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Week-Ahead Load Forecasting by ANN Approach

Vinod.B.Jammanakatti[1], Dr.Ashok Kusagur[2]

P.G. Student, E.E.E Department, UBDT College of Engineering, Davangere, Karnataka, India [1]

Associate Professor, E.E.EDepartment,UBDT Collegeof Engineering, Davangere, Karnataka, India[2]

Abstract:This paper presents artificial neural network (ANN) for a week ahead load forecasting. Load forecasting has become one of the major areas of research in electrical engineering and is an important problem in operation and planning of electric power generation. In this paper three months of hourly load data is collected from the 66/11kv substation davanagere city and application of short term load forecasting (STLF) using multilayer feed forward network (MLFFN) with gradient descent back propagation algorithm is used in MATLAB environment. The results shows that this method is simple and more accurate with the minimum error and can be used for short term load forecasting.

Keywords: Artificial neural network, Short term load forecasting, multilayer feed forward network.

I. INTRODUCTION

This Load forecasting is one of the central functions in power systems operations. In general, the required load forecasts can be categorized into short-term, mid-term, and long-term forecasts. The short-term forecasts refer to hourly prediction of the load for a lead time ranging from one hour to several days out [9]. The mid-term forecasts can either be hourly or peak load forecasts for a forecast horizon of one to several months ahead. Scheduling of fuel purchases, load flow studies or contingency analysis, and planning for energy, while the long-term forecasts refer to forecasts made for one to several years in the future[3,4]. It is extremely important for energy suppliers, financial institutions, and other participants involved in electric energy generation, transmission, distribution, and supply. The quality of short-term hourly load forecasts has a significant impact on the economic operation of the electric utility since decisions such as economic scheduling of generating capacity, transactions such as ATC (Available Transmission Capacity) are based on these forecasts and they have significant economic consequences .their outstanding performance in data classifications and function approximation.

ANN is also capable of detecting dependencies from historical data without the need to develop a specific regression model [7]. First publications on ANN application to the load forecasting problem were made in late 1980s and early 1990s. Since then ANN have been well accepted in practice, and are used by many utilities. For different operations within the utility, different time horizon forecast are important. For a particular region, the accuracy of load forecasting is approximately 1-3%for short term. However, with same accuracy it is impossible to predict the next year load since long-term weather forecast are not available with similar accuracy [5]. Due to change in weather conditions, supply and demand fluctuations the electricity price increases by a factor of ten or more during peak load condition which causes overloading [6]. STLF can help to prevent overloading and consequently reduces occurrence of blackouts andequipment failures.

For accurate load forecasting various factors are considered as perquisite. Generally, electric load forecasting is a complex exercise. Although ANN proven superior methodologies for STLF compared to traditional techniques, the design of optimal network structures has not yet been successfully implemented. And the fact that an electric load is a non-linear function, traditional forecasting methods are simply not suitable for the application due to the lack of non linear mapping ability. The operation and planning of a company requires an adequate model for electric power load forecasting. Load forecasting plays a key role in helping an electric utility to make important decisions on power, load switching, voltage control, network reconfiguration, and infrastructure development.

II. NEURAL NETWORKS

Artificial neural network (ANN) is a machine learning approach that models human brain and consists of a number of artificial neurons. The neuron is the basic information processing unit of a ANN. It consists of a set of links, describing the neuron inputs, with weights W_1, W_2, …, W_m.An adder function (linear combiner) for computing the weighted sum of the inputs:(real numbers) .Activation function for limiting the amplitude of the neuron output.

Here ‘b’ denotes bias. Neuron in ANNs tends to have fewer connections than biological neurons. Each neuron in ANN receives a number of inputs. An activation function is applied to these inputs which results in activation level of neuron (output value of the neuron).Knowledge about the learning task is given in the form of examples called training examples.

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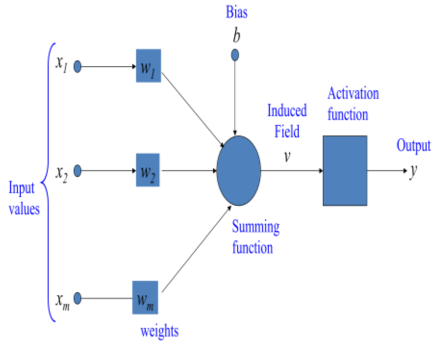
Fig.1.Mathematical model of a neuron



III.ANN ARCHITECTURE DESIGN

A. Network topology for total load model

The Network used is Multilayer Feed forward with back propagation algorithm.The Transfer function used in the two layers is the tan sigmoid function for the hidden layers and the Prelim function at the output layers; this is to enable the network to be able to take care of any non-linearity in the input data and at the output, to be able to give a wide range of values. One input layer, one hidden layer and one output layer. Total number of inputs used is 5.Number of hidden neurons is used 5.Total number of output neurons used 1. The training algorithm used "Traingdm" i.e Gradient descent with momentum learning algorithm. Learningrate 0.3.Momentum factor 0.75.

B. Multi-layer Feed forward Network

Feed forward neural network distinguishes itself by the presence of one or more hidden layers, whose computational nodes are correspondingly called hidden neurons. The function of hidden neuron is to intervene between the external input and the network output in some useful manner. By adding more hidden layers, the network is enabled to extract higher order statistics. The input signal is applied to the neurons in the second layer. The output signal of second layer is used as inputs to the third layer, and so on for the rest of the network.

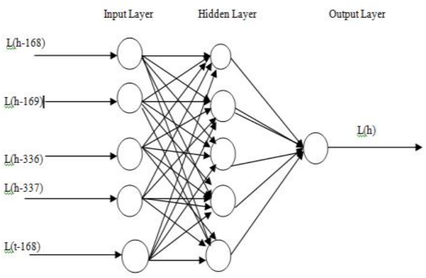


Fig. 2.Network Structure for Load Forecasting .

IV.GRADIENT DESCENT WITH BACK PROPAGATION ALGORITHM

Every MLFFN been applied successfully to solve some difficult diverse problems by training them in a supervised manner with a highly popular algorithm known as the error back-propagation algorithm [1].

In the forward pass

- Initialize weights and learning rates.
- During the forward pass the weights of the networks are all fixed.
- Each input unit receives input signal and sends it to the hidden unit.
- Calculate output of hidden unit by applying transfer function.
- For each output unit calculate net input and apply the activation function to compare output signal.
- During the backward pass, the weights are all adjusted in accordance with an error correction rule [10].
- The actual response of the network is subtracted from a desired response to produce an error signal.
- This error signal is then propagated backward through the network, against the direction of synaptic connections.
- "Traingd" is a network training function that updates weights and bias values according to gradient descent.

$$\Delta w_{ij} = \eta \frac{\partial \varepsilon}{\partial W_{ij}} \qquad (1)$$

Where ηis learning rate parameter $\frac{\partial \varepsilon}{\partial w_{ij}}$ is error gradient with respect to weight w_{ij}.

- The weights are adjusted to make the actual response of the network move closer to the desired response [8].

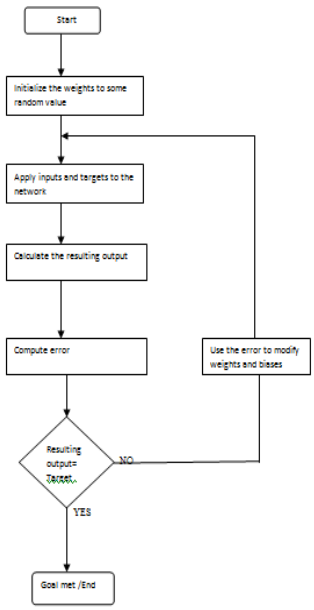


Fig. 3.Gradient Descent with Back propagation algorithm.

V. RESULTS & DISCUSSIONS

- The STLF model using ANN is designed and M-codes are written in Matlab software.
- For this study three months of hourly data in MW is collected from 66/11 KV substation *Davangere* and corresponding temperature values in are also collected.
- Data collection is a significant function of any type of research study. Inaccurate or insufficient data can impact the results of a study and ultimately lead to invalid or skewed results. Some bad data were detected in the total load data.

- The bad data replacement is done by taking the average of the previous hour and the next hour.The data is normalized prior to presenting them to a model for or any forecasting attempt.
- Data scaling is essential due to the fact that neural networks are often vulnerable to raw data, it is extremely important that data are scaled (typically between 0 and 1 or -1 and 1) to avoid convergence problems.

$$\text{Normalizedvalue} = \frac{\text{Actualvalue}}{\text{Maximumvalue}} \quad (2)$$

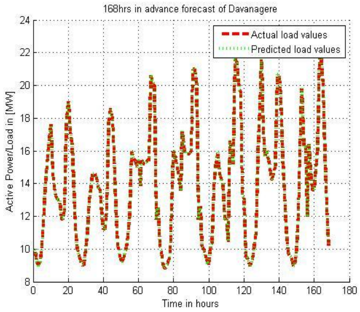


Fig. 4.Comparison one week of actual and forecasted load of Davangere .

Fig4 shows the graph of actual and forecast from this graph .The red colour indicates the actual load and green line indicates forecasted load. .Power consumption during the night is much lower than at daytime i.e. from 12 am to 16 am; furthermore, power consumption during the daytime varies with the time of the day. For example, the morning rush hour i.e. from 7 am to 10 am has a different load demand than the lunch hour or the afternoon period.We can see that predicted and the forecasted values are close to actual values and the error is less.

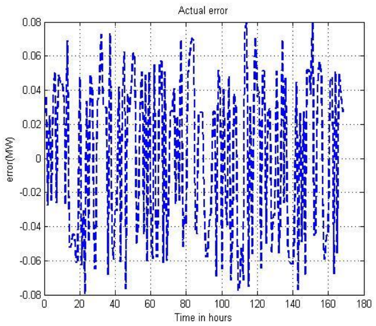
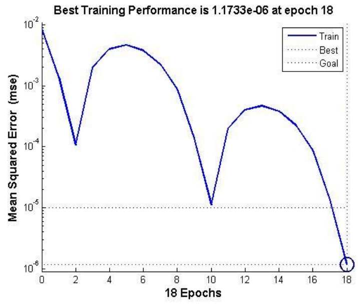


Fig.5.Actual error in forecast

Fig.5 shows the actual error in MW of one week ahead load forecasting from the graph we can observe that the error varies from -0.08 MW to +0.08 MW '+ 'sign indicates under forecast and'-' indicates over forecast. Fig.6 shows the performance (MSE) Vs number of epochs plot describes the plot against mean square error against the number of training epochs. From the graphs it can be concluded that the network was trained to zero error and the best value of $1.733e^{-6}$ at 18 epochs.

This is obviously negligible and the network is said to be have successfully learned the non linear relationship. Table I and II shows comparison of one week actual and forecasted load.



VI.CONCLUSION

In this paper presents an Artificial Neural Network based Short-term load forecasting (STLF) model. The forecast model predicts one week ahead weekly electrical loads. A multilayer feed forward neural network one hidden layer and one output layer is used. The weights of this non-linear model are estimated with gradient-descent with back-propagation algorithm. Hourly Load data (MW) and corresponding temperature data (℃) is obtained from the KPTCL and the simulation of algorithm is done using MATLAB.

This method is simple and more accurate with the minimum error. The results suggest that ANN model with the developed structure can perform good prediction with least error and finally this neural network is an important tool for short term load forecasting.

REFERENCES

[1] Yegnanarayan B.,'Artificial Neural Networks' Prentice Hall India Private Limited,New Delhi.

[2] Howard Demuth, *Mark Beale,* Matlab Neural Network Users Guide

[3] George Gross and Francisco.D.Galiana"Short-Term Load Forecasting "PROCEEDINGS OF THE IEEE, VOL. 75, NO. 12, DECEMBER 1987

[4] T. M. Peng,N. E Hubele and G G. Karady"An adaptive neural network approach to one-week ahead load forecasting "IEEE Transactions on Power Systems, Vol. 8, No. 3, August 1993.

[5] M.Y. Cho, J.C. Hwang and C.S. Chen "Customer short term load forecasting by using arima transfer function model "IEEE Catalogue No. 95TH8130 1995.

[6] D.C. Park, M.A. El-Sharkawi, R.J. Marks 11,L.E. Atlas and M.J. Damborg "Electric Load Forecasting Using An Artificial Neural Network "IEEE Transactions on Power Systems, Vo1.6, No. 2, May 1991.Mohsen Hayati and Yazdan "Artificial Neural Network Approach for Term Load Forecasting for Illam Region"INTERNATIONAL JOURNAL OF ELECTRICAL, COMPUTER, AND SYSTEMS ENGINEERING VOLUME 1

[7] NUMBER 2 2007 ISSN 1307-5179.

[8] Wenjin Dai and ping Wang "Application of Pattern Recognition and Artificial Neural Network to Load Forecasting in Electric Power System "IEEE Third International Conference on Natural Computation (ICNC 2007).

[9] Mohsen Hayati and Yazdan "Artificial Neural Network Approach for Term Load Forecasting for Illam Region"INTERNATIONAL JOURNAL OF ELECTRICAL, COMPUTER, AND SYSTEMS ENGINEERING VOLUME 1 NUMBER 2 2007 ISSN 1307-5179.

[10] Sandeep Sachdeva, and Chander Mohan Verma"Load Forecasting using Fuzzy Methods "IEEE 2008.

[11] Ying-chun guo and Dong-xiao niu"Intelligent short-term load forecasting based on pattern-base "Proceedings of the Seventh International Conference on Machine Learning and Cybernetics, Kunming, 12-15 July 2008 .

[12] Yun Lu"Short- Term Load Forecasting Method Based on Structural Neural Network "Proceedings of the 7th World Congress on Intelligent Control and Automation June 25 - 27, 2008, Chongqing, China.

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[13] Zainab H. Osman, Mohamed L. Awad and Tawfik K. Mahmoud "Neural Network Based Approach for Short-Term Load Forecasting" IEEE 2009

[14] Wenjin Dai and ping Wang "Application of Pattern Recognition and Artificial Neural Network to Load Forecasting in Electric Power System "IEEE Third International Conference on Natural Computation (ICNC 2007).

[15] Mohsen Hayati and Yazdan "Artificial Neural Network Approach for Term Load Forecasting for Illam Region"INTERNATIONAL JOURNAL OF ELECTRICAL, COMPUTER, AND SYSTEMS ENGINEERING VOLUME 1 NUMBER 2 2007 ISSN 1307-5179.

[16].Sandeep Sachdeva, and Chander Mohan Verma"Load Forecasting using Fuzzy Methods "IEEE 2008

[16] Ying-chun guo and Dong-xiao niu"Intelligent short-term load forecasting based on pattern-base "Proceedings of the Seventh International Conference on Machine Learning and Cybernetics, Kunming, 12-15 July 2008 .

[17] Yun Lu"Short- Term Load Forecasting Method Based on Structural Neural Network "Proceedings of the 7th World Congress on Intelligent Control and Automation June 25 - 27, 2008, Chongqing, China.

[18] Zainab H. Osman, Mohamed L. Awad and Tawfik K. Mahmoud "Neural Network Based Approach for Short-Term Load Forecasting" IEEE 2009

TABLE ACTUAL VS FORECAST LOAD

No.of. hours	Actual load (Mw)	Forecasted Load (Mw)	No.of. hours	Actual load (Mw)	Forecasted Load (Mw)	No.of. hours	Actual load (Mw)	Forecasted Load (Mw)
1	10	9.96239	25	10	10.0488	49	9.8	9.75901
2	9.2	9.22724	26	9.6	9.55063	50	9.2	9.13851
3	9	8.975	27	9.2	9.16143	51	9.2	9.13851
4	9.2	9.22475	28	9	9.06457	52	9.6	9.65076
5	10.2	10.1652	29	9	9.06457	53	10	10.0384
6	11.6	11.5487	30	10	9.96658	54	10.8	10.7728
7	13.8	13.8261	31	11	10.9631	55	12.2	12.149
8	15.2	15.1509	32	13	12.9272	56	16	16.0447
9	16.4	16.3554	33	13.8	13.7688	57	15.6	15.5511
10	17.6	17.5555	34	14.6	14.5703	58	15.4	15.4604
11	14.6	14.5657	35	14.6	14.5703	59	15	14.9494
12	13.8	13.8274	36	14.4	14.4681	60	15.4	15.4496
13	13.2	13.131	37	13.8	13.7265	61	13.8	13.8589
14	13	13.0524	38	13.6	13.6506	62	15.4	15.3449
15	13	13.0524	39	12	12.059	63	15.2	15.258
16	11.8	11.8447	40	11.2	11.2307	64	15.2	15.258
17	11.8	11.8447	41	11.2	11.2307	65	15.4	15.3432
18	12.4	12.4611	42	12.4	12.3582	66	15.4	15.3432
19	17.6	17.6596	43	17.6	17.6608	67	20.6	20.661
20	19	18.9521	44	18.6	18.5664	68	20.2	20.1493
21	17.2	17.2626	45	18	17.9377	69	20	20.0597
22	16.4	16.4308	46	15.8	15.8764	70	11.8	11.8311
23	14.2	14.2797	47	12.6	12.562	71	12.6	12.5725
24	11.4	11.3666	48	10.2	10.1726	72	10.2	10.1725

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73	9.8	9.75	97	10	10.06	121	9.6	9.56	145	9.8	9.84
74	9	9.02	98	9.6	9.54	122	9.4	9.46	146	9.6	9.57
75	8.8	8.77	99	9.2	9.16	123	9	8.94	147	9.4	9.46
76	9	9.02	100	9	9.06	124	9	8.94	148	9	8.94
77	9.2	9.12	101	10.2	10.15	125	9.4	9.44	149	9	8.94
78	9.6	9.65	102	10.4	10.42	126	10.2	10.17	150	10	9.96
79	12.6	12.63	103	13.8	13.83	127	11	10.97	151	12.2	12.12
80	16	16.039	104	15.2	15.15	128	15.8	15.85	152	16	16.04
81	15.6	15.55	105	15.8	15.87	129	18.7	18.73	153	19.8	19.84
82	15	14.93	106	14.6	14.64	130	21.6	21.63	154	16.2	16.15
83	14.3	14.22	107	14.3	14.26	131	17.2	17.14	155	16.3	16.24
84	13.6	13.53	108	14	13.97	132	15.6	15.65	156	12	11.95
85	17.2	17.24	109	11.8	11.87	133	16	16.03	157	16.4	16.45
86	16	16.04	110	11.8	11.87	134	15.4	15.32	158	14.8	14.85
87	15.8	15.77	111	10.4	10.4528	135	14.6	14.62	159	13.6	13.64
88	15.8	15.77	112	16.6	16.6713	136	14.2	14.15	160	13.6	13.64
89	15.8	15.77	113	16	15.9262	137	14.6	14.64	161	14.9	14.85
90	16	16.025	114	15.2	15.1201	138	15.2	15.26	162	16.2	16.15
91	21	21.057	115	21.6	21.6751	139	20.6	20.66	163	22	22.06
92	21	21.057	116	21.4	21.3697	140	20.6	20.66	164	21.6	21.54
93	20	20.037	117	19.8	19.8561	141	19.4	19.44	165	20	20.05
94	11.8	11.83	118	19.6	19.5718	142	15.6	15.5554	166	15.8	15.75
95	12.6	12.57	119	13.4	13.3284	143	13.4	13.477	167	12.6	12.56
96	10.2	10.17	120	13	12.9639	144	11.2	11.1736	168	10.2	10.17