

A comparative study for Short Term Load Forecasting usingANN with and without Wavelet transform

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ABSTRACT

In this paper a work is presented to forecast week ahead loadusing ANN model with wavelet transform signal processing. The used datasets in this work are based on the past weather records. To demonstrate the effectiveness of the proposed approach data of load from 132 KV substation of Rajgarh (Dhar), M.P. has been taken to forecast the daily peak load for the Indore City of Madhya Pradesh. The data used in this work is from 1st Jan 2017 to 31st Dec 2017. All input variables have per day peak readings, so a total of 365 samples of each parameter are used in study. Further seven days load is forecasted from the above data and all this process is done on MATLAB environment. **KEYWORDS:**Short-term load forecasting; multi-layer perceptron; artificial neural network, wavelet transform.

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I. INTRODUCTION

The first crucial step of any planning study is load forecasting. Forecasting refers to the prediction of the load behavior for the future. Load forecasting is important to all energy companies especially after deregulation for conducting operational planning. With continuous fluctuation in demand and supply and variation in weather behavior and energy prices increasing by peak load demands, load forecasting had become very important.

A precise forecasting is very helpful in preventing system from getting over loaded and under loaded. This will make system more stable. Electrical load forecasting also effects price of electricity by managing generation in the most economical way.Such forecasting of loadwill be far beneficial for power companies to prepare for future load demand variation. Also, this will help them in utilizing the renewable sources more efficiently and also in reducing reserve capacities of power plans there by increasing plant utilization factor which will lead to reduction in generation cost.

ANN is far superior to other statistical methods. Also, it has been clear that load forecasting is a sensitive issue which require special attention and is dependence on input parameters and the way this input parameters are presented also affects output. Hence in this section it has been concluded that ANN and WT are a great combination to forecast load.

Load Curve for 132 KV Rajgarh Substation

Figure 1 shows the actual peak load for 132 KV Rajgarh substation from 1st January 2017 to 31st January 2017.

From the above graph, the peak load is maximum at the festival seasons especially in the month of January and October, while it is minimum in June to September and in November month.



Figure 1 Load Curve Graph for 132 KV Substation

II. SHORT TERM LOAD FORECASTING USING ANN

Work on ANN has been inspired right from its inception by the acknowledgement that the human brain computes in an entirely different way from the conventional digital computer. ANN has an astonishing ability to find a relationship between completely non-linear data's which can be implemented successfully to detect trends and thus find the pattern followed by our targets which is impossible for human brains to notice.

ANN poses great ability to train itself based on the data provided to it for initial training. It has the tendency of self-organization during learning period and it can perform during real time operation. The speed of human brain is several thousand time faster than traditional computer because in brain unlike traditional computer as whole information is not passed from neuron to neuron they are rather encoded in the neuron network. This is reason why neural network is also named as connectionism.

ANN process input data information to learn and get knowledge for forecasting or classifying patterns etc. type of work. All information processing is done within neuron only. A network of connected artificial neurons can be designed, and a learning algorithm can be applied to train it.

The weights indicate the information being used by the network to solve certain problem. The weighted sum is worked upon by an activation function (usually nonlinear), and output data are conveyed to other neurons. The weights are continuously changed while training to improve accuracy.

III. PROPOSED METHODOLOGY

Figure 2 shows the block diagram for proposed scheme. There are different stages through which load forecasted via, data extraction & preparation; data refining; divide data into testing and training samples; train the neutral network and simulation will be done on above data and the forecasted data will be compared with the actual data.



Figure 2 Block Diagram of Proposed Scheme

The proposed ANN diagram have seven input variables via, temperature, pressure, humidity, radiation, wind speed and load before one hour. There are 30 different hidden layers and thus provides the output forecasted load with ANN.



The Levenberg –Marquardt algorithm is a fine mixture of the steepest descent method and the Gauss–Newton algorithm. The following relation helps on understanding LM algorithm computation

$$W_{k+1} = W_{k} - [J_{K}^{T}J_{k} + \mu I]^{-1}J_{K}^{T}e_{k} (1)$$

Where, W_k represents current weight, $W_{(k+1)}$ represents next weight, I represent the identity matrix and e_k represents last error, μ represents combination coefficient.

W



Figure 4 Proposed diagram for training using Levenberg-Marquardt algorithm

The main ingredient in forecasting using ANN is historical data set. Based on this historical data weights and bias are calculated in training stage. For a proper training of network, accurate value of all the parameters are required otherwise it will lead to wrong training of network which will result in incorrect weight value and finally inefficient forecasting. Hence data should be processed before feeding it to network as an input.

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Figure 5 Flow chart for proposed solution using Wavelet transform based ANN training algorithm

IV. RESULTS

In this section results obtained from both proposed models using two different methods for load forecasting are presented and discussed. Data has been used as the main source for training and testing. The comparison of better model out of two is done for the purpose of short term per day peak load forecasting.

The used datasets in this work are based on the past weather records. To demonstrate the effectiveness of the proposed approach data of load from 132 KV substation of Rajgarh (Dhar), M.P. has been taken to forecast the daily peak load for the Indore City of Madhya Pradesh. The data used in this work is from 1st Jan 2017 to 31st Dec 2017. All input variables have per day peak readings, so a total of 365 samples of each parameter are used in study.

Date	MAX TEMP	MAX HUMIDITY	MAX PRESSURE	MAX RADIATION	MAX WIND SPEED
01-01-17	27.11	53	1014.3	708.44	12.25
02-01-17	25.76	71	1014.9	712.89	13.9
03-01-17	25.48	42	1017.1	731.58	16.45
04-01-17	26.8	37	1016.8	722.68	13.75
05-01-17	26.76	45	1014.9	723.57	9.72
06-01-17	26.51	47	1014.7	725.35	10.64
07-01-17	25.86	51	1016	728.02	13.44
08-01-17	26.02	53	1017	729.8	13.32
09-01-17	27.19	48	1018.5	724.46	15.12
10-01-17	27.94	45	1019.6	722.68	10.7

Table 1Data sheet utilized

With Levenberg-Marquardt (LM) training

The following study is done using MATLAB Environment. In MATLAB, the command used for training network using Levenberg-Marquardt backpropagation algorithm is "train".



Figure 6 Forecasted electrical load employing the proposed model using LM

The plot is for peak electrical load from 25 Dec 2017 to next 7 days. The results have a Mean Absolute Percentage Error of 9.8 % and Mean Absolute Error is 2.78 MW. This figure is obtained when number of hidden layers are 30 and optimization is done using Levenberg-Marquardt (LM) training algorithm.

Table 2Forecasted peak load using LM						
Date	Actual Peak Load	Forecasted Peak Load	Error			
25/Dec/2017	30.400	29.463294316962	0.936705683037772			
26/Dec/2017	33.200	31.816187394099	1.38381260590015			
27/Dec/2017	28.600	33.582196538182	-4.98219653818274			
28/Dec/2017	32.200	31.767784857650	0.432215142349701			
29/Dec/2017	31.2000	31.904789668227	-0.70478966822714			
30/Dec/2017	35	32.279309502528	2.72069049747140			
31/Dec/2017	25.400	33.716330320607	-8.31633032060793			
MAPE			9.83%			

Figure 7 shows the comparative graphs for actual peak load and forecasted peak load from 25th December 2017 to 31st December 2017 by using LM without wavelet transform.



Figure 7 Comparative Graph for Actual Peak Load & Forecasted Peak Load by using LM without WT

Thus, the Mean Absolute Percentage Error from the LM training without wavelet transform is approximately 9.83 %.

Training with wavelet transform function

The following study is done using MATLAB/SIMULINK Environment. Following figures will describe in detail the various network performance factors at this point.

The plot is for peak electrical load from 25 Dec 2017 to next 7 days. The results have a Mean Absolute Percentage Error of 7.62 %. This figure is obtained when number of hidden layers are 20-10 and optimization is done using WT training algorithm.



Figure 8 Forecasted electrical load employing the proposed model using LM+WT training

Date	Actual Peak Load	Forecasted Peak Load	Error
25/Dec/2017	30.400	30.3793075154502	0.0206924845498477
26/Dec/2017	33.200	32.5203555305979	0.679644469402156
27/Dec/2017	28.600	32.5722209041032	-3.97222090410320
28/Dec/2017	32.200	33.4753596481570	-1.27535964815695
29/Dec/2017	31.200	33.2954501107345	-2.09545011073451
30/Dec/2017	35	34.6430290140666	0.356970985933373
31/Dec/2017	25.400	31.9157834470574	-6.51578344705744
MAPE			7.62 %

Table 3Forecasted peak load using LM with WT

The below figure shows the comparative graphs for actual peak load and forecasted peak load from 25th December 2017 to 31st December 2017 by using LM with wavelet transform.



Figure 9 Comparative Graph for Actual Peak Load & Forecasted Peak Load by using LM with WT

Thus, the Mean Absolute Percentage Error from the LM training with wavelet transform is approximately 7.62 % which is lower as compared to training with LM without wavelet transform.

V. CONCLUSION

After analyzing the results, it has been found that forecasted data is very similar to actual measured data with Mean Absolute Percentage Error of 7.5% which is a great improvement and hence Artificial Neural Networkcan be used to predict the electricity demand for short term. Also, this resulthas concluded that Artificial Neural

Network along with wavelet will give far better result in load forecasting. This result is very accurate and will prove to be very helpful for power generation companies.

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