ISSN 2278-3091
Volume 8, No.3, May - June 2019
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse45832019.pdf
https://doi.org/10.30534/ijatcse/2019/45832019

Electrical Load Forecasting Using Machine Learning

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ABSTRACT
Variable electrical load and ever-increasing load demand need to be predicted or forecasted to avoid the energy crisis. In this paper, machine learning based ANN is explored for short term load forecasting (STLF) with 24 hours duration. The live load data from a typical 66kV sub-station of the Punjab State Power Corporation Limited (PSPCL) for a selected site at Bhai Roopa sub-station, Bathinda, situated in the Punjab state of India, is procured for the presented simulation study. The collected live data is divided into three categories, i.e., validation, training, and testing for the simulation study considering a neural network approach. The obtained results from simulation were validated with the live load data of the selected site and found to be within the permissible limits. The mean absolute percentage error (MAPE) and root-mean-square error (RMSE) were calculated to show the effectiveness of the proposed machine learning based STLF, and from the errors so observed, it can be safely concluded that the proposed methodology gives reasonably accurate results, and is reliable in predicting the electric load forecast. This would help to ascertain the fluctuation in electric load well in advance and making an opportunity or scope for preparation to meet the sudden increase in load demand thereby meeting the expectations of an active load forecasting with numerous applications in power system arena.

Key words-electric load, machine learning, neural network toolbox, neural network, short term load forecasting.

Nomenclature

x_i inputs to the artificial neuron i

w_{ki} weight attached to the input link i

1. INTRODUCTION

Short-term load forecasting (STLF) [1]-[2] starts with a short interval of time to a couple of days which play a vital role in the secure and effective operation of power systems. It is helpful in solving the unit commitment, interchange evaluation, security assessment, and hydrothermal coordination problems related to the power system network.

Forecast error in load predictions ends up in better-operating costs. Over-prediction of load ends up in an un-necessary increase in reserves and thus, higher operating costs. Under-prediction of load results could lead to a failure in supplying the required reserves, thereby attracting higher costs because of the use of costly peaking units. Several STLF models have been proposed in the previous era and are mainly classified into two broad categories viz. regressive model [3]-[5] and time series models [6]-[8].

Continuous technological advancements have lead artificial intelligence to penetrate almost every aspect of real daily life. In this work, an attempt has been made to apply artificial neural network (ANN) to solve the STLF problem. The proposed technique provides an effective solution for an accurate forecasting and practical training of the complete system. The neural network is a revolution in the artificial intelligence [9]-[13] eliminates the need of human experience as the system learns and matures by itself with the help of input and output relationships although, it does not allow the adoption of a functional relationship between the previous load and the forecasted load. As of now, the neural network gets trained by itself, but previously past input-output patterns were required to be fed in the system for the adequate training. Once trained, the system could predict output according to the input.

The neural network based first STLF model comes in a picture three years back. [8] gives a three-year forecasting plan in terms of hours, peaks, and regular days, and the resulting error comes under two hundred while including three-month load and temperature data as well.

In this manuscript, after introduction in section I, an attempt has been made to throw some light on STLF and ANN, in section II and section III, respectively. Section IV discusses the methodology adopted to carry out the presented work.

Section V presents the experimental result, which is followed by conclusions in section VI.

2. 2. SHORT TERM LOAD FORECASTING

Short-term load forecasting is mostly used for the small period, i.e., one hour to seven days to predict the load on the system. Electrical short-term load forecasting has a lot of importance [14-15] in the sense that it offers correct and beneficial managing of electrical utilities. The primary requisite in short-term load forecasting is that it should have high accuracy and speed. In India, there's a lot of wastage of power within the transmission, generation, and distribution systems. It may happen due to lack of proper load forecasting in India [16]. Planning and operational applications of load forecasting want a particular 'lead time' additionally called forecasting intervals. An attempt has been made to summarize the nature of forecasts, lead time, and applications.

Types of Load Forecasting

Load forecasting may be divided into three main categories:

i. Short-term load forecasting
ii. Medium-term load forecasting
iii. Long-term load forecasting

The forecasting for various time zones was highly necessary for the efficient system operation within a utility company due to which the behavior of every single forecast was completely different in comparison to another one. Sometimes, the next day load can easily be predicted within the accuracy of 1.3 % approximately but the very next day load cannot be predicted at a similar accuracy. The normalized weather load is a load measured in terms of typical weather, which is an average value of the previously generated peak value of historical data over a precious interval of time [3]. Most of the corporations considered 25 to 30 years of data for electrical load forecasting as it helps in the overall planning and decision making for the efficient operation of the network. The fundamental role of short term forecasting is to forecast load flows and helps in the decision-making process to prevent overloading for the protection purpose such as system failure, complete blackout, etc., to improve the reliability and efficiency of the power system network [3]. Load forecasting is highly necessary for bond assessment, the evolution of discrete, artificial products by the deregulated market for the energy forecasted. The choice of load forecasting precisely long term forecasting was highly recommended in the deregulated market economy in comparison to the non-deregulated market. During a non-deregulated economy, the rate of rising in the running cost might be even higher than the capital expenditure involved in the project.

3. ARTIFICIAL NEURAL NETWORK

The motivation for the effectual working in the field of the neural network comes from the fact that the human brain can also be analyzed more accurately with the help of different methods except for digital computers. It can also be a complicated structure as well as nonlinear and parallel information processing system. It is more effective in comparison to the conventionally developed digital computer due to having higher potential for developing its constituents called neurons for the faster computational response. The machine learning based optimized artificial neural network is the best suited for the electrical load forecasting.

Definition

The artificial neural network is highly inspired with the biological nerve cells as it composed of extensive parallel processing system entirely depends upon the interconnected network form by every single neuron with its neighbor neuron to develop a capability of learning new things by analyzing previous situations.

Basic Neural Structure

The primary neuron structure of artificial intelligence is of two types i.e., Biological neural and artificial neural structure.

Biological Neural: Every single neuron varied in terms of shape and size in comparison to other and introducing cell body having several processes undergoing over its surface called neuritis. The neurites, also known as dendrites, are entirely responsible for the bidirectional connectivity. The basic structure of a biological neuron is shown in Figure1. The basic diagram of human brain and block diagram of human brain is shown in Figure 2 and 3. The various parts of a biological neuron are:

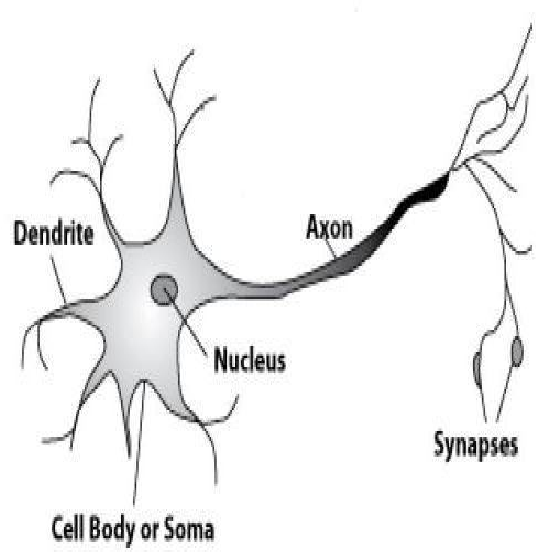

Figure 1: Biological Neural Network [17]

- Dendrite: The dendrites are the branched structures formed by the interconnected neurons to cause conduction of electrochemical stimulation within the neural based architecture. The electrochemical signals can be received with the help of synapses that are present throughout the dendrites [17]-[18] for signal transfer.

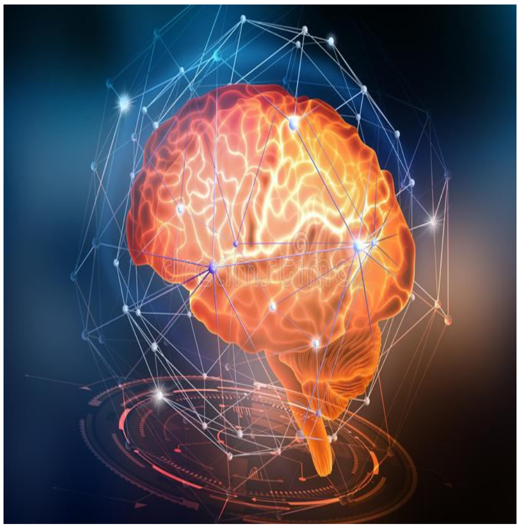

Figure 2: Human Brain [17]

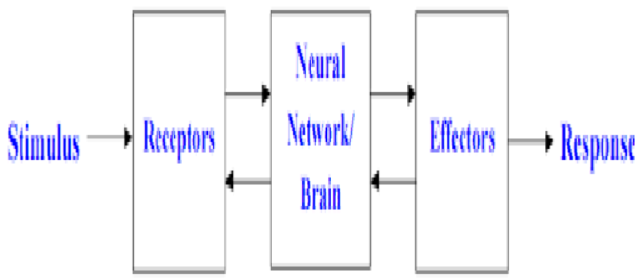

Figure 3: Block Diagram of Human Nervous System [17]

- Soma: This is where the signals from the dendrites are joined and passed on [17]-[18].

- Axon: Nerve fiber is also known as axon. It is quite long, lean projection of nerve cells and also causes conduction of electrical impulse away from the cell body or soma [17]-[18]. Axons are also differentiated in comparison to dendrites in terms of shape or size and function. There are also few neurons having no axon still they transmit a signal through their dendrites. No neurons in the artificial neural network contain more than a single axon, but in some of the cases, several axons were found.

Artificial Neural: The artificial neural network is an interconnected network of several artificial constituents that worked similarly as biological neurons called artificial neurons. The simple model of an artificial neuron is shown in Figure 4.

Here, $x_1, x_2, \ldots, x_p$ are the p inputs to the artificial neuron, and $w_{k1}, w_{k2}, \ldots, w_{kp}$ are the weights attached to the input links.

Hence, the total input I received by the soma of the artificial neuron is given below in equation (1),

$$I = \sum_{i=1}^{n} w_{ki} x_i \qquad (1)$$

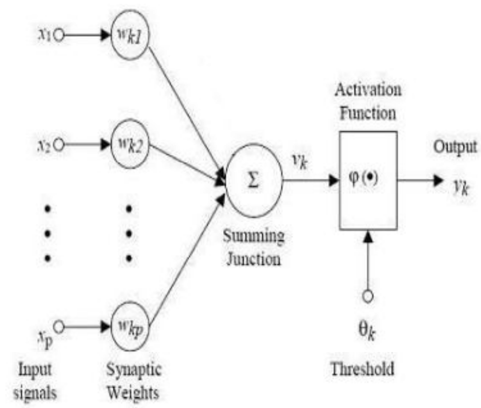

Figure 4: Artificial Neural Network [17]

4. METHODOLOGY

There are five significant steps to get the outcome or to train the network. The five steps are briefly clarified beneath one by one.

(i) Network Structure Design: The network structural design composed of several hidden layers, several output layers, and several output nodes.

(ii) The number of hidden layers: The hidden layer is used to examine the problem and provide the most accurate solution for that particular problem, but theoretically, a hidden layer with a number of neurons are used to perform a specific task. In practice, the neural network is considered mostly single or in some cases, more than one layer for performing specific function efficiently.

(iii) The number of hidden nodes: Basically, there was no such formula for calculating the exact value of hidden neurons used for training network, but sometimes, thumb rule was used to get the approximate number. Pyramid rule was used roughly for the calculation purpose, which was also not accurate.

(iv) The number of output nodes depends upon the parameter of number of the input nodes.

(v) Evaluation criteria: The most common error function that can be easily obtained is the total of squared error. There were also some of the error functions that can be obtained by different software such as least absolute deviation.

(vi) Neural network training: Training a neural network to learn various patterns present in the data involve training from the exact solution for the efficient learning process. The training aims to resolve the global maximum by locating the various set of weights between the neurons.

5. EXPERIMENTAL RESULTS

In this paper, authors present and discuss the results of short term electrical load forecasting using machine learning optimized technique i.e., ANN is obtained using the neural toolbox. In this work, the input data is taken as Dew point, Dry bulb temperature, and humidity, and output is taken the load data of the first day of January 2015. To find the results, the data set is divided into three parts i.e., validation, training, and testing. The validation is kept 70% and training 15% and testing 15%. From the data set, the error is calculated. The Levenberg Marquardt algorithm is used in this work. The mean absolute percentage error (MAPE) and root mean square error (RMSE) were calculated, as shown in Table 1. These errors are calculated for 24 hours, i.e., one day of January 2015, as shown in the performance graph in Figure 5. The results are implemented in MATLAB, and with the help of Neural Network toolbox, the errors are calculated. The performance graph between Epoch and Mean squared error is shown in Figure 5.

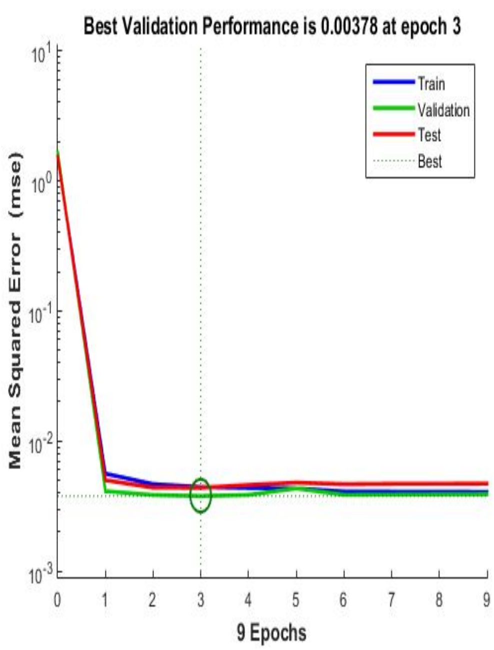

Figure 5: Performance Graph

Table 1: Actual and Predicted Load

Hour	Actual Load(MW)	Predicted Load(MW)
1	0.869	0.954
2	0.815	0.956
3	0.815	1
4	0.847	0.998
5	0.891	0.974
6	0.934	0.967
7	0.956	0.943
8	1	0.930
9	1	0.980
10	0.967	0.969
11	0.923	0.958
12	0.923	0.950
13	0.934	0.975
14	0.956	0.968
15	0.956	0.951
16	0.913	0.954
17	0.934	0.978
18	0.934	0.983
19	0.956	0.951
20	0.978	0.996
21	1	0.954
22	0.978	0.964
23	0945	0.993
24	0.953	0.971

6.CONCLUSION

The error is calculated with the help of the input and output data in this paper. In this work, electrical load forecasting using machine learning is done with the help of neural network toolbox. The error of the Bhai Roopa feeder was obtained. The weather data is taken from the IMD, and load data is taken from one of the 66kV substations of PSPCL situated in Bhai Roopa. The MAPE and RMSE error was calculated to show the effectiveness of the proposed machine learning based STLF. The MAPE and RMSE errors calculated are of the order of 0.029 and 0.170. From the errors so observed, it can be safely concluded that the proposed methodology gives relatively accurate results, and is reliable in predicting the electric load forecast. The machine learning based ANN approach has proved to be an effective technique of electric load forecasting with minimum deviation from the actual live data. Electrical load forecasting helps to reduce the generation cost, spinning reserve capacity, and increase the reliability of the power system. The unit commitment and economic allotment of generation are essential applications of STLF which ensure the proper estimation about the load and the committed generating units at any time of the day for meeting the customer load demand most economically.

ACKNOWLEDGEMENT

Thapar Institute of Engineering and Technology Patiala, India has well-equipped laboratories for effective academic and research work. The authors are grateful to the Thapar Institute of Engineering and Technology for providing the necessary support and facilities to carry out the work presented in this manuscript.

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