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

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I Abstract

Due to centralized power system and continuous varying nature of load it is very difficult to balance demand and generation at all time. It is due to the fact that generation can't be controlled with the same pace as load due to restriction in instantaneous change in input to power plant. In this paper a work is presented to forecast week ahead loadusing ANN model with wavelet transform signal processing which has outperform all previous method due to the exceptional nature of leaning in neural network.

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.

Keywords: Short-term load forecasting; multi-layer perceptron; artificial neural network, wavelet transform.

II Introduction

Load forecasting is a term used for power needed to meet the demand and supply equilibrium. Short term load forecast ranges fromfew days to few weeks. Load connected/power demand to any system is dependent on many factors which can be weather and regional[1]. Artificial Neural network is used in short term load forecasting due to its capacity to find relation between non-linear values thus making it very efficient model;in such type of cases[2]. Since result of artificial neural network is dependent on the way data is presented to it hence wavelet transform when performed on short term load forecasting parameters will help neural network to train better.

Such forecasting of load will 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 [12].

III Literature Review

Abdollah kavousiFard have developed hybrid combination of evolutionary algorithms and ANN to forecast loadand found the most optimum results using modified Honey Bee Optimization[14].Kishan Bhushan Sahay prepared a model to STLF for Toronto Canada and on evaluating results LM and BR showed almost same results hence should be used in forecasting load for short term[15].Sharad Kumar at al. in present study found that ANN is better performing model than regression hence it should be preferred for forecasting short term load[16].Victor Mayrink have generated a hybrid model combining exponential smoothing and gradient boostingusing a base learning model [17].Ni Ding have developed machine learning model for distribution system and found that it is far more accurate than time series forecasting. [18].Penghua Li et al. have developed a hybrid quantized Elman Neural Network for the purpose of STLF as for every 1 percent increase in forecasting error will lead to 10 million dollars increase in operating cost, which is sufficient enough motivation for forecasting[19].Hao Quanused Programmable System Optimization, along with Neural Network to fulfil the objective and are compared with models named ARIMA, ES and naïve models[20].Hao Quan have utilized lower upper bound estimation method and PSO for optimizing weightsafter studying concluded that this model has significant forecasting[21].Ajay Gupta developed a forecasting model using GA-ANN algorithm authors found GA has good capability in function optimization and thus GA has efficient optimized neural network [22].

Hence from above mentioned previous work it is clear that ANN is far superior than other statical methods. Also, its 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.

IV Proposed Methodology

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.

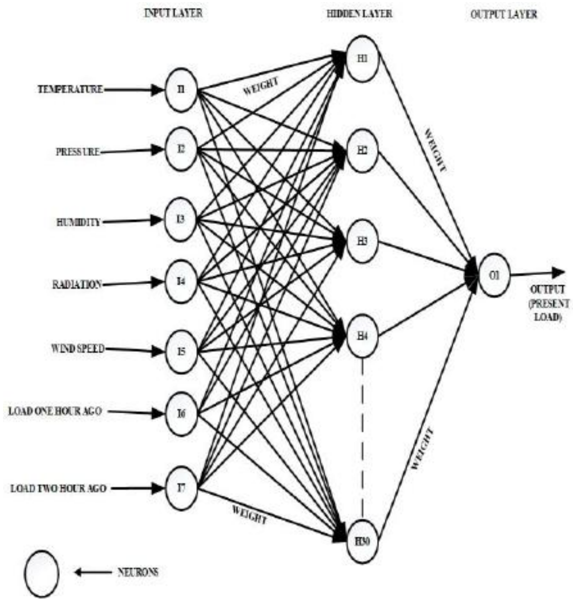

Figure2 Proposed ANN diagram

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,

$$W_{k+1} = W_k - [J_K{}^T J_k + \mu I]^{-1} J_K{}^T e_k \quad (1)$$

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.

Discrete Wavelet Transform (DWT):The disadvantage of the continuous wavelet transform lies in its computational complexity and redundancy. In order to solve these problems, the discrete wavelet transform is introduced. Unlike CWT, the DWT decomposes the signal into mutually orthogonal set of wavelets. The discrete wavelet is defined as:

$$\psi_{j,k}(t) = \frac{1}{\sqrt{s_0^j}} \psi\left(\frac{t - k\,\tau_0^j s_0^j}{s_0^j}\right) \quad (2)$$

where j and k are integers, $s_0 > 1$ is a fixed dilation step and the translation factor τ_0 depends on the dilation step. The scaling function and the wavelet function of DWT are defined as:

$$\phi(2^j t) = \sum_{i=1}^{k} h_{j+1}(k)\, \phi(2^{j+1}t - k) \qquad (3)$$

$$\psi(2^j t) = \sum_{i=1}^{k} g_{j+1}(k)\, \phi(2^{j+1}t - k) \qquad (4)$$

And then, a signal f(t) can be written as:

$$f(t) = \sum_{i=1}^{k} \lambda_{j-1}(k)\ \phi(2^{j-1}t - k) + \sum_{i=1}^{k} v_{j-1}(k)\ \phi(2^{j-1}t - k) \qquad (5)$$

The reconstruction is just a reversed process of the decomposition and for perfect reconstruction filter banks, we have x = x'.

V 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.

Table 1

Data sheet utilized

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

Results for 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".

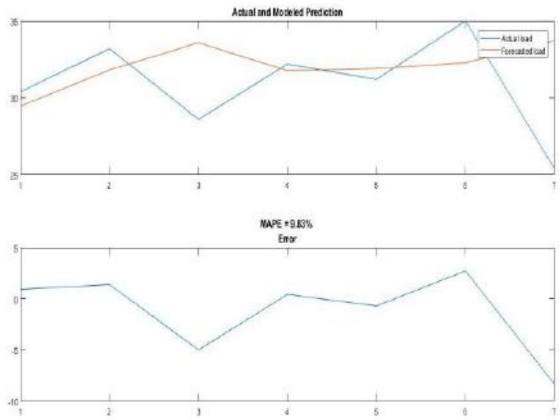

Figure 3: Forecasted electrical *load employing the proposed model using LM*

The plot is for peak electrical load from 25 Dec 2017 to next 7 days. The results have a MAPE of 9.8 % and MAE: 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 2

Forecasted peak load using LM

Date	Actual Peak Load	Forecasted Peak Load	Error
25/Dec/2017	30.400	29.4632943169622	0.936705683037772
26/Dec/2017	33.200	31.8161873940999	1.38381260590015
27/Dec/2017	28.600	33.5821965381827	-4.98219653818274
28/Dec/2017	32.200	31.7677848576503	0.432215142349701
29/Dec/2017	31.2000	31.9047896682271	-0.704789668227146
30/Dec/2017	35	32.2793095025286	2.72069049747140
31/Dec/2017	25.400	33.7163303206079	-8.31633032060793
MAPE			9.83%

Results for 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 MAPE of 7.6 %. This figure is obtained when number of hidden layers are 20-10 and optimization is done using WT training algorithm.

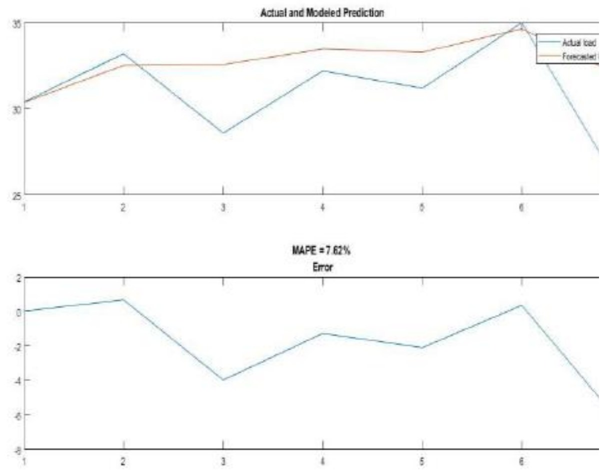

Figure 4: Forecasted electrical load employing the proposed model using LM+WT training.

Table 3

Forecasted peak load using LM with WT

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 %**

VI Conclusion

After analyzing the results, it has been found that forecasted data is very similar to actual measured data with an MAPE of 7.5% which is a great improvement and hence ANN can be used to predict the electricity demand for short term. Also,this resulthas concluded that ANN 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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