APPLICATION OF A NEURO-FUZZY MODEL TO EVALUATE THE THERMAL PERFORMANCE OF TYPICAL AUSTRALIAN RESIDENTIAL MASONRY BUILDINGS

HAITHAM ALASHAARY, BEHDAD MOGHTADERI, JOSE DE DONA, ADRIAN PAGE

Priority Research Centre for Energy
Faculty of Engineering & Built Environment
The University of Newcastle
Callaghan, NSW 2308, Australia

SUMMARY

This paper describes the utilisation of a predictive model for studying the thermal performance of masonry housing based on a Neuro-Fuzzy approach using a set of training data collected from four test house modules. The room temperatures for the four modules have been predicted from a collection of interior surface temperatures using the ANFIS platform. It has been shown that for the test modules the ANFIS Sugeno-type modelling approach offers an accurate and reliable prediction tool by which given input-output patterns could be achieved with a satisfactory level of accuracy.

INTRODUCTION

A considerable fraction of the total energy produced in the world is supplied to and consumed within buildings. It is estimated that less than one-third of the overall global energy provisions is consumed in buildings in different forms, of which the most dominant forms are heating, ventilation and air-conditioning (HVAC). This, in turn, will lead to higher electricity demand and, hence, greater levels of greenhouse emissions. As such, energy efficiency in buildings is an important topic in the debate on global warming which results from the emissions of greenhouse gases (Hong et al. 2000). Minimising the operational energy in buildings can make a major contribution towards achieving better energy efficiency and, thus, reduction in greenhouse gas emissions.

In Australia, the percentage of energy usage in residential buildings is greater than the average global energy consumption indicated above. It is estimated that approximately 39% of the energy supplied to residential buildings is consumed by space heating and cooling systems (AGO 2004). The thermal performance of Australian residential buildings is evaluated by assessing two main measures: the indoor thermal comfort which compares the indoor air temperature to a predefined comfort temperature range; and the energy required to keep the indoor temperature within that comfort range (Sugo et al. 2004). This assessment mechanism is achieved using a smart energy star rating tool which estimates the energy required to maintain defined internal conditions and allocates an appropriate star rating according to the assessed energy efficiency (McLaren 2004).

In order to better understand the thermal behavior of typical Australian masonry houses and various associated walling systems, the Priority Research Centre for Energy at the University of Newcastle is involved in an in-depth investigation of the thermal performance of such buildings using both experimental and analytical modelling approaches. Four typical Australian housing types have been reproduced in the form of 4 test house modules constructed on the Callaghan campus of the University of Newcastle.

The overall project has parallel analytical and experimental strands. The experimental strand involves the assessment of the thermal resistance of individual walling systems using the ASTM Hot Box Apparatus, together with the monitoring of the detailed thermal performance of the four housing modules built on campus.

In the analytical strand, two distinct approaches have been employed to simulate the thermal performance of the test modules: (i) a first principles approach (i.e. using conservation of mass, energy, momentum, etc), and (ii) a neuro-fuzzy approach in which the model is trained based on the experimental data. This paper is concerned with the second strand and utilises an innovative hybrid modelling approach referred to as adaptive neuro-fuzzy inference system (ANFIS) of Sugeno-type.

A BRIEF DESCRIPTION OF THE MODULES AND WALLING STRUCTURES

The four test modules studied in this investigation were built in an open area so that obstruction of solar radiation and light is minimal. The northern walls of the modules are at right angles to the astronomical north. To diminish wind shielding and avoid shading, the modules have been spaced 7 m apart from one another (except for the LW module which is located separately near and far enough from the other three modules for the same purpose).

The modules are of equal dimensions and of typical Australian construction, each with a different walling system. Each module has a 6m x 6m floor plan and stands on a concrete slab-on-ground with a ceiling height of 2450 mm.

Each module can be accessed via standard solid timber door that is located on the southern wall and is well fitted and especially treated to minimise the heat losses using a 75 mm thick polystyrene layer attached to the internal face of the door (Sugo et al. 2004). No carpet or floor covering has been used to cover the concrete slab. All modules have white-painted interior wall surfaces.

This part of the experimental study has concentrated on the detailed assessment of the behavior of each walling system in isolation from any other factors. This raised the need to prevent direct solar access or ventilation by having the modules not been ‘initially’ fitted with windows or openings with the exception of the ICB module. North-facing, single-glazed windows, however, were installed at a later stage in the other three modules to investigate their thermal effect on the modules. Description of the modules in terms of the structure of their walls and specifications of the insulation materials (if any) used is summarised as follows:

Module 1 - Brick Veneer (BV): 110 mm external brickwork skin, 50 mm air cavity with low-glare wall-wrap insulation fixed onto 70x35 mm pine studs at 600 mm centres and finished with 10 mm thick plasterboard.

Module 2 - Cavity Brick (CB): Conventional cavity brick construction, 110 mm external brickwork skin, 50 mm air cavity, 110 mm internal brickwork skin finished with 10 mm cement/sand render, no insulation provided.
Module 3 - Insulated Cavity Brick (ICB): 110 mm external brickwork skin, 50 mm air cavity with R1 rigid polystyrene insulation attached to the 110 mm internal brickwork skin and finished with 10 mm cement render.
Module 4 - Lightweight construction (LW): Polymer render over 7 mm fibro-cement sheeting, breathable membrane fixed onto 90x35 mm pine studs @ 600 mm centres, R1.5 bulk insulation in frame cavity and finished with 10 mm thick plasterboard interior.

The experimental investigation of the thermal response of the test modules involves the continuous monitoring of temperatures and heat flux profiles for all surfaces. Each building has been instrumented with 105 sensors, monitoring wall surface and profile temperatures, heat flux and indoor air temperature and humidity. The external weather conditions are also monitored using a small weather station mounted on the roof of one the modules. The thermal performance is analysed and evaluated under two conditions: a free-floating mode (i.e. no heating or cooling provided) which allows interaction between the indoor temperature and the external weather conditions; and a driven mode where the indoor temperature is controlled by a cooling-heating system and the energy consumption is monitored (Sugo et al. 2004).

A BRIEF DISCRIPTION OF THE NEURO-FUZZY MODEL

As mentioned earlier, the framework implemented in this study is represented by a neuro-fuzzy system which is essentially an ANFIS Sugeno-type model. The model has a hybrid framework that combines the concepts of fuzzy logic and neural networking into a unified platform. The model has a fuzzy inference in the form of an adaptive network for system identification (Jang 1993, Jang et al. 1997) and a predictive tool that maps a given input space to its corresponding output space based on a training data set.

The ANFIS inference system relies on both fuzzified human knowledge (human knowledge presented in the form of fuzzy rules) and input-output patterns to accomplish the process of input-output mapping (Jang 1993).

The ANFIS modelling strategy is widely used in applications or systems that involve uncertainty in the definitions or variables constituting the system's behavior. In other words, it has the ability to qualitatively model and represent human knowledge without the need for precise or quantitative definitions. Moreover, it is capable of modelling and identifying nonlinear systems as well as predicting chaotic time-dependant behavior. Further understanding of the architecture and learning procedures of ANFIS modelling paradigm can be sought in Jang's 1993 study (Jang 1993).

In this study, a very simple ANFIS Sugeno-type architecture has been implemented. This simplified version is constructed so that it has five fuzzy "*if-then*" governing rules and processes a set of applied input variables to produce a single predicted output. The number of input variables can be readily adjusted according to the actual number of inputs to be modelled. Each input variable attracts five Gaussian-shaped membership functions that represent its fuzzy linguistic labels or values (i.e. very low, low, medium, high and very high). The consequent part (crisp output) of each fuzzy "*if-then*" rule is calculated by performing a

linear combination of all inputs in the corresponding antecedent (or premise) part and adding a constant term. Finally, the overall (or predicted) output is obtained by summing the weighted average of each rule's output (Jang 1993).

The inputs contained in each rule are connected to one another by the logical connector "*AND*" which is implemented by performing algebraic multiplication process. The defuzzification method employed in our model is called weighted average. A typical fuzzy if-then rule base used in our models to perform and control the prediction process by the ANFIS tool is of the form that appears in equation (1):

$$
\begin{array}{c}
\text{IF } (\text{input}_1) \text{ is } (A_1) \text{ AND } (\text{input}_2) \text{ is } (B_1) \text{ AND } \ldots \text{ AND } (\text{input}_n) \text{ is } (Y_1) \text{ THEN} \\
(\text{output}_1 = a_1.\text{input}_1 + b_1.\text{input}_2 + \ldots + y_1.\text{input}_n + z_1) \\
\text{IF } (\text{input}_1) \text{ is } (A_2) \text{ AND } (\text{input}_2) \text{ is } (B_2) \text{ AND } \ldots \text{ AND } (\text{input}_n) \text{ is } (Y_2) \text{ THEN} \\
(\text{output}_2 = a_2.\text{input}_1 + b_2.\text{input}_2 + \ldots y_2.\text{input}_n + z_2) \\
\vdots \\
\text{IF } (\text{input}_1) \text{ is } (A_m) \text{ AND } (\text{input}_2) \text{ is } (B_m) \text{ AND } \ldots \text{ AND } (\text{input}_n) \text{ is } (Y_m) \text{ THEN} \\
(\text{output}_m = a_m.\text{input}_1 + b_m.\text{input}_2 + \ldots + y_m.\text{input}_n + z_m)
\end{array} \tag{1}
$$

where m is the number of fuzzy values associated with each input variable, and n is the number of input variables of the system (in our case, $m = 5$ for all models, and n varies from model to model - definitions of the models developed are explained in the next section).

The ANFIS model has default epochs (or training iterations) and error tolerance values of '3' and '0' respectively. It uses either a backpropagation or a hybrid learning approach. The latter method implies that Least Squares Error (LSE) principle is used to identify the consequent parameters of each rule, and the error rates are back-propagated in order to update the premise parameters by means of gradient descent computational tool (Jang 1993, Jang et al. 1997). The hybrid learning method is used throughout this study to ensure optimal results.

METHODOLOGY

The experimental model implemented in this study is purely based on a comprehensive series of time-dependant weather data and adopts the ANFIS modelling technique to achieve the desired objective of this study. As stated earlier, ANFIS uses its prediction facility to map a given input to its corresponding output with the indoor air temperature being the target output of this prediction process. In predicting this target output using the ANFIS tool, the entire modelling process has been divided into four different stages or models, namely: model 1, model 2, model 3 and model 4 as a means to acquire sufficient understanding of the thermal performance of the test modules before proceeding with the ultimate stage which is concerned with modelling a real house. Figure 1 is a simple flow chart illustrating the stages of the overall project under study.

The four models are similar in their structure, parameters and evaluated output and they only differ in the associated input variables introduced to the ANFIS system. This study, however, focuses on 'model 1' which estimates (predicts) the indoor air temperature of each module from a set of six input interior surface temperature variables applied to the ANFIS system. Below is a brief outline of the above-named models in terms of the input variables of each model.

Model 1: Incorporates 6 input variables representing interior surface temperatures, namely: slab, ceiling, north; south; east; and west walls.
Model 2: Incorporates 6 input variables representing exterior surface temperatures, namely: under-slab, top-of-roof, north; south; east; and west walls.
Model 3: Incorporates 4 input variables representing external weather conditions, namely: ambient air temperature, wind speed, wind direction and horizontal-plane solar radiation.
Model 4: A combination of external weather data (as in model 3), projected dimensions of walls and windows facing each direction, percentage shading on walls and windows facing each direction and time of day; totalling 21 inputs (this figure is subject to change based on introducing new variables or eliminating existing ones).

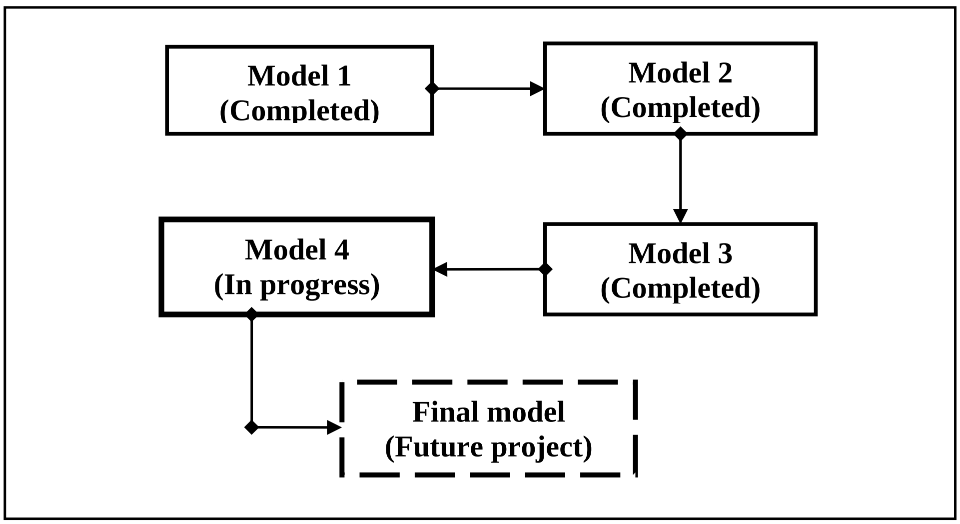


Figure 1: A simple flow chart that outlines the four stages of the overall project preceding the final stage of modelling a real house.

The prediction process can only be accomplished by first conducting a model training session against a comprehensive and representative training data set of input-output data pairs (or input-output patterns). The training process is repeatedly executed until either the produced error of the training output reaches a predefined threshold (tolerance error) or the specified training iterations (epochs or number of training cycles) is achieved; whichever occurs first.

On completion of the training phase, new input data sets (testing data sets) are applied to the model to predict the corresponding outputs (indoor air temperature values) which, in turn, are compared to the actual recorded values to evaluate the accuracy of the model.

Recording of all data began in 2003 for the BV and CB modules, in 2004 for the ICB module and in 2006 for the LW module with the data being measured every 10 minutes (i.e. 144 data points available per single day). The required input and output data were extracted from the original data files and grouped into two main sets: a training data set and a testing data set. Each data file within these two sets contains the recorded data of the above-mentioned 6 inputs (see model 1 above) and the single output.

For each module, data obtained during the first year of recording was used as the training data set for that module. This set is, in turn, divided into 4 subsets according to the size of the training data used out of each month's data of that year: an equivalent of 1-day, 1-week, 2-week and 3-week worth of data (denoted hereafter as 1DPM, 1WPM, 2WPM and 3WPM

respectively). Data recorded during later years was arranged in a monthly basis and used as the testing data sets to validate the trained model.

The model output (indoor air temperature) was predicted at three different heights (relative to the floor level): 650, 1350 and 2050 mm for the BV and LW modules; and 600, 1200 and 1800 mm for the CB and ICB modules. It is also to be mentioned that the room temperatures were predicted only for free-floating conditions (i.e. no heating and/or cooling is provided).

RESULTS AND DISCUSSION

As an initial step, the sensitivity of the ANFIS model was first examined against the size of the training data set as well as the number of training iterations (epochs). This sensitivity evaluation process was only conducted for model 1 exclusively on the BV module. Figure 2 shows graphically the sensitivity behavior of the model against both size of the training data set and training iterations (epochs) at lower-height room temperature predictions. The parameter that was observed to measure and compare the performance of our model for all cases is the *average relative training error* which is defined as the 'normalised' absolute errors (differences) between the predicted training outputs and the target outputs averaged over the number of input/output training data pairs (normalised to the actual outputs). Intuitively, the optimal case is that when the average 'absolute' training error satisfies the default zero-error tolerance value specified above. This ideally means that the numerical predictions exactly match the actual measurements which are practically unachievable.

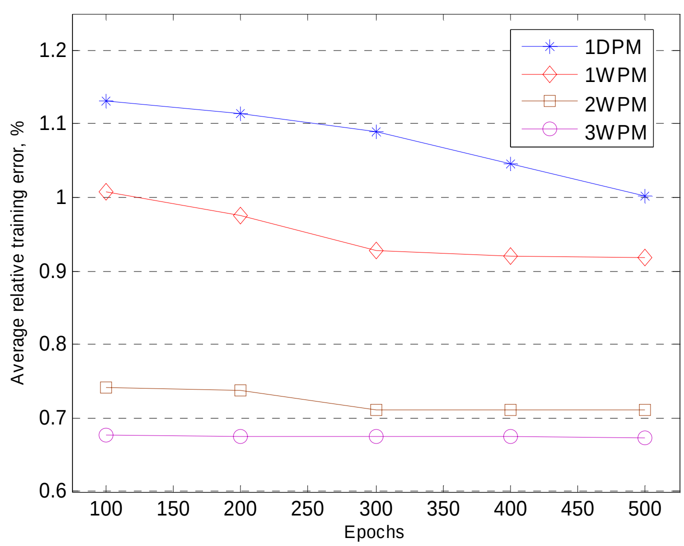


Figure 2: Sensitivity behavior of the ANFIS model against size of training data set as well as epochs at lower-height (650 mm) indoor air temperature predictions for BV.

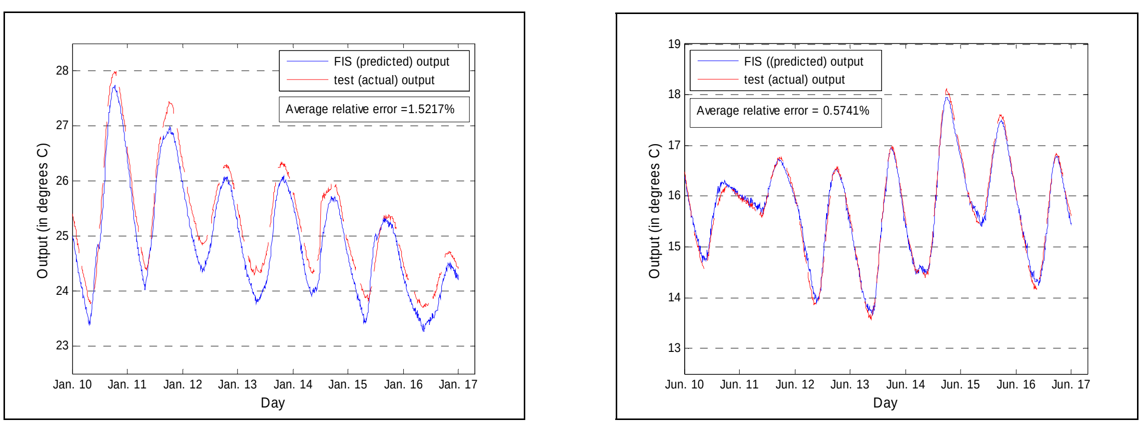
In reference to Figure 2, it can be seen that the average training error tends to decrease as the training cycles increase (as expected) until the model reaches a steady state training point after which it cannot perform any better, i.e. the ANFIS model is over-trained such that the training error cannot be reduced any further. This situation clearly occurs when using 1WPM and 2WPM training data sets. For the worst scenario (1DPM), the curve suggests that the model could not attain a steady state condition within the given range of epochs; however, it might (or might not) do better and reach this condition if it was tested for more training

cycles. The fourth case associated with the largest training data set (3WPM) exhibits, somewhat, steady state behaviour over the entire range of epochs. In essence, we are interested in the two curves where a clear steady state criterion is obtained to guarantee optimal results, namely 1WPM and 2WPM.

On the other hand, the four error curves explicitly show that the model under consideration performs better (produces less errors) when the size of the training data set is expanded, i.e. the larger the training data set the more accurate the model is. In particular, the 1WPM curve becomes stable at an epoch value of 400, whereas that of the 2WPM achieves stability at a lower number of training cycles (300) with less errors, however, this comes at the cost of dealing with a doubled training data set which implies greater execution time and storage space. Having said that, and based on the marginal error differences between the two cases it was decided that a training data set of **1WPM** and an epoch value of **400** shall be used throughout this study and all other related future studies, unless otherwise specified.

To assess the performance and accuracy of the ANFIS predictor, the ANFIS was tested against 'unused' input data sets (i.e. input data the ANFIS model has never dealt with or been trained on before) taken from the evaluation years for each module. Numerical predictions for the indoor air temperatures (output of the ANFIS) were then generated and compared with the actual temperature measurements. Figures 3-6 depict some predictions obtained by the ANFIS predictor for the lower-height room temperatures for all modules. Each figure presents 'sample' predictions for two selected months representing both cold (June) and hot (January or December) weather conditions of a given evaluation year(s) of the relevant module.

In each case, the prediction curve tends to follow the trend of the actual room temperature distribution curve which indicates that the ANFIS model offers a high level of accuracy represented by the marginal errors between the predicted and actual temperature values. In most cases, however, the prediction curve seems to be almost exactly following the actual output curve. This can obviously be observed in Figures 3(b), 4(b), 5(b), 6(a) and 6(b) with average relative prediction errors of 0.5741, 0.3167, 0.6417, 0.7598 and 0.4651 %, respectively.

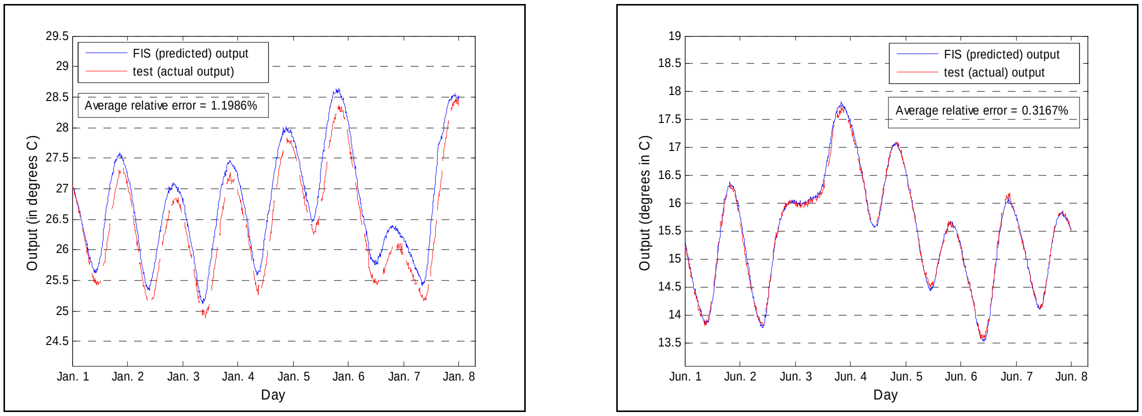


a **b**

Figure 3: Lower-height room temperature ANFIS predictions for the BV module: (a) 10th (midnight) - 17th (midnight), Jan. 2004, (b) 10th (midnight) – 17th (midnight), Jun. 2004.

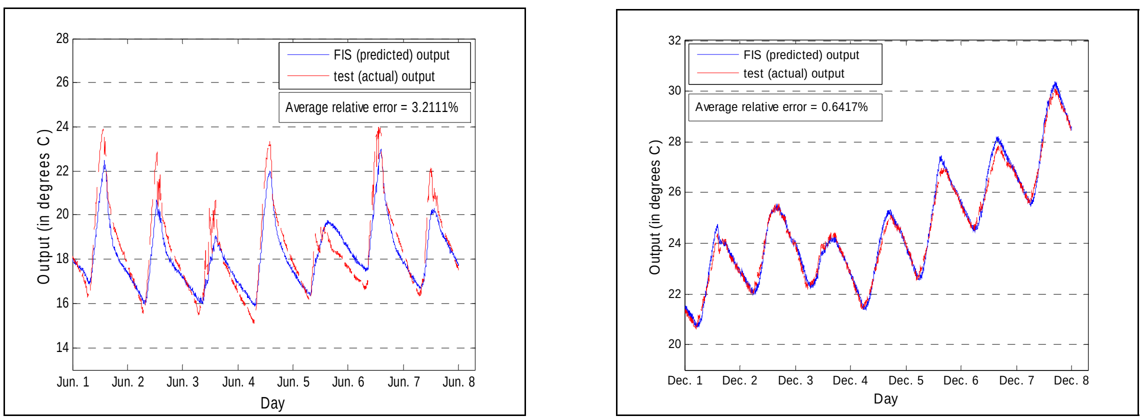
In Figure 7 the average relative monthly prediction errors are plotted for all 'available' months of a selected evaluation year of the 4 modules. The missing month(s) of each module

was (were) deliberately neglected because either the corresponding module was air-conditioned or necessary data was not available (due to technical or constructional reasons) during that (those) whole period(s).



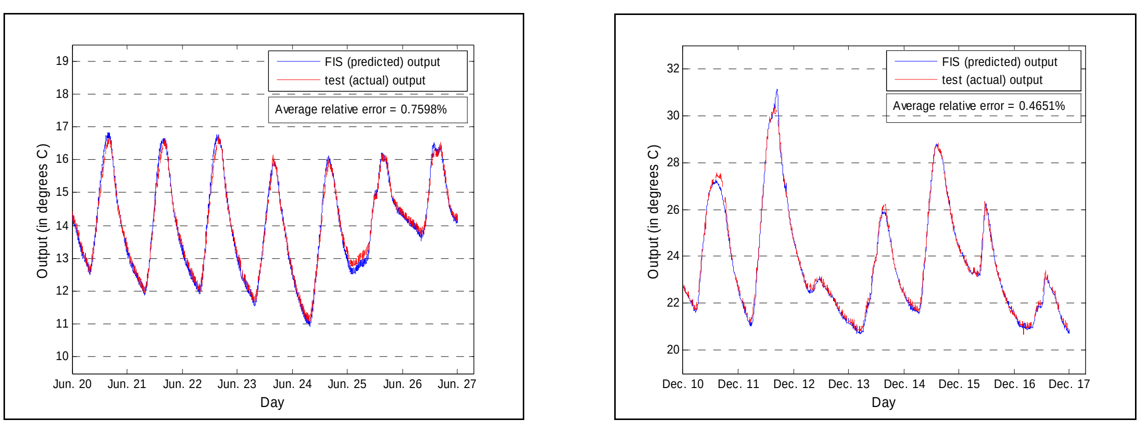
a b

Figure 4: Lower-height room temperature ANFIS predictions for the CB module: (a) 1st (midnight) – 8th (midnight), Jan. 2004, (b) 1st (midnight) – 8th (midnight), Jun. 2004.



a b

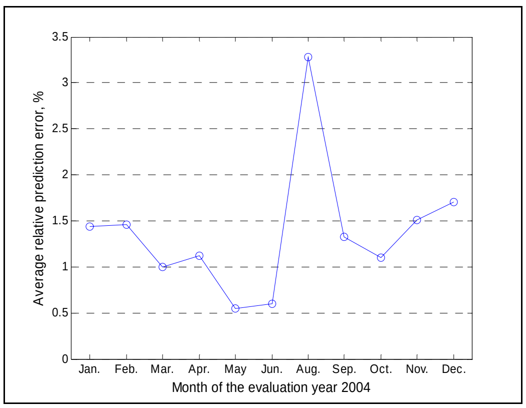
Figure 5: Lower-height room temperature ANFIS predictions for the ICB module: (a) 1st (midnight) – 8th (midnight), Jun. 2005, (b) 1st (midnight) – 8th (midnight), Dec. 2005.



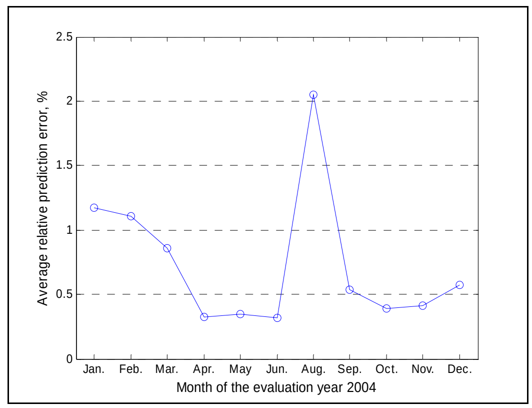
a b

Figure 6: Lower-height room temperature ANFIS predictions for the LW module: (a) 20th (midnight) – 27th (midnight), Jun. 2006, (b) 10th (midnight) – 17th (midnight) Dec. 2006.

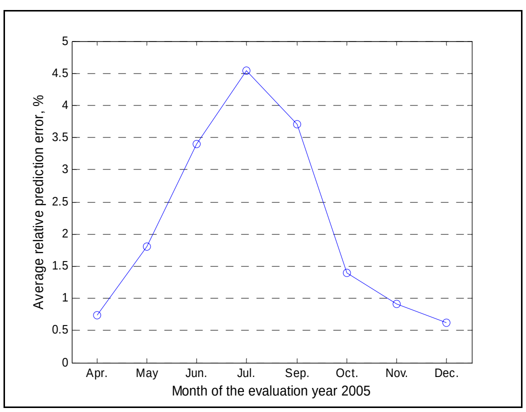
The error curves in Figure 7 show that the normalised prediction errors for all modules are marginally small with the best predictions are provided by the LW module and the worst -but still acceptable- by the ICB module. The BV and CB modules show, somehow, similar tendencies in terms of the prediction error curves with the CB performing relatively better. However, being better or worse in terms of the prediction process outcomes does not mean better or worse 'thermal performance' of one module over the other. This has absolutely nothing to do with the thermal performance of the modules as quality of the prediction process might be strongly dependent on many other factors such as the training process of the ANFIS model itself. For example, the prediction outcomes for the LW module (Figure 7(d)) are relatively more acceptable than those of the BV module (Figure 7(a)) or the CB module (Figure 7(b)) which does not reflect the fact that BV and CB constructions are more preferable over the LW construction in terms of their thermal performance (which is justified next).



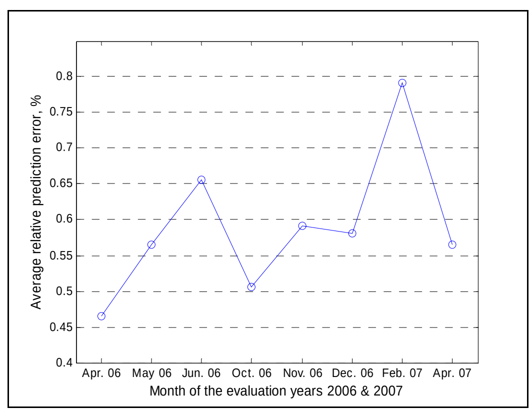
a



b



c

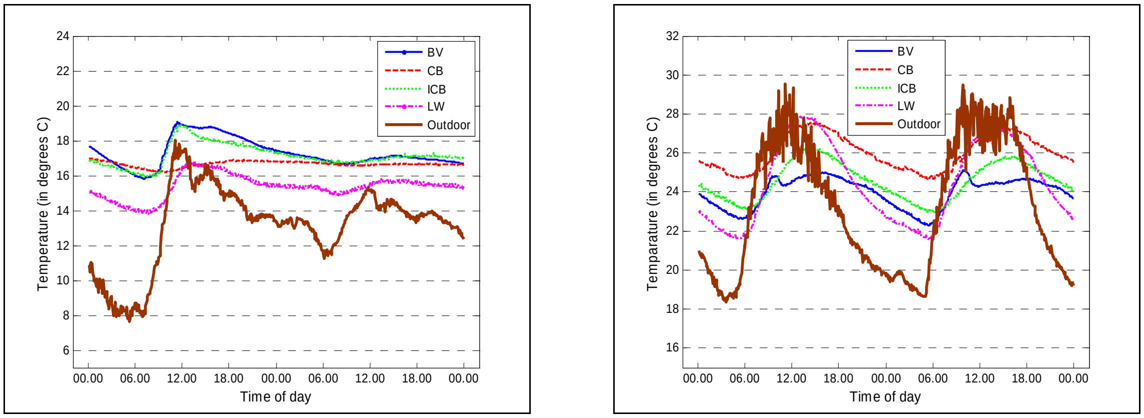


d

Figure 7: Monthly average relative prediction error for the lower-height room temperature: (a) BV - 2004, (b) CB - 2004, (c) ICB - 2005 and (d) LW - 2006/2007.

Finally, "free-floating" temperature predictions for all modules were simulated and then compared to the corresponding outdoor temperature for both hot and cold weather cycles to assess the thermal performance of each module. A 48-hour period was selected from the winter and summer periods in the year 2006 for this evaluation purpose. Figure 8 depicts the "free-floating" simulations (predictions) obtained by the ANFIS model over the specified time spans.

It is stated earlier that thermal performance of a building is assessed by considering two main factors: the indoor thermal comfort in terms of the indoor temperature fluctuation range; and the energy required to maintain the indoor temperature within that range. This study is only concerned with the former factor as the analysis of energy consumption and rating in buildings, along with thermal comfort, is the topic of another study conducted by the 'Priority Research Centre for Energy' at the University of Newcastle (refer to Gregory et al. 2007).



a **b**

Figure 8: Predicted indoor temperature curves compared to outdoor temperature: (a) winter weather cycle (9th-10th, Jun. 2006), (b) summer weather cycle (9th-10th, Dec. 2006).

When considering thermal comfort within a building, the indoor temperature fluctuations has to be desirably minimal such that the temperature swing over a given cycle is limited by the smallest possible temperature range so as to diminish the reliance on heating/cooling systems and, hence, energy consumption. Furthermore, the temperature fluctuation range is, besides being minimal, preferably wanted to be within a predefined comfort range (say 20 – 24 °C); it is of no interest to have a small fluctuation range (1 °C, for example) and at the same time the temperature curve is centred around a very low or very high temperature baseline as this increases the demand on heating or cooling.

From Figure 8, and based on this standard definition of thermal comfort, it can be seen that for cool weather conditions the highest level of thermal comfort (in the sense of least fluctuations only) is offered by the CB walling system module which maintains the indoor temperature oscillation within 1 °C (variation range of approximately 16 – 17 °C). However, this comes at the expense of lower temperatures that means more energy consumption due to increased desire of heating as explained above. The other three modules exhibit similar behaviour with the BV and ICB providing higher measures of thermal comfort (in spite of the greater variations) and the LW module being the least in this regard since its predicted indoor temperature ranges between 14 – 17 °C. In other words the LW module presents cooler air inside the building which is undesirable for a winter time that may require extended time of heating and, thus, more energy usage, whereas the BV and ICB modules perform better by keeping the room temperature remained in the range 16 – 19 °C (2 °C above the LW module) which is more preferable in the winter that could reduce the need for excess operation of heating systems.

On the other hand, the modules behaviour during the summer months is slightly different. In this scenario, the BV and CB offer the same tendency of temperature fluctuations (2 °C range), however, the BV building provides more comfortable temperature range (23 – 25 °C

for BV and 25 – 27 °C for CB). The ICB module behaves very similarly to the BV module with expanded temperature oscillation (23 – 26 °C), this implies that some more cooling might be required. As for the LW module, it is apparent that, from the two scenarios of cool and hot conditions, the worst thermal performance in terms of the thermal comfort is provided by this type of walling system.

CONCLUSION AND FUTURE WORK

This study explains the utilisation of a Neuro-Fuzzy predictive approach, the so-called ANFIS Sugeno-type model, for analysing the thermal performance of various walling designs used in Australian residential buildings using data collected from four test housing modules. The indoor air temperature for each module was predicted from a collection of interior surface temperatures using the ANFIS platform. It has been found that for the test modules the ANFIS Sugeno-type modelling approach offers a powerful and reliable prediction tool by which given input-output patterns could be achieved with a satisfactory level of accuracy. It is also found that the BV walling system type predicts the best results in terms of the indoor thermal comfort, while the LW walling system is not, somewhat, of any benefit at this stage as it anticipates unsatisfactorily.

The current model has been extended to allow prediction of room temperatures based on other sets of input variables such as exterior surface temperatures and external weather conditions (consult Figure 1 and description of the four models above for further clarification).

In the longer term, with the knowledge gained from the idealised modules, the model will be extended further to allow predictions of the thermal performance of real houses, thus having the potential to provide a fast and effective predictive tool.

ACKNOLEDGEMENT

Funding for this work has been provided by Think Brick Australia and the Australian Research Council. The support of both these organisations is gratefully acknowledged.

Acknowledgment is also to be appreciated to Dr Jose De Dona from the University of Newcastle for his invaluable technical support and academic expertise he offered.

REFERENCES

- Australian Greenhouse Office (AGO), (2004). Australian Residential Building Sector, Greenhouse Gas Emissions 1990-2010. Executive Summary Report 2004, Australian Greenhouse Office, Canberra.

- Gregory, K. E.; B. Moghtaderi; H. Sugo; A. Page, (2007). Effect of Thermal Mass on the Thermal Performance of Various Australian Residential Constructions Systems. Energy and Buildings Journal (In Press).

- Hong, T.; Chou, S. K.; and Bong, T. Y., (2000). Building Simulation: an overview of developments and information sources. Building and Environment, 35: 347-361.

- Jang, J.-S. R., (1993). ANFIS: Adaptive-Network-Based Fuzzy Inference System. IEEE Transactions on Systems, 23 (3): 665-685.

- Jang, J.-S. R.; Sun, C.-T.; and Mizutani, E., (1997). Neuro-Fuzzy and Soft Computing: a computational approach to learning and machine intelligence. Prentice-Hall, Inc., Upper Saddle River, N.J.

- McLaren, W., (2004), The Ratings Game. Environ Magazine, Winter 2004, pp. 22-24.

- Sugo, H. O.; Page, A. W.; Moghtaderi, B., (2004). A Comparative Study of the Thermal Performance of Cavity and Brick Veneer Construction. Proceedings of the 13th International Brick and Block Masonry Conference, Amsterdam, Holland, Vol. 3, pp. 767-776.