voltage ride-through grid code for large-scale wind farm generators: a case study in Egypt. *SN Appl Sci* 1(6):515
- Panapakidis IP, Dagoumas AS (2016) Day-ahead electricity price forecasting via the application of artificial neural network based models. *Appl Energy* 172:132
- Rafei M, Niknam T, Khooban MH (2016) Probabilistic forecasting of hourly electricity price by generalization of ELM for usage in improved wavelet neural network. *IEEE Trans Ind Inform* 13(1):71
- Gazijahani FS, Salehi J (2019) IGDT based complementarity approach for dealing with strategic decision making of price maker VPP considering demand flexibility. *IEEE Trans Ind Inform*. <https://doi.org/10.1109/TII.2019.2932107>
- Yang Z, Ce L, Lian L (2017) Electricity price forecasting by a hybrid model, combining wavelet transform, ARMA and kernel-based extreme learning machine methods. *Appl Energy* 190:291
- Abdolahi A, Gazijahani FS, Alizadeh A, Kalantari NT (2019) Chance-constrained CAES and DRP scheduling to maximize wind power harvesting in congested transmission systems considering operational flexibility. *Sustain Cities Soc* 51:101792
- Gazijahani FS, Salehi J (2018) Game theory based profit maximization model for microgrid aggregators with presence of EDRP using information gap decision theory. *IEEE Syst J* 13(2):1767
- Shaloudegi K, Madinehi N, Hosseini S, Abyaneh HA (2012) A novel policy for locational marginal price calculation in distribution systems based on loss reduction allocation using game theory. *IEEE Trans Power Syst* 27(2):811
- Veeramsetty V, Chintham V, Vinod Kumar D (2018) Proportional nucleolus game theory-based locational marginal price computation for loss and emission reduction in a radial distribution system. *Int Trans Electr Energy Syst* 28(8):e2573
- Veeramsetty V, Chintham V (2018) LMP computation at DG buses in radial distribution system. *Int J Energy Sect Manag* 12(3):364
- Chen Y, Xu P, Chu Y, Li W, Wu Y, Ni L, Bao Y, Wang K (2017) Short-term electrical load forecasting using the support vector regression (SVR) model to calculate the demand response baseline for office buildings. *Appl Energy* 195:659
- Arik OA (2019) Artificial bee colony algorithm to forecast natural gas consumption of Turkey. *SN Appl Sci* 1(10):1138
- Temurtas F, Gulbag A, Yumusak N (2004) A study on neural networks using Taylor series expansion of sigmoid activation function. In: *International conference on computational science and its applications*. Springer, Berlin, pp 389–397
- Unnikrishnan R, Madhu G (2019) Comparative study on the effects of meteorological and pollutant parameters on ANN modelling for prediction of SO₂. *SN Appl Sci* 1(11):1394
- Pu C, Sun ZS, Zhao SM (2006) Comparison of BP algorithms in MATLAB NN toolbox. *Comput Simul* 5:142

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