Indian Journal of Science and Technology, *Vol 10(25), DOI: 10.17485/ijst/2017/v10i25/112807, July 2017*

ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Electrical Load Forecasting using GFF Neural Network-A Sensitivity Analysis Perspective

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Abstract

Objective: Prediction of Short term electrical load forecasting with the help of Sensitivity Analysis. **Methods/Statistical Analysis:** Traditional and Intelligent methods are available for electrical load forecasting. As the results from traditional methods are not accurate, modern methods like neural networks are preferred to predict the electrical load. **Findings:** There are various parameters used for prediction of electrical load. By performing sensitivity analysis significant inputs can be identified and load can be predicted. Accuracy is maintained even after performing sensitivity analysis. **Application/ Improvements:** The complexity of the electrical load forecasting system can be reduced.

Keywords: Forecast, Neural network (NN), Short-Term Load Forecasting (STLF), Sensitivity Analysis

1. Introduction

The prime concern in present situation is energy. To get continuous supply to the customers there must be an appropriate assessment of present and upcoming requirement for of electricity. To provide reliable power to the consumer, careful assessment should be done. As the number of equipments, which affects the electrical load increases, the complexity increases. To reduce the complexity sensitivity analysis is used. With the help of sensitivity analysis, significant input parameters are identified. We predict the load and calculate the Mean Absolute Percentage Error (MAPE). Input data is taken from Andhra Pradesh Southern Power Distribution Company Limited and National Atomic Research Laboratory, GADANKI.

2. Load Forecasting

Load forecasting is however a difficult task. It deals with the situation of existing and upcoming load demand. Load prediction is utilized in load dispatch, unit commitment etc.

It is divided into 3 categories viz, Short term, medium term and long term forecasting depending on the duration for which the load is to be predicted.

The nature of these predictions is totally diverse. The period of this era varies from one utility to different utilities. According to the weather conditions, most of the corporations take the last 25-30 years of information to predict the load demand. The aim of STLF is to forecast the load for a period of hours, days and weeks ahead. Humidity and temperature are the foremost weather factors. The future load is predicted by inserting the predicted weather information in to the predetermined relationship[1]. Social variables that have an effect on the load due to work, faculty & diversion. Load varies according to seasonal effects.

2.1 Significant Factors for Forecasts

Selection of proper inputs to predict the load is an important task here. The inputs are given below such as,

- Past load
- Time
- Temperature

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- Humidity

The above are the most significant in forecasting the load demand. Weather is an important factor for household and farming customers, and also changes the load report of industry customers. Humidity and temperature plays an important role in evaluating the load precisely.

Diversified models, changing in the complexity of functional form and evaluation procedures, has been anticipated for the enhancement of forecasting precision[3]. Past data is nothing but the existing real time data.

2.2 Methods for Electrical Load Forecasting

Most forecasting methods have already been tried out to carry forecasting as shown in figure 1. They are divided into two wide categories like traditional and intelligent methods[4].

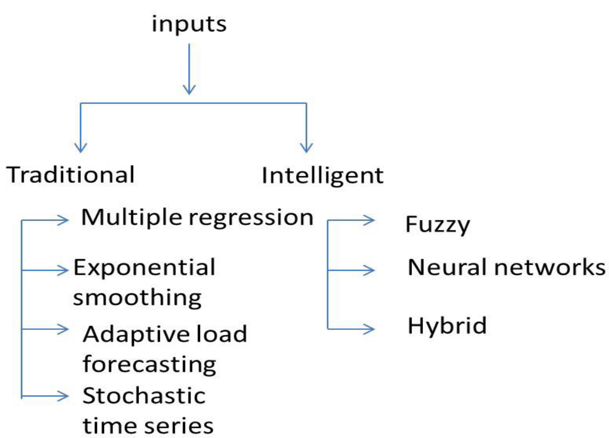

Figure 1. Different types of load forecasting.

3. Neural Networks (NN)

A neural system uses a diverse approach to crack problems than that of traditional systems which employ an algorithmic approach. If neural networks are used intelligently they can generate remarkable results. Neural networks (NN) possess good number of applications in various fields of engineering and economics because of their ability to learn[5,6]. In this paper we have used generalizes feed forward neural network to predict the load. Inputs layers are connected to hidden layers and output layers further through weights which dictate learning in neural networks. In each epoch the output weights are updated using back propagation algorithm to improve the hidden layer weights.

3.1 Artificial Neural Network

Artificial neural network is inspired the human brain and it mimics the behavior of brain[8]. ANNs are able to handle the interactions as shown in figure 2. It does not require complex mathematical model to describe the associations between the inputs and the load. They use the back propagation algorithm, which is a gradient-decent technique.

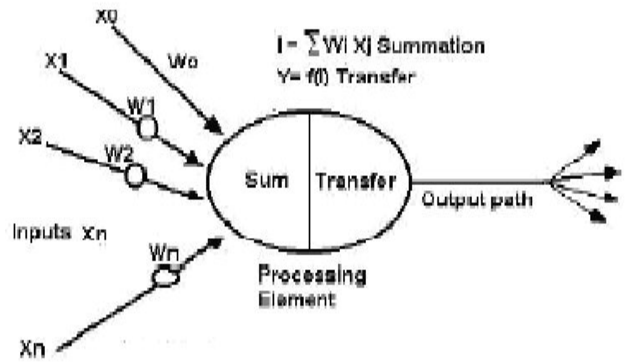

Figure 2. Working principle of ANN system.

Neural networks are of different types depending on their architecture and the type of learning which is used. They are categorized as multilayer neural network, SOFM network, recurrent neural networks etc. Each and every network may contain hidden layers. The sum of weighted inputs is compared with a threshold value to generate the desired output. We have different types of learning strategies to train the neurons. For back propagation we use supervised learning.

3.1.1 Supervised

Here the learning is done with the help of a supervisor or teacher component. The actual output of the system will be compared with the desired output and the error is generated. Depending on this error the weights will be adjusted and the process will continue to generate new output. In this manner the error can be minimized.

3.2 Feed Forward Network

This network is basically an interconnection of neurons in which the information flow is in one direction i.e forward direction as shown in figure 3. It contains one or more layers of computation nodes[9]. An MLP is also called as FFN. The information will transmit in the network layer by layer and is entirely connected to the last layer. The input layer consists of input nodes which receive input signals and each input has a weight. A sigmoid activation function is used to generate the output.

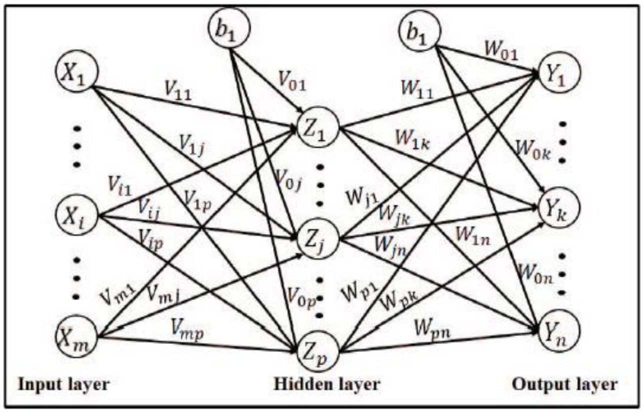

Figure 3. Multilayer perceptron (MLP).

Stage- I: Feed forward:

$$Zinj = Voj + \sum_{i=1}^{n} x_i * Vij \qquad (1)$$

$$Yinj = Wok + \sum_{j=1}^{p} z_j * Wjk \qquad (2)$$

Stage- II: Back propagation:

$$\delta_k = (tk-yk)*f'(yink) \qquad (3)$$

$$\delta_{inj} = \sum_{k=1}^{m} \delta_j * Wjk \qquad (4)$$

$$\Delta\delta j = \delta inj * f'(Zinj) \qquad (5)$$

Stage- III: Weights updating:

$$Wjk\ (new) = Wjk\ (old) + \Delta Wjk \qquad (6)$$

Table 1. Results for 24 hours with various factors

Actual Load (mw)	Predicted Load(mw)	Error(1)	Predicted Load	Error(2)	Predicted Load	Error(3)
50	57.6317	15.2634	56.597	13.194	49.861	0.2778
50	53.9683	7.9366	56.3301	12.6602	49.156	1.6864
50	54.0388	8.0776	56.3545	12.709	49.205	1.5888
50	54.6642	9.3284	56.4239	12.8478	49.492	1.0146
50	55.4342	10.8684	56.5557	13.1114	50.019	0.0388
60	55.7471	7.088167	56.5439	5.760167	49.787	17.021
60	56.2777	6.203833	56.6451	5.5915	50.142	16.428
60	56.592	5.68	56.6402	5.599667	50.011	16.648
60	57.0305	4.949167	56.705	5.491667	50.240	16.266
60	57.3277	4.453833	56.7017	5.497167	50.275	16.208
60	57.7855	3.690833	56.8238	5.293667	50.705	15.490
57	57.1627	0.285439	56.5641	0.764737	49.772	12.68
55	57.512	4.567273	56.7308	3.146909	49.904	9.2645
57	57.5241	0.919474	56.7167	0.497018	49.973	12.327
50	57.4975	14.995	56.667	13.334	49.862	0.275
25	57.3705	129.482	56.577	126.308	49.570	98.281
47	57.3957	22.11851	56.5973	20.41979	49.666	5.6727
50	57.2988	14.5976	56.5299	13.0598	49.534	0.9314
65	57.4279	11.64938	56.6153	12.89954	49.832	23.334
65	57.4329	11.64169	56.605	12.91538	49.834	23.332
65	57.3796	11.72369	56.5793	12.95492	49.709	23.523
60	57.3192	4.468	56.5526	5.745667	49.659	17.233
55	57.3701	4.309273	56.5764	2.866182	49.742	9.5598
55	57.4554	4.464364	56.6442	2.989455	49.809	9.4374
Average error		13.2817		13.59		14.521

$$Wok = Wok\ (old) + \Delta Wok \quad (7)$$

$$Vij\ (new) = Vij\ (old) + \Delta Vij \quad (8)$$

$$Voj = Voj\ (old) + \Delta Voj \quad (9)$$

4. Sensitivity Analysis

Sensitivity Analysis that finds how sensitive an output is to any change in input while further inputs kept constant. Sensitivity Analysis is used for Short Term Load Forecasting to identify the significant inputs.

Sensitivity analysis assists to make the assurance in the model by studying the uncertainties that are frequently related with inputs. Sensitivity analysis tests the effects of varying parameter values of a model through a defined range and observing the resultant changes in the outcome[10]. Sensitivity analysis graphically represents the effects of input variables.

Sensitivity Analysis has been performed to reduce the number of inputs by ensuring the performance of the forecasting system will remain same. By using this analysis the complexity of the system is reduced. Sensitivity analysis results in finding the significant parameters which are necessary to predict the accurate output and the correlation between the parameters and output.

5. Results and Discussion

Various input parameters are used to predict the load. So the complexity in load forecasting increases using all parameters. The number of input parameters can be opti-

Table 2. Results for four input parameters

Actual Load	Predicted Load(MW)	Error 1	Predicted Load	Error 2	Predicted Load	Error 3
50	54.311	8.622	53.463	6.9278	51.9202	3.8404
50	54.318	8.6362	53.466	6.9326	51.9207	3.8414
50	54.356	8.7132	53.471	6.9422	51.9217	3.8434
50	54.455	8.9106	53.484	6.9682	51.9239	3.8478
50	54.582	9.1652	53.499	6.998	51.9262	3.8524
60	54.512	9.1451	53.489	10.850	51.9248	13.458
60	54.632	8.9466	53.501	10.830	51.9266	13.455
60	54.595	9.0075	53.496	10.839	51.9259	13.456
60	54.642	8.9296	53.501	10.831	51.9266	13.455
60	54.622	8.963	53.5	10.833	51.9264	13.456
60	54.711	8.8146	53.508	10.819	51.9275	13.454
57	54.416	4.5329	53.480	6.1749	51.9239	8.9054
55	54.339	1.2012	53.466	2.7890	51.9216	5.5970
57	54.379	4.5971	53.472	6.1880	51.9225	8.9078
50	54.355	8.71	53.467	6.9342	51.9212	3.8424
25	54.268	117.07	53.456	113.82	51.918	107.67
47	54.294	15.520	53.452	13.727	51.9193	10.466
50	54.269	8.5384	53.468	6.9366	51.9185	3.837
65	54.348	16.386	53.467	17.742	51.9213	20.121
65	54.342	16.3967	53.459	17.755	51.9211	20.121
65	54.294	16.4693	53.457	17.757	51.9196	20.123
60	54.276	9.5385	53.460	10.899	51.9195	13.46
55	54.290	1.29072	53.456	2.8065	51.9199	5.6001
55	54.267	1.33181	53.445	2.8190	51.9192	5.6014
Average error		13.3099		13.588		13.926

mized by using sensitivity analysis. We can calculate the error with the help of MAPE[12]. It is the better measurement to find accurate errors.

$$\text{MAPE}=\frac{\left(\frac{actual\ load - predicted\ load}{actual\ load}\right)}{n} * 100 \quad (10)$$

Table 1. Indicates MAPE for 8 input parameters like temperature, humidity, sun duration, battery voltage etc without using sensitivity analysis.

After performing Sensitivity Analysis the number of input parameters can be reduced to four which include humidity, temperature, time and past load.

Table 2. Indicates MAPE for 4 input parameters

6. Conclusion

The Short term load forecasting has been performed using Generalized Feed Forward network. The real time data for training is taken from APSPDCL and NARL. MAPE is use as a performance metric for the above load forecasting. The MAPE is 13.28%, when we consider the eight possible inputs to predict the electrical load. The Sensitivity analysis can be performed here to identify the significant inputs. With this analysis, we consider only four inputs and eliminated the other four inputs which are insignificant. Again the load forecasting is performed with reduced number of inputs and the MAPE is found to be approximately same i.e., 13.3%. It is concluded that the performance of electrical load forecasting doesn't vary even though some insignificant inputs were eliminated from the system. Due to the sensitivity analysis the model became less complex and the convergence time will also be less.

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