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Short Term Load Forecasting Model for UGVCL, MGVCL, DGVCL and PGVCL using ANN

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ABSTRACT

Artificial neural network has been used for many years in sectors like medical science, defense industry, robotics, electronics, economy, forecasts, etc. The learning property of ANN in solving nonlinear and complex problems called for its application to forecasting problems. This paper present the development of an ANN based short-term load forecasting model for the MGVCL(Madhya Gujarat Vij Co. Ltd), DGVCL(Dakshin Gujarat Vij Co. Ltd), PGVCL (Paschim Gujarat Vij Co. Ltd) , UGVCL(Uttar Gujarat Vij Co. Ltd). The recorded daily load profile for the year 2014 was obtained from the SLDC (State Load Dispatch Center). The Levenberg-Marquardt optimization technique which has one of the best learning rates was used as a back propagation algorithm for the Multilayer Feed Forward ANN model using MATLAB® R2010b. Selection of input neurons is the most crucial part of the ANN model. ANN model output is compared with the utility hourly data.
The results have shown that the proposed model is give more accurate forecasting future load demands for the daily operational planning of power system and hence improve the system reliability.

INDEX TERMS--- *Short term load forecasting, artificial neural network, back propagation algorithm.*

I. INTRODUCTION

As Electric load forecasting is the process used to forecast future electric load from the given historical load and weather information. In the past few decades, several models have been developed to forecast electric load more accurately as compare with analytical methods. Load forecasting can be divided into three major categories:
1. Long-term electric load forecasting, used to supply electric utility company management with prediction of future needs for future expansion, equipment purchases, or new staff hiring
2. Medium-term forecasting, used for the purpose of scheduling fuel supplies and maintenance.
3. Short-term forecasting used to supply necessary information for the system management of day-to-day operations and unit commitment for economic load dispatch.

Short term load forecasting mainly aim the forecast of one hour to one week. Daily load behavior is highly non linear and random. It is very difficult to obtain higher accuracy using conventional method. To improve the accuracy of short term load forecasting Artificial intelligence techniques is the advanced approach.

II. LITERATURE SURVEY

Due to signification of load forecasting to a utility, in last decade, a wide divergence of approaches for power load forecasting have been suggested. These approaches can extensively be classified into: time series approach, regression approach, expert system approach and artificial intelligence approach.

Short-Term Load Forecasting Using Artificial Neural Network by Muhammad Buhari and and Sanusi Sani Adamu [1] present the development of an ANN based short-term load forecasting model for the 132/33KV sub- Station, Kano, Nigeria. The recorded daily load profile with a lead time of 1-24 hours for the year 2005 was obtained from the utility company. The Levenberg-Marquardt optimization technique which has one of the best learning rates was used as a back propagation algorithm for the Multilayer Feed Forward ANN model using MATLAB®.

An Analysis of Short Term Load Forecasting by Using Time Series Analysis by Anshu tiwari and Dr.Vivek Dubey [2] presents time series analysis for short-term Maharashtra electricity demand forecasting. Two time series models are proposed, namely, the multiplicative decomposition model and the smoothing techniques model. Forecasting errors of both models are computed and compared.

Factor Affecting Short Term Load Forecasting by Muhammad Usman Fahad and Naeem Arbab [3] evaluate that total system load is the load seen at the generating end of the power system, which includes the sum of all types of loads connected to the system plus the losses. To design efficient and accurate forecasting model one must have good understanding of the characteristics of the system. There are various factors which influence the behavior of the consumer load and also impact the total losses in transmission lines. These factors can be categorized as Time factor, weather, economy and random disturbances.

III. ARTIFICIAL NEURAL NETWORK

Artificial Neural Networks are relatively crude electronic models based on the neural structure of the brain. The brain basically learns from experience. The fundamental processing element of a neural network is a neuron. This building block of human awareness encompasses a few general capabilities. Basically, a biological neuron receives inputs from other sources, combines them in some way, performs a generally nonlinear operation on the result, and then outputs the final result.

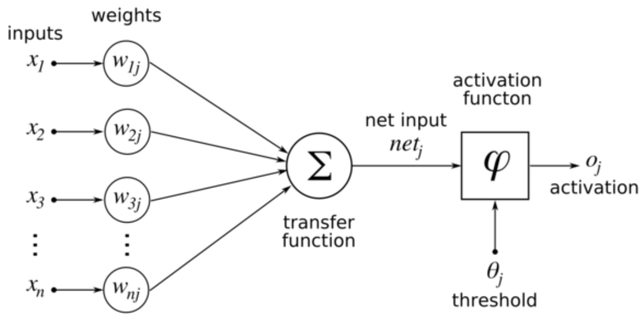

Fig: 1 Basic Artificial Neural Network Model

As shown in Fig: 1 x_1, x_2 … x_n is input neuron. W_{ij} is weight of respective neuron. Transfer function is selected based on application.

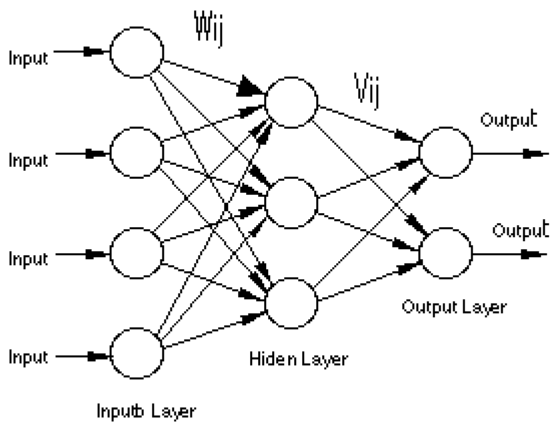

Fig: 2 Modified Neural Network with hidden layer

X_i Input neurons, Y_i Hidden Neurons, O_i Output Neurons, W_{ij} is the weight between input layer and hidden layer, V_{ij} is the weight between hidden layer and output layer.

3.1 Learning Algorithm

Artificial neural networks work through the optimized weight values. The method by which the optimized weight values are attained is called *learning*. In the process of learning we present the neural network with pairs of input and output data and try to teach the network how to produce the output when the corresponding input is presented. When learning is complete, the trained neural network, with the updated optimal weights, should be able to produce the output within desired accuracy corresponding to an input pattern.

There are several learning algorithms. They can be broadly categorized into two classes: supervised and unsupervised. Supervised learning means guided learning, i.e. when the network is trained by showing the input and the desired result side by-side. This is similar to the learning experience in our childhood. As a child, we learn about various things (input) when we see them and simultaneously are told (supervised) about their names and the respective functionalities (desired result). This is unlike the unsupervised case where learning takes place from the input pattern itself. In unsupervised learning the system learns about the pattern from the data itself without *a priori* knowledge. This is similar to our learning experience in adulthood. For example, often in our working environment we are thrown into a project or situation which we know very little about. However, we try to familiarize with the situation as quickly as possible using our previous experiences, education, willingness and similar other factors. This adaptive mechanism is referred to as unsupervised learning.

3.2 *The Back propagation Algorithm*

The back propagation algorithm is one of the well-known algorithms for calculating the neural network weights.

The output values *Oj* of a given input pattern *Xi* do not always correspond to their predetermined values *Rj*. The error *E j* is given by the difference of *Rj* and *Oj* and is to be minimized by the weight changes. In order to achieve this, the error which originates at the output is propagated backwards to the hidden layers. That is, we take the error and back-calculate to arrive at the correct solution. This is the principle of the back propagation algorithm (the error propagates in the backward direction), the error of a neuron *j* in the output layer is:

$$Ej = \frac{1}{2}(Rj - Oj)^2$$

The total error *E* of an output layer is

$$E = \sum_j Ej = \frac{1}{2}\sum_j (Rj - Oj)^2 \qquad (2.1)$$

So, we need to minimize the error *E*, with respect to the weight changes *(_Wi j)*. We follow the delta rule to incorporate the learning rate α. Gradient descent algorithm is used to choose the weight change method. We use these two techniques to define the weight change,

$$\Delta Wkj = -\alpha \frac{\partial E}{\partial Wkj}; 0 < \alpha < 1 \qquad (2.2)$$

If the gradient $\partial E/\partial Wkj$ is positive then the weight change should be negative and vice versa. Hence, a minus sign is added at the right hand side of (2.1). Considering neuron j,

$$\Delta Wkj = -\alpha \frac{\partial Ej}{\partial Wkj} \qquad (2.3)$$

Using a sigmoid transfer function *Tj (S)*, the output *Oj* is defined as

$$Oj = Tj\,(Sj) = \frac{1}{1 + e^{-Sj}} \qquad (2.4)$$

For the hidden layer input (H_k) to the output layer,

$$Sj = \sum_k Wkj.Hk \qquad (2.5)$$

From equation (2.1) and (2.2)

$$\Delta\, Wkj = -\alpha \frac{\partial Ej}{\partial Wkj} = -\alpha \frac{\partial Ej}{\partial Oj}.\frac{\partial Oj}{\partial Wkj}$$

$$= -\alpha \frac{\partial Ej}{\partial Oj}.\frac{\partial Oj}{\partial Sj}.\frac{\partial Sj}{\partial Wkj} \qquad (2.6)$$

we get,

$$\frac{\partial Ej}{\partial Oj} = \frac{-2}{2}\,(Rj - Oj) = -(Rj - Oj) \qquad (2.7)$$

Using (2.4)

$$\frac{\partial Oj}{\partial Sj} = Oj\,(1 - Oj) \qquad (2.8)$$

From (2.5)

$$\frac{\partial Sj}{\partial Wkj} = \frac{\partial \sum Wkj.Hk}{\partial Wkj} = Hk \qquad (2.9)$$

Combining equation we get,

$$\Delta Wkj = \alpha.(Rj - Oj).Oj(1 - Oj).Hk \qquad (2.10)$$

So new weights are

$$W'kj = Wkj + \Delta Wkj \qquad (2.11)$$

The error of the output layer is back propagated to the weights of the hidden and the input layer. ΔWkj is the change in weights from the output layer to the hidden layer. The back propagated error *Ek* of the hidden layer is given by:

$$Ek = \sum_j Ej = \frac{1}{2}\sum_j (Rj - Oj)^2 \qquad (2.12)$$

Corresponding to (2.1) is the weight change ΔWik . We introduce a new learning rate α'.

$$\Delta Wik = -\alpha'.\frac{\partial Ek}{\partial Wik}; 0 < \alpha' \leq 1;\ \alpha' \neq \alpha. \qquad (2.13)$$

Using (2.4) and (2.5)

$$\Delta Wik = -\alpha'.\left(\frac{\partial Ek}{\partial Wik}\right) = -\alpha.\frac{\partial \mathrm{Ek}}{\partial \mathrm{Hk}}.\frac{\partial \mathrm{Hk}}{\partial \mathrm{Wik}} \qquad (2.14)$$

$$\frac{\partial Ek}{\partial Hk} = \frac{\partial \sum_j Ek}{\partial Hk} = \sum_j \frac{\partial Ej}{\partial Hk} \qquad (2.15)$$

$$\frac{\partial Ej}{\partial Hk} = \frac{\partial EJ}{\partial Oj}.\frac{\partial Oj}{\partial Sj}.\frac{\partial Sj}{\partial Hk} \qquad (2.16)$$

From (2.7) and (2.8),

$$\frac{\partial Ej}{\partial Oj}.\frac{\partial Oj}{\partial Sj} = (Rj - Oj).Oj.(1 - Oj) \qquad (2.17)$$

For the hidden layer we have,

$$\frac{\partial Sj}{\partial Hk} = \frac{\partial(\sum_k Wkj.Hk)}{\partial Hk} = Wkj \qquad (2.18)$$

$$Hk = \frac{1}{1+e^{-sk}} \qquad (2.19)$$

$$Sk = \sum_i Wik.Xi \qquad (2.20)$$

Using (2.19) we get,

$$\frac{\partial Hk}{\partial Sk} = Hk\,(1 - Hk) \qquad (2.21)$$

From (2.20),

$$\frac{\partial Sk}{\partial Wik} = Xi \qquad (2.22)$$

So,

$$\frac{\partial Hk}{\partial Wik} = \frac{\partial Hk}{\partial Sk}.\frac{\partial Sk}{\partial Wik} = Hk\,(1 - Hk).Xi \qquad (2.23)$$

Using (2.14) to (2.23) we finally get the weight changes in the hidden layer as,

$$\Delta Wik = \alpha'.\sum_j (Rj - Oj).Oj(1 - Oj).\ Wkj.Hk\,(1 - Hk).Xi \qquad (2.24)$$

IV. ANN MODEL TRAINING PROCESS

The Training goal was set at 0 so as to ensure zero tolerance to network computational errors. The transfer functions used were the tan-sigmoid in the Hidden layer neurons while the Purel in function was used in the output layer neurons so as not to constrain the output's values. The learning function used is the default steepest gradient descent method. The Levenberg-Marquardt learning function was used as it has a better learning rate compared to the other available functions in forecasting problems. The training function used was the steepest gradient descent function and in some tests the steepest gradient descent method with momentum.

Basically the input data set was divided into three: 70% was used for as training set while 15% each was used for testing and validation of the network output results. The training data set is necessary for obtaining the neural network's weight and bias values during network training. The validation data set is used to periodically test the ability of the network to generalize. Finally, the test data set is used in the evaluation of generalization error

V. ANN MODEL RESULT

Table: 1 Result of ANN Model for MGVCL Jan-2014

Date	Average % Error for forecasted load	Average % Error for ANN output
2nd	3.93	0.3
3rd	4.13	0.23
4th	2.5	0.4
5th	1.4	0.5
6th	1.29	0.9
7th	1.3	0.4
8th	2.6	0.2
9th	2.6	0.1
10th	1.2	0.5
11th	0.6	0.1
12th	1.2	0.4
13th	0.8	0.3
14th	0.1	0.001
15th	10.9	0.7
16th	1.2	0.5
17th	5.9	0.2
18th	3.2	0.5
19th	0.4	0.07
20th	1.7	0.03
21st	11.7	1.4
22nd	1.9	0.6
23rd	0.8	0.18
24th	0.9	0.8
25th	2.02	0.07
26th	0.7	0.2
27th	4.7	0.1
28th	1.6	0.1
29th	0.8	0.5
30th	4.3	0.6

Table 1 shows the % Average error for ANN model output. Forecasted error is calculated with reference to forecasted data collected from SLDC – Gotri.

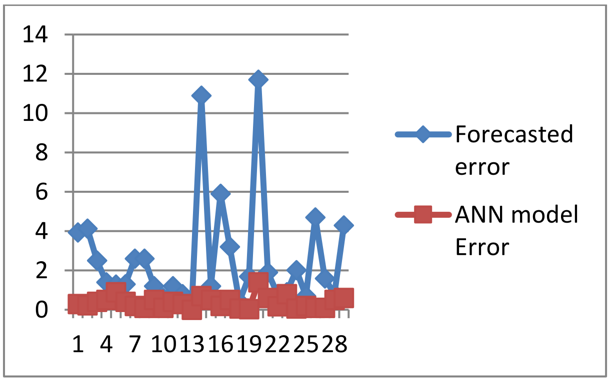

Fig 1 comparison of ANN output with SLDC Data.

It shows ANN error is very less as compared with SLDC data. After getting the satisfactory results for other month, I try this model for PGVCL load; DGVCL load and UGVCL load also.
Here are the results for the same.

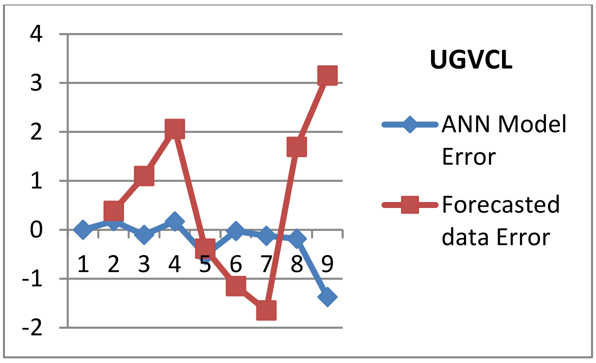

Fig 2 Error comparison for UGVCL Load Profile

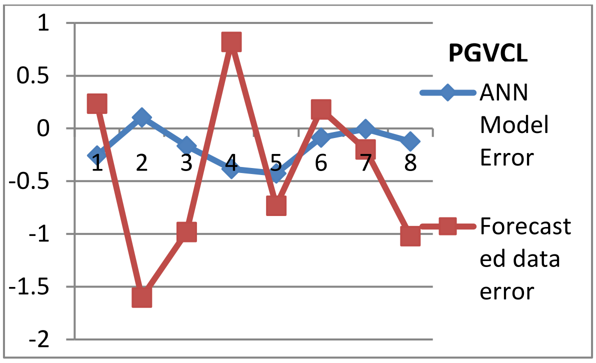

Fig 3 Error comparison for PGVCL Load Profile
(Refer Appendix - II for PGVCL Load profile)

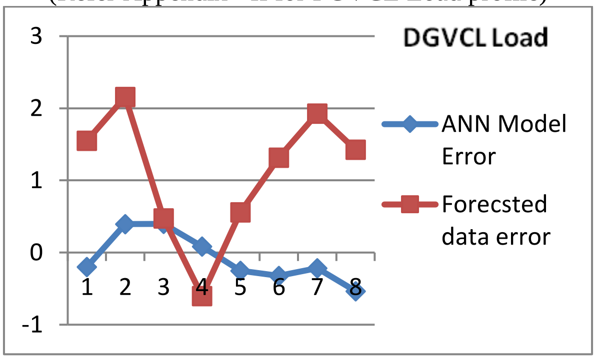

Fig 4 Error comparison for DGVCL Load Profile
(Refer Appendix - I for DGVCL Load profile)

VI. CONCLUSION

This paper presents an application of ANN for short term load forecasting in power systems. Performance of Model for hourly load forecast for STLF is investigated. The main features of the work presented in this paper are:

1. Development of model using ANN.
2. Percentage error for model on hourly basis and average daily error
3. Percentage error of a month.
4. An adaptive BP learning algorithm which leads to faster convergence of network learning is presented.
5. Extensive testing with load data of MGVCL, DGVCL, PGVCL, UGVCL system indicates that ANN provides very accurate results.

On the basis of the above mentioned features one can conclude that ANNs are quite effective for short term load forecasting in power systems.

5. Similarly can develop model for all the month to improve the accuracy of load forecasting with consideration of correlation, which reduce training time drastically as compare to individual model.

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APPENDIX - I

DGVCL Load Profile Jan 2014.

Forecasted Load (MW)	Actual Load (MW)	ANN Error (%)	Forecasted Error (%)
1739	**1732**	0.612	-0.380
1734	**1712**	0.025	-1.273
1703	**1676**	-0.003	-1.620
1621	**1618**	-0.001	-0.164
1611	**1609**	-1.114	-0.130
1677	**1681**	-0.004	0.228
1739	**1765**	0.014	1.463

1781	**1764**	-0.003	-0.954
1934	**1907**	0.001	-1.397
2005	**2005**	-0.886	-0.018
2014	**2043**	-0.021	1.406
1970	**2015**	-1.432	2.234
1888	**1926**	-0.013	1.973
1875	**1912**	-0.268	1.921
1915	**1978**	-1.548	3.196
1909	**1955**	-0.021	2.312
1842	**1903**	0.020	3.207
1851	**1918**	-2.156	3.487
1968	**2046**	-0.021	3.768
1968	**2055**	-0.017	4.216
1908	**1961**	-0.018	2.670
1834	**1912**	0.672	4.056
1792	**1854**	0.005	3.369
1799	**1867**	-0.009	3.655
Avg. % Error		-0.258	1.551

	DGVCL	
Date	ANN Model Error	Forecasted Error
1 Jan 2014	-0.197100936	1.551000257
2 Jan 2014	0.396255816	2.158860471
3 Jan 2014	0.397281358	0.475508878
4 Jan 2014	0.085093547	-0.599850708
5 Jan 2014	-0.250679526	0.559948857
6 Jan 2014	-0.322502767	1.315391364
7 Jan 2014	-0.218442457	1.926358677
8 Jan 2014	-0.53398065	1.428650052

APPENDIX - II

PGVCL Load Profile Jan 2014.

Forecasted Load (MW)	Actual Load (MW)	ANN Error (%)	Forecasted Error (%)
2840	2778	-0.01726	-2.24947
2770	2770	0.002206	0.002206
2810	2797	-2.58506	-0.47398
2730	2700	-2.56811	-1.12802

2740	2767	0.01062	0.986303
3000	2986	4.121272	-0.45446
3100	3102	-0.71487	0.078818
3480	3353	0.00915	-3.77816
3530	3473	2.46472	-1.63294
3510	3458	0.004196	-1.4995
3510	3411	-0.01199	-2.91472
3460	3392	-1.73627	-1.99757
3310	3231	2.771746	-2.44392
3160	3063	-0.00467	-3.17165
3230	3233	-0.00482	0.087973
3320	3221	0.014089	-3.05906
3270	3197	-0.01179	-2.29545
3290	3182	0.000361	-3.39372
3120	3062	-0.00967	-1.90404
2870	2805	0.010655	-2.30639
2810	2730	0.007505	-2.92268
2830	2806	0.000887	-0.85442
2810	2803	0.780496	-0.26604
2830	2806	0.000887	-0.85442
Avg. % Error		0.105594	-1.60189

	PGVCL	
Date	ANN Model % Error	Forecasted % Error
1-Jan-14	-0.257856007	0.234935483
2-Jan-14	0.105594377	-1.601886152
3-Jan-14	-0.166723951	-0.980291269
4-Jan-14	-0.383627052	0.821551191
5-Jan-14	-0.426679725	-0.732213396
6-Jan-14	-0.085615949	0.181071398
7-Jan-14	-0.003674708	-0.198170212
8-Jan-14	-0.124163862	-1.020907055

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