# Environmental comfort models for individual occupants

I W Matthews, G S Virk, D Azzi and I A Raja.

Department of Electrical and Electronic Engineering
University of Portsmouth
Anglesea Building,
Portsmouth PO1 3DJ, UK.
E-mail: ian.mathews@port.ac.uk
Tel: (023) 9284 2580
Fax: (023) 9284 2766

## Synopsis

Conventional models of building occupants' environmental preferences such as thermal comfort are used to give guidelines for the average environmental conditions that will satisfy large groups of people. The research described in this paper investigates how the preferences of an individual occupant can be modelled to predict their preferred thermal and environmental conditions. A novel, Internet based questionnaire was developed to gather thermal sensation votes. Using 361 subjective responses various models were used to predict the thermal sensation vote of the occupant and the results were compared with the Predicted Mean Vote (PMV) and the actual vote. Preliminary results show that Neuro-Fuzzy model produces better results than PMV, Parametric and Fuzzy models.

**Keywords:** Thermal comfort, Fuzzy model, Parametric model, Internet questionnaire, PMV.

## 1. Introduction

The thermal interaction between man and the environment is highly complex. The internal processes by which human produces and responds to heat have been studied by physiologists, our conscious feelings about the environment by psychologists and the processes of heat transfer between man and environment by physicists. The physiological basis of human thermo-regulation is the maintenance of the core body temperature between limits of around 36.1 – 37.8°C [1]. The central nervous system controls this using the body's internal thermostat, the hypothalamus, which is located at the root of the spinal column. For mild changes in temperature, the heat loss from the skin is altered either through vaso-dilation, bringing the blood vessels closer to the surface or through vaso-constriction when the heat loss is reduced by moving the blood further away from the surface. The secondary involuntary mechanisms the body employs if vaso-regulation is not sufficient are shivering and sweating. These reflex mechanisms cause conscious sensory feedback that we perceive as 'discomfort' which leads us to change the heat loss to our environment consciously. These conscious mechanisms include behavioural changes such as posture, changing the thermal resistance of our clothing by either adding or removing garments and changing the temperature of the environment through mechanical means. The study of thermal comfort is one in which the limits of unconscious thermo-regulation or comfort are found statistically for large groups of people given different environmental conditions.

The field of thermal comfort exists in two fairly distinct camps. The first developed by Fanger [2] takes a prescriptive approach claiming that, given a set of six physical parameters the mean comfort vote on an arbitrary scale can be calculated. This field is sometimes known as 'steady state' because, it uses a steady state heat balance, a certain combination of the six parameters will always produce the same effect in 95% of the population regardless of their personal circumstances. The other camp sometimes called 'adaptive' asserts that there is a change in the temperature, called the neutral temperature, at which comfort exists and this is proportional to the average external temperature [3-6]. This means that when the external temperature is high then the acceptable indoor temperature is also higher and vice versa for lower external temperatures

There has been some recent work to reconcile these two camps [7] and try to produce a standard based on Fanger's approach but incorporating an additional parameter for the external temperature, which makes this new model adaptive. All these approaches however take a statistical approach to present guidelines for comfort limits [8,9] that can be used in the design or assessment of environmental management systems. This research aims to demonstrate that personal comfort models can be identified which can be used to predict comfort requirements more accurately than the current standards.

A fully monitored, air-conditioned test facility at the University of Portsmouth was used to gather environmental data and occupant responses. Subjective responses of occupants during the occupancy period inside the monitored zone were obtained. A novel Internet based questionnaire was used to monitor occupants' sensations and preferences about the environmental conditions. Quantitative data about the indoor environment were collected from the sensors in the zone along with external weather data. Using the same input variables as in Fanger's Predicted Mean Vote equation for thermal comfort, models of an individual's thermal preference were identified. These include Parametric models and models using Fuzzy-logic. The models were then used to simulate an occupant under the same environmental conditions as those experienced by the test subjects.

## 2. Using the Internet to gather comfort data

One of the most difficult parts of any experiment involving subjective responses is gathering the data in a reliable fashion that is easy to distribute and then collect as well as being easy to revise. The spread of the Internet and the proliferation of personal computers in the work place mean that millions of subjects world wide can be questioned on their perception of their environment whilst sat in their normal place of work at their desk. We developed a questionnaire [10] in dynamic HTML written in JavaScript, which was published, on the Internet. The questionnaire is of a simple visual form and asks the respondent how he/she is feeling about his/her environment including the temperature and a few simple questions about what activity he/she is engaged in and what clothing he/she is wearing. The advantages of this technique is that it is easy to make changes to the questionnaire, the data is in an electronic form already so there is no need to laboriously transfer it from hand written response sheets. For the subjects there is no need to repeat information such as the date and the time on each sheet and the questionnaire appears automatically at the sampling instant.

## 3.Experimental set up

The experiments were conducted in the University of Portsmouth's Building Energy Management test facility [11], which consists of a fully instrumented test zone with a dedicated Variable Air Volume (VAV) air-conditioning plant. The test facility is divided into three zones that serve as the offices of members of the research group. The temperature and humidity in each zone can be controlled independently to set points but the research staff normally have no control over these set points or access to any other environmental controls such as windows or fans. The air-conditioning plant records the space temperature and humidity of each zone. The other environmental conditions such as local air velocity and globe temperature were recorded by dedicated, portable data logging equipment. The monitoring equipment was set up as close to the test subject as was possible without interfering with their normal work. An Internet based questionnaire was posted on the research group's web-server and was accessed by the test subjects from their personal computers. The results of the survey were recorded into a database along with the time the questionnaire was posted.

## 4. Experimental method

Test subjects were chosen from the researchers in the group who normally use the office so their reactions to the environment would be as natural as possible. The data logging equipment was set up at seated head height as close to the subject without being intrusive. Each subject was asked to log on to the Internet and access the questionnaire as soon as they started work each morning. They were asked for their feelings about the environment at that moment. Once the questionnaire was posted they could continue with their work and questionnaire would reappear every 15 minutes ready for the next survey. The questionnaire consisted of six fields each with seven different choices from which the subjects would select the most relevant options. They were asked to select how they felt about their thermal comfort from the 7-point ASHRAE thermal sensation index [8].

**Table 1 : Questionnaire fields**

| Field | Options |
|---|---|
| Name | Subject Name – used to identify subjects |
| Clothing | Seven clothing ensembles from ISO 9920 |
| Activity | 'Reclining', 'Relaxed', 'Sedentary', 'Standing light activity', 'Standing medium activity', 'Walk 2km/h', 'Walking 3km/h' |
| Comfort Vote | 'Cold', 'Cool', 'Slightly cool', 'Comfortable', 'Slightly warm', 'Warm', 'Hot' |
| Air quality | Stale → Fresh – seven point scale |
| Air movement | Still → Draughty – seven point scale |

The test subjects were asked to select the clothing ensemble that most closely matched what they were wearing at the time and to select the activity that they had been doing for the previous 15 minutes. Clothing insulation and metabolic rate values were assigned to these inputs from tables of standard clothing ensembles and activities [9]. The time and date were recorded automatically when the questionnaire was submitted. The test subjects were not required to remain in the test zone for the duration of the trial but were asked to complete the questionnaire when they were present.

## 5. Individual comfort models

Two types of models were considered. A parametric approach based on fitting parameters to Fanger's Predicted Mean Vote (PMV) equation [2]. The second uses a fuzzy relational model, which then has its parameters fine-tuned using an artificial neural network that learns the occupant's response to varying conditions.

### 5.1 Parametric model

Fanger's PMV equation in the form used in ISO 7730 [9] for moderate thermal environments links the thermal stress felt by a subject to the vote on a thermal sensation scale. Comfort studies carried out in environmental chambers were used to identify a curve plotted through data points representing the mean vote at different levels of thermal stress against different metabolic rates. We have used a similar technique but instead of taking the mean vote of a large number of test subjects we have used the vote of an individual to try to identify parameters which best fit a model for that individual. Fanger related the thermal stress to the mean vote by fitting an exponential curve through points of thermal-stress gradient against metabolic rate.

Where the Thermal Stress (L) is given by the equation,

$$\begin{aligned} L = \; & \{(M-W) - 3.05*10^{-3}[5733 - 6.99(M-W) - P_a] \\ & -0.42[(M-W) - 58.15] - 1.7*10^{-5} M (5867 - P_a) -0.0014 M (34 - T_a) \\ & - 3.96*10^{-8} f_{cl} [(T_{cl} + 273)^4 - (T_{mrt} + 273)^4] - f_{cl} . h_c (T_{cl} - T_a)\} \end{aligned} \tag{1}$$

where,

$$T_{cl} = 35.7 - 0.028(M-W) - I_{cl}\{3.96*10^{-8} f_{cl} \; [(T_{cl} +273)^4 - (T_{mrt} +273)^4] + f_{cl} h_c(T_{cl}-T_a)\} \tag{2}$$

$$h_c = \begin{cases} 2.38(T_{cl} - T_a)^{0.25} & \text{for } 2.38(T_{cl} - T_a)^{0.25} \geq 12.1 \sqrt{V_a} \\ 12.1 \sqrt{V_a} & \text{for } 2.38(T_{cl} - T_a)^{0.25} \leq 12.1 \sqrt{V_a} \end{cases} \tag{3}$$

and the Predicted Mean Vote is given by

$$PMV = (0.303 \, e^{-0.036 M} + 0.028) * L \tag{4}$$

the parameters are given as:

- PMV: predicted mean vote
- M: metabolic rate ($W/m^2$)
- W: external work, zero for most activities ($W/m^2$)
- $I_{cl}$: thermal resistance of clothing (Clo)
- $f_{cl}$: ratio of body's surface area clothed to that nude
- $T_a$: air temperature (°C)
- $T_{mrt}$: mean radiant temperature (°C)
- $V_a$: relative air velocity (m/s)
- $P_a$: partial water vapour pressure (Pa)
- $h_c$: convective heat transfer coefficient (($W/m^2$ K)
- $T_{cl}$: surface temperature of clothing (°C)

Using least squares we identified the parameters which fit the vote of an individual occupant against the thermal stress as calculated using Fanger's equation.
Thus, the Individual Comfort Vote is given by,

$$ICV = (A\, e^{-B.M} + C) * L \qquad (5)$$

Where, A, B and C are parameters identified by least squares for an individual and L is the thermal stress calculated using equation 1. This model represents an individual's perception of thermal conditions and may be useful in defining temperature set points and acceptable environmental conditions in buildings based on the personnel that actually use the buildings.

### 5.2 Fuzzy Logic models

Of all the modelling techniques that are available for modelling thermal comfort, Fuzzy logic based approaches are the most attractive. The fundamental reasoning behind the development by Zadeh [12] of fuzzy logic was the ability to describe vague, linguistic statements in a mathematically crisp form. When we consider modelling the relationship between measurable environmental factors such as room temperature and subjective, linguistic responses that relate to the human perception of thermal comfort then using fuzzy logic becomes attractive.

Using data from the questionnaires and from the environmental monitoring equipment a relational fuzzy model was identified. We used four input variables: effective temperature (the mean of the air and radiant temperatures), air velocity, clothing thermal resistance and activity and one output: thermal sensation vote. The relative humidity was not considered to simplify the model because it only has a small effect on the comfort vote at moderate temperatures. A series of relational rules was developed of the form:

If *Effective temperature* is **High** and *Air velocity* is **Low** and *Clothing* is **Light** and *Activity* is **Heavy** then *Thermal sensation* is **Hot.**

Where **High, Low, Light** and **Heavy** are arbitrary fuzzy sets described by membership functions mapped on the inputs and **Hot** is mapped on to the thermal sensation scale. The output sets are single valued fuzzy singletons as this model is of the Tagaki – Sugeno [13] type.

We used three evenly spaced gaussian membership functions to represent the range of the inputs and seven singleton points to represent the output corresponding to the seven levels on the ASHRAE comfort scale. We used seven rules from a maximum of 81 to represent the system. The position of the input membership functions was chosen arbitrarily to cover equally the expected ranges of the inputs.

We then used a neural network with a hybrid learning algorithm (ANFIS) [14] to adapt the parameters of the input membership functions to improve the model fit. The parameters of the fuzzy model are assigned as the nodes of an artificial neural network The model is evaluated and the error is fed back through the network using a hybrid least squares and gradient-descent learning algorithm to update the nodes and optimise the model. The initial membership functions and the final optimised membership functions are shown in Figure 1.

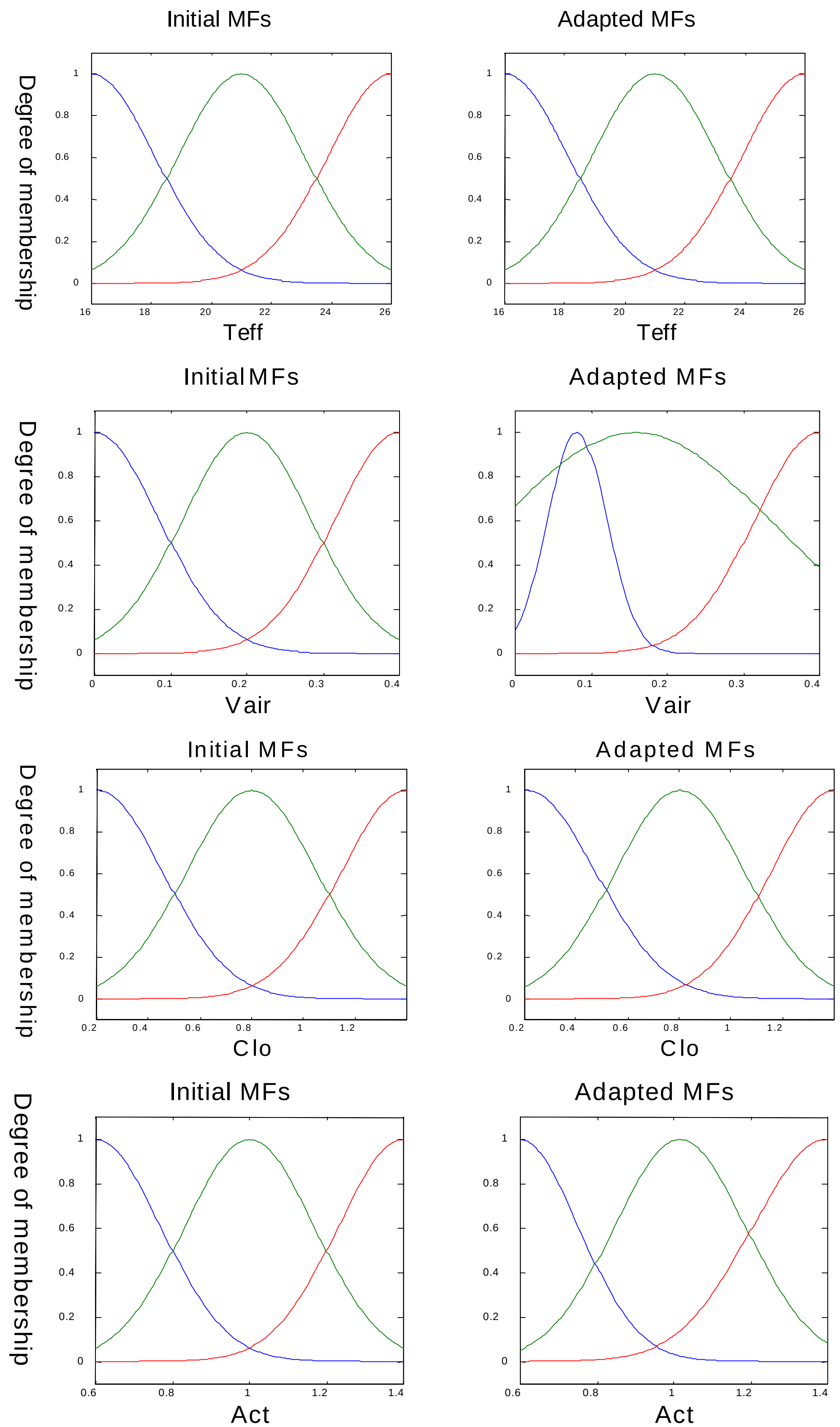


**Figure 1 : Fuzzy membership functions**

## 6. Modelling results

The models presented here are generated for a single occupant over a period of four working days. Each model is identified and compared with the recorded vote of the occupant and the predicted mean vote, which is calculated using the ISO 7730 method.

**Table 2: Errors for all models**

| Error | PMV | Parametric | Fuzzy | Neuro -Fuzzy |
|---|---|---|---|---|
| Maximum | 2.50 | 1.37 | 0.98 | 1.03 |
| Minimum | 0.13 | 0.00 | -1.64 | 0.00 |
| RMS error | 0.74 | 0.48 | 0.73 | 0.40 |

### 6.1 Parametric model

Although as expected the majority of the activities that were recorded were sedentary as the occupant was at their desk during the trial the parameters were calculated for a range of metabolic rates. The parameters for the individual comfort model were:

$$ICV = (2.256\ e^{-0.0068} - 1.392) * L$$

The maximum error is 1.37, which represents a shift in the vote from 'comfortable' to 'slightly warm'. Given the nature of human sensation this is still acceptable and is better than the maximum error of 2.50 for the PMV, which would represent a person expressing 'comfort' being described as 'hot'. The root mean-squared error is only 0.48, which is within the range of the +/- 0.5 limits of each thermal sensation category.

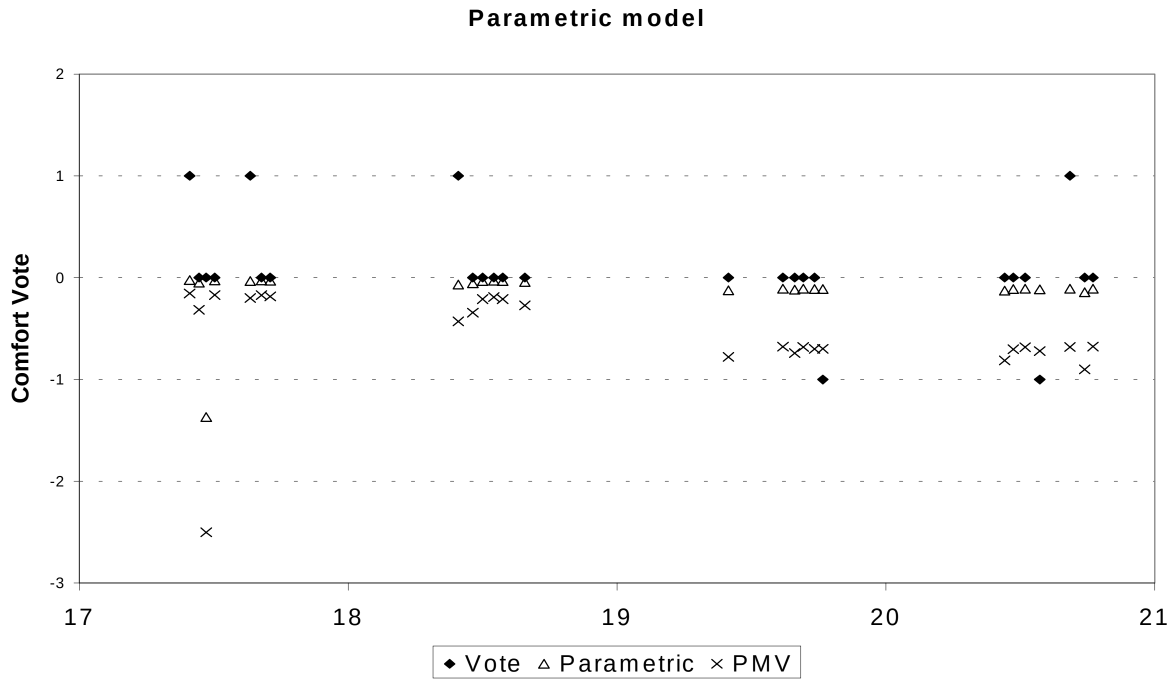


**Figure 2: Parametric model**

### 6.2 Fuzzy models

The initial fuzzy model with no optimisation was evaluated using the experimental data gathered for a single occupant. The model performs quite well given that the membership functions are placed arbitrarily on the input domains, showing that the fuzzy model is quite robust. The maximum error is 0.98 with a minimum error of –1.64 so this model may underestimate how cold the subject is feeling at certain conditions. A root mean-square error of 0.73 is about the same as the PMV equation.

Once the learning algorithm is applied to the fuzzy model the membership functions are optimised to fit the data as shown in Figure 1. As gaussian membership functions are used which cover the entire input domain and given the good approximation of the initial fuzzy model it appears that the parameters of the model are not changed greatly. The results of the optimised model are very good, the maximum error of 1.03 and a root mean square error of 0.40. This model seems to have learnt the occupant's responses even with a reduced set of inputs and to represent the individual's choices more closely than the PMV model.

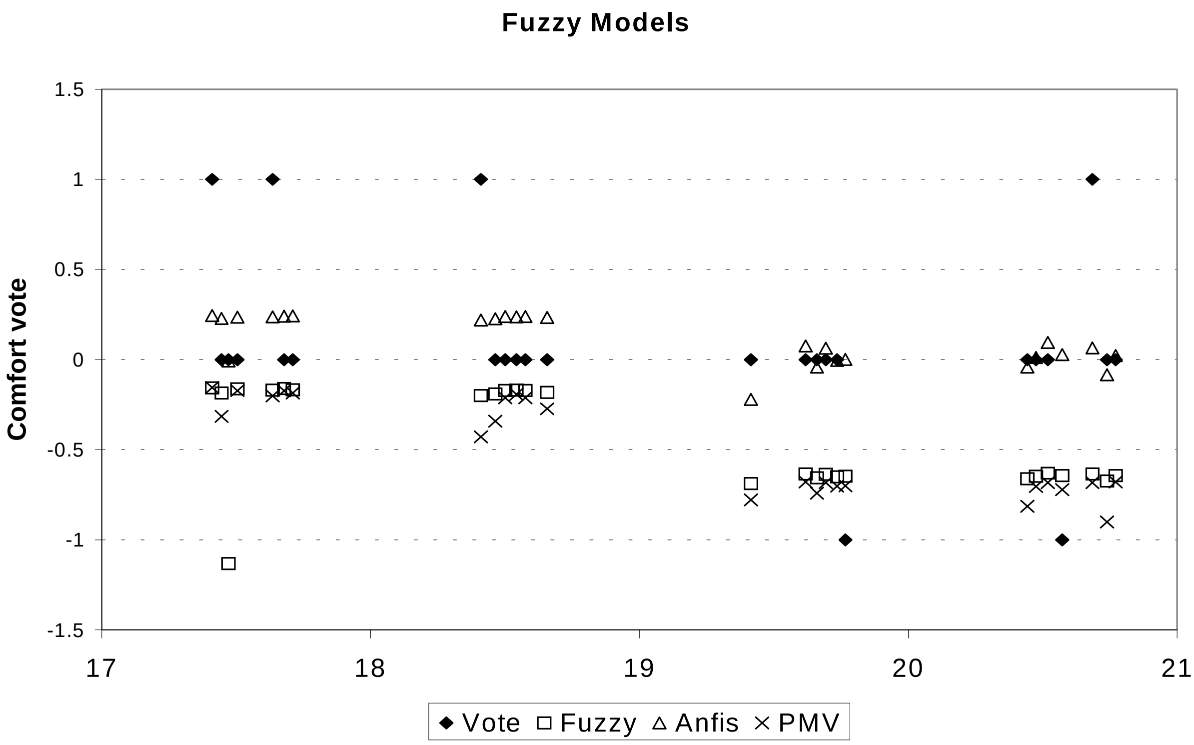


**Figure 3: Fuzzy models**

### 7. Conclusions

One of the advantages of the fuzzy model in both the basic and adapted form would seem to be that while the PMV equation is sensitive to even quite small changes in the inputs, the fuzzy models are more robust to these changes. This seems to be the case with the actual perception of comfort as well, with occupants making use of other adaptation mechanisms to control their level of comfort or having wider ranges of what they perceive to be comfortable than the standards would suggest. Whilst it may be considered unfair to use what is a statistically based PMV as a model for comfort and compare it with models derived from field studies for an individual, the standards are used in practice to set levels of heating and cooling in buildings. With a more 'adaptive' view towards comfort, acknowledging that people can change their behaviour to maintain core temperature as well as resorting to altering their environment. The use of individual models even summing the net effects of multiple individuals in a particular controlled zone can lead to an expansion of the limits that produce acceptable comfort conditions. Further work is required to extend the application of these models to different individuals and conditions where there is a significant level of expected discomfort. Although with a limited data set of 361 subjective responses, the Neuro-Fuzzy model seems to produce better results than PMV, Parametric and Fuzzy models, the results need to be verified with larger data set.

Another point that can be drawn from this work is the benefits of using the Internet for developing on-line comfort questionnaires. In the authors' own experience of gathering the amount of information from even a small questionnaire and then processing those results. The impact of using on-line technology is expected to be substantial.

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