© 2016 IJSRSET | Volume 2 | Issue 2 | Print ISSN : 2395-1990 | Online ISSN : 2394-4099
Themed Section: Engineering and Technology

Short Term Load Prediction in Distributed System Using Machine Learning

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ABSTRACT

Accurate forecasts of electrical substations are mandatory for the efficiency of the Advanced Distribution Automation functions in distribution systems. Artificial Neural Network (ANN) model have been extensively implemented to produce accurate results for short-term load forecasting with time lead ranging from an hour to a week. The proposed system describes the design of a class of machine-learning models, namely neural networks, for the load forecasts of medium-voltage/low-voltage substations. Four weather seasons are defined by the Meteorological Department, India. Each season includes the group of month. Representative months are selected from each season by observing the variation in load behavior patterns. An input vector composed of load and temperature values at previous instants, is employed to train ANN designed for each selected month by using Back-Propagation algorithm with Momentum learning rule. We focus on the methodology of neural network model design in order to obtain a model that has the best achievable predictive ability given the available data. ANN testing is carried out and their performance is evaluated using mean absolute percentage error (MAPE) criterion. Finally, error values are compared for each month and hence the deviation in forecasting ability of ANN is observed for each month and season.

Keywords : Artificial Neural network, Short-term Load Forecasting, Back Propagation Algorithm

I. INTRODUCTION

The smart grid imports healthy changes to the existing electricity system. The affiliation between customers, electricity supplier, and distribution system operator (DSO) becomes complex. The customers play an active role such as adapting their electricity consumption to the dynamic electricity. The situation is both challenging and benefiting for DSO. To receive a more capable and transparent distribution system, it is mandatory to provide the advanced distribution automation functions, with accurate load forecasts. The current paper describes the design of a neural network-based predictive model for the 1-year forecasting of medium-voltage/low-voltage (MV/LV) substation load.

Artificial Neural Network (ANN) approach is enforced to forecast the short-term load for a large power system. A nonlinear load model is advanced and several structures of ANN for short-term load forecasting are certified. Inputs to the ANN are previous (past) loads and the output of the ANN is the load forecast for a disposed day. The network with one or two hidden layers is certified with various consolidations of neurons, and the outcomes are compared in rate of forecasting error. The neural network, when group into various load patterns, gives optimized load forecast. This work introduces a study of short-term Yearly load prediction using Artificial Neural Networks (ANNs).

II. METHODS AND MATERIAL

1. Problem in the Load Forecasting Based On Neural Network

A. Principle of Load Forecasting Based on Neural Network

Among the neural network based models used for load forecasting, the static one, implemented as a feed forward neural network, has been used most successfully. This model can be portraying by the following equation:

$$\hat{L}_{t+1} = f(t, L_t, L_{t-1}, \delta_t) + \varepsilon_{t+1}$$

where t is time of day, L_t and L_{t-1} is the load at time t and t-1

Correspondingly, $\hat{L}_{t+1}$ is the load forecasting value at time t+1, ε_{t+1} represents a random load component, and δ_t is the load deviation between the current time interval and the previous time interval. The nonlinear function f is approximated by a neural network. The structure of neural network based STLF model is showed as Fig.1. The feed forward neural network model has a total of 4 layers and the node number of each layer is 4, 10,5, 1. The inputs of the neural network are t, L_t, Lt_{-1} and δ_t. The forecasting load at following time interval $\hat{L}_{t+1}$ is the output of the neural network. The trained neural network model by the historical load data can realize load forecasting t at following time interval.

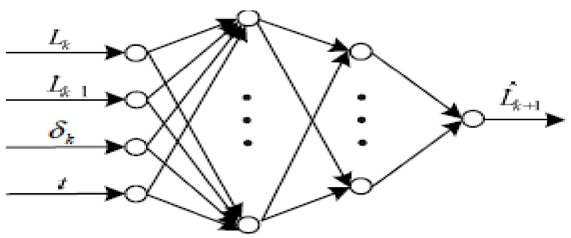

Figure 1. Neural Networks Model

B. Problems of Neural Network Based STLF Method

The load data were collected from a region for this research. The solid line curve in Fig.2 shows a plot of the summer load data of one day in 15-minute interval. The data set have 96 points. The forecasting data based on neural network are showed as the dashed line in Fig.2. The data set of other days will be used for testing and validating the model. The figure show that the errors between the real load data and the forecasting load data are larger near each peak, especially when the slope difference on both side of a peak is large. So the forecasting data must be processed to improve the forecasting accuracy. The rough set theory can extract knowledge from data as a tool of knowledge discovery, data mining and data processing.

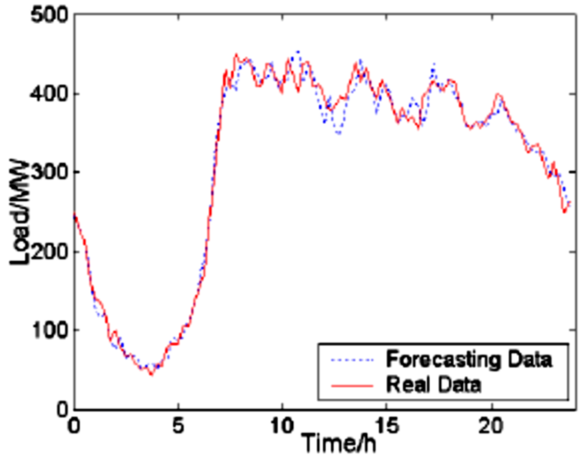

Figure 2. Real load data and the corresponding forecasting data

2. Back Propacation Algorithm

Multiple layer perceptron's have been enforced successfully to determine some tough diverse issues by training them in a supervised aspect with a highly suitable algorithm known as error back-propagation algorithm. The Back Propagation Algorithm is based on the error-correction training rule. It may be explored as a observation of an equally suitable filtering and adaptive algorithm the least mean square (LMS) algorithm. Error back-propagation learning subsist of two passes over the different layers of the network: a forward pass and a backward pass. In the forward pass, an input vector is activated to the nodes of the network, and its effect propagates over the network layer by layer. Finally, a set of outcomes is composed as the actual response of the network. In the time of forward pass the weights of the networks are all fixed. At the time of backward pass, the weights are all adjusted in consonance with an error correction rule. The actual acknowledgement of the network is subtracted from a desired response to yield an error signal. This error signal is then propagated backward over the network, against the direction of synaptic connections. The weights are altered to make the absolute response of the network move closer to the desired response. A multilayer perceptron has three distinctive characteristics:

1. The model of each neuron in the network includes a nonlinear activation function. The sigmoid function is

commonly used which is defined by the logistic function:

$$y = \frac{1}{1+\exp(-x)}$$

Another commonly used function is hyperbolic tangent.

$$y = \frac{1-\exp(-x)}{1+\exp(-x)}$$

The presence of nonlinearities is important because otherwise the input- output relation of the network could be reduced to that of single layer perceptron.

2. The network contains one or more layers of hidden neurons that are not part of the input or output of the network. These hidden neurons enable the network to learn complex tasks.

3. The network exhibits a high degree of connectivity. A change in the connectivity of the network requires a change in the population of their weights.

A. Learning Process

To represents the process a three layer of neural network with two inputs and one output, which is demonstrated below, is used.

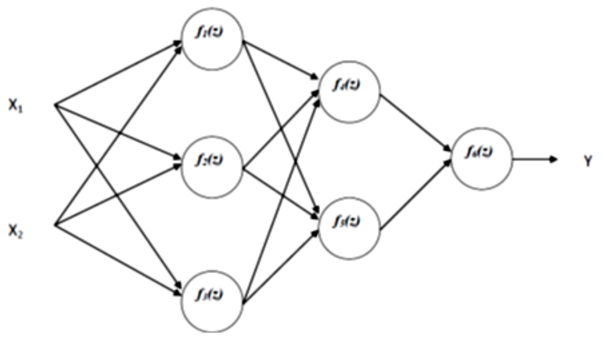

Figure 3. Three layer neural network with two inputs and single output

Signal z is adder output signal, and *y = f(z)* is outcome signal of nonlinear aspect. Signal *y* is also outcome signal of neuron. The practicing data set contains of input signals (*x1* and *x2*) appointed with correspondent target (desired output) *y'*. The network practicing is an iterative process. In each and every iteration weights coefficients of nodes are altered using new modern data from practicing data set. Symbols w_{mn} assume the weights of connections among outcome of neuron *m* and input of neuron *n* in the next layer. Symbols y_n shows outcome signal of neuron *n*.

$$y_1 = f1(w_{11}\, x_1 + w_{21}\, x_2)$$
$$y_2 = f2(w_{12}\, x_1 + w_{22}\, x_2)$$
$$y_3 = f3(w_{13}\, x_1 + w_{23}\, x_2)$$
$$y_4 = f4(w_{14}\, y_1 + w_{24}\, y_2 + w_{34}\, y_3)$$
$$y_5 = f5(w_{15}\, y_1 + w_{25}\, y_2 + w_{35}\, y_3)$$
$$y_6 = f6(w_{46}\, y_4 + w_{56}\, y_5)$$

The desired outcome value (the target), which is found in practicing data set. The variance is called error signal δ of outcome layer neuron.

$$\delta = y'' - y$$
$$\delta_4 = w_{46}\, \delta$$
$$\delta_5 = w_{56}\, \delta$$
$$\delta_3 = w_{34}\, \delta_4 + w_{35}\, \delta_5$$
$$\delta_2 = w_{24}\, \delta_4 + w_{25}\, \delta_5$$
$$\delta_1 = w_{14}\, \delta_4 + w_{15}\, \delta_5$$

When the error signal for each neuron is enumerates, the weights coefficients of each neuron input node may be modified. In formulas *df(z)/dz* represents derivative of neuron activation function. The correction $w_{ij}(n)$ applied to the weight connecting neuron *j* to neuron *i* is characterized by the delta rule:

Weight correction = learning rate parameter*local gradient*i/p signal of neuron *i*

$$\Delta w_{ij}(n) = \eta\, .\, \delta_i(n)\, .\, y_j(n).$$

The local gradient $\delta_i(n)$ depends on whether neuron i is an outcome node or a hidden node:

i. If neuron *i* is an output node, $\delta_i(n)$ equals the product of the derivative $df_i(z)/dz$ and the error signal $e_i(n)$, both of which are associated with neuron i.

ii. If neuron *j* is a hidden node, $\delta i(n)$ equals the product of the associated derivative *dfi(z)/dz* and the weighted sum of the δ_s computed for the neurons in the next hidden or output layer that are connected to neuron *j*.

B. Flow Chart

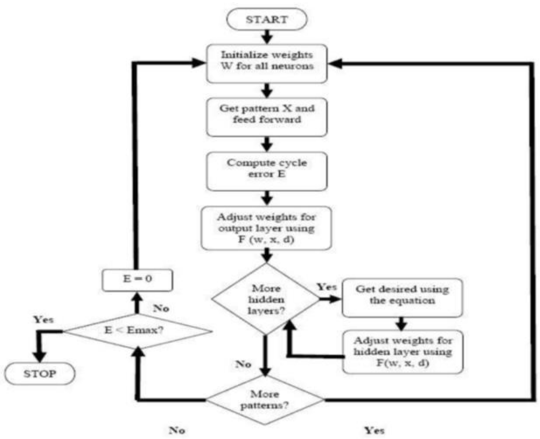

Figure 4. Flowchart showing working of BPA

C. Load Forecasting Using ANN

Short-term power load forecasting is used to afford utility company management with prospective information about electric load demand in order to assist them in working more economical and reliable day-to-day Activities. The power load during the year followed the same as well as daily and weekly periods of electric load, which shows the daily and weekly cycles of human activities and behavior template, with some cyclical and random modification.

The connotation of space cooling on the electric load is very clear during the summer time. When temperature rises, the demand for electricity also rises. On the other hand, in the wintertime the reversal relationship between temperature and electric demand exists by cause of the need for space heating. When temperature decline, the load demand for electricity rises.

C. Approach

A broad spectrum of factors induce the systems load level such as cyclic-time effects, trend effects, and weather effects, random effects as human activities, rainstorm and load management. Thus the load portrait is dynamic in nature with seasonal, temporal and annual variations. In this project we developed a system that predicted 24 hour at a time load demand. The inputs took as the past 24 load and the day of the week, month and year. The inputs were fed into Artificial Neural Network (ANN) and after sufficient practicing were used to predict the load demand for the next week, month and year. The inputs given are:

1. Hourly load demand for the full day.
2. Day of the week.
3. Min/Max/ Average daily temperature (Melbourne).
4. Min/Max daily Humidity (Melbourne).
5. Daily wind speed (Melbourne).

And the output obtained was the predicted hourly load demand for the next day. The flow chart is shown below.

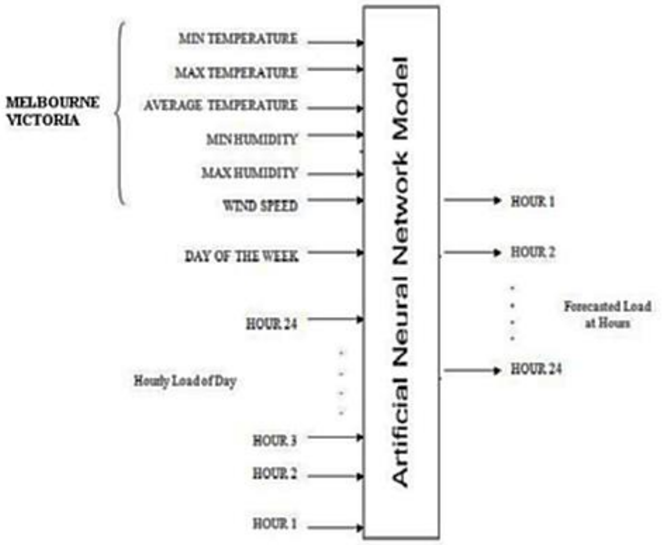

Figure 5. Input-Output Schematic for Load Forecasting.

III. RESULTS AND DISCUSSION

The outcomes achieved from examinations the trained neural network on current data for month over a one year duration are presented below in graphical form. The Graph shows a frame of both predicted and actual load. The absolute mean error AME (%) among the predicted and actual loads for every individual day has been estimated and given in the table. This assumes the role of a high degree of exactitude in the ability of neural networks to forecast electric load.

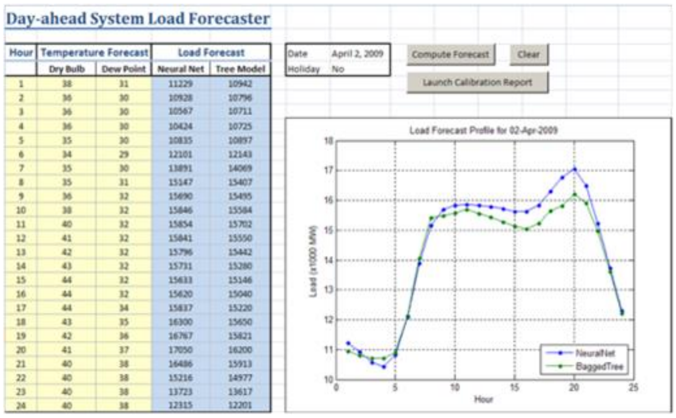

Figure 6. Graph for prediction and actual load

IV. CONCLUSION

The outcome of network specimen used because a year ahead short term load forecast as long as the Victorian region, expos that network has a satisfying achievement and feasible prediction efficiency was achieved for this approach. Its forecasting accuracies were analyzed out by computing the mean absolute error among the perfect and predicted values. We were capable to achieve an Absolute Mean Error (AME) of which shows a high degree of accuracy. The outcomes suggest that ANN model with the developed framework can perform good prediction with minimum error and finally this neural network could be a necessary tool for short term load forecasting. Future studies on this work can incorporate additional information into the network so as to secure a more representative forecast of future load.

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