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Half Hourly Electricity Load Prediction using Echo State Network

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Abstract: ***Prediction of time series is a task that cannot be efficiently done by using feed forward neural network. Recurrent neural network are the suitable neural networks for time series prediction task. Electricity load series is also a kind of chaotic time series. In this paper a echo state network is proposed to calculate the electricity load after half an hour. No other type of data is used for prediction except the previous electricity load values. The predicted values obtained from various simulation runs are very close to the actual value.***

Keywords: Recurrent Neural Network, Time Series prediction, Echo State Network, Electricity load forecasting.

1. Introduction

Forecasting can be defined as a planning tool that helps management in its attempt to cope with the uncertainty of the future, relying mainly on data from the past and present and analysis of trends. Accurate models for electric power load forecasting are essential to the operation and planning of a utility company [5]. Load forecasting helps an electric utility company to make important decisions including decisions on purchasing and generating electric power, load switching and infrastructure development.

Load forecasts can be divided into three categories: short-term forecasts which are usually from one hour to one week, medium forecasts which are usually from week to a year and long-term forecast which are longer than a year [3].

The aim of this paper is to predict the electricity load after half an hour using Echo State Networks. The electric load values can be considered as a time series and the future value of this time series is going to be predicted by the proposed method.

Time series methods are based on the assumption that the data have an internal structure, such as autocorrelation, trend, or seasonal variation [21]. The significance of prediction models is particularly important in the field of financial engineering where they have been a subject of research for several decades. Many financial models contain some sort of time series forecasting in order to adequately predict future market movements. First models have been based on traditional statistical linear or nonlinear techniques. However, none of these techniques have continuously shown satisfactory prediction success rates owing to the presence of noise and nonlinearity in forecasting financial markets, together with the fact that much is assumed and little is known about the nature of the financial engineering processes [13].

The task of time series prediction can informally be stated as follows: given several past values of the series, predict its future value(s) within predefined horizon. Depending on the horizon length prediction tasks are generally divided into short –term predictions and long-term ones [3].

This work is focused mainly on short term predictions. The major research thrust in this area is determining better network architectures, because the commonly used feed–forward back–propagation network offers good performance, but this performance could be improved by using recurrence or reusing past inputs and outputs. The motivation behind using recurrence is that some patterns may repeat in time. A network which remembers previous inputs or feedbacks previous outputs may have greater success in determining these time dependent patterns.

This paper is organized as follows. The ESN is introduced in Section II. The proposed prediction algorithm is discussed in Section III. Section IV gives the forecasting simulation result and discussion. Finally a conclusion is drawn in Section V.

2. Echo State Network

The ESN system architecture contains three layers: an input layer, a hidden layer, and an output layer, just as illustrated with Figure 1. The hidden layer is called dynamic reservoir (DR). DR consists of a large number of neurons, usually about 20~500 neurons and the values of the connection weights in DR are created randomly. ESN exploits the dynamics of this large randomly initialized dynamic reservoir for extraction of interesting properties from the input sequence. The output layer is notes as a readout, which is made of some neurons in parallel; the number of the readout neurons is equal to the output number [20].

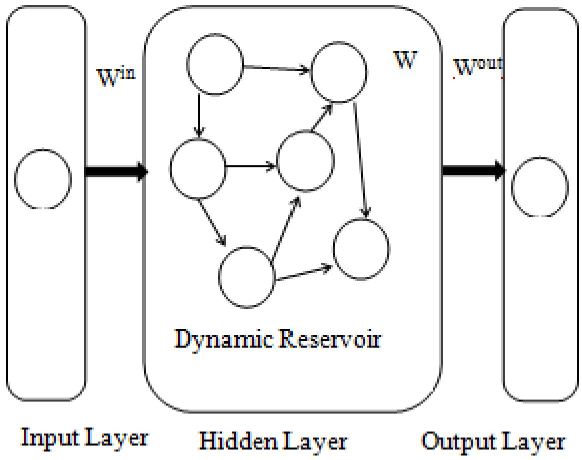

Figure 1: Echo State Network

Basically in Echo State Networks a huge dynamic reservoir is used which is the source of dynamic behaviour of the neural network. ESN provides fast and simple algorithm for supervised learning.

Let us assume that ESN has L inputs, M outputs and N hidden neurons. The weights of the connections from input layer to the hidden layer are W_{in} , the weights within the hidden layer are W and the weights from the hidden layer to the output layer are W_{out} . The sizes of the weight matrices W_{in}, W, W_{out} are respectively N.L, N. N, M.N. All other weights except W_{out} are initialized randomly. The only weight trained in ESN is W_{out}. Activations of the input layer at time step n are $u(n)=(u_1(n),\ldots\ldots.u_k(n))$. Activations of the hidden layer are $x(n)=(x_1(n),\ldots\ldots\ldots.x_N(N))$ and the activations for the output layer are $y(n)=(y_1(n),\ldots\ldots.y_L(n))$.

The activation of hidden layer is updated according to

$$x(n+1)=f(W_{in}u(n+1) + Wx(n) + W_{back}y(n)) \quad (1)$$

where f is typically sigmoidal function.

3. Proposed Algorithm

In the proposed system first a data set is selected. The data set is a chaotic time series of load. 80% of this time series data will be used as training data and 20% time series data will be used as test data. The input is first normalized and a Echo State Network is constructed with a random dynamic reservoir. The training data is inputted to this ESN to compute the output weights. Once we are done with the training data, the network is ready for prediction. Now the network is tested with the test data.

The proposed block diagrams of the system are shown in Figure 2 and Figure 3.

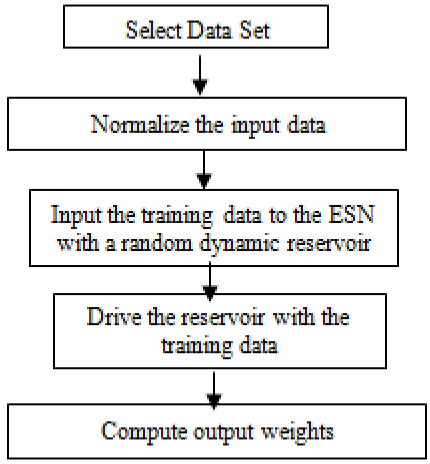

Figure 2: Block diagram of training the Echo State Network

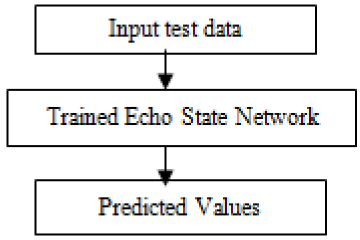

Figure 3: Block diagram of testing the Echo State Network

The proposed system will be able to forecast the values for short term. The algorithm consists of five steps as follows:

Step 1:
Remove missing and zero values from the input data.

Step 2:
The data to be processed is first normalized using the following equation:

$$data_{new} = \frac{data - data_{min}}{data_{max} - data_{min}} \quad (2)$$

where
$data_{new}$ is the normalized data
data is the input data
$data_{min}$ is the minimum load value in the input data
$data_{max}$ is the maximum load value in the input data

Step 3:
Build an untrained Recurrent Neural Network (W_{in}, W) which has the echo state property:
a) Generate a random weight matrix W_0.
b) Normalize matrix W_0 to matrix W_1 with spectral radius of W_0,$W_1 = W_0/W_1$ has now unit spectral radius.
c) Scale matrix W_1 to matrix W with a < 1, W = a $\cdot W_0$. W has now a spectral radius of a.
d) Generate random weight matrices W_{in} .

Step 4 :
Sample the RNN training dynamics:
a) Initialize arbitrarily the state of the units.
b) Run the RNN by driving it with the teaching input signal and by applying the equation:

$$x(n+1)= (1-a)\times x(n) + a\times \tanh(W_{in}\times u(n+1) + W\times x(n)) \quad (2)$$

where tanh is the sigmoidal function used in the proposed algorithm.

c) Collect remaining input and network states row-wise into a matrix M.

d) Collect simultaneously the remaining training pre-signals into a column vector T.

Step 5:

Compute the output weights:

a) Multiply the pseudo-inverse of M with T:

$$(W_{out})^t = M^{-1} \cdot T \qquad (3)$$

whose i-th column contains output weights from all network units to the i-th output unit.

b) Transpose (Wout)t to Wout

4. Simulation Experiment

The data set used for training and testing purpose is taken from the UP Electricity Board. It is a series of electric load of household measured half hourly. The data from January 30 ,2014 to March 15, 2014 are used to predict the half hourly load. Each day comprises of 48 data points. Figure 4 shows a plot of the input data which shows that the input series is very chaotic and non linear in nature.

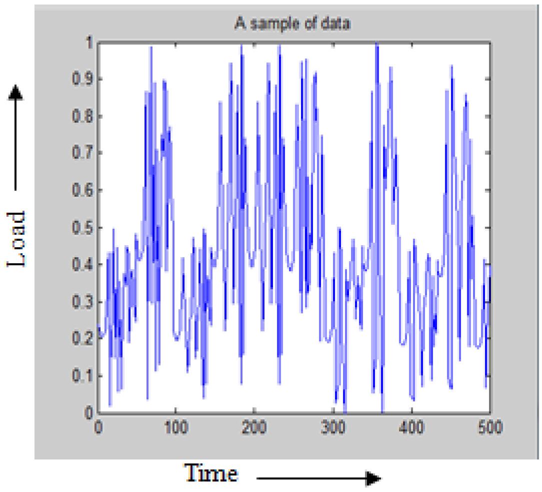

Figure 4: A Sample of the input data

Figure 5 is showing the comparison graph of actual load and the predicted load.

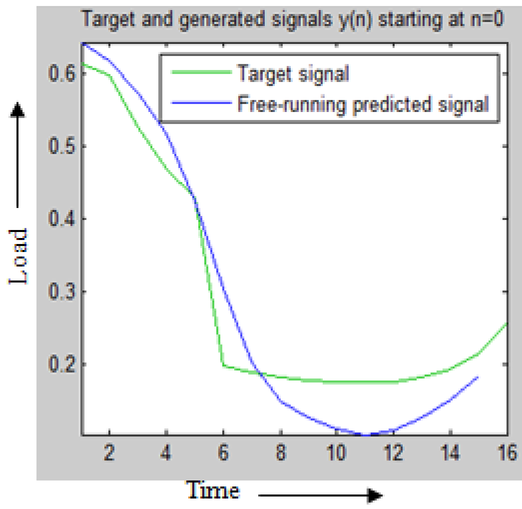

Figure 5: Predicted Vs Actual Data

The prediction performance has been measured by the root-mean-squared error (RMSE) on the test sequence.

$$NRMSE = \sqrt{\sum_{t=0}^{T_n} \frac{(A(i) - F(i))^2}{T_n}}$$

where A(i) is the actual load value and F(i) is the predicted value. T_n is the value of the time interval upto which the values are predicted.

5. Conclusion

An ESN-based short-term electric load prediction algorithm is proposed in this paper. It is verified on the half hourly load. It is demonstrated from the results of the experiment that the proposed algorithm is much efficient and faster. In this algorithm weights from output layer to the hidden layer W_{out} are not considered which saves computation time. The NRMSE obtained is 0.00237, which is negligible. Electric load prediction is very difficult task and is influenced by many factors like, temperature, humidity, weekday, economy class etc. Impact of these external factors needs to be worked out.

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