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Research Paper

Load Forecasting Analysis by Time Series Method

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Abstract

Load forecasting is a very important factor for designing power systems. A good knowledge of load pattern and behavior is very important for proper coordination, design and economic operation. Though a lot of research has been done on load forecasting, there are many tools and methods still being developed to accurately predict load behavior. This paper does an analysis of sample load data and predicts the next instant load using feedforward time series neural network model

Keywords: *ANN, Neural Network, Short Term Load Forecasting, Time Series, Feed Forward*

1. Introduction

Load forecasting is a way of estimating what future electric load will be for a given forecast horizon based on the available information about the state of the system [1]

Classification of load forecasting methods:

a) Long-term forecasting: Months to years. This is used to supply electric utility company management with prediction of future needs for expansion, equipment purchases, or staff hiring
b) Mid-term forecasting: Weeks to months. This is used for the purpose of scheduling fuel supplies and unit maintenance
c) Short-term forecasting: Hours to weeks. This is used to schedule the generation and transmission of electricity
d) Very short-term forecasting: Shorter than a day. This is used to supply necessary information for the system management of day- to-day operations and unit commitment.

A. Factors influencing system load behaviour [2]

1) Time of day, the day of the week, workdays, holidays, and weekends
2) Weather factors include temperature, humidity, precipitation, wind speed, cloud cover, light intensity.
3) Economic factors, such as the degree of industrialization, price of electricity and load management policy have significant impacts on the system load growth/decline trend.
4) Random disturbance factors like start and shut down of large loads, erratic loads etc

B. Characteristics of loads [3]

Time dependant loads can vary over the week. Loads on weekdays and weekends are different. Even weekdays neighboring weekends, like Mondays and Fridays, loads can be different from that midweek. Holidays can have load patterns similar to weekends if they are midweek, but may vary if they are neighboring the weekends. Religious festival holidays can have a different pattern than non religious holidays.

2. Short Term Load Forecasting

Short-Term Load Forecasting (STLF) is basically aimed at predicting system load with a leading time of one hour to a few days, which is necessary for adequate scheduling and operation of power systems. It is used for planning the installation, and the operation on a day to day basis. STLF must be accurate, quick, portable, and must be able to sort out bad data automatically.

Load forecasting methods can be broadly classified as parametric and artificial intelligence methods.
* Parametric methods use previous data as a reference. They can be regression, similar day approach.
* Artificial intelligence methods consist of Artificial Neural Networks (ANN), Fuzzy logic, Expert Systems (ES), Machine Learning, Support Vector Machines (SVM) and Hybrid.

3. Time Series

Time series depend on historical load data to predict future load. These models assure that the load term in stationary and treat any abnormal data as bad data [4]. Load is considered as a time series signal with known seasonal, weekly, and daily periodicities. These periodicities give a rough prediction of the load at the given season, day of the week, and time of the day. The difference between the prediction and the actual load can be considered as a stochastic process. Stochastic means situations, patterns or phenomenon which are unpredictable. The traditional time series and regression methods are simple, but not accurate. They cannot handle nonlinear data. Most of the conventional load forecasting methods use either time series or regression approaches. But due to the non linear nature of the load, the results of these two approaches are not that accurate [3].

Time series refers to data taken at regular time intervals. Here, past events are used as reference to predict the next events. The past values at a particular time period are checked for patterns to extrapolate the future values. A prediction problem is a special case of approximation problems, in which the function values are represented using a time series. A time series is a sequence of values measured over time units. To make predictions, a training set is extracted from the series. Short-term predictions are one-lag, long term are multi-lag predictions. In one-lag prediction, next value is forecasted only on actual past values. If input data is a1 to a5, prediction at the 6th instant, p6 is made only using actual data from a2 to a5.

In multi-lag prediction, predicted values are appended to input database and used to predict future values. Value of the sixth instant predicted without knowing the values of the next five instants

p6 predicted from a1, a2, a3, a4, a5
p7 predicted from a2, a3, a4, a5, p6
p8 predicted from a3, a4, a5, p6, p7
and so on.

Prediction problems constitute a special subclass of function approximation problems in which the values of variables are determined from values at previous instants. Two classes for prediction are-
-Recurrent networks
-Feedforward networks

*** Recurrent Neural Networks:**
Contain connections from output nodes to hidden and/or input layer nodes. They allow interconnections between nodes of the same (hidden) layer.

*** Feedforward networks:**
Simple gradient descent procedures do not perform well in complex prediction tasks which have many local optima. An external input vector x(t) is transformed into a preprocessed vector x'(t) and supplied to the feedforward network. The feedforward network is trained to compute the desired output value for a specific input x'(t).

x(t) consists of single input x(t)
x'(t) consists of vector (x(t-1),x(t-2)) supplied as input to the feedforward network.

Preprocessing consists of storing past values of the variable and supplying them to the network along with the latest value. Also called Tapped Delay line Neural Network (TDNN) consisting of a sequence of delay units or buffers with the values of variables at recent instants being supplied to the feedforward predictor component [5].

For a short term forecasting, feedforward time series can be suitable [6].

4. Case Study

The preliminary work can be divided into tasks as below:
a. Collection of data and pre-processing:
The research work requires collecting load data. This data first needs to be sorted according to the type of day (weekdays, weekends, holidays etc.). This study is based on the data provided by Bengaluru Electric Supply Company (BESCOM) for the month of March 2016. The data for a single day of March 1 is taken for training the feedforward neural network.
b. The sorted data must then be normalized, that is, reduced to a base value.

A. What is Normalization?
By normalizing the data, all values come in the range of 0 to 1, making calculation easier. Data in all columns is reduced to a base value such that values fall in the range from 0 to 1. The highest value is taken as the base and all data in that column are divided by the base. To normalize this data, all column data are divided by the maximum value in that column.

Table 1: Actual and normalized data

Actual	Normalized
4141	0.887674
4045	0.867095
4341	0.930547
4665	1
4542	0.973633
4454	0.95477

For example, in the table above, the maximum value in the column is 4665 MW. This is used as a base, and all the values in the column are divided by it. 4141/4665 = 0.887674. Even the time instant column values, whether in hours, days or weeks, are normalized. If time instant column is also used in the processing, if it is over a period of 24 hours, then the base will be the largest number 24, and all values in this column will be scaled to 24.

B. Why normalize data?
Usually neural networks work with data between 0 and 1, or -1 and +1. Data pre-processing, that is scaling and normalizing, makes the training faster and more accurate. Once processed, the data is denormalized to get the actual values.

The network used is nonlinear autoregressive neural network (NARNET) using single input. NARNET predicts the targets series only using past values of the target series. NAR neural networks can be trained to predict a time series from that series past values. One lag predictive model with a delay of one datum variable is used. The transfer function used is hyperbolic tangent sigmoid. The maximum training epochs is limited to 2000 and increasing this number may lead to overfitting. The data taken is for a period of 23 hours in one single day. It is randomly divided into training and testing data.

Different training functions were tried in MATLAB [7] and their responses are below:
traingdm: Gradient descent with momentum backpropagation. Updates weight and bias values according to gradient descent with momentum. Epochs can go up to 1000, but more errors can be seen.

traingdx: Gradient descent with momentum and adaptive learning rate backpropagation. Updates weight and bias values according to gradient descent momentum and an adaptive learning rate. Epochs can go just above 100 with more errors.

trainlm: Levenberg-Marquardt backpropagation. Updates weight and bias values according to Levenberg-Marquardt optimization. Stops after few epochs and has lot of errors.
trainscg: Scaled conjugate gradient backpropagation. Updates weight and bias values according to the scaled conjugate gradient method. Stops after few epochs and has lot of errors.

trainrp: Resilient backpropagation. Updates weight and bias values according to the resilient backpropagation algorithm. Stops after few epochs and has lot of errors

trainoss: One-step secant backpropagation. Updates weight and bias values according to the one-step secant method. Stops after few epochs and has lot of errors

trainbr: Bayesian regularization backpropagation.
The function updates the weight and bias values according to Levenberg-Marquardt optimization. It minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well. Good results were seen when the network was trained multiple times.

The training function used in Bayesian regularization backpropagation. Since there is no clear number for the number of hidden neurons to be used for the best training, the dataset is trained with different number of hidden neurons. The number of hidden neurons depends on the number of input variables used, input dataset types used. Here one dataset is used which is reused by the network to predict the next time instant variable.

For a set of 23 variables, for a 23 hour period, initially the network is trained using Bayesian regularization backpropagation. This trained network is then used to predict the next time instant, that is the 24th instant, by giving a delay of one. The network trained multiple times for the best responses give the best number of hidden neurons for this set of data as 40. As noted earlier, this number of hidden neurons may vary depending on the type and number of inputs.

5. Observations

The graphs comparing the delayed response output

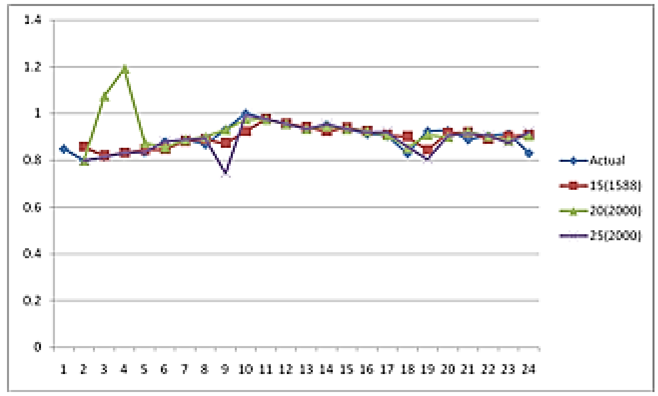

Fig 1: Actual data and 15, 20, 25 hidden neurons

As can be seen from the Figure 1, the graph line with diamond markers represents the actual data. The numbers represent the number of hidden neurons and the numbers in brackets represent the maximum epochs reached.

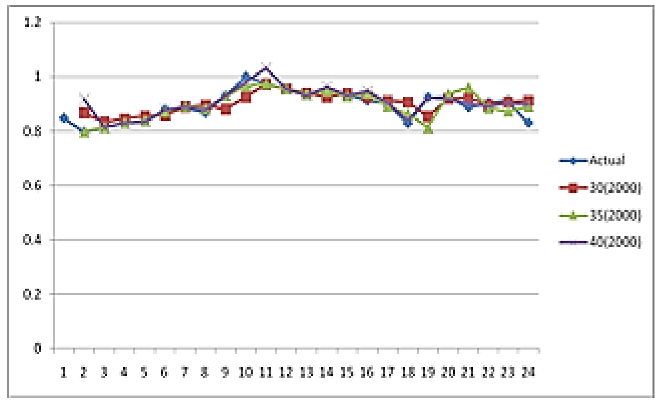

Fig 2: Actual data and 30, 35, 40 hidden neurons

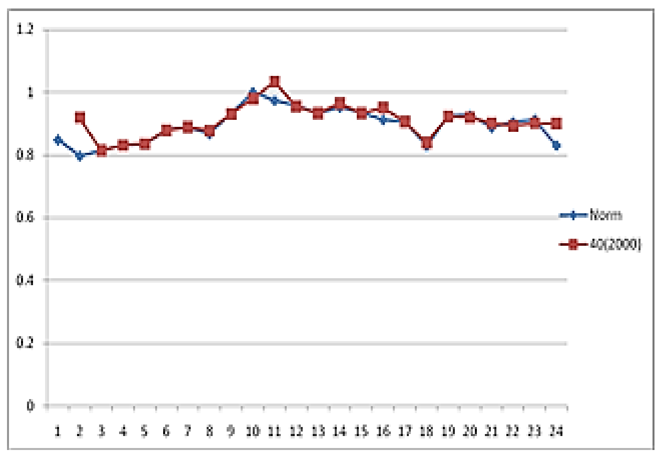

Fig 3: Comparison of the actual and predicted for 40 hidden neurons

This graph is a comparison of the actual data with the outputs for a single delay trained network, for different hidden neurons. The network is fed with 23 data variables, and the time series feedforward network uses them to predict the next time instant value, the 24th one. A comparison of the actual data and the predicted outputs for all these hidden number of neurons.

The BESCOM data available for March 1, at the 24th hour is 3870 MW, which equals to 0.82958 when normalized. The predicted value for the network with 40 hidden neurons is 0.899563 with an error of -0.069983, as also can be seen from the Figure 3.

When the trained network is applied to a completely fresh test data, of March 2, it can be seen that the results are not too accurate

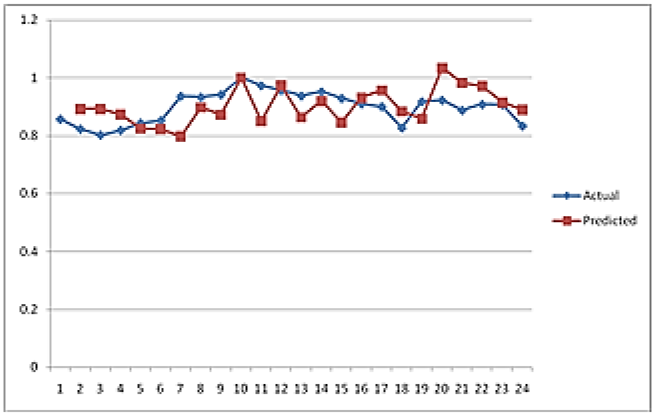

Fig 4: Test data results

6. Conclusion

As noted earlier, in a one lag or multilag feedforward time series model, the previous data is carried forward to predict the subsequent values. It may be observed here that the data sample taken here is raw data as it is, without any segregation. More accurate results can be had by segregating the data into components such as time of day, or type of day, like a holiday, weekday. One of the limitations of using only time series model is that it does not take into account the weather factor. A combination of two or more models will yield more accurate results. Future scope of this work is in his regard.

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