Forecasting Electricity Demand Using Dynamic Artificial Neural Network Model

Mohammad Y. El-Sharkh
University of South Alabama
Mobile, Alabama 36688-002

Mohammad Anwar Rahman
The University of Southern Mississippi
Hattiesburg, MS 39406 USA

Abstract

Electricity demand forecast plays an important role in the energy section. The future demand for electricity is the basis for the respective electricity production planning, distribution and development mechanism, crucial for economic development in a country. Electricity usage is a rapidly grown phenomenon in developing region, increasingly complex to forecast. Artificial neural networks (ANN) have been applied to many complex and high-dimensional forecasting problems. The inference of ANN concerns the imitation of the human brain functioning, emerged as a great performance tool to obtain classification, pattern recognition and complex forecasts. Layer recurrent neural network (LRNN) is a dynamic neural network uses a feedback and time delay element, the output is based on the current input and the pervious input and output. This paper considers dynamic neural network model that implement LRNN principles to forecast household Electricity demand. LRNN is a sequential network rather than a combinational, made the networks fault-tolerant.

Keywords
Artificial neural networks, Layer recurrent neural network

1. Layer Recurrent Neural Network:

Precise demand forecasts and the equilibrium between energy consumption demand and its sourcing is of vital interest. It is considered indispensable to effectively manage energy planning and sourcing for industrial and economic development.

The artificial neural network (ANN) is inspired by the human biological neural network. ANN can capture any relationship between a set of input and out for a system without any prior knowledge of the nature of the system. The captured information is stored in the internal weights between neurons. Layer recurrent neural network (LRNN) is classified as one of the dynamic neural network. Unlike static neural network (feed forward neural network), the dynamic neural network has a feedback and time delay element. The model incorporates the feedback and the time delay element. The output of dynamic network is based on the current input and the pervious input and output. In addition, because of the feedback, recurrent networks are sequential rather than combinational which makes recurrent networks to be fault-tolerant. This paper considers nonlinear dynamic neural network model that implement LRNN principles to model non-stationary time series with multiple input variables. The simulation results shows that the model is competent to capture multiple predictants in a complex non linear systems and exhibits efficient forecast

Many approaches have been considered for electricity demand (or load) forecasting, including multiple regression models [1], time-varying splines [2]), and artificial neural networks [3]. Neural networks have been used in many different applications that include, linear/nonlinear prediction [1]-[7] and filtering [8]-[10] and modeling and identification of nonlinear system [11]-[13]. The LRNN has been used much less frequently for electricity demand forecast. The LRNN have been applied to complex and high-dimensional forecasting problems. These methods are very different in terms of model constituents and functionality in terms of providing useful approximations of model parameters for forecasting.

This paper presents the details of the Layer recurrent neural network and electricity consumption demand analysis. Section 2 outlines the constituents of LRNN Model. Section 3 focuses on LRNN performance analysis, results and model validation. Conclusions drawn from the study are discussed in the last section.

2. Constituents of LRNN Model

ANN models generally consist of a combination of layers made of neurons, which is widely known as ANN multi layer perceptron (MLP) for forecasting. This method is very different in terms of model constituents and functionality in order to provide useful approximations of model parameters for forecasting. ANN models have been successfully used to forecast linear and non-linear model processes. The application of ANN models in short-term and long-term energy demand forecasting is presented in literatures [6, 7, 8]. In designing an ANN-MLP for time series forecasting, the variables that are depended to develop the model process include the number of input, hidden and output neurons are important. There are no specific ways to determine these parameters, but through the iteration process. For example, the number of input neurons needed to develop the forecasting model can be identified only through trial and error and heuristic approaches [9]. Similarly, determination of number of hidden layers, hidden neurons and number of output neurons are important for model development and its performance. These parameters are also subjective, depends on the experimental design, experience and judgment of the forecaster. To obtain the best performance in prediction, ANN model requires an experimental approach to analyze the ANN design space and application of different training strategies.

Using a feedback with one time delay around each layer of the network except for the output layer and enough recurrent layer neurons and delay, the LRNN can predict the dynamic output from the past input [1]. The proposed LRNN consists of a fully connected two-layer network. The input layer receives five inputs namely: (a) the electricity price, (b) the TV price index, (c) the refrigerator price index, (d) the urban house hold size, and (e) the urban base house hold income. Based on the five inputs the network will be used to predict the electric load. The network is used to predict the load value one year ahead of the current year based on the current and previous input values. The network has one hidden layer with ten neurons. Each neuron has a tan-sigmoid activation function and four layer-delays. The output layer has one neuron with linear activation function, which will produce the predicated load value. MATLAB™ software is used to train the proposed LRNN using the Levenberg-Marquardt technique. The proposed LRNN is illustrated in Figure 1.

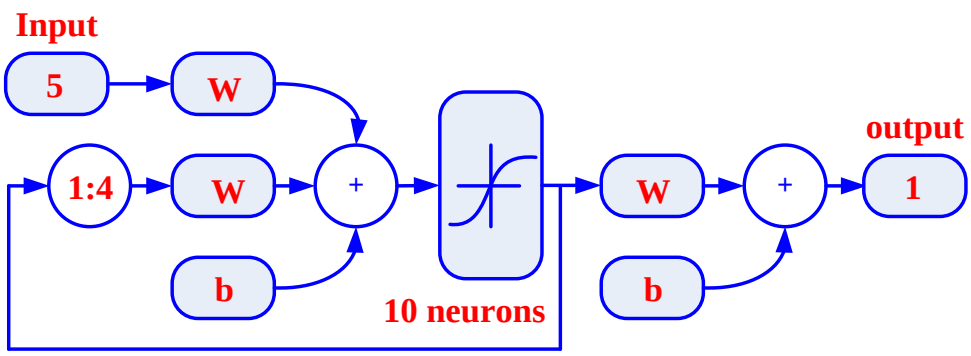

Figure 1. Layer recurrent neural network

Referring to [14], the load data along with the electricity price, the TV price index, the refrigerator price index, the urban house hold size, and the urban base house hold income are available for the period between 1974 and 2003. The available data is divided into a training set and testing set. The training set includes the data for the input and the output for the period between 1974 and 1995. The training data is then converted to a time series and used to train the proposed layer recurrent neural network. The remaining data (1996-2003) is used to validate the performance of the proposed layer recurrent neural network. During the training, the first four data points (input and output data) are reserved as initial values for the four layer-delays. The neural network training process is shown in figure 2. As shown in figure 2, the training program successfully drove the mean square error between the predicated and the actual load value to $1.0921*10^{-19}$ at iteration 6.

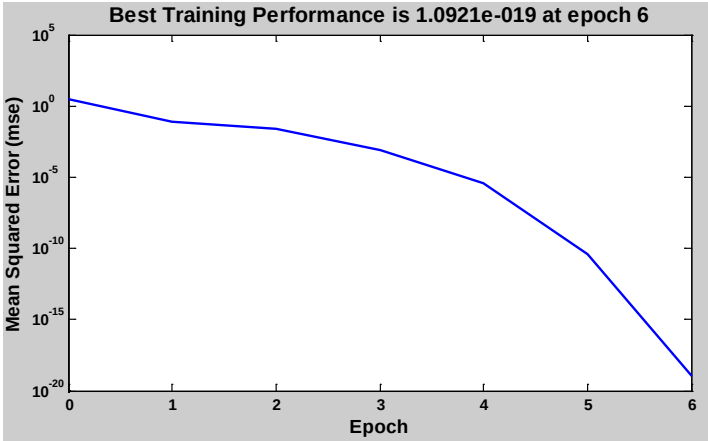

Figure 2. Training performance of layer recurrent network

3. LRNN Performance Analysis

To validate the performance of the proposed layer recurrent neural network, the network is tested with the training data set and the testing data set. When tested with the training data set, the network produced the exact load values as the target. The obtained results were expected since the mean squared error (mse) was $1.0921*10^{-19}$ as shown in Figure 2. With the testing data set, the network predicted and actual load values are shown in figure 3 and given in Table 1. As shown in figure 3, the proposed neural network successfully predicted load with small deviation from the actual load values. The root mean square error between the predicated and the actual load value is 439.

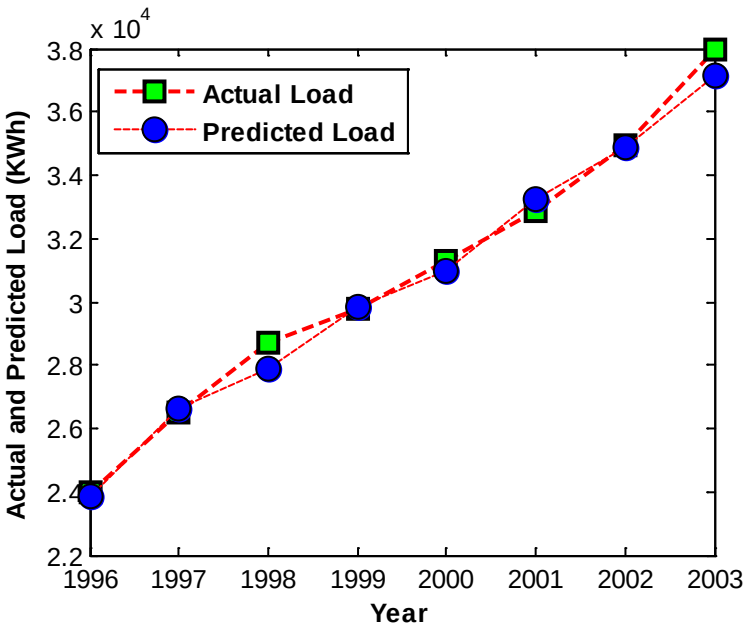

Figure 3: Actual and predicted load value using testing data

Table 1. The exact values of the predicted and actual load value

Load	1996	1997	1998	1999	2000	2001	2002	2003
Actual	23993	26523	28686	29754	31266	32891	34946	37967
Predicted	23828	26613	27882	29838	31004	33250	34880	37160

4. Conclusion

The method that has been proposed for computing the electricity consumption demand forecast is a layer recurrent neural network (LRNN) model, which is classified as one of the dynamic neural network model. It is widely recognized that the classical neural network forecasting procedures are not adequate to draw a fair forecast conclusion for non-stationary, nonlinear time series. In light of current practices, LRNN method has appeared to be suitable for the energy sector forecasts. This study shows that the change in electricity price, urban household size, price index of various household electrical appliances, and urban household income have important implication for energy use. With the increase of the urbanization, and urban household income, the total domestic energy consumption can be expected to increase irrespective of price increase of electricity and electrical appliances.

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