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 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. 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
• 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. 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.

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. In this paper we have used generalized 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. 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. 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.

Stage- I: Feed forward:

$$Z_{inj} = \sum_{i=1}^{n} x_i^t V_{ij}$$

$$Y_{inj} = \sum_{j=1}^{p} z_j W_{jk}$$

Stage- II: Back propagation:

$$\delta_k = (t_k - y_k) f'(y_{inj})$$

$$\delta_{inj} = \sum_{k=1}^{m} \delta_k W_{jk}$$

$$\Delta \delta_{ij} = \delta_{inj} f'(Z_{inj})$$

Stage- III: Weights updating:

$$W_{jk} (new) = W_{jk} (old) + \Delta W_{jk}$$

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   | 56.3031        | 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    |
| 57               | 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         |          |                |          |
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\[ W_{\text{ok}} = W_{\text{ok (old)}} + \Delta W_{\text{ok}} \quad (7) \]
\[ V_{\text{ij (new)}} = V_{\text{ij (old)}} + \Delta V_{\text{ij}} \quad (8) \]
\[ V_{\text{oj}} = V_{\text{oj (old)}} + \Delta V_{\text{oj}} \quad (9) \]

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. 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 optimised by using sensitivity analysis. Sensitivity analysis results in finding the significant parameters which are necessary to predict the accurate output and the correlation between the parameters and output.

Table 2. Results for four input parameters

| Actual Load | Predicted Load(MW) | Error 1 Predicted Load | Error 2 Predicted Load | Error 3 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\(^\text{12}\). It is the better measurement to find accurate errors. 

\[
\text{MAPE} = \frac{\sum_{i=1}^{n} |\text{actual load} - \text{predicted load}|}{\sum_{i=1}^{n} \text{actual load}} \times 100 \quad (10)
\]

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.

7. References

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