Neuro-Fuzzy Adaptive Modelling of Air Conditioning Systems

A Gegov, G S Virk, D Azzi, B P Haynes, K I Alkadhimi and I Matthews
University of Portsmouth , Department of Electrical & Electronic Engineering
Anglesea Building, Anglesea Road, Portsmouth PO1 3DJ, United Kingdom
Phone: +44-1705-842765, Fax: +44-1705-842766
email: alexander.gegov@port.ac.uk

ABSTRACT: The paper presents recent results on the application of the Soft-Computing methodology for modelling of internal temperature and humidity in Building Management Systems. The approach adopted is based on fuzzy logic for modelling and neural networks for model adaptation. A regressional delay model structure is considered where the temperature and humidity values are predicted on the basis of past measurements of the inputs incorporating (auto) regression and (auto)delay input terms. The best fuzzy model corresponding to the smallest validation error is determined by evaluating all possible model structures, i.e. involving all combinations of inputs up to some order. The results presented show that the neural network improves slightly the prediction accuracy of the fuzzy model.

KEYWORDS: soft-computing, fuzzy modelling, neural adaptation, building management systems, air-conditioning.

INTRODUCTION

Soft Computing (SC) is a heuristic methodology which has attracted significant interest in recent years and has shown to be successful in many areas such as modelling, control, fault diagnosis and pattern recognition. It is based on the implementation of different Intelligent Techniques (ITs) such as Fuzzy Logic (FL), Neural Networks (NNs), Genetic Algorithms (GAs), and some other techniques [Jang et al,1997]. Each of these techniques is suited for solving specific types of problems. In this respect, FL is powerful for approximate modelling and reasoning, NNs are well suited for learning-based adaptation, while GAs are efficient for evolutionary-based optimization. The underlying idea of SC is to use these heuristic IT in combination with each other as well as with some Classical Techniques (CTs), rather than using each of them separately. The reasoning behind this is to utilise the advantages of all the techniques cooperatively rather than to select them in a competitive fashion. More specifically, ITs are more adequate to the uncertainty inherent in many real plants while CTs give the tools for enriching the heuristic nature of ITs in a more systematic fashion, thus gradually transforming the original notion of SC from a diversity of heuristic approaches into a well defined and reasonable methodology. The notions of ITs and SC are illustrated in Figure 1.

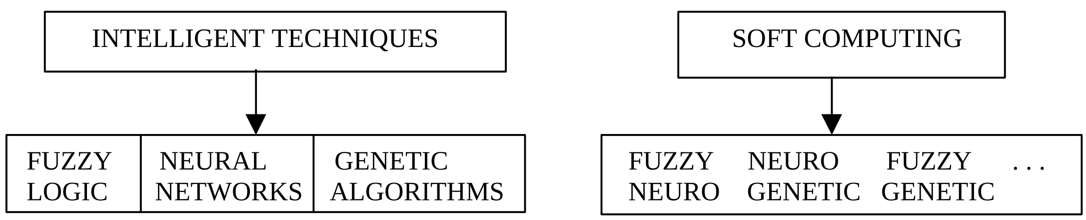

Figure 1: Intelligent techniques vs soft computing.

MODELLING ISSUES

To control the internal climate of office buildings efficiently, it is necessary to develop good predictive models which would allow a proactive control policy rather than a reactive one. In other words, instead of applying a control action only on the basis of the current sensed values, use is also made of projected readings (predictions) over a certain time in order to make future forecasts to help in the decision making. The main advantage of such a proactive philosophy is that the heating and cooling control efforts can be applied more efficiently and hence the controlled parameters become smoother, with less overshoots and shorter settling times. This leads to decreased energy consumptions and reduced pollution of the environment. However, to obtain predictive models for these buildings is not an easy task because of the overall complexity and effects due to climatic and occupancy factors which are characterised by major levels of uncertainty. Besides this, the initially derived models are usually rough approximations of the data from the plant and therefore some adaptation procedures have to be applied.

It would be interesting to see, if the SC methodology can provide reliable alternative modelling solutions to CTs for Building Management Systems (BMSs). Some investigations have recently been carried out in this domain but most of them are too narrow and lead to constrained conclusions [So et al, 1994], [Virk et al, 1996]. In most cases, they are concentrated on the usage of separate ITs, rather than using them in combination together and with CTs in the SC sense. In other words, the potentials of the SC methodology for modelling of BMS are yet to be explored in detail and this paper presents recent results from a research project whose purpose is to address these concerns. More specifically, the project aims to systematically investigate the capabilities of the SC methodology for predictive modelling of internal parameters in office buildings, e.g. temperature, relative humidity, etc. In this respect, three types of buildings are considered: Heated, Ventilated and Air Conditioned (HVAC), Naturally Ventilated (NV) and Ambient Energy (AE) buildings. The popularity of these types of office buildings is growing nowadays but they differ substantially in their mode of functioning. Therefore, it is intended to find as part of the project to what extent the SC methodology is suited to each type of building.

NEURO-FUZZY BACKGROUND

The Adaptive Neuro Fuzzy Inference System (ANFIS) method is used in the paper for adaptive modelling of internal parameters in office buildings. This method is a typical SC approach using FL for building of the initial model and NNs for parametric adaptation of this model [Jang, 1993]. It is based on a Takagi-Sugeno (TS) fuzzy model which has received considerable attention recently because of its suitability for processing information from input-output measurements. This applies for the case of BMSs where the main information source is from sensor readings rather than expert knowledge which is difficult to obtain because of the multivariable and coupled nature of the process [Gegov, 1996]. Another advantage of the TS fuzzy model is its ability to approximate non-linear input-output mappings by a number of locally linearised models.

The TS fuzzy model consists of linguistic if-then rules in the antecedent part and linear algebraic equations in the consequent part. There are two types of parameters in this model: non-linear (in the membership functions in the antecedent part) and linear (in the algebraic equations in the consequent part). The task of the fuzzy model is to determine the initial values of both types of parameters on the basis of the input-output data. There are different methods for this purpose but the one that is most often used with ANFIS is based on the idea of subtractive clustering, i.e. by assuming that each data point is a potential cluster centre and gradually finding the final clustering. The task of the neural adaptation is to adjust the model parameters in order to obtain a better fit to the measured data. There are also different methods for achieving this. The one used in ANFIS is based on the idea of back-propagation, i.e. by iteratively propagating of the error (the difference between the real plant output and the modelled value) from the consequent to the antecedent part of the fuzzy rules until a desired accuracy is achieved or a pre-specified number of iterations is reached.

The TS fuzzy model for a system with two rules, two inputs u_1, u_2 and one output y_1 is presented in Figure 2. The linguistic labels (membership functions) of the inputs are denoted by A_i, B_i, $i=1,2$ and their parameters are in fact the non-linear antecedent parameters. The coefficients p_i, r_i, q_i, $i=1,2$ are the linear consequent parameters used for the computation of the output by the locally linearised models.

If u_1 is A_1 and u_2 is B_1 then $y_1 = p_1.u_1 + q_1.u_2 + r_1$
If u_1 is A_2 and u_2 is B_2 then $y_1 = p_2.u_1 + q_2.u_2 + r_2$

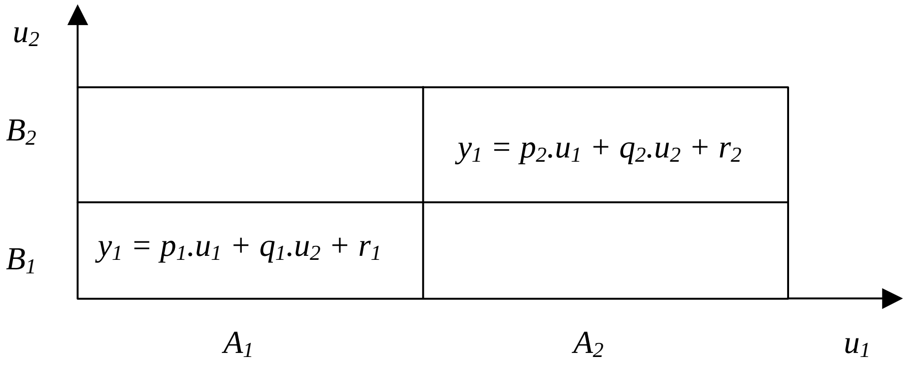

Figure 2: Takagi-Sugeno fuzzy model

The back-propagation neural network for adaptation of the fuzzy model is shown in Figure 3. The adaptive nodes are indicated with squares while the constant ones are given as circles. The network consists of five sequential layers. Each node in the first layer refers to the antecedent parameters of a membership function. The nodes in the second layer represent the firing strengths of the rules. Each node in the third layer reflects the normalized firing strengths. The nodes in the fourth layer refer to the consequent parameters of a linear equation. The fifth layer computes the overall output of the network.

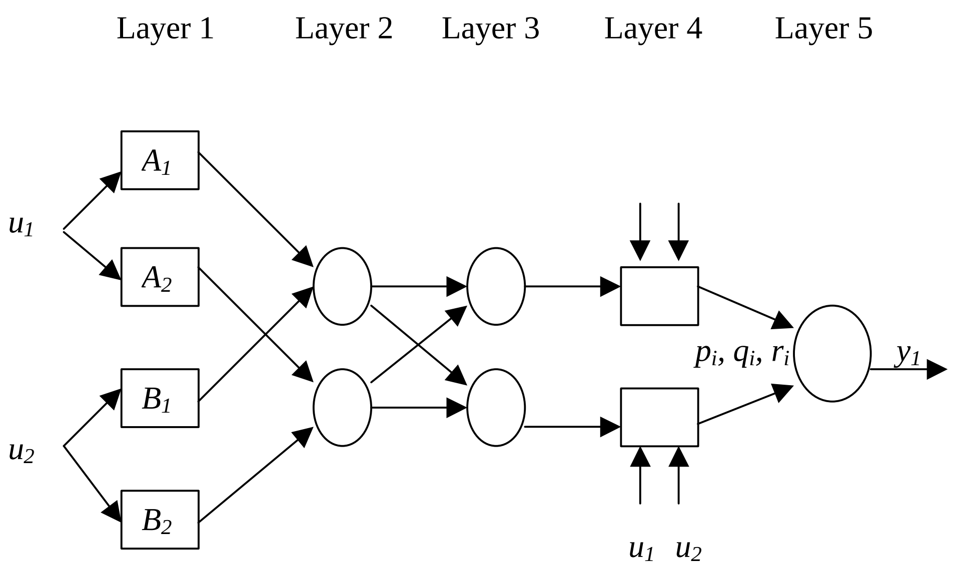

Figure 3: Back-propagation neural network.

SIMULATION RESULTS

This section presents some recent results obtained with the ANFIS method for the Anglesea Building at the University of Portsmouth. More specifically, a real HVAC plant is considered which operates in three interconnected offices within the Anglesea Building of the University of Portsmouth. The office zones are continuously monitored with temperature and humidity sensors. There is also a number of sensors on the roof of the building which monitor outside climatic parameters, e.g. wind speed and direction, solar radiance, outside air temperature and humidity. The modelled parameters are the internal temperature and humidity in one of the offices (number 3) in the building which has one south facing external wall (with window), two walls to the neighbouring air-conditioned rooms and one wall to a corridor. All these zones are continuously monitored with both temperature and humidity sensors.

The simulations presented in this paper have been carried out for a simplified free response model, i.e. the heating, cooling and humidifying units were switched off in order to evaluate the impact of the outside conditions. For this purpose, only some of the sensor readings were taken into account. These are the readings from the sensors on the roof of the building and in the office. The data was recorded during September 1998. The training data represents a period of one night and the following day while the testing (validation) was made on a data obtained during the next night.

The inputs of the model were chosen as follows:

- wind direction (W_d),
- solar radiance (S_r),
- external temperature (T_{ext}),
- external relative humidity (RH_{ext}),
- internal temperature in office 3 (T_3),
- internal relative humidity in office 3 (RH_3).

The last two inputs are the same physical variables as the modelled outputs because these models are known to have auto-regression terms.

The monitored offices in the Anglesea Building and the black-box scheme of the model used are given in Figure 4. The neighbouring offices (rooms 1 and 2) are shown for information only and they are not explicitly taken into account in the modelling of room 3.

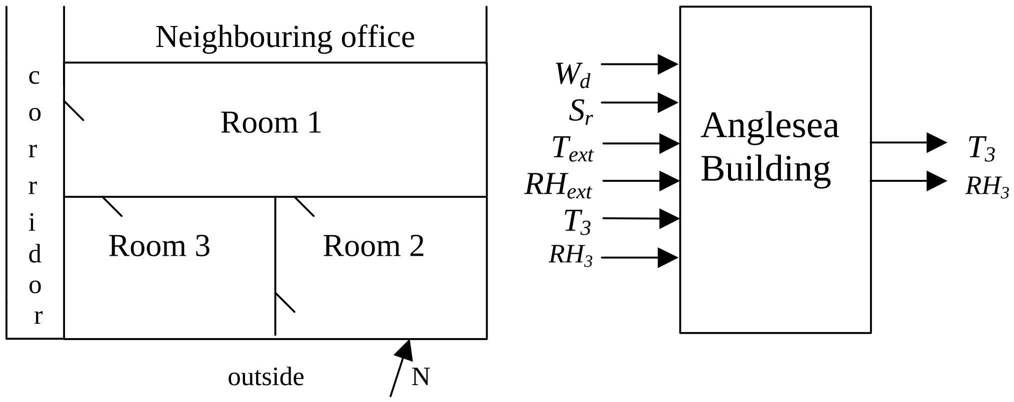

Figure 4: Monitored zones and a black-box model.

The prediction was made over an interval of 5 minutes which is equal to the sensors sampling time. Such a prediction would allow the control actions to be computed in advance which is expected to improve the tracking of the temperature and humidity reference points. The best model was chosen from a full set of possible models, representing all combinations of (auto)regression and (auto)delay terms, as well as present and absent inputs. The regression/delay backward horizon was chosen as equal to 2, i.e. the predicted value of the internal temperature at the current time instant k is obtained from measurements at time instants *(k-1)* and *(k-2)*.

The initial fuzzy model was built by subtractive clustering where the number of the membership functions of inputs is defined on the basis of the number of clusters of input-output data. These membership functions were chosen to be of a Gaussian type which is known to be well suited for the ANFIS method. The model adaptation was carried out by a back-propagation neural network. The selected learning options of the network were 500 epochs and an initial step size equal to 0.1.

A Regression-Delay (RD) model structure is used where the temperature and humidity values are predicted on the basis of past measurements of the inputs incorporating (auto)regression and (auto)delay terms. The results are shown in Figures 5-8.

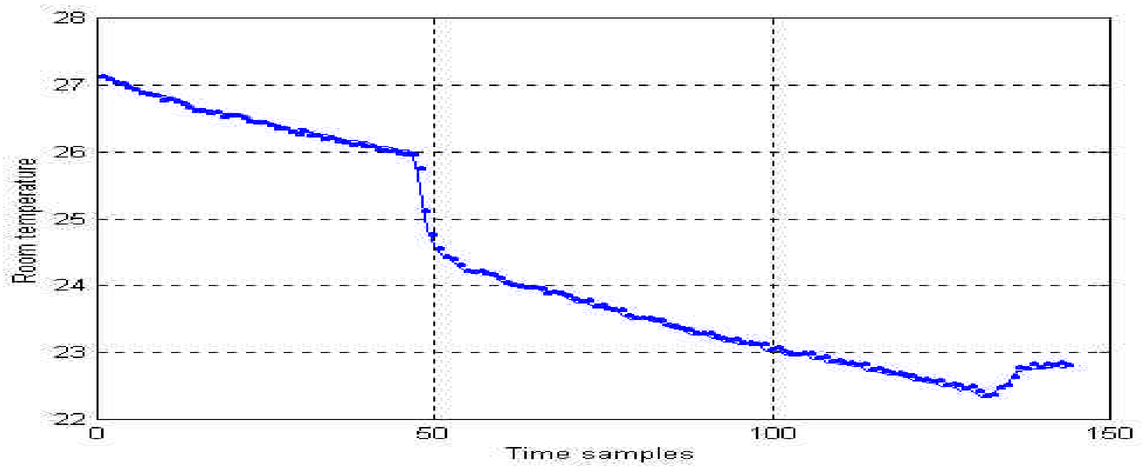

Figure 5: Plant (-) and model (.) outputs for the temperature.

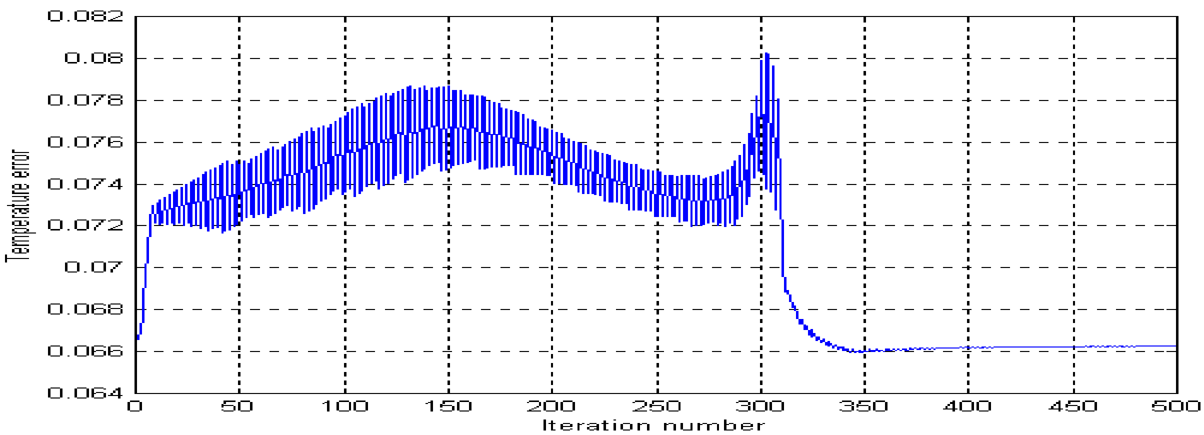

Figure 6: Neural adaptation of the temperature fuzzy model.

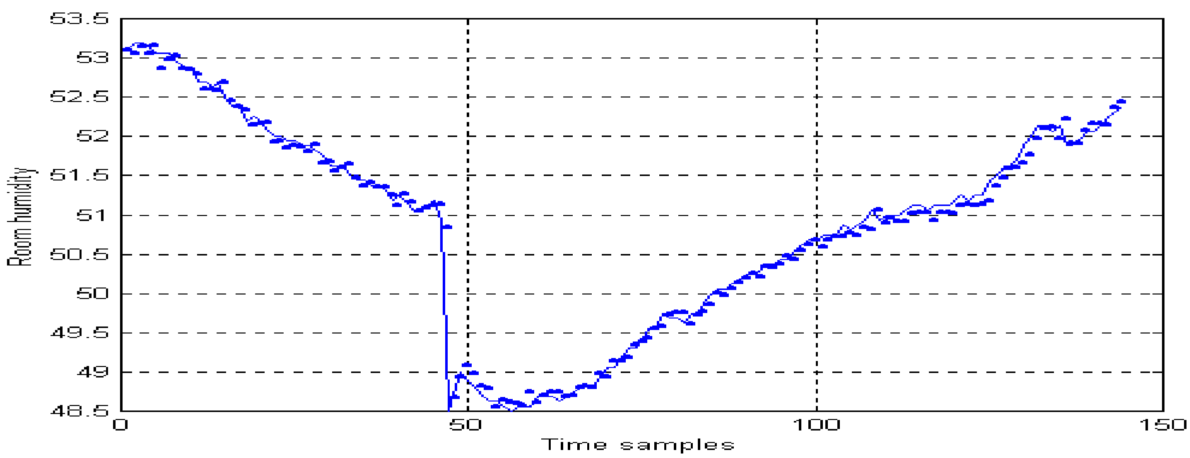

Figure 7: Plant (-) and model (.) outputs for the humidity.

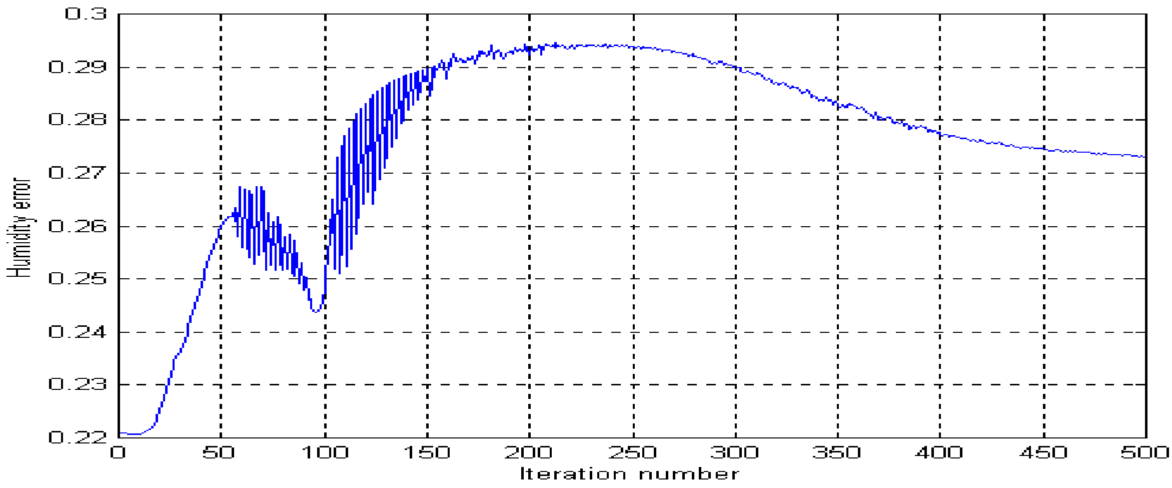

Figure 8: Neural adaptation of the humidity fuzzy model.

It can be seen from the figures that the neural network leads to a slight improvement of the prediction accuracy of the fuzzy model which is possibly due to the good prediction properties of the initial fuzzy model rather than to bad adaptive capabilities of the neural network. This improvement in terms of the root mean squared error is from 0.0665 to 0.0659 for the temperature (iteration step 347) and from 0.2210 to 0.2208 for the humidity (iteration step 8).

CONCLUSIONS

This paper shows that the SC methodology can be successfully used for predictive modelling of internal air temperature and humidity in office buildings. In this respect, the results presented are promising and further work is underway to fully analyse the capabilities of these models.

Another investigated direction is the application of GAs for tuning of the initial fuzzy model parameters. This is being done in parallel with NNs in order to compare the adaptation / optimisation properties of both approaches and research results will be reported in the near future.

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