Neural Networks in Forecasting Electrical Energy Consumption

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Abstract

This paper presents an artificial neural network (ANN) approach to electric energy consumption (EEC) forecasting. In order to provide the forecasted energy consumption, the ANN interpolates between the EEC and its determinants in a training data set. In this study, two ANN models are presented and implemented on real EEC data. The first model is a univariate model based on past consumption values. The second model is a multivariate model based on EEC time series and a weather dependent variable, namely, degree days (DD). Forecasting performance measures such as mean square errors (MSE), mean absolute deviations (MAD), mean percentage square errors (MPSE) and mean absolute percentage errors (MAPE) are presented for both models.

Introduction

Electric energy consumption forecasting is a crucial component of any energy management system. Traditional forecasting models can be classified as time series or regression models. Various techniques for forecasting energy consumption have been proposed in the last decade. Specifically, Multivariate modeling along with cointegration techniques (Dincer and Dost 1997; Eltony and Hosque 1997; Eltony and Al-Mutairi 1995; Eltony 1996; Ranjan and Jain 1999; Nasr, Badr and Dibeh 2000) are used to study the impact of different determinants on energy demand in different countries. Also, univariate modeling such as the AutoRegressive Moving Average (ARMA) modeling technique has been successfully used for forecasting (Abdel-Aal and Al Garni 1997). Neural and abductive network models have also been successfully used for energy forecasting (Al-Shehri 1999; Abdel-Aal, Al-Garni and Al-Nassar 1997; Park et al. 1991). The determinants of electricity consumption have also been studied using econometric models (Nasr, Badr and Dibeh 2000). Moreover, autoregressive and ARIMA modeling was applied (Saab, Badr and Nasr 2001).

In this paper, two models were built to forecast electrical energy consumption (EEC) in Lebanon using artificial neural networks (ANN). The first model is a univariate and fully connected model based on past EEC values. The second model is a multivariate not fully connected model based on past degree days (DD) and EEC time series. The monthly DD data is calculated from the daily mean temperatures obtained from climatological monthly bulletins (Ghaddar, 1995-1999). DD is used to indicate the days requiring energy usage for comfortable indoor living.

ANN Implementation

The study period spans the time period from 1995 to 1999. This period is used to train, test and evaluate the ANN models. The training of the models is based on a three year training set, January 1995 to December 1997 while the testing stage covers the period from January 1998 to February 1999. The evaluation stage covers the period between January 1998 and December 1999.
Since the purpose of this paper is to forecast future data, the backpropagation algorithm is used. This method is proven to be highly successful in training of multi-layered neural nets.

The training of the network by backpropagation consists of three stages:

- The *feedforward* of the input training pattern.
- The *calculation* and *backpropagation* of the associated error.
- The *adjustment* of the *weights*

Before applying the BPN algorithm, two steps are required:

1. Initialize Weights: the weights from the input layer to the hidden layer and the weights from the hidden layer to the output layer are randomly chosen to have values between –0.5 and 0.5.
2. Normalize data: The monthly data are normalized in order to have values between 0.1 and 0.9. The formula used is the following:

$$\frac{Data-Min}{Max-Min} \times (Hi - Lo) + Lo$$

Where:
Min = Monthly minimum data.
Max = Monthly maximum data.
Hi = 0.9 = Maximum value for the normalized data.
Lo = 0.1 = Minimum value for the normalized data.

The ANN models are implemented in a C program using Microsoft Visual C++. This program is used to train, test and evaluate the net.
The C program involves many steps:

1. The weights are chosen randomly.
2. The learning rate, the momentum parameter and the slope parameter are initialized.
3. The minimum test error is initialized to the maximum real value.
4. The data are normalized.
5. The training data set is used more than once.
6. The net is tested using the testing data set and the test error is computed.
7. If the test error is less than the minimum test error, the weights are saved and the test error will be the minimum test error.
8. Otherwise, if the net is tested for more than 100 times, the weights are restored.
9. Otherwise, step 4 to 7 are repeated.
10. The net is evaluated. The mean square error (MSE), the mean absolute deviation (MAD), the mean percentage square error (MPSE), and the mean absolute percentage error (MAPE) are calculated.

ANN Models

Model I

Since present and future electric energy demand depends on previous electric energy consumptions, a univariate ANN model is implemented. The ANN model I (EEC model) requires real monthly EEC data as input parameters and has the structure as shown in Figure 1. The network architecture selected consists of an input, a hidden layer and an output layer. This model is a fully connected model since each input unit broadcasts its signal to each hidden unit. The parameters are selected following extensive testing by varying the values of the learning rate, the momentum parameter, the slope parameter and the number of input units. Parameter values yielding lowest error figures are given in Table 1. The error measures used in this study are the mean square error (MSE), the mean absolute deviation (MAD), the mean percentage square error (MPSE) and the mean absolute percentage error (MAPE).

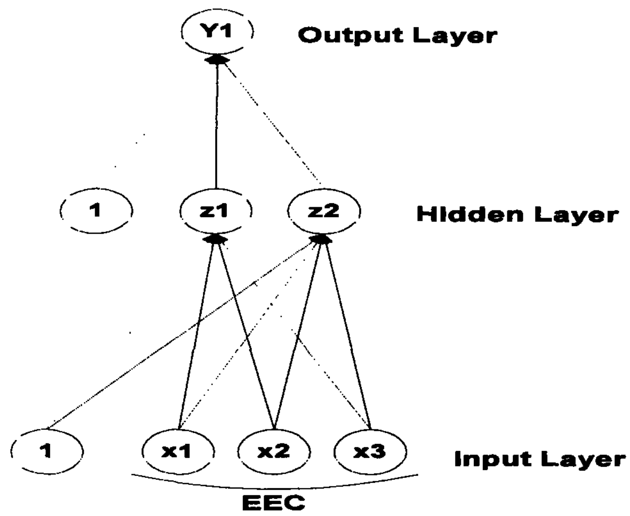

Figure 1. ANN Model I

Experiments show that varying the parameters above or below the values in Table 1 decreases the performance of the built model. In addition, the training becomes unreasonably long. The prediction results are shown in Figure 2.

Table 1: Model I Parameters and Errors

Parameters and Errors	Value
Learning Rate (α)	2.5
Momentum Parameter (μ)	0.45
Slope Parameter (σ)	1
Input Units	3
MSE	2641.4027
MAD	38.3841
MAPE	5.0303
MPSE	0.4498

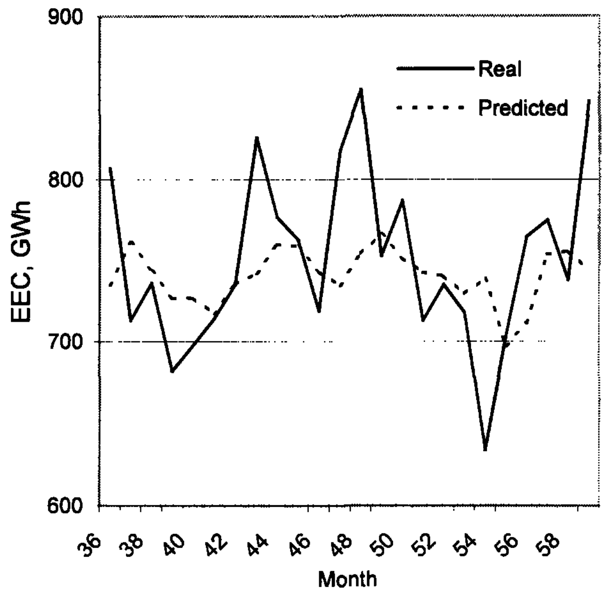

Figure 2. Actual and Forecasted Data using Model I

Model II

Since DD has been shown to be a determinant of EEC (Nasr, Badr, and Dibeh 2000), model II (EEC-DD model) is based on two sets of data, namely, EEC and DD. This model is partially connected as shown in Figure 3. Each set of inputs has its own hidden nodes. The three EEC input nodes are fully connected to two hidden nodes while the five DD input nodes are fully connected to other four hidden nodes.

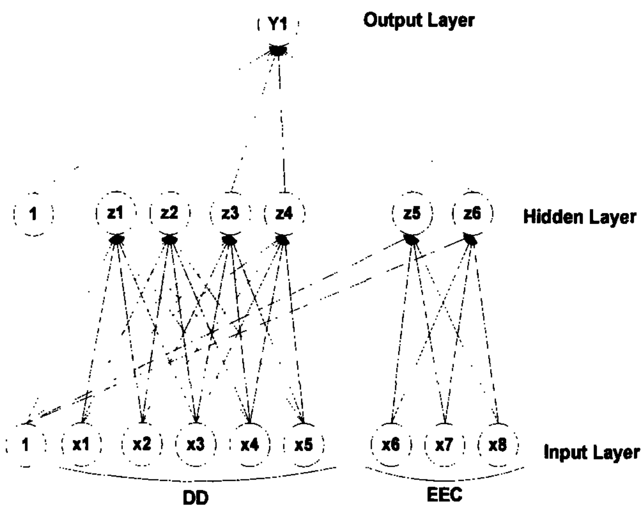

Figure 3. ANN Model II

The output of all hidden nodes are then fully connected to the output node. Model II is also tested for different values of the learning rate, the momentum parameter, the slope parameter and the number of input units. Moreover, model II is found to yield lower error figures for the parameter values shown in Table 2. It is important to note that testing results concerning the number of EEC and DD inputs is consistent with the seasonality of EEC and DD data sets. In addition, the prediction results are shown in Figure 4.

Table 2: Model II Parameters and Errors

Parameters and Errors	Value
Learning Rate (α)	5.0
Momentum Parameter (μ)	0.6
Slope Parameter (σ)	1
DD Input Units	5
EEC Input Units	3
MSE	1862.936
MAD	33.0795
MAPE	4.4327
MPSE	0.3490

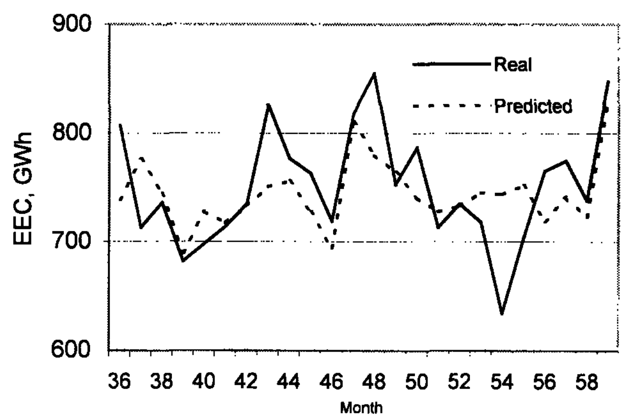

Figure 4. Actual and Forecasted Data using Model II.

Conclusion

In this study, two Artificial Neural Network models are built and used to predict electrical energy consumption. The first model is a univariate model with three electrical energy consumption (EEC) input units and is a fully connected model. The second model is a multivariate partially connected model and has both EEC and degree days (DD) as input units. To build the models, the network is processed into three stages: the training stage, the testing stage and the evaluation stage. The training algorithm used in this study is the *backpropagation* algorithm. This algorithm allows the input signal to be broadcasted to the output layers, then the error is computed at the output layer and propagated back to the input layer to adjust the weights so that the network is trained.

The models are trained, tested and evaluated using electrical energy consumption and degree days data from Lebanon during the period extending from January 1995 to December 1999. Both models show good forecasting performance using the traditional error measures namely, the mean square error (MSE), the mean absolute deviation (MAD), the mean percentage square error (MPSE) and the mean absolute percentage error (MAPE). Also, the multivariate model outperforms the univariate model.

References

Abdel-Aal, R. E. and Al-Garni, A. Z. 1997. Forecasting monthly electric energy consumption in eastern Saudi Arabia using univariate time-series analysis. *Energy* 22 (11): 1059-1069.

Abdel-Aal, R. E., Al-Garni, A. Z. and Al-Nassar Y.N. 1997. Modeling and forecasting monthly electric energy consumption in eastern Saudi Arabia using abductive networks. *Energy* 22 (9): 911-921.

Al-Shehri, A. 1999. Artificial neural network for forecasting residential electrical energy. *International Journal of Energy Research* 23 (8): 649-661.

Dincer, I. and Dost, S. 1997. Energy and GDP. *International Journal of energy Research* 21 (2): 153-167.
Eltony, M.N. 1996. Demand for natural gas in Kuwait: An empirical analysis using two econometric models. *International Journal of Energy Research* 20 (11): 957-963.

Eltony, M.N. and Al-Mutairi, N.H. 1995. *Demand for gasoline in Kuwait. Energy Economics* 17 (3): 249-253.

Eltony, M.N. and Hosque, A.A 1997. Cointegrating relationship in the demand for energy: The case of electricity in Kuwait. Journal of Energy and Development 21 (2): 293-301.

Ghaddar N. 1992-1999. *American University of Beirut Climatological Data-Monthly Reports.* AUB Press. Beirut, Lebanon.

Nasr, G.E., Badr, E.A. and Dibeh, G.L. 2000. Econometric modeling of electricity consumption in postwar Lebanon. *Energy Economics* 22 (6): 627-640.

Park, D.C., El-Sharkawi, M.A., Marks, R.J., Atlas, L.E. and Damborg, M.J. 1991. Electric load forecasting using an artificial neural network. *IEEE Transactions on Power Systems* 6 (2): 442-449.

Ranjan, M. and Jain, V.K. 1999. Modeling of electrical energy consumption in Delhi. *Energy* 24: 351-361.

Saab, S., Badr, E.A.and Nasr, G.E. 2001. Univariate Modeling and Forecasting of Energy Consumption: The case of Electricity in Lebanon. *Energy* 26 (1): 1-14.