Application of Neural Networks for the Prediction of the Energy Consumption in a Supermarket

Savvas Tassou
Brunel University London

D. Marriott

Application of Neural Networks for the Prediction of the Energy Consumption in a Supermarket

D. Datta and S. A. Tassou
Department of Mechanical Engineering, Brunel University
Uxbridge, Middlesex UB8 3PH

D. Marriott
Safeway Stores Plc
6 Millington Road, Hayes, Middlesex UB3 4AY

Abstract:

It has been shown by previous researchers that Artificial Neural Networks (ANNs) not only be used to predict energy more reliably than traditional simulation models and regression techniques but can also from the basis for a predictive controller of thermal systems such as HVAC equipment. This work is directed towards the identification of the important inputs (independent variables) to facilitate on-line prediction and thereby implement refrigeration and HVAC system diagnostics, process control, optimisation and energy management in retail food stores. This paper presents preliminary results on the prediction of electricity consumption with different independent input variables in a supermarket. The paper also compares the prediction performance of neural networks with the more traditional multiple regression techniques.

INTRODUCTION

Most Supermarkets in the UK qualify to join the competitive power market and thus they purchase power from a pool established by the Power generating companies on a half hourly basis. The half hourly rate paid by the supermarket owner to the supplier is to a large extent depended on his ability to predict accurately his maximum half-hourly demand and the competitive rates offered by various suppliers. If the actual consumption exceeds the predicted value, the purchaser is penalised for the extra supply needed by paying at a higher than the negotiated rate. The ability, therefore, to predict the power consumption every half hour as accurately as possible will facilitate negotiations on electricity tariffs with the suppliers and will also enable the control of maximum demand by shifting some of the load to periods of reduced demand.

To date, neural networks have been applied successfully to a number of engineering problems. Several researchers have demonstrated that they can be more reliable at predicting energy consumption in a building than other traditional statistical approach [1,2,3,4] because of their ability to model non-linear patterns. The neural network learns the main characteristics of a system through an iterative training process. It can also automatically update its learned knowledge on-line over time. This automatic learning facility makes a neural network based system inherently adaptive. Furthermore, its predictive capability can be used to optimise the operations of the refrigeration, heating and ventilation plant in a building or supermarket, and thus spread the demand of power over the day, reducing maximum demand charges.

This paper address the performance of a neural network in the prediction of electricity demand in a supermarket. It evaluates the capability of a neural network to forecast the overall power consumption of the store every half hour with respect to time of day and environmental conditions. A comparison of the prediction performance of the network against more traditional statistical approaches is also presented.

ARTIFICIAL NEURAL NETWORKS

A neural network is a non-linear mapping of the space between an input data set and an output data set and consists of three parts - an input vector (independent variables), an output vector (dependent variables), and an algorithm that maps the input space to the output space. One or more hidden layers connect the external layers by a set of "weights", expressed as two-dimensional matrices, W. In a feed-forward neural network, the value of each node in a particular hidden layer is the result of a non-linear transfer function whose argument is the weighted sum over all the nodes in the previous layer plus a constant bias B.

A variety of training algorithms are available but in general, to train a network, one begins with a set of training data consisting of the input vector, X_0^m and corresponding target vector, T_m. The internal weights are adjusted until the sum of differences between the neural net outputs Y_m and the corresponding target T_m is minimised to a predetermined level for all the training data.

A neural network with zero hidden layers is a linear expansion and a network with one hidden layer and a single output can be represented by[5]:

$$Y_m = \sum_{i=1}^{N_1} W_2(i) F \sum_{j=1}^{N_0} W_1(i.j) X_0^m(j) + B_1 \tag{1}$$

In the above equation, N_1 is the number of nodes in the hidden layer and N_0 is the number of independent variables.

A sigmoidal function is usually used for the transfer function F as it enables a finite number of nodes in the single hidden layer to uniformly approximate any continuous function. Training of neural networks is frequently performed using a back-propagation algorithm. This algorithm iteratively adjusts the weights to reduce the error between the actual and desired outputs of the network. Detailed descriptions of different network configurations and training techniques are given by Rumelhart and McClelland[6] amongst many others.

One facet of neural networks is that a statistical understanding of the relationships between the independent and the dependent variables is not needed. Continuous analysis of the independent variables can lead to well chosen network inputs.

TRAINING AND TESTING OF NEURAL NETWORKS

Supermarkets are one of the largest single end users of electricity with refrigeration systems accounting for more than 50% of the electricity used. About 25% is accounted for by the HVAC equipment and lighting while the other utilities account for the remainder. The energy consumption of supermarket refrigeration systems is a function of a number of variables which include the building fabric, the ambient conditions (temperature and humidity) and the internal environment. In the UK, it is a common practice for the refrigeration and HVAC system to be part of an integrated design taking advantage of the rejected heat from the refrigeration packs to provide heating in the store. In trying to minimise energy consumption, therefore, the various energy consuming subsystems cannot be viewed in isolation but their interactions should be considered as well as their influence on the sales revenue and profitability of the store.

Energy consumption can be minimised only through better understanding of the consumption patterns and better control of the major energy consuming equipment in response to external and internal environmental conditions.

Computer based monitoring and control systems provide the opportunity to characterise the various energy consuming processes in the store and relate the consumption patterns to fuel pricing and tariff structures. These systems can further be developed to incorporate advanced control techniques to minimise maximum electricity demand, energy consumption and fuel costs. To this end, we propose the use of Artificial Neural Networks because unlike traditional system modelling techniques ANNs are not system specific and can be easily adapted to different building types, HVAC systems and refrigeration equipment.

The current investigations are based on a Safeway supermarket situated in Airdrie, Scotland. This store has been equipped with a central monitoring and control system which monitors the temperatures of the display cases in the store and controls the refrigeration packs. For the purpose of the project the system has been extended to incorporate a number of additional variables which include:

Temperature and relative humidity in the store,
External air temperature and humidity,
Total electrical power consumption of the store,
Electrical power consumption of the refrigeration packs,
Gas Consumption and
Underfloor heating flow and return temperatures.

Simple three layered feed-forward neural networks were trained using the actual measured data collected from the store. The networks varied in terms of the number of input variables, i.e. input nodes, n. The number of nodes of the hidden layer varied as a function of the input nodes as (2n + 1). The standard back-propagation algorithm was employed to train all the networks. Back-propagation is an integrative training algorithm designed to minimise the mean square error between the output of the network and the actual value.

Both training and testing were carried out using a 32-bit commercially available neural network modelling package.

The input variables (input nodes) used in each network configuration are listed in Table 1.

Table 1. Input variables used for each network configuration

Network 1	Day, Time, External Humidity and Temperature and Internal humidity and temperature for short term i.e. a month
Network 2	Day, Time, External and Internal Humidity for a month
Network 3	Day, Time, External and Internal Temperature for a month
Network 4	Day, Time, External Humidity and Temperature for a month
Network 5	Day, Time, Internal Humidity and Temperature for a month
Network 6	Day, Time, External Humidity and Temperature over long term i.e. four months
Network 7	Time-Series Prediction using past six time steps
Output Variable	Electrical Power Consumption in kW

PREDICTION RESULTS USING NEURAL NETWORKS

Table 2 compares the performance parameters of the various networks during training and prediction testing.

It can be seen that all the networks show a good correlation between the target and network output with some being marginally better than others. Network 6 which was trained using data spanning a longer period i.e. 4 months instead of the 1 month used for the other networks, shows the lowest correlation coefficient and highest RMS error. This indicates that using a short-term data-set i.e. the previous month's data may be adequate to accurately predict half hourly electrical demand in retail food stores.

The time series prediction using neural nets, network 7, shows the lowest RMS error. This network also predicted discrepancies in the data set (such as lower electrical consumption on Christmas day) better than the other neural nets. It can be concluded, therefore, that a combination of time series and multiple independent variables modelling may improve the performance of the network in regions of seemingly random fluctuations as has already been indicated in references [5] and [7].

Table 2: Summary of Network Performance

	Std Dev	Bias	Max. Error	Correlation	RMS Error
Network 1 train	25.31871	0.11955	93.41388	0.95499	0.064212
Network 2 train	25.70705	0.08542	86.10153	0.95338	0.065199
Network 3 train	25.62318	-0.12272	95.7804	0.95492	0.064986
Network 4 train	25.31243	0.22915	84.23462	0.95613	0.064198
Network 5 train	27.06486	0.06571	91.19052	0.94941	0.068643
Network 6 train	32.374	0.24329	139.5237	0.91693	0.077081
Network 7 train	27.89556	-0.08114	131.9612	0.94387	0.037408
Network 1 test	21.10767	-1.3099	69.93298	0.97172	0.053529
Network 2 test	25.21509	-3.33877	72.2988	0.9606	0.063951
Network 3 test	27.05021	0.58168	66.40054	0.94369	0.068606
Network 4 test	28.54436	1.74505	96.72766	0.93538	0.072395
Network 5 test	27.08099	-2.20536	73.18829	0.949619	0.068684
Network 6 test	33.89543	0.29409	124.5504	0.91037	0.080703
Network 7 test	31.33043	-2.70963	125.7037	0.93866	0.042014

Table 3. Percentage contribution of the independent variables towards the prediction accuracy of the dependent variables

	Day	Time	Ext. Humidity	Int. Humidity	Ext. Temp	Int. Temp
Network 1	7.36	52.6	11.58	9.21	6.32	13.68
Network 2	10	58.42	15.79	16.84	×	×
Network 3	9.65	61.38	×	×	13.1	15.17
Network 4	7.59	64.48	14.48	×	12.76	×
Network 5	6.55	65.17	×	13.79	×	10.345
Network 6	10.69	66.21	3.45	×	20	×

Table 3 shows the percentage contribution of the various independent variables to the accuracy of prediction of the dependent variable. It can be seen that the time of day is the most significant independent variable with percentage contributions ranging between 52% and 66%. All the other have much lower contributions in the range between 5% and 20%. Here more detailed analysis is required to determine the relative importance of each variable and hence the instrumentation required for on-line electrical power prediction.

MULTIPLE REGRESSION TECHNIQUES

An approach frequently used for the determination of the energy consumption of commercial buildings is regression modelling. Since the electrical energy consumption of a supermarket is a function of several variables, multiple linear regression (MLP) models would be more appropriate for electrical energy consumption prediction than simple regression models. A possible linear regression model for the prediction of the electrical energy consumption prediction of a supermarket can be as follows:

$$P = a_1 + a_2(\text{Ext. Temp}) + a_3(\text{Ext. Hum}) + a_4(\text{Int. Temp}) + a_5(\text{Int. Hum}) + a_6(\text{Time}) + a_7(\text{Day})$$

where a_1, a_2 etc. are the regression coefficients to be determined statistically.

The above equation can be represented in general terms as:

$$P = a_1 + \sum_{i=1}^{n} a_i x_i \tag{2}$$

where a_1 are the coefficients of the equations and x_i are the independent variables such as external temperature and humidity, internal temperature and humidity, day and time of day.

The regression model can be further improved by using a polynomial form of independent variables such as:

$$P = a_1 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} a_i x_i^2 \tag{3}$$

Equations 2 and 3 represent different forms of multiple linear regression models. The linear parameters, a_i , in both the models can be estimated using the usual linear model techniques available in statistical packages. The two equations are non-linear in only the independent variables, x. The multiple regression analysis assumes that the regressor variables are independent of each other.

In order to make a distinction between the two methods, in this paper model 2 is referred to as Multiple Linear Regression and model 3 as Multiple Polynomial Regression.

A 32-bit commercial statistical package was used to carry out the multiple regression modelling.

COMPARISON BETWEEN NEURAL NETWORK AND MULTIPLE REGRESSION PREDICTIONS

The prediction accuracy of the multiple polynomial regression and the ANN modelling is compared graphically in Figure 1, for data set 1, and Figure 2 for data set 6. It can be seen that for both data sets the ANN modelling provides a much better prediction of electrical energy consumption than regression modelling. Table 4 shows the correlation coefficient for each prediction method. The correlation coefficient is a statistical measure of how well the predictions agree with the targets. A value of 1 indicates perfect agreement.

Table 4: Comparison between Neural Network and Multiple Linear Regression

Prediction method	Correlation
Data set 1 (ANN)	0.95499
Data set 1 (Multiple Linear Regression)	0.48673
Data set 1 (Multiple Polynomial Regression)	0.79810
Data set 6 (ANN)	0.91693
Data set 6 (Multiple Polynomial Regression)	0.75360

The results in Table 4 show that the simple linear regression model based on equation 2 performs very poorly compared to a simple neural net. However, when the polynomial combination of the input variables were used in the regression analysis the performance of the regression model improved considerably even though not as much as the neural nets.

CONCLUSIONS:

1. The ANN approach is a generic technique for mapping the relationships between inputs and outputs and requires less expertise and experimentation than traditional modelling of non-linear multivariate systems.

2. Results in this paper show that a simple ANN architecture with one hidden layer can provide half hourly predictions of electrical energy use in supermarkets with a reasonable accuracy with correlation coefficient ranging from 0.91 to 0.95.

3. To arrive at an optimal ANN architecture for on-line electrical energy consumption prediction the contributing factors of the various input variables were analysed. It shows the time of day as the most important factor in all the cases. The external and internal environmental conditions also have significant effect.

4. A comparison of the prediction performance between the ANNs and regression analysis based on the same data sets showed the ANNs to perform much better. A correlation coefficient of 0.95 was obtained for the ANNs compared to 0.79 for regression analysis.

5. Further work will involve development of ANNs to predict electrical energy on-

line and also predict the energy consumed by the various subsystems such as the refrigeration system in a supermarket.

REFERENCES:

1. Kreider, J. F. and Wang, X. A. (1991), "Artificial Neural Network demonstration for automated generation of energy use predictors for commercial buildings", ASHRAE Transactions, 97(2), pp. 775-779.

2. Anstett, M. and Kreider, J. F. (1992), "Application of Neural Networking Models to predict energy use", ASHRAE Transactions, Paper No. 3672, pp. 505-517.

3. Stevenson, W. J.(1994), "Using Artificial Neural Networks to predict building energy parameters", ASHRAE Transactions, 100(2), Paper No. OR-94-17-4.

4. Mackay, D. J. C. (1994), "Bayesian non-linear modeling for the prediction competition", ASHRAE Transactions, 100(2), Paper No. OR-94-17-1.

5. Feuston, B. P. and Thurtell, J. H. (1994), "Generalized nonlinear regression with ensemble of Neural Nets: The Great Energy Predictor Shootout", ASHRAE Transactions, 100(2), Paper No. OR-17-3.

6. Rumelhart, D. E. and McClelland, J. L. (1986), "Parallel distributed processing explorations in the microstructure of cognition", Cambridge, MA; MIT Press.

7. Kawashima, M., Dorgan, C. E. and Mitchell, J. W. (1995), "Hourly thermal load prediction for the next 24 hours by ARIMA, EWMA, LR and an Artificial Neural Nework", ASHRAE Transactions 101(1), pp. 186-200

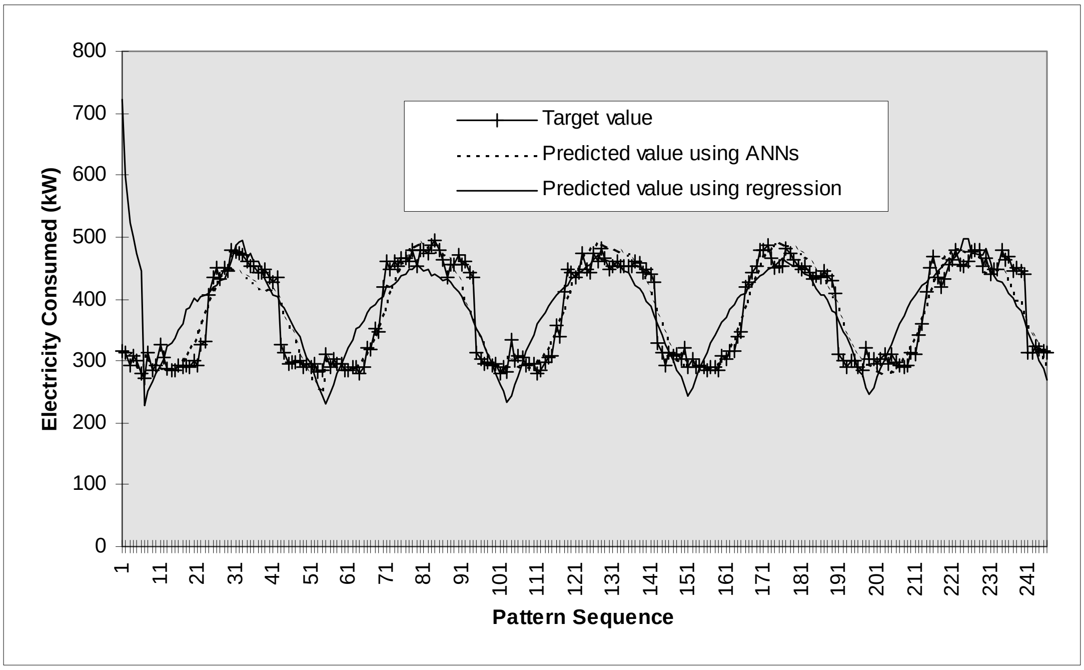

Figure 1: Neural Networks and Regression Output for Network 1 (Correlation for ANNs = 0.95 and for Regression = 0.79)

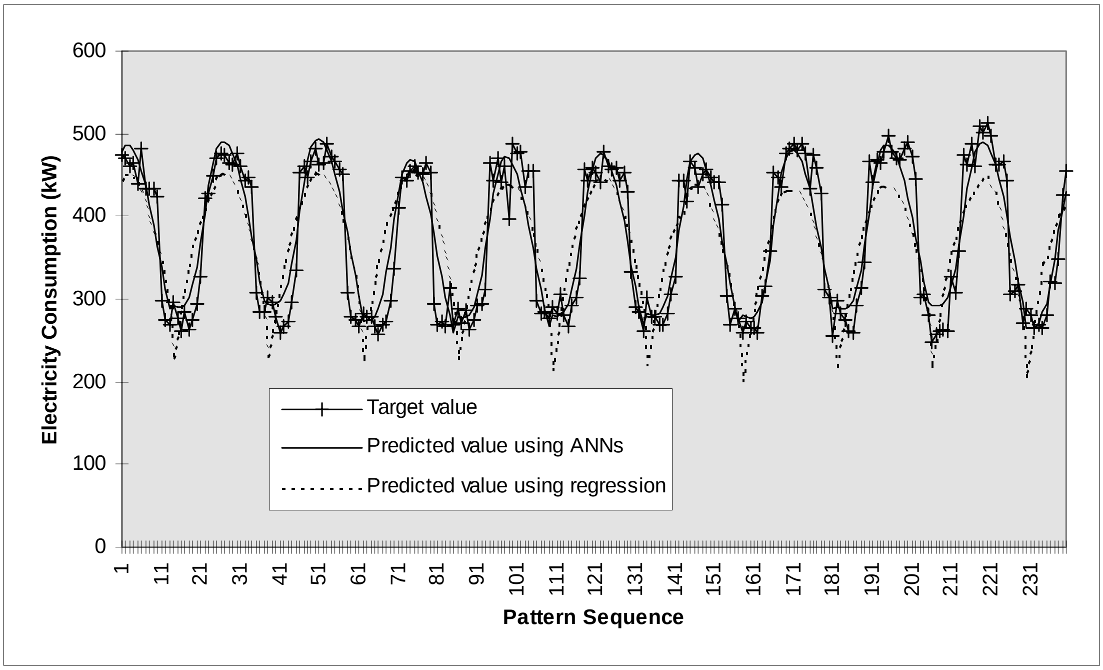

Figure 2: Neural Networks and Regression Output for Network 6 (Correlation for ANNs = 0.91 and for Regression = 0.75)

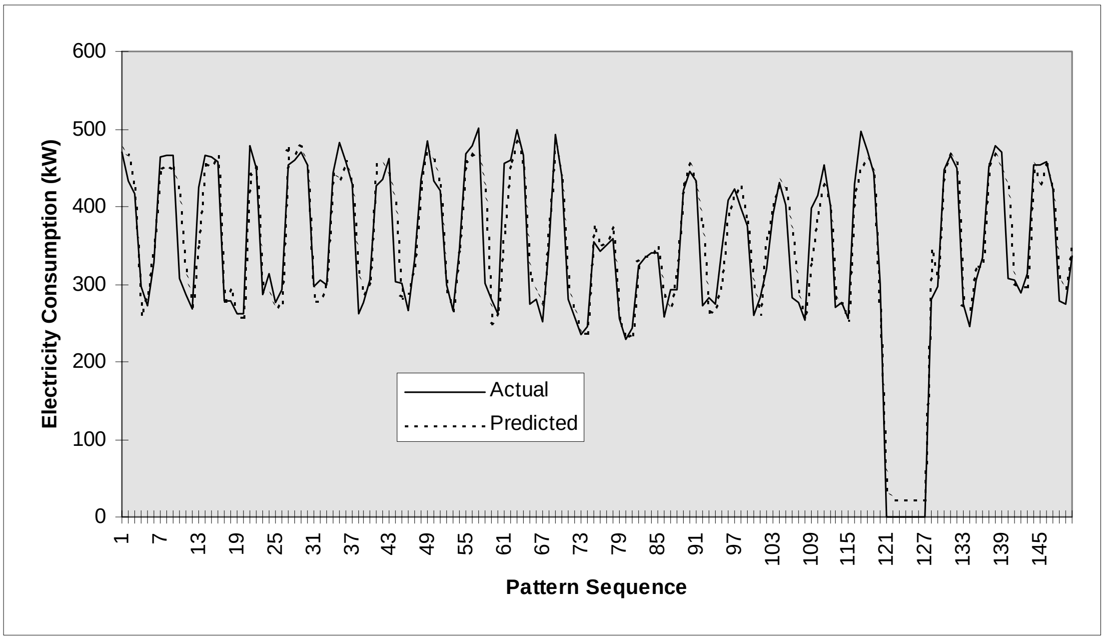

Figure 3: Network Output for the Time Series prediction using Neural Networks (Network 7)