Proceedings of the
International Conference on Mechanical Engineering 2003
(ICME2003) 26- 28 December 2003, Dhaka, Bangladesh

ICME2003-TH-26

APPLICATION OF NEURAL NETWORK MODEL FOR OPTIMIZING THERMAL STORAGE LOAD IN HUMID TROPICS

Ahmadul Ameen and Khizir Mahmud
University Sains Malaysia, 14300 Nibong Tebal, Pulau Pinang
Tang YingTang
Formerly post graduate student, Nanyang Technological University, Singapore.

ABSTRACT

In the present study an artificial neural network (ANN) model has been adopted to develop software to predict an ice storage cooling load for an office building. More specifically, a feedforward neural network with backpropagation training rule has been used as a prediction tool. The input parameters include information about temperatures and cooling loads of the building within a period of one month before predicted days. The output comprises one neuron providing hourly cooling load. The average of hourly prediction errors per day was generally less than 5%. The prediction accuracy is considered acceptable and the input parameters are practical. The results of the study shows that the designed software should be able to provide cooling load prediction for a target office building should it employ an ice storage air conditioning for its cooling.

Keywords*:* Neural model; Thermal storage air conditioning; load prediction

1.INTRODUCTION

Thermal energy storage for cooling or cool storage air conditioning has become well established in many countries e.g. USA, Japan and Taiwan as a useful load management technique. Cool storage utilizes an inexpensive storage medium with a high specific or latent heat, e.g. water, ice or eutectic salts to store cooling produced during off-peak hours for utilisation during peak hours. Conventional air conditioning chillers or industrial-grade ice making plants may provide refrigeration, which charge the storage tanks during off-peak hours. Circulating chilled liquid from storage through the building's air handling units, fan coils or a secondary heat exchanger provides on-peak cooling. A cool storage system in fact provides a "buffer" between a refrigeration plant and the building or premises it serves. By shifting electricity use to off-peak hours, both utilities and their customers are benefited. Cool storage helps utilities improve load factors, off-peak sales and enable them to defer the need for capacity expansion, whereas the commercial customers lower their electricity bills. Most utilities offer rate incentives to encourage customers to consider this alternative, which has substantially lower life cycle cost, particularly due to longer equipment and system life [Dorgan, 1994].

Accurate prediction of cooling load is very important in respect of efficient performance of an ice storage system. A system will not work efficiently without proper control even if it is designed correctly. Ice-storage systems can be optimized at two stages -one in the design stage and the other in the operating stage [Potter, 1995; Brady, 1994; Simmonds, 1994]. In ice storage systems, the capacity is specified for chillers and storage tanks to meet the designed loads. The system should work as expected on the designed days; however, its effectiveness on off-design day is of significance. Similarly, optimisation at operating stage is necessary for economical operation. It is generally perceived that there is no problem if energy remains in the tank at the end of the occupied hours because the same could be used on the next day. However this is not correct. For example, with regard to partial storage system, the fact that there is a significant amount of energy remaining at the end of the occupied hours indicates that there was unnecessary chiller operation during on-peak hours when the energy charge is much more expensive than during off-peak hours. On the other hand, if the system uses the stored energy first and is completely discharged, there will be an energy shortage in the afternoon because the system normally does not have a large enough chiller to meet the peak loads alone. Therefore, the discharge of the storage must be properly controlled to minimize costs and maintain comfort. Accurate prediction of next day's cooling load thus is a key for successful operation of any cool-storage system.

Examples where accurate prediction of thermal load is useful in cool-storage systems to optimize cost and energy include scheduling the charging and discharging cycle of the system, adjusting the starting time of cooling to meet the start-up loads, minimizing or limiting the electric on-peak demand.

Thermal load trend of a building can be considered as a time series with a very strong periodicity of 24 hours. Seasonal and weekly periodicities are other characteristics of the thermal storage system load. The variation of the day to day load shape depends on the type of the load and is affected by the customer usage behaviour, special event, climatic condition, etc. In general, the weather variations are the main factors which affect the variation of cooling load of an office building.

2.OVERVIEW

Ferrano and Wong (1990) developed a neural network computer program to predict the cooling load and use this prediction in conjunction with real-time expert system to simulate management of a thermal storage system. In their work, only temperature data was used as inputs and insolation and humidity were not included. Mackay (1994) developed a Bayesian non-linear model in which an automatic relevance determination (ARD) was used. ARD puts a prior probability distribution over the regression parameter that embodies the concept of relevance. The demand for electricity and water for cooling and heating of a building was predicted based on four input variables - temperature, humidity, solar flux and wind. Mattias and Ohlsson (1994) devised a feed forward artificial neural network for predicting utility loads. Multilayer perception and a method for determining relevant inputs were used in the program.

Kawashima (1994) developed an artificial neural network back propagation model with three-phase annealing. Three-phase annealing is an empirical method to gradually reduce the learning rate during the training period in order to improve accuracy in a relatively short time. This model was used to predict the energy use of a building. Kimbrara (1995) developed an auto regression integrated moving average (ARIMA) model. The modelling is first done using the past load data followed by predicting load profiles for the next day. In the modelling procedure, only the past data on load are used. The utilisation of the weather-related parameters is not taken into account. Sakawa et al **(**1995) investigated recurrent neural networks and their performance to predict cooling load. For making the learning process easier, a model, which preserves output values observed within an appropriate period, was presented in their work. Kashiwagi and Tobi (1995) proposed an artificial neural network with Kohonen's feature map as a network model and the extended learning vector quantization as a learning algorithm. Heating and cooling load of a system were predicted and satisfactory results were obtained. Kawashima et al (1995) investigated four generally used prediction methods, ARIMA, EWMA (exponential weighted moving average), LR (recursively linear regressive) and ANN and compared their performance. A cooling and heating seasonal data set with known next-day weather was used to evaluate the accuracy of each prediction method. The results indicate that the artificial neural network (ANN) model produces the most accurate thermal load predictions. Curtiss et al (1996) described some prediction examples using neural networks applied to the commercial and residential buildings. The prediction of neural network was involved in the control process of the HVAC systems, which got good results. Yang et al (1996) developed an analytical design method to predict the cooling load of a thermal storage air conditioning system with the purpose of determining operational strategies for seasonal weather changes. In their work, system performance was successfully validated in a full-scale experiment for which the power demand was limited to 50% of original value, resulting in 25% savings of operational cost. Kawashima et al (1996) described the performance of a partial ice storage system that has a controller that predicted the load by neural network. A predictive control strategy was presented, which was compared with chiller priority strategy. The predictive control proposed in their work used an hourly thermal load prediction by neural network, in which outdoor temperature, solar insolation, internal load, and room temperature were input parameters. The results showed that the predictive control can significantly reduce the operating cost without energy shortage. Yang et al (1997) used the method of cooling load prediction to optimise the start/stop operation of of the chiller of cool storage air conditioning system. Furthermore, controlling the chiller output temperature and in turn, the storage tank inlet temperature and flow rate, the tank discharge characteristics were managed to cope with various electrical charges for minimal operation cost.

This paper discusses a case study where neural model was used for predicting cool storage load for air conditioning of a building.

3.METHODOLOGY

The prediction of thermal storage air conditioning system consists of two major steps.

1. The first part relates to the creation of an input data file about the target building in order to obtain cooling load profiles of the building by DOE-2 program. This was created with a view to using the same information as actual cooling load, which is a prerequisite for the second part of the study.
2. The second part involves the development of the software for predicting the cooling load of the target building and subsequent evaluation of the software performance.

4.COOLING LOAD SIMULATION

An office building is chosen for the case study. The building is occupied from 8 a.m. to 5 p.m. by about 95% of the total occupants during the working hours and decreases to about 50 % during the lunch time from 12 noon to 1 p.m. The rest of the period is not occupied. Saturday, Sunday and public holidays are non-working days. Most of the offices in the building are equipped with computers.

In the absence of actual load a cooling load profile of the building was created by DOE-2 programme. This was preceded by developing an input file using the information related to the building. The information included weather data of a specific year, the general usages pattern and other physical characteristics of the building. After the input file was created it was run under the environment of DOE-2 and the cooling load profile of the building was obtained. The cooling load profile consisted of year round hourly cooling loads and their corresponding weather data. The cooling load profile would be used to train the ANN and subsequent evaluation of its performance.

5.DEVELOPING A NEURAL NETWORK MODEL

5.1 Model Architecture

Multilayer feedforward neural network is used in the cooling load prediction. Its architecture generally consists of an input layer, a hidden layer and an output layer. The input parameters comprises (i) the input layer; (ii) hidden layer consisting a variable neuron; and (iii) the output layer consisting of only the neuron which output hourly cooling load of an office building. The input signal is normally further processed by a Sigmoid activation function F (.) to produce the output signal.

$$OUT = F(NET) = 1/\left(1 + \exp(-NET)\right)$$

Figure 1 shows the architecture of an ANN model discussed above. It is a squashing function which is able to compress the range of NET so that OUT lies between 0 and 1. The sigmoid function produces the non-linearity essential in the building of multilayer network.

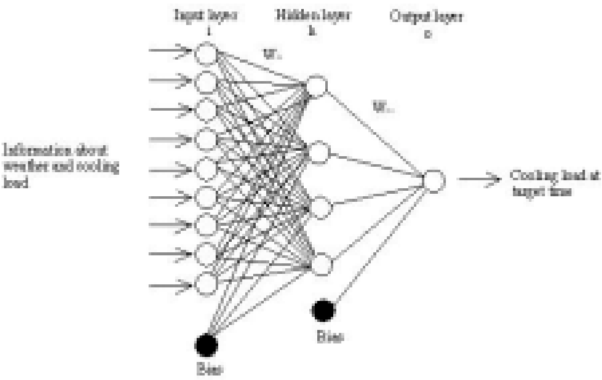

Fig. 1 Figure Diagram of an ANN model for cooling load prediction

5.2Training the ANN model

For the cooling load prediction, the desired output cooling load (hour-by-hour) of each input data set is known in advance in the training set. Thus a supervised learning is needed. Back propagation is a systematic method for training neural networks. It has a strong mathematical foundation and is often used as the learning algorithm because of its efficiency. Back propagation is based on the steepest descent search. It follows the slope of error surface downward, constantly training the weights toward an optimal value as shown in Fig. 2.

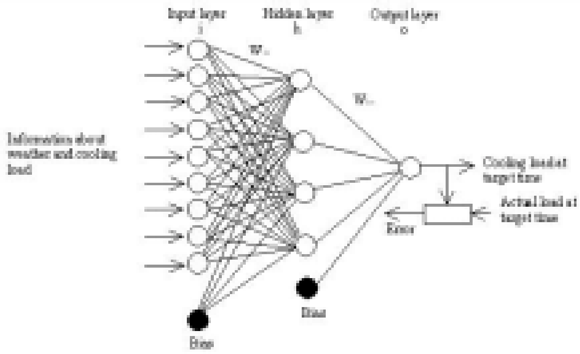

Fig. 2 Diagram of ANN's training: back propagation

5.3 Input Parameter

All variables, which affect the cooling load of an office building, could be considered for use as input parameters. The variables affecting the cooling load of an office building are numerous, such as building characteristics and configuration, indoor design conditions, outdoor weather data (i.e. temperature, solar insulation, humidity and wind speed), and operating schedules of the office building.

However, weather is the main factor which influences the daily variation of cooling load, considering the daily utility behaviour of the office building is basically steady. Accordingly, weather data is generally chosen as input parameters and the other variables are not taken into account in the cooling load prediction. Records of past cooling load of office building and weather data can be used for cooling load prediction in the future. In general, following parameters may be chosen as the input parameters in the ANN model:

- Temperature
- Solar insulation
- Humidity
- Cooling load

5.4 Neural Network Computational Details

Past cooling loads were used to form the input parameters based on the consideration that the weather pattern in the humid tropics is uniformly hot and humid throughout the year. In the present case study, information about the cooling loads of the building one month before the target time had been used in order to tell the ANN the basic characteristics of cooling loads during the period.

MatLab, an interactive, matrix-based system for numeric computation and visualization was used as the platform of the software. The same was used to obtain hourly cooling load for each hour of the working days (i.e. between 7 a.m. and 5 p.m.) and daily cooling load for the week days (i.e. Monday to Friday). Prior to that hourly cooling load of of the building had been established from the data file created by DOE-2. Each discharging hour had particular neural network to predict its cooling load, although the architecture of ANN for different hours were similar. The input parameter set of each hour's ANN took particular information from the data file about this hour.

6. OPTIMIZING ANN ARCHITECTURE

6.1 Investigation about the hidden layer

To determine the suitable neuron number in the hidden layer, an investigation was carried out. It is a necessary prerequisite to establish the optimum number of neurons in the hidden layer for maximum accuracy. The effects of different neuron numbers in the hidden layer were investigated. In order to determine the accuracy of prediction, a graph of prediction error versus number of neuron in the hidden layer was plotted tree different days, as shown in Fig. 3. It was found that using 6 neurons in the hidden layer of the ANN was the most suitable for the present model.

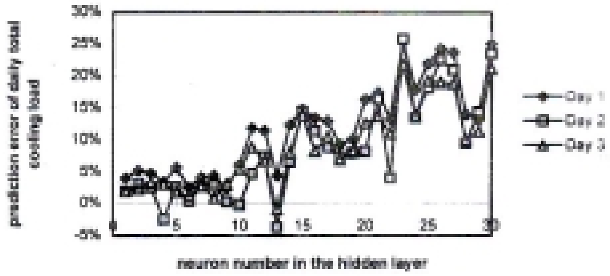

Fig. 3 graph of prediction error versus number of neuron in the hidden layer

6.2 Evaluation of the designed ANN

For evaluating the performance of the ANN, the average of hourly prediction errors per day was used as the criteria to judge the performance of the ANN model. If the average value was acceptable, then the ANN would be considered as suitable, otherwise further improvement of the ANN should be attempted. The hourly prediction error was defined as follows:

$$\text{Error (\%)} = \{(\text{predicted load} - \text{actual load}) / \text{actual load}\} \times 100$$

where, actual load is the hourly load established by DOE-2 program. Efforts to improve the performance of the ANN mainly included trying different types of input parameters and investigating the suitable neuron number in the hidden layer. The evaluation was carried out by the day types e.g. Monday, Tuesday, Wednesday, Thursday, and Friday. For example, cooling load prediction for the last four Mondays in the year was done together after training the ANN for Monday. The average of hourly prediction errors per day is generally less than 5%. The average is the arithmetic mean of the absolute values of the hourly prediction error of each day. The hourly actual loads, hourly predicted loads and hourly prediction errors in the evaluation period were tabulated. Fig. 4 shows graphically the variation trend of the predicted loads in relation to the actual load.

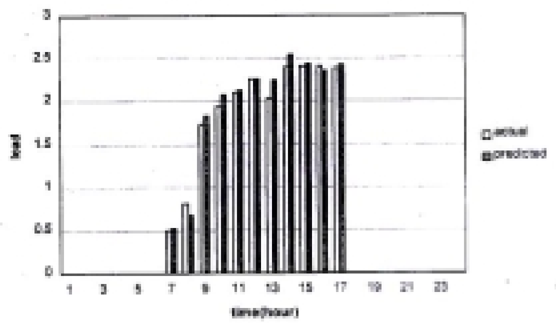

Fig. 4 Predicted load versus actual load

7.CONCLUDING REMARKS

The designed software shows its sensitivity to the architectural change of neural networks. The optimum number of neuron in the hidden layer was found to be six. The input parameters including the information about cooling load within the period one month before the prediction days has proven feasible through evaluating the performance of the designed ANN (software). The average of the hourly prediction errors per day is generally less than 5%. The prediction accuracy is acceptable and the input parameters considered are appropriate. The designed software was run under the environment of personal computer-Pentium 3. The total run time of around 10 minutes allows timely control of the charging of the ice storage system.

The results of the case study show that the designed software should be able to provide the cooling load prediction for the specific target office building should it employ an ice storage air-conditioning system for its cooling at a later date.

8.REFERENCES

1. Dorgan, C.E. and Elleson, J.S. *"ASHRAE Design Guide for Cool Thermal Storage"*, ASHRAE Transactions, vol. 100 no. 1, pp 33-38, 1994.
2. Loh, P.S. " *A National Building Energy Utilization Index for Singapore*", Journal of the Institution of Engineers, *Singapore*, vol. 28, no. 2, pp. 17-23, 1988.
3. Potter, R.A. Jr., Weitzel, Jr.,King, D.J., Boettner, D.D. 1995. ASHRAE 766: Study of operational experience with thermal storage systems. ASHRAE Transaction 101(2), pp. 549-557.
4. Brady, T.W. 1994. Achieving energy conservation with ice-based thermal storage. ASHRAE Transaction 100(1), pp. 1735-1745.
5. Simmonds, P. 1994. A comparison of energy consumption for storage priority and chiller priority for ice-based thermal storage system. ASHRAE Transaction 100(1), pp.1746-1753.
6. Ferano, F.J.,Jr. and Wong, K. V. 1990. Prediction of thermal storage loads using a neural network. ASHRAE Transaction 96(2), pp. 723-732.
7. Mackay, D.J.C. 1994. Bayesion nonlinear modelling for the prediction competition. ASHRAE Transaction 100 (2), pp.1053-1062.

8. Mattias, B.O., and Ohlsson 1994. Predicting system loads with artificial neural –network methods and results from “the great energy predictor shootout”. ASHRAE Transaction 100(2), pp. 1063-1074.
9. Kawashima, M. 1994. Artificial neural network backpropagation model with three-phase annealing developed for the building energy predictor shootout. ASHRAE Transaction 101(2), pp.1096-1103.
10. Kimbara, A., Kurosi, S. Endo, R., Kaminura, K., Matsuba, T., Yamada, A. 1995. On-line prediction for the load profileof an air-conditioning system. ASHRAE Transaction 101(2), pp. 198-207.
11. Sakawa, M., Kato, K., Misaka, M. and Ushiro, S. 1995. Cooling load prediction through recurrent neural networks. Proceeding of 1995 IEEE international conference on fuzzy systems. Yokohama, Japan.
12. Kashiwagi, N and Tobi, T.1995. Heating and cooling load prediction using a neural network system. Proceeding of 1993 international joint conference on neural network. Nagoya, Japan.
13. Kawashima, M., Dorgan, C.E. and Mitchell, J.W. 1995. Hourly Thermal load performance for the next 24 hours by ARIMA, EWMA, LR, and an Artificial neural network. ASHRAE Transaction 101(1), pp. 186-200.
14. Curtisse, P.S., Shavit, G. and Kreider, J.F. 1996. Neural Networks applied to buildings- a tutorial and case studies in prediction and adaptive control. ASHRAE Transaction 102(1), pp. 1141-1146.
15. Yang, K.H., Su, C.H., and Hwang, R.L. 1996. The analysis on intelligent control strategies of a thermal energy storage air-conditioning system. ENERGY. VOL: 21 ISS: 4. UK.
16. Kawashima, M., Dorgan, C.E. and Mitchell, J.W. 1996. Optimization system control with load prediction by neural networks for ice-storage system. ASHRAE Transaction 102(2), pp. 1169-1178.
17. Yang, K.H., Hwang, W.J. 1997. The dynamic system in Taiwan area. Proceeding of IASTED international conference: Modeling, Simulation and Identification. Canada.