Thermal Comfort Estimation Using a Neurocomputational Model

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Abstract— **Thermal comfort conditions are important for the normal development of human tasks, and as such they have been analyzed in the context of several areas including human physiology, ergonomics, heating and cooling systems, architectural design, etc. In this work, we analyze the estimation of the thermal comfort perception by human subjects using a neurocomputational model based on the C-Mantec constructive neural network architecture, comparing it with two standard methods for modeling thermal comfort: Fanger and COMFA models. The results indicate a significative advantage of C-Mantec in terms of the predictive accuracy obtained, consider also that the flexibility of the neural model would permit the introduction of extra variables that can increase further the thermal comfort estimation.**

Keywords: Thermal Comfort, Supervised learning, Constructive Neural Networks.

I. Introduction

Thermal comfort can be defined as the condition regarding temperature, humidity and wind speed in which an individual feels comfortable for developing its activities (work, relax, sports activities, etc.). Thermal comfort is a subjective sensation and then it is a magnitude difficult to evaluate as its depend on subjects and the experiments' conditions. Issues regarding thermal comfort have been addressed by building scientists, urban planners, social scientists, anthropologists and HVAC design engineers, among other professions, also attracting more recently the attention of climate researchers in relationship to climate change issues [1].

Analysis done around heat balance models provided the basis for the experiments used for defining the standards of thermal comfort during most of the XX century. Around 1970 Povl Ole Fanger, a Danish physiologist, made a great advance in the field of comfort theory focusing on the relationship between the physical parameters of the environment and the physiological parameters of people, and the perception of wellbeing expressed by the people themselves. Fanger developed a "comfort equation" combining ambient parameters (i.e. air temperature, mean radiant temperature, relative air velocity and humidity level) in which the highest proportion of people are likely to be comfortable, for any specified level of activity and clothing [2]. He proposed a quantity named Predicted Mean Vote (PMV) in order to measure the quality of indoor environments assessing the degree of discomfort of the occupants.

Knowing the thermal comfort in outdoor spaces has become very important in recent years due to its implications on urban and architectural planning. The Fanger method does not take into account the solar radiation, an important factor afecting thermal comfort in outdoor spaces, and thus a model named COMFA has been proposed by Brown and Gillespie [3] in 1986 to take into account this factor.

The application of the two previous mentioned models are usually carried out by a simple computer programme that given a set of determined conditions outputs the predicted subjective estimation of thermal comfort, hoping to get on average good estimates of the PMV.

Artificial Neural Networks (ANN) are mathematical models inspired by the functioning of the brain of living beings that have shown to have interesting application in several practical domains, in particular to a wide range of problem in pattern recognition, clustering and classification problems in the last three decades [4], [5], [6]. They are flexible models that can be trained on recorded data and then used for making predictions for novel data. For supervised problems, for which a set of data containing input-output samples the multilayer perceptron trained by back-propagation has been the standard solution for many years [7], but several other alternative models exist. Among them, constructive neural network algorithms [8] offer the advantage of avoiding the complex problem of selecting an adequate architecture, as this is selected simultaneously as the training of the data occurs. Neural Network models have been applied in recent years to the problem of estimation of thermal comfort in relationship to an efficient implementation of heating and ventilation control systems (HVAC) [9], [10].

In this work, using new data collected from 49 volunteers artificial neural networks implemented through the C-Mantec algorithm [11] have been utilized for the estimation of the subjective thermal comfort, comparing the predicted values with those perceived by the subjects and from the values obtained from Fanger and COMFA models.

II. Methodology

A. The Fanger Model

The Fanger model of thermal comfort is based on the mechanisms that utilizes the human body to regulate its temperature, taking into account physiological and ambient

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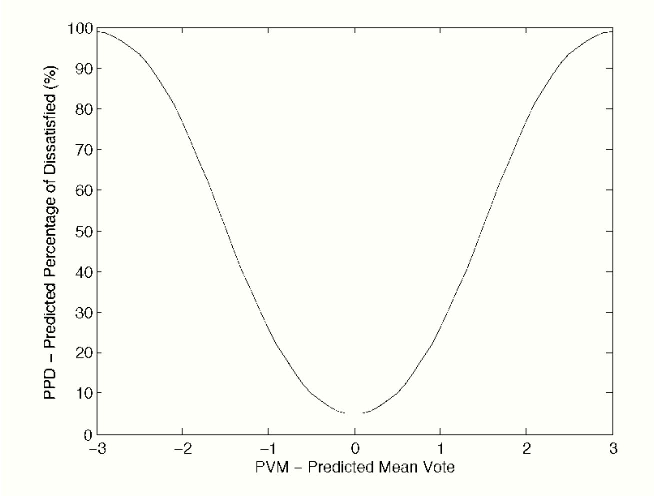

Fig. 1. Percentage of non-satisfied people from a group in relationship to the PMV value in the range [-3,3]

conditions for which thermal equilibrium is obtained, as in such state body thermoregulated activity would be at its minimum. In this context, Fanger observed that the two physiological mechanisms relevant for thermal equilibrium are sudoration (sweating) and skin mean temperature, both also depending on the physical activity, and so he tried to find a relationship between them. For sudoration, he found a linear relationship with the physical activity, and experimentally this situation can be verified whenever the subject feels inmerse in a confortable situation. For the skin mean temperature a similar relationship exists but noting that skin temperature decreases as the physical activity increases. From these two relationships, Fanger writes a heat balance equation from which a thermal neutrality condition can be obtained, taking into account factors as methabolic rate, clothing insulation, air temperature and speed, mean radiation temperature and relative humidity. Further, the equation was modified to permit the estimation of the thermal sensation for a group of people in a scale known as Predicted Mean Vote (PMV). PMV values are widely used for setting international ergonomic ambient standards in indoor spaces (ANSI/AHSRAE 55 and ISO 7730) and have been also used for tuning self-regulated cooling-heating systems HVAC4. Figure 1 show the relationship between the percentage of non-satisfied people from a group in relationship to PMV values ranging from -3 to 3.

B. The COMFA Model

The Fanger method does not take into account surrounding and solar radiation and then it cannot be applied for outdoor environments. In order to model these situations, Robert Brown and Terry Gillespie introduced in 1986 an equation for the estimation of thermal comfort known as COMFA method [3]. It is based on the energy balance of a person in relationship to the ambient, permitting its use in outdoor spaces, as the model takes into account absorbed surrounding and solar radiation. According to the COMFA method the energy balance can be computed as:

$$\text{balance} = M + R - E - C - L$$

.

In the previous equation, M is the metabolic heat, R is the absorbed surrounding and solar radiation, E is the evaporation energy, C refers to convective energy and L is the emitted radiation. All sources of heat are expressed in W/m^2, and so is the final balance relationship. The energetic balance can then be related to thermal comfort using the relationship shown in table I.

Balance (B)	Sensation
$150 < B$	Very Hot
$50 < B < 150 <$	Hot
$-50 < B < 50 <$	Comfort
$-150 < B < -50 <$	Cold
$B < -150 <$	Very Cold

TABLE I
THERMAL COMFORT IN RELATIONSHIP TO THE ENERGY BALANCE OBTAINED FROM THE COMFA SCALE.

Estimating outdoor comfort sensation is a complex task given the several factors that can influence it, and the COMFA model is one of the simplest one for which good results can be obtained. Several alternative models have been developed using the COMFA model as a reference, mainly by adjusting the parameters that relates the factors with the estimated value [12].

C. The C-Mantec Constructive Neural Network Model

C-Mantec is a constructive neural network algorithm for supervised problems that generates the network topology in an on-line manner during the learning phase, avoiding the complex problem of selecting an adequate neural architecture [11]. The novelty of C-Mantec in comparison to previous proposed constructive algorithms is that the neurons in the single hidden layer compete for learning the incoming data, and this process permits the creation of very compact neural architectures with good predictive capabilities.

The binary activation state (S_j) of each of the neurons in the hidden layer depends on N input signals, ψ_i, and on the actual value of the N synaptic weights (ω_{ji}) and bias (b_j) as follows:

$$S_j = \begin{cases} 1 & \text{if } h_j \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where h is the synaptic potential of the neuron defined as:

$$h_j = \sum_{i=1}^{N} \omega_{ji}\, \psi_i - b_j \tag{2}$$

The weight updating in the C-Mantec algorithm at the single neuron level is done using the thermal perceptron rule [13], in which the modification of the synaptic weights, $\Delta\omega_i$, is done on-line (after the presentation of a single input pattern) according to the following equation:

$$\Delta\omega_{ji} = (t - S_j)\, \psi_i\, T_{fac}, \tag{3}$$

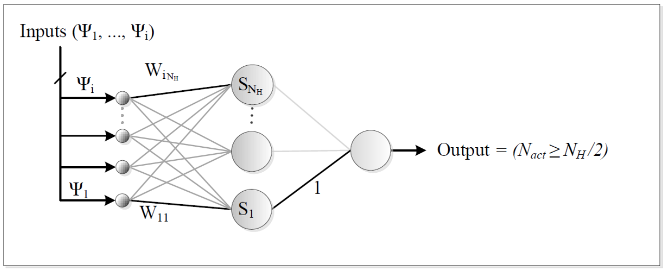

Fig. 2. Example of a neural network architecture constructed by the C-Mantec algorithm.

where t is the target value (desired output of the whole network for the presented input), and ψ represents the value of input unit i connected to the hidden neuron S_j by synaptic weight ω_{ji}. The difference to the standard perceptron learning rule is that the thermal perceptron incorporates the T_{fac} factor. This factor, whose value is computed as shown in Eq. 4, depends on the value of the synaptic potential and on an artificially introduced temperature (T):

$$T_{fac} = \frac{T}{T_0} e^{-\frac{|h|}{T}}, \tag{4}$$

The value of the temperature T decreases as the learning process advances according to Eq. 5, similarly to a simulated annealing process.

$$T = T_0 \cdot (1 - \frac{I}{I_{max}}), \tag{5}$$

where I is a cycle counter that defines an iteration of the algorithm on one learning cycle, and I_{max} is the maximum number of iterations allowed. One learning cycle of the algorithm is the process that starts when a chosen pattern is presented to the network and finishes after checking that all neurons respond correctly to the input or when the synaptic weights of the neuron chosen to learn the actual pattern (whether an existing or a new neuron) modifies its synaptic weights. The C-Mantec algorithm has three parameters (g_{fac}, I_{max} and ϕ) to be set at the time of starting the learning procedure, and several experiments have shown the robustness of the algorithm that operates fairly well in a wide range of parameter values.

The output of a C-Mantec network consists in a single output that computes the majority function (see Eq.6) of the neuron activation of the hidden layer units, like in a voting process. The network output is active (1) if more than half of the N_H hidden neurons are active:

$$\text{Output} = \begin{cases} 1 & \text{if } \sum_j^{N_H} S_j \geq \frac{N_H}{2} \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

Fig. 2 shows a network architecture of the type built by the C-Mantec algorithm. The network contains a single hidden layer of threshold neurons (S_j) with output values $\{0, 1\}$.

III. RESULTS

Data from 49 volunteers of both sexes and with ages between 18 and 50 have been recorded in a series of controlled experiments under variations of solar radiation, humidity, temperature, wind, clothing and activity as indicated in II. The subjects have to indicate after a minimum of 120 seconds its comfort sensations in range of continuum values according to the ASHRAE scale.

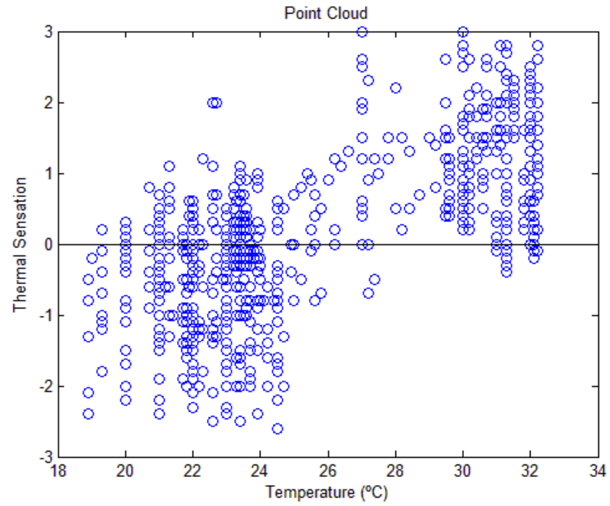

Fig. 3. Data used as input variables for obtaining the thermal comfort estimation from the three models used, as a function of the temperature, that is one of the several factors considered.

Variable	Range/Categories
Solar Radiation	$\{15, 250, 550, 850\}$
Humidity %	$[33 - 45]$
Temperature	$[18 - 32]$
Wind	$[0 - 4]$
Clothing	[Winter, Spring, Summer]
Activity	[None, office type]

TABLE II
MAIN VARIABLES AND THEIR RANGE OR CATEGORY USED FOR THE ESTIMATION OF THE THERMAL COMFORT IN DIFFERENT EXPERIMENTS.

Fig. 3 display the data recorded from the different experiments, showing the comfort sensation expressed by the subjects as a function of the temperature, one of the many controlled variables used later to adjust the estimation models.

Figs. 4 top and bottom shows two examples of the estimation of the thermal comfort subjective sensation obtained from the different models used in experiments with standard indoor lighting. In a second set of experiments extra controlled radiation was used in order to simulate different outdoor conditions, using a solar lamp at different distances while the radiation was measured with a luxometer. Note that for this second set of tests the Fanger model cannot be used as this model cannot incorporate external radiation sources. With the data grouped in two sets of experiments (indoor and outdoor simulated conditions) the Fanger and COMFA model were used to obtained a comfort sensation estimation that is later compared to the reported values from the subjects. A further offset adjustement was done in order to recalibrate Fanger and COMFA models, using a constant value that was added to all outputs. This modification permits to increase the generalization ability of both Fanger and COMFA models without altering the results from the neural network generated by the C-Mantec algorithm. The neural network C-Mantec

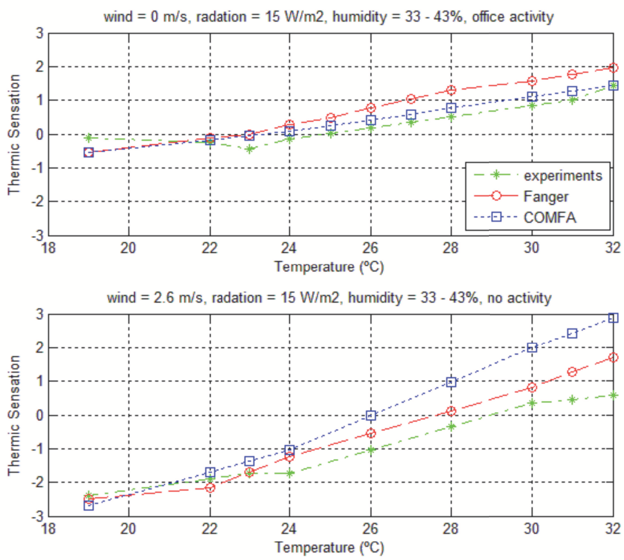

Fig. 4. Thermal comfort sensation as a function of the temperature obtained from subjects with standard office activity and Fanger and COMFA models under conditions of wind, radiation and humidity indicated on top of the graph.

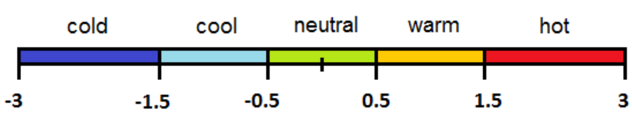

Fig. 5. Five categories in which data have been clustered to analyze the predictive accuracy of the models.

model was trained with the same data using a ten fold cross-validation procedure from which the generalization ability can be computed. Standard parameter values were used for testing the C-Mantec neural network model, using 2000 for the maximum number of iterations, $g_{fac} = 0.05$, and $\phi = 3$. The output data even if registered in a continuum scale, was clustered in 5 categories according to the scale shown in Fig. 5.

Table III shows the generalization ability obtained COMFA and C-Mantec neural network model for a set of controlled experiments in indoor conditions, while Table IV shows the generalization ability obtained for a set of controlled experiments that includes an extra light sources to simulate different outdoor conditions.

Interval	FANGER	COMFA	C-Mantec
$[-3, 1.5)$	49.2	48.7	73.2
$[-1.5, -0.5)$	46.3	47.2	72.5
$[-0.5, 0.5]$	48.9	48.3	73.7
$(0.5, 1.5]$	45.1	47.4	71.9
$(1.5, 3]$	47.8	48.1	73.3

TABLE III
GENERALIZATION ABILITY FOR COMFA AND C-MANTEC NEURAL NETWORK MODEL FOR A SET OF CONTROLLED EXPERIMENTS IN INDOOR CONDITIONS.

Interval	COMFA	C-Mantec
$[-3, 1.5)$	52.7	71.2
$[-1.5, -0.5)$	51.2	69.5
$[-0.5, 0.5]$	52.1	71.1
$(0.5, 1.5]$	51.5	70.1
$(1.5, 3]$	51.9	70.8

TABLE IV
GENERALIZATION ABILITY FOR COMFA AND C-MANTEC NEURAL NETWORK MODEL FOR A SET OF CONTROLLED EXPERIMENTS THAT INCLUDES EXTRA LIGHTS SOURCES TO SIMULATE DIFFERENT OUTDOOR CONDITIONS.

IV. DISCUSSION AND CONCLUSIONS

A series of controlled experiments under different ambient conditions were carried out while the comfort sensation of the human subjects was recorded. Fanger and COMFA models were then used for testing the prediction accuracy between the output model and the subjects reported sensation, obtaining a measure of the generalization ability. With the same data and using a cross-validated procedure, a neural network trained by the C-Mantec constructive algorithm was also analyzed, measuring the accuracy of their predictions. The results obtained and displayed in tables III and IV as they are divided in two groups according to whether indoor or outdoord conditions. For the first group of indoor conditions experiments similar results for the predictions of Fanger and COMFA models were obtained, with values a bit below 50%, while the generalization ability obtained from C-Mantec is clearly superior with values above 71%. For the simulated outdoor conditions for which only the COMFA model can be used and compared to the neural network model, the results are similar, showing a clear advantage of using C-Mantec as a predictive model.

As an overall conclusion the results presented in this work show that it seems very adequate to use neurocomputational models for the estimation of indoor and outdoor subjective comfort sensation by human subjects, as prediction values much larger than those obtained from standard energy balance models can be observed. Given the present results, and considering that C-Mantec generates very compact architectures that can be easily applied in microcontrollers, we are working towards the implementation of a sensor-actuator device that may be suitable for controlling HVAC systems. We further note that we have registered the body mass index of the subjects, and that this value can be incorporated into the neural network model as an extra parameter, expecting even better predictions.

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