Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 8 (11): 2124-2129, 2008
ISSN 1812-5654

Application of Artificial Neural Networks to Investigate the Energy Performance of Household Refrigerator-Freezers

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Abstract: In this study, the energy consumption of 149 domestic refrigerators has been monitored in Malaysian households. A questionnaire was used to get relevant information regarding the usage of this appliance in the actual kitchen environment to feed into neural networks. Prediction performance of Artificial Neural Networks (ANN) approach was investigated using actual monitored and survey data. Statistical analyses in terms of fraction of variance R^2, Coefficient of Variation (COV), RMS are calculated to judge the performance of NN model. It has been found that the regression coefficient R^2 is very close to unity for the best prediction performance results.

Key words: Refrigerator-freezers, neural networks, actual energy consumption, statistical analysis

INTRODUCTION

Malaysia, like other developing countries, has experienced dramatic growth in the use of household refrigerator-freezers. Economic growth is the main driving factor for higher use of refrigerator-freezers which, in turn, leads to the increasing need for comfort and a high style of living that has consequently caused a substantial increase in household energy consumption (ECM, 2003). It has been found that refrigerator-freezer ownership level increased from 2,073,726 units in 1991 to 59, 33,476 in 2004 in Malaysia (Masjuki *et al.*, 2003). This appliance is one of the major energy users in the household environment as it has to operate 24 h in a day. Figure 1 shows global trend of residential energy uses by varieties of household appliances. It is shown that in Malaysia residential sector consumes about 19% of the total energy consumption. It is also found that refrigerator-freezers consume about 23% of total residential energy consumption.

A survey was conducted to investigate household energy patterns (DSM, 2001). Their study revealed that about 100% of total residential homes are equipped with one refrigerator-freezer. In some cases, it has been found that multiple number of refrigerator-freezers owned by a single house owner. So, assessing (i.e., forecasting) its energy performance for policy implementation and efficiency improvement is very important.

Various forecasting techniques (i.e., time series, multiple linear regressions, engineering and econometric) have been proposed in the last few decades. Each of the techniques has its own advantages, disadvantages and limitations. Recently artificial neural networks received tremendous attention for the prediction purpose in the field of energy and others (Kalogirou, 2000; Adnan *et al.*, 2004a, b, 2005; Mohandes *et al.*, 1998; Bechtler *et al.*, 2001).

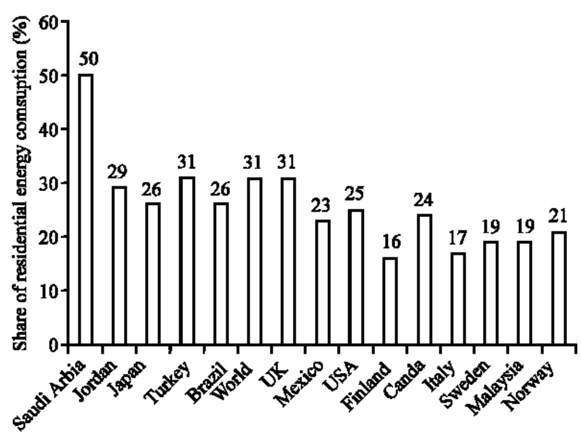

Fig. 1: World wide residential energy consumption (Meyers *et al.*, 2003; Nicola, 2001; Boardman, 2004; Ueno *et al.*, 2006; Almeida *et al.*, 2001; Kamal, 1997; Lenzena *et al.*, 2006)

The comparison of the results from NNs and statistical approaches indicated that neural networks offer an accurate alternative to classical methods such as multiple regression or autoregressive models. A more accurate prediction may be achieved with this method (Al Fuhaid *et al.*, 1997).

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From the literatures it has been found that NN has been applied in the diverse field of energy, refrigeration properties, heat pump, engine performance and so on. However, it has not been applied for the energy performance investigation of refrigerator-freezers. So the objective of this paper is to predict refrigerator-freezers' energy consumption using NN approach.

MATERIALS AND METHODS

Working principle of ANN: It is time consuming and expensive to monitor the actual energy consumption of a household refrigerator-freezer. Therefore, a mathematical model may be used to predict the energy consumption of a refrigerator-freezer using actual energy consumption data. But, the resulting accuracies may not always be satisfactory. One alternative to the mathematical model is the data driven-based approach, such as Artificial Neural Networks (ANNs) with high prediction performance. ANNs use simple processing units, called neurons, to combine data and store relationships between independent and dependent variables. An NN consists of several layers with neurons that are connected to each other.

A widely used NN model called the Multi-Layer Perceptron (MLP) NN is shown in Fig. 2. The MLP type ANN consists of one input layer, one or more hidden layer (s) (middle) in between input and output layers and one output layer. Each layer employs several neurons (nodes) and each neuron in a layer is connected to the neurons in the adjacent layer with different weights. The weights, after training, contain meaningful information, whereas before training they are random and have no meaning (Adnan and Arcaklioglu, 2005).

Signals flow into the input layer, pass through the hidden layer(s) and arrive at the output layer. With the exception of the input layer, each neuron receives signals from the neurons of the previous layer. The incoming signals or input (x_{ij}) are multiplied by the weights (v_{ij}) and summed up with the bias (b_j) contribution. Mathematically it can be expressed as:

$$\text{net}_j = \sum_{i=1}^{n} X_i V_{ij} + b_j \quad (1)$$

The output of a neuron is determined by applying an activation function to the total input and calculated using Eq. 1 (Kreider and Wang, 1992). If the computed outputs do not match the known (i.e., target) values, NN model is in error. Then, a portion of this error is propagated backward through the network. This error is used to adjust the weight and bias of each neuron throughout the network so the next iteration error will be less for the same units. The procedure is applied continuously and repetitively for each set of inputs until there are no measurable errors, or the total error is smaller than a specified value.

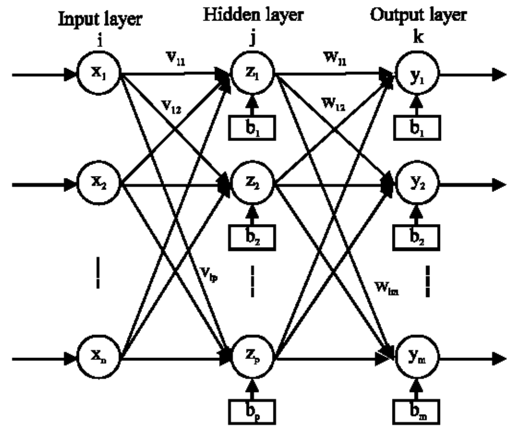

Fig. 2: Architectural graph of an MLP with one hidden layer (Kalogirou, 2000)

The following procedure is executed in all the models developed, (i) database collection, (ii) analysis and preprocessing of the data, (iii) training of the neural network, (iv) testing the trained network and (v) using the trained ANN for simulation and prediction. An important stage of a neural network is the training step, in which an input is introduced to the network together with the desired output. The weights and bias values are initially chosen randomly and the weights are adjusted so that the network produces the desired output. After training, the weights contain meaningful information, contrary to the initial stage where they are random and meaningless. When a satisfactory level of performance is reached, the training stops and the network uses the weights to make decisions.

Measure of prediction performance: Using the results produced by the network, statistical methods have been used to investigate the prediction performance of NN results. To judge the prediction performance of a network, several performance measures are used. This includes statistical analysis in terms of Root-Mean-Squared (RMS), absolute fraction of variance (R^2), as well as mean error percentage values has been calculated and defined as below (Adnan and Arcaklioglu, 2005; Aydinalp *et al.*, 2002; Stuttgart Neural Network Simulator, 1998).

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{i=N} (E_a - E_p)^2}{\sum_{I=1}^{I=N} (E_a - E_m)^2} \right) \quad (2)$$

$$\mathrm{RMS} = \sqrt{\frac{\sum_{i=1}^{i=N}\left(E_a - E_p\right)^2}{N}} \quad (3)$$

$$\mathrm{COV} = \frac{\mathrm{RMS}}{E_m} \times 100 \quad (4)$$

$$\text{Mean \% Error} = \frac{1}{N}\sum_{i=1}^{i=N}\left(\frac{E_a - E_p}{E_a} \times 100\right) \quad (5)$$

Where:
E_a = Actual result
E_p = Predicted result
E_m = Mean value
N = No. of pattern

The coefficient of multiple determinations R^2 compares the accuracy of the model to the accuracy of a trivial benchmark model. A perfect fit would result in an R^2 value of 1 and a very good fit near 1. The quality of fit decreases as the value of R^2 decreases.

Data collection: This research data has been collected from September 2005 to January 2006 using two approaches: field energy monitoring and questionnaire survey. These are elaborated below:

Field energy monitoring: The aim of this monitoring was to measure actual refrigerator-freezers energy consumption. Energy monitoring was carried out by randomly visiting various types of residential dwelling such as double-storey, single storey, condominium and medium cost apartment at different locations of Malaysia.

A Phoenix single phase electronic energy meter (model SM68, class 2.0) manufactured by Smart meters technologies (M) Sdn. Bhd. was used to monitor the daily energy consumption. Specifications of the meter are shown in Table 1.

Data collection through questionnaire: The survey was conducted from house to house with the questionnaire and power meter to monitor actual daily energy consumption. First permission was sought from the respondent before starting any survey. Once permission was granted, the survey was started with the questionnaire to get the pertinent information about the usage behavior of refrigerator-freezers and respondents profile. An explanation was provided to the respondent in case he/she is confused regarding any question. Once the questionnaire was filled completely, the power meter was connected with the refrigerator-freezers to monitor the actual energy consumption. Necessary data has been collected same way for the 149 refrigerator-freezers. The most important data that have been collected by this questionnaire is listed below:

- Personal profile of respondent
- Specifications of the refrigerator-freezer
- Usage pattern of the refrigerator-freezer (i.e., frequency of door opening, location of refrigerator)
- Age of refrigerator-freezer
- Type of refrigerator-freezer
- Food loading (whether empty, fully loaded, or half loaded)
- Income level of respondent and
- Daily energy consumption in kWh

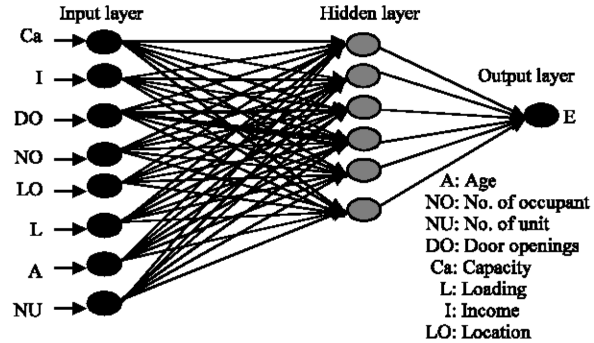

Fig. 3: Network architecture with input, hidden and output layers

Table 1: Specifications of the power meter

Power range (kWh)	0-1000
Current range (A)	0-12
Accuracy	±0.001

Application of ANN in the present study: Two data sets are needed for ANNs: one for training the network and the second for testing it. The usual approach is to prepare a single data-set and differentiate it by a random selection. In this study, the actual monitored data were used to train and test an artificial neural-network. In the present study, 8 input parameters (i.e., C_a (Capacity), DO (Door opening), L (loading), LO (Location), A (Age), NO (No of occupant), NU (No of unit), I (Income)) and one output parameter (i.e., energy consumption, E) were chosen. It may be mentioned that these data have been collected using approaches explained. Figure 3 shows a single hidden-layer ANN architecture used in this work.

The learning algorithm called the back-propagation was applied for the single hidden layer. Scaled Conjugate Gradient (SCG) and Levenberg-Marquardt (LM) algorithms have been used for the training and testing the network. Normalization of inputs and output are performed between the values of zero and unity. Neurons in the input layer have no transfer function. A logistic sigmoid (logsig) transfer-function has been used in

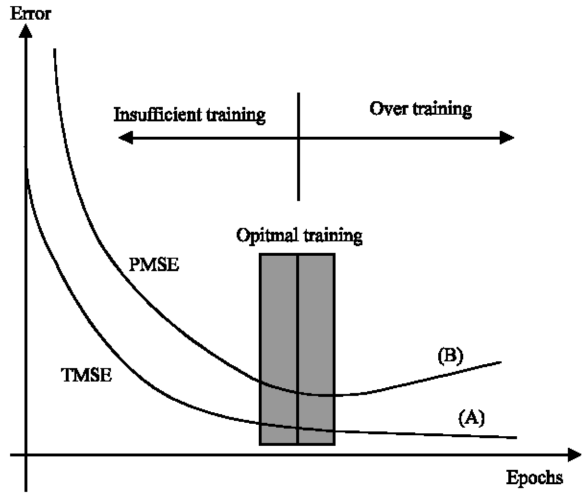

Fig. 4: Error patterns for training of ANN

hidden layer and a linear transfer function was used in output layer. The Neural Network has been optimized using the MATLAB Version 7 Neural Network Toolbox. The MATLAB software has been used to train and test the ANN on a personal computer. In the training stage, to define the output accurately, authors tried to increase the number of neurons step-by-step (i.e., 3-10) in the hidden layer. After the successful training of the network, the network was tested with the test data set (Fig. 4).

RESULTS AND DISCUSSION

Prediction results using ANN: Figure 5 and 6 show the prediction performance (i.e., prediction results with actual results) for different ranges. Figure 7 and 8 observed that margin of deviation for different algorithms and ranges are very small. Summary of statistical analysis in terms of R^2, COV, RMS have been performed and shown in Table 2. From the Table 3, it has been observed that regression coefficient R^2 is very good for all the networks, algorithms and ranges used in this study for testing and training data sets. It also has been observed that % relative error is very small for testing and training data sets.

It also has been found that it is better compared to work carried out by Adnan *et al*. (2005).

Using the results produced by the network, statistical methods have been used to make comparisons. Inputs and output have been normalized in the range shown in

Table 2 and 3 as ANN works efficiently within this range.

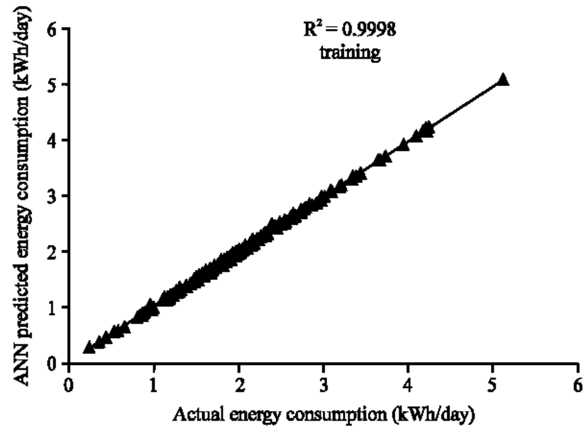

Fig. 5: Prediction performances for training data set of range 0 to 1

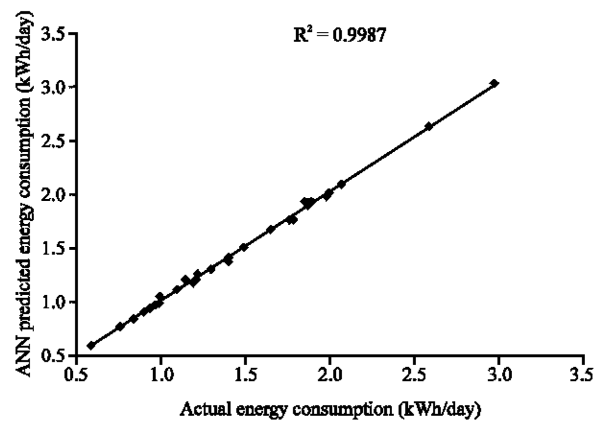

Fig. 6: Prediction performance for testing data set of range 0 to 1

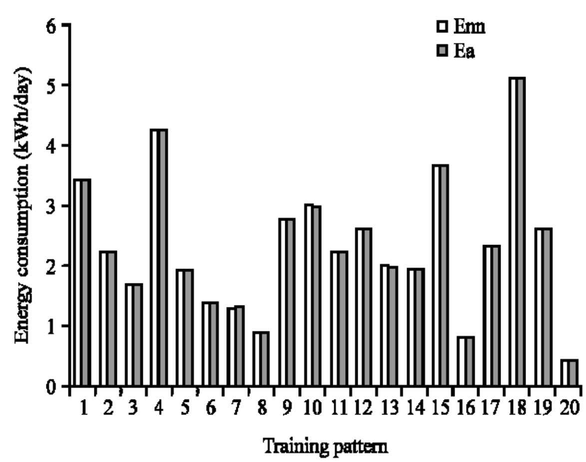

Fig. 7: Prediction performances for training data set of range 0 to 1 for 20 pattern

Table 2: Prediction performance of different network for training and testing data set

Scaling range	Learning algori- Hidden layer	Cycle	Training R^2	Training RMS	Training COV	Training Relative error (%)	Testing R^2	Testing RMS	Testing COV	Testing Relative error (%)
(-0.9-0.9)	LM-15	208	0.993	0.0026	0.1252	0.0283	0.983	0.0125	0.8380	-2.312
(-1-1)	LM-15	254	0.999	0.0001	0.0034	0.0002	0.999	0.0040	0.2726	0.7490
(0-1)	LM-15	240	0.9999	0.0005	0.0234	-0.0164	0.999	0.0034	0.2332	1.1424
(-0.5-0.5)	SCG-15	247	0.999	0.0014	0.0694	0.3017	0.981	0.0121	0.8156	-2.652
(0.1-0.9)	SCG-13	280	0.999	0.0009	0.0454	0.3373	0.994	0.0045	0.2235	-0.781

Table 3: Comparison of R^2 value for the best prediction performance of others work with present study

Scaling interval	Activation function	Learning algorithms	R^2	Application	Reference
0-1	logsig	SCG	0.9994	Turkey's Net energy consumption	Adnan *et al.* (2004b)
0-1	logsig	SCG/LM	0.9999	Thermodynamic analysis of refrigerant mixtures	Arcaklıoglu *et al.* (2004)
-0.5-0.5	logsig	Backpropagation	0.8950	Modeling residential energy consumption	Aydinalp (2002)
0-1 and -1-1	logsig	LM	0.9999	Present work	-

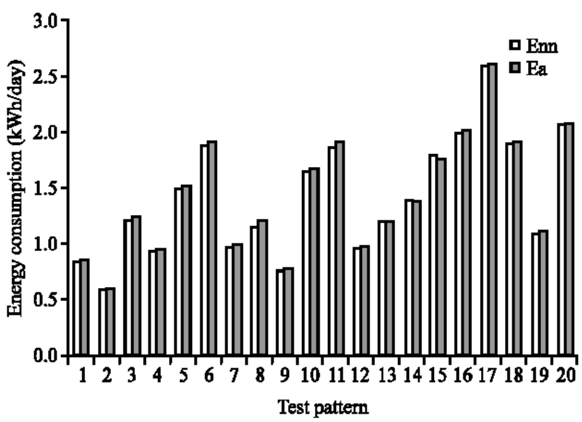

Fig. 8: Prediction performance for testing data set of range 0 to 1 for 20 pattern

CONCLUSION

The aim of this study has been to show the possibility of using the neural networks for predictions of refrigerator-freezers energy consumption. In most cases, the network produces the predicted results parallel to the experimental ones. The RMS error values are very small, R^2 values are about 0.9990 and mean error also small, which may easily be considered within the acceptable range. It has been found that the best results were obtained from the LM algorithm. The overall results show that the networks can be used as an alternative way for predicting the performances of refrigerator-freezers energy consumption.

The result of this study shows that ANN has ability to learn and generalize a wide range of experimental conditions. Therefore, the usage of ANNs may be highly recommended to predict the refrigerator-freezers energy consumption instead of having to undertake complex, expensive and time-consuming experimental studies.

ACKNOWLEDGMENT

The authors gratefully acknowledge the financial support by University of Malaya (UM), Malaysia to carry out this research project. The project was funded under the project PJP No: FS196/2007C.

REFERENCES

Adnan, S., E. Arcaklioglu and M. Ozalp, 2004a. Performance analysis of ejector absorption heat pump using ozone safe fluid couple through artificial neural networks. Energy Convers. Manage., 45 (13-14): 2233-2253.

Adnan, S., E. Arcaklioglu, M., Ozalp and E.G. Kanit, 2004b. Use of artificial neural networks for mapping of solar potential in Turkey. Applied Energy, 77 (3): 273-286.

Adnan, S., E. Arcaklioglu and M. Ozkaymak, 2005. Turkey's net energy consumption. Applied Energy (In Press).

Adnan, S. and E. Arcaklioglu, 2005. Solar potential in Turkey. Applied Energy, 80 (1): 35-45.

Al Fuhaid, A.S., M.A. El-Sayed and M.S. Mahmoud, 1997. Cascaded artificial neural networks for short-term load forecasting. IEEE Trans. Power Syst., 12 (4): 524-529.

Almeida, M.A., R. Schaeffer and E.L. La Rovere, 2001. The potential for electricity conservation and peak load reduction in the residential sector of Brazil. Energy, 26 (4): 413-429.

Arcaklıoglu, E., C. Abdullah and E. Ali, 2004. Thermodynamic analyses of refrigerant mixtures using artificial neural networks. Applied Energy, 78 (2): 219-230.

Aydinalp, M., V. I. Ugursal and S.F. Alan, 2002. Modeling of the appliance, lighting and space cooling energy consumptions in the residential sector using neural networks. Applied Energy, 71 (2): 87-110.

Bechtler, H., M.W. Browne, P.K. Bansal and V. Kecman, 2001. New approach to dynamic modeling of vapor compression liquid chillers: Artificial neural-networks. Applied Thermal Eng., 21 (9): 941-953.

Boardman, B., 2004. Achieving energy efficiency through product policy: The UK experience. Environ. Sci. Policy, 7 (3): 165-176.

DSM., 2001. Study on residential customer load profile, Demand Side Management, Final Report. Petaling Jaya, Malaysia.

ECM., 2003. Energy commission Malaysia, Statistics of electricity in Malaysia, Energy Commission of Malaysia, Kuala Lumpur.

Kalogirou, S.A., 2000. Applications of artificial neural-networks for energy systems. Applied Energy, 67 (1): 17-35.

Kamal, W.A., 1997. Improving energy efficiency-the cost-effective way to mitigate global warming. Energy Convers. Manage., 38 (1): 39-59.

Kreider, J.F. and X.A. Wang, 1992. Artificial neural networks demonstrations for automated generation of energy use predictors for commercial buildings. ASHRAE. Trans., 97 (1): 775-779.

Lenzena, M., W. Mette, C. Claude, H. Hitoshi, P. Shonali and S. Roberto, 2006. A comparative multivariate analysis of household energy requirements in Australia, Brazil, Denmark, India and Japan. Energy, 31 (2-3): 181-207.

Masjuki, H.H., T.M.I. Mahlia, R. Saidur, I.A. Choudhury and A.R. Noor Leha, 2003. Projecting electricity savings from implementing minimum energy efficiency standards for household refrigerator in Malaysia. Energy-The Int. J., 28 (7): 751-754.

Meyers, S., J.E. McMahon, M. McNeil and X. Liu, 2003. Impacts of US federal energy efficiency standards for residential appliances. Energy, 28 (8): 755-767.

Mohandes, M., S. Rehman and T.O. Halawani, 1998. Estimation of global solar radiation using artificial neural networks. Renewable Energy, 14 (1): 179-184.

Nicola, M., 2001. Technical innovation and resource efficiency. A model for Australian household appliances. J. Sustainable Prod. Des., 1 (1): 3-17.

Stuttgart Neural Network Simulator, 1998. User manual version 4.2. Stuttgart, University of Stuttgart, Germany.

Ueno, T., S. Fuminori, S. Osamu and T. Kiichiro, 2006. Effectiveness of an energy-consumption information system on energy savings in residential houses based on monitored data. Applied Energy, 83 (2): 166-183.