Neural Control of Thermal Comfort Considering User Vote

José Luis Torres† and Marcelo Luis Martin‡

†Departamento Electrotecnia. Facultad Regional Santa Fe - Universidad Tecnológica Nacional. Santa Fe, Argentina.
‡Instituto de Automática (INAUT). Facultad de Ingeniería - Universidad Nacional de San Juan. San Juan, Argentina.
{jtorres,mmartin}@inaut.unsj.edu.ar

Abstract. In modern office buildings, the customary trend is to use state of the art technology to ensure the users find it thermally comfortable, among other variables. Among the various statistical studies on comfort index vs. work efficiency of users, the most widely adopted index is the Predicted Mean Vote (PMV). Due to the subjective variables involved in computing the comfort index, it has to be contrasted with the real comfort sensation of persons. Taking into account these premises, the present work proposes a control scheme that shows the capability of neural networks of not only modifying the environmental conditions of the space but also of adapting the thermal comfort index to the requirements of the space users.

Key words: Thermal Comfort, Neural Network, Control, Thermal Space.

1 Introduction

A healthy thermal environment of indoor spaces helps their users improve their work efficiency by keeping within a range of pleasance several climatic variables, with temperature among the important ones. Human thermal comfort is defined as "that condition of mind which expresses satisfaction with the thermal environmental" [1]. In building spaces such as offices, the requirement is that the room air-conditioning control system has to provide a comfortable thermal feeling for the user. In previous research works, many indexes have been developed to evaluate the comfort level, but one of the most widespread is the Predicted Mean Vote (PMV) index [2]. It considers four environmental variables and two personal variables.

A starting point in the analysis to establish a comfortable thermal environment in a closed space is that the thermal comfort of the users must be correctly evaluated [3]. On account of the subjective variables involved in this task, it is necessary to contrast the computed PMV with the opinion of the persons using the space. Adaptive models have been developed to calculate the thermal comfort in [4] and [5].

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Today, artificial neural networks are an important area of study within the field of applied artificial intelligence. This paper proposes a control technique that is based on modifying the set-point temperature a PI through a neural network. This network takes into account all factors affecting the thermal comfort. The objective is to keep the comfort level for users within a pre-defined range only by controlling the temperature indoor the office space. Besides, it is proposed here to calculate the PMV using a neural network that adapts itself to the real requirements of users through periodic questioning.

2 Comfort Index PMV

The PMV index predicts the mean response of a large group of people according to the following thermal sensation scale [6]:

+3	hot
+2	warm
+1	slightly warm
0	neutral
-1	slightly cool
-2	cool
-3	cold

These are given in annex of [6] gives the recommended comfort requirements which are predicted to provide acceptable thermal sensation for 90% of occupants (i.e. $-0.5 < PMV < +0.5$). Fanger [2] related PMV to the imbalance between the actual heat flow from the body in a given environment and the heat flow required for optimum comfort at the specified activity by the following equation:

$$PMV = [0.303 exp(-0.036M) + 0.028]\, L \; . \tag{1}$$

where L is the thermal load on the body and M is the metabolic rate. The thermal load depend of environmental and personal variables and is calculated by means of equation 2.

$$\begin{aligned} L = {} & (M-W) - 3.96 \times 10^{-8} f_{cl}[(t_{cl}+273)^4 - (t_{mr}+273)^4] - f_{cl}h_c(t_{cl}-t_a) \\ & -3.05[5.73 - 0.007(M-W) - \phi] - 0.42[M - W - 58.15] \\ & -0.0173M(5.87-\phi) - 0.0014M(34-t_a) \; . \end{aligned} \tag{2}$$

where W denotes the external work accomplished in $[\frac{W}{m^2}]$, ϕ relative humidity, t_a indoor temperature in $[^\circ C]$, f_{cl} clothing area factor, t_{cl} clothing surface temperature in $[^\circ C]$, t_{mr} mean radiant temperature in $[^\circ C]$ and h_c convective coefficient. As part of this calculation t_{cl}, h_c and f_{cl} are determined respectively by the equations listed as follows.

$$\begin{aligned} t_{cl} = {} & 35.7 - 0.028(M-W) - 3.96 \times 10^{-8} f_{cl}[(t_{cl}+273)^4 - (t_{mr}+273)^4] \\ & -f_{cl}h_c(t_{cl}-t_a) \; . \end{aligned} \tag{3}$$

$$h_c = \begin{cases} 2.38(t_{cl} - t_a)^{0.25} & 2.38(t_{cl} - t_a)^{0.25} > 12.1\sqrt{v_a} \\ 12.1\sqrt{v_a} & 2.38(t_{cl} - t_a)^{0.25} > 12.1\sqrt{v_a} \end{cases} \quad (4)$$

$$f_{cl} = \begin{cases} 1.0 + 0.2I_{cl} & I_{cl} < 0.5clo \\ 1.05 + 0.1I_{cl} & I_{cl} > 0.5clo \end{cases} \quad (5)$$

where v_a denotes indoor air flow velocity in $[\frac{m}{s^2}]$ and I_{cl} clothing thermal resistance in $[clo]$ $(1[clo] = 0.155[\frac{^{\text{o}}Km^2}{W}])$. The personal variables (activity and clothing level) are estimated for typical tasks of office and summer season. The environmental variables (t_a, ϕ, t_{mr} and v_a) are extracted of the building model.

3 Heat Transfer Model in Buildings

3.1 Description of the Environment

An environment can be seen as a multivariable dynamic system where the main input signals are the temperature (t_{amb}) and the external relative humidity (ϕ_{ext}), the wind speed (v_w), the solar radiation and the heat extraction rate ($\dot{Q}_{aux}$) (for the cooling case). The output signals are, in general, the temperature (t_a) and the internal relative humidity (ϕ). To study the thermal confort, additional factors that need to be known are the mean radiant temperature (t_{mr}) and the air velocity inside the room or building (v_a). The environment that has been modeled is a room for office activities. Fig. 1 shows the room dimensions and wall orientation. The room orientation and geographical location (31.61° S latitude, 68.53 W longitude) are vital data to calculate the solar radiation. The south wall has a roof overhang that prevents the solar radiation impinging directly on the windows. The roof is the only building component that is subjected to direct solar radiation. The contiguous rooms have the same constructive characteristics of the room under study.

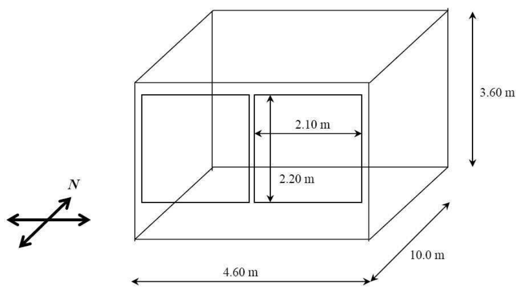

Fig. 1. Thermal Space.

The modeling system used in this work is based on the energy balance of walls and on the air volume enclosed in the room [7].

3.2 Thermal Energy Balance

The estimation of cooling load for a space involves calculating a surface-by-surface conductive, convective, and radiative heat balance for each room surface and a convective heat balance for the room air.

The result from this simplified formulation is called *the model of termal energy balance*. Considering the energy storage of the walls and the air volume, the following expression can be written:

$$m_p c_p \frac{dt_{si}}{dt} = \dot{Q}_{rad} + \dot{Q}_{rad\_lights} + \dot{Q}_{rad\_GI} + \dot{Q}_{conduction} - \dot{Q}_{conv\_int} \quad (6)$$

where m_p is the mass, in [kg]; c_p is the heat capacity (depending on the type of construction material), in $[\frac{J}{kg^oC}]$; t_{si} is the surface temperature, in $[^oC]$; $\dot{Q}_{rad}$ is the heat exchange by radiation between walls, in $[W]$; $\dot{Q}_{rad\_lights}$ is the heat exchange by radiation from light fixtures, in $[W]$; $\dot{Q}_{rad\_GI}$ is the heat exchange from internal sources (from individuals and operating equipment), in $[W]$, $\dot{Q}_{conduction}$ is the thermal flux from conduction through the walls, roof of floor, in $[W]$; $\dot{Q}_{conv\_int}$ is the convective heat exchange between the building components and the air mass, given in $[W]$.

The temperature of the air is computed as:

$$m_a c_a \frac{dt_a}{dt} = \dot{Q}_{conv\_int} + \dot{Q}_{windows} + \dot{Q}_{conv\_GI} + \dot{Q}_{ventilation} + \\ + \dot{Q}_{infiltration} \pm \dot{Q}_{aux} \quad (7)$$

with m_a, the air mass measured in [kg]; c_a is the air heat capacity given as 1005 $[\frac{J}{kg^oC}]$; t_a is the air temperature, in $[^oC]$; $\dot{Q}_{windows}$ is the heat flux through the windows, in $[W]$; $\dot{Q}_{conv\_GI}$ is the convective part of the internal loads, in $[W]$; $\dot{Q}_{ventilation}$ is the sensible load due to ventilation, given in $[W]$; $\dot{Q}_{infiltration}$ is the sensible load due to infiltration, in $[W]$; $\dot{Q}_{aux}$ is the thermal flow rendered by the weather conditioning system, given in $[W]$.

4 Parameters of Thermal Comfort

To determine the thermal comfort level in a thermal environment implies analysing a complex interaction of many variables. This means that the concept of thermal comfort is compounded by both the subjective evaluations made by the users and by objectively metered physical parameters as well. Among the first ones, and as stated in Section 2, are the activity level of the user, represented by the metabolic rate, and the insulation index of clothing. On the other hand, a main value among physically measurements is the room temperature which is computed at every instant by solving the differential equations 6 and 7.

The mean radiant temperature $t_{mr}$is defined as the temperature of a black body that exchanges the same quantity of thermal radiation with the user as it would with the real space. This temperature is affected by all direct or indirect radiation that impinges onto the individual. For estimating this value, however, an acceptable approximation can be made by regarding only the thermal radiation given off by the walls [8].

$$t_{mr} = \frac{A_1 t_{s1} + \ldots + A_6 t_{s6}}{t_1 + \ldots + A_6} \tag{8}$$

where t_{si} represents the surface temperature of walls, in $[^oC]$, and A_i the surface area of walls, in $[m^2]$.

The simplified dynamic model of water vapour mass contained in the air is given by the following differential equation 9 [9].

$$G \frac{dx_i}{dt} = \rho_a \Phi_v (x_i - x_o) \tag{9}$$

where G is the weight of dry air contained in the room, in $[kg]$; ρ_a is the air density, in $[\frac{kg}{m^3}]$; Φ_v is the natural ventilation air flow, in $[\frac{m^3}{s}]$; and x_i and x_o are the fraction of water vapour mass in air indoors (internal) and outdoors (external) the room, given in $[\frac{g}{kg}]$ respectively. The value of indoor relative humidity can be obtained as the quotient between the partial water vapour pressure p_w of the internal air and the partial saturated vapour pressure p_{ws}, being both values measured in $[Pa]$.

$$\phi = \frac{p_w}{p_{ws}} \tag{10}$$

The speed of indoor air v_a is another factor to consider in the heat exchange process and comfort level experienced by the space user. In this work, it was decided that the room is kept with windows closed. Hence, the speed of air flow remains practically constant at a value of 0.1 $[\frac{m}{s}]$.

Typical metabolic rates for skin area unit M for the average adult man can be found in [1]. In the work here developed, the activity levels correspond to those of office work which range between 1.0 and 1.7 $[met]$. As regards the thermal insulation of clothing, the index I_{cl} ranges between 0.6 y 0.8 $[clo]$ for summer.

5 Scheme of Control

The purpose of the controller is to keep within the acceptable range the PMV index (-0.5/+0.5) by modifying the internal room temperature. Fig. 2 shows the designed control scheme. It can be noted that the temperature control is through a PI (Proportional-Integral) controller, whose set point is governed by a neural network (NN Control). The climate conditioner, namely a heating, ventilating and air conditioning or HVAC equipment, is modelled as:

$$\dot{Q}_{aux} = r \dot{Q}_{max} \tag{11}$$

where r represents the percentage of the total capacity of the conditioning equipment, ranging between -1 and 0 for cooling, and 0 to +1 for heating. The maximum capacity of the equipment is given by $\dot{Q}_{max}$ in $[W]$.

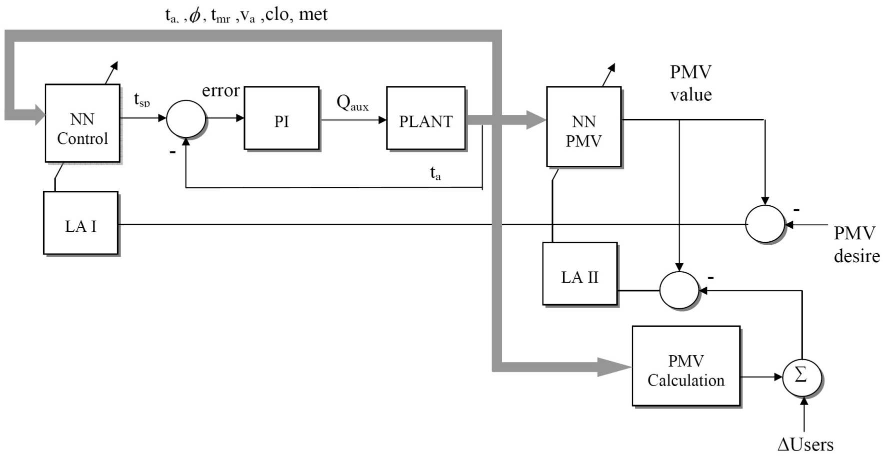

Fig. 2. Block diagram of the Control Scheme.

The objective of the neural network that computes the PMV index (NN PMV) is to adapt itself to the real thermal sensation of the user for the studied space. The persons vote every 2 hours according to the comfort scale presented in Section 2. This vote is compared with the value obtained with the simplified PMV calculation mode proposed in [6]; the difference ($\Delta Users$) is added to the computations, and it is finally contrasted with the network output. Therefore, as long as this difference remains being null, the network output will coincide with the simplified analytic computation method, whereas, if there arises a difference, the network weights will be modified by the learning algorithm LA I so as to make the network output coincide with the users vote.

Both neural networks of Fig. 2 has one input layer and one output layer (Fig. 3). The network inputs are the same parameters as those used to compute the thermal comfort index. They are rated between 0 and 1 before entering the network. The activation functions of the input layers are of sigmoid logarithmic type. The activation function of the output is of linear type.

5.1 On-line Training

The adopted rule for adjusting the weights in both NNs is back-propagation, which is based on the gradient descent method. The input layer weights are denoted as IW, and those of the output are denoted with OW. Considering,

$$x = [t_a\ \phi\ t_{mr}\ v_a\ clo\ met]^T \tag{12}$$

$$u_1 = [t_{sp}] \qquad \text{(for NN Control)} \tag{13}$$

$$u_2 = [PMV_{value}] \qquad \text{(for NN PMV)} \tag{14}$$

$$PMV_{users} = PMV_{calculation} + \Delta Users \tag{15}$$

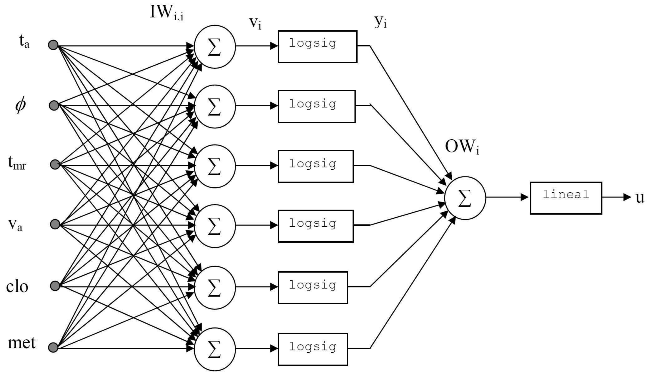

Fig. 3. Structure of both neural networks.

Learning Algorithm I (LA I) Defining the error function as $J = \frac{1}{2}(PMV_{desire} - u_2)^2$, where PMV_{desire} is equal to zero; then,

$$\Delta OW_i = \frac{\partial J}{\partial OW_i} = \frac{\partial J}{\partial u_2}\frac{\partial u_2}{\partial u_1}\frac{\partial u_2}{\partial OW_i} \tag{16}$$

$$\Delta IW_{i,j} = \frac{\partial J}{\partial IW_{i,j}} = \frac{\partial J}{\partial u_2}\frac{\partial u_2}{\partial u_1}\frac{\partial u_1}{\partial IW_{i,j}} \tag{17}$$

Hence to effectively use these gradients, we need to know $\frac{\partial u_2}{\partial u_1}$, which is difficult to calculate when the system model is unknown. To estimate this quantity, sometimes another NN is used. This is frequently the reason why two NNs are used in one control structure. However, for SISO systems we may use an approximation [10]:

$$\frac{\partial u_2}{\partial u_1} \cong \left|\frac{\Delta u_2}{\Delta u_1}\right| sgn\left(\frac{\Delta u_2}{\Delta u_1}\right). \tag{18}$$

Where $\left|\frac{\Delta u_2}{\Delta u_1}\right|$ is bounded it can play the role of a learning rate α. Meanwhile, according to the thermal comfort concept is important to note that $sgn\left(\frac{\Delta u_2}{\Delta u_1}\right) = 1$; hence

$$\Delta OW_i = \alpha(PMV_{desire} - u_2)y_i \tag{19}$$

$$\Delta IW_{i,j} = \alpha(PMV_{desire} - u_2)OW_i \ \ logsig'(v_i) \ \ x_j \tag{20}$$

The rate of learning in the simulations were 0.032.

Learning Algorithm II (LA II) Defining the error function as $J = \frac{1}{2}(PMV_{users} - u_2)^2$; then,

$$\Delta OW_i = \frac{\partial J}{\partial OW_i} = \frac{\partial J}{\partial u_2}\frac{\partial u_2}{\partial OW_i} = \beta(PMV_{users} - u_2)y_i \tag{21}$$

$$\Delta IW_{i,j} = \frac{\partial J}{\partial IW_{i,j}} = \frac{\partial J}{\partial u_2}\frac{\partial u_2}{\partial IW_{i,j}} = \beta(PMV_{users} - u_2)OW_i \ \ logsig'(v_i) \ \ x_j \tag{22}$$

Where β is the rate of learning and in the simulations were 0.05.

6 Simulation Results

Using the dynamic model for the above described space, various simulations were carried out with the purpose of studying the behaviour and performance of the proposed scheme. The models were implemented and validated in MATLAB®. The external weather variables, excepting the solar radiation, are obtained from a weather metering station **Davis** -Model **Weather Monitor II-**, installed on the south side of the room. In the experiences, one day of April 2008 was considered, with a sampling time of one minute. The plot of weather variables is shown in Fig. 4.

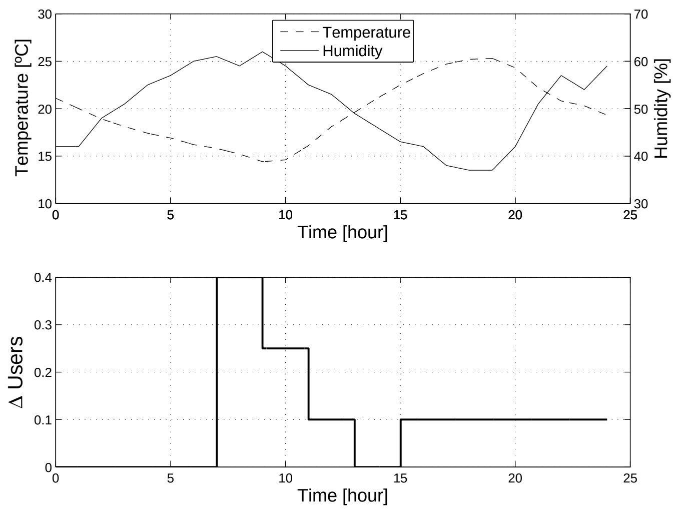

Fig. 4. Outdoor temperature and humidity; and difference between the computed comfort sensation and the value voted by the users. The origin on the time axis corresponds to 00:00 AM.

The parameters used for the experiences are shown in Table 1. The experience implied keeping constant the activity level of users and clothing insulation indexes, and observing the behaviour of the PMV index for the propose controller. Besides, during the experience, the users vote is simulated every two

Table 1. Simulations parameters.

	Clothing [clo]	Metabolic Rate [met]	PI
Experiment	0.65	1.1(Typing)	kp = 10, Ti = 1.25

hours since 8:00 AM until 04:00PM. The difference between the PMV compute with the analytical model and the mean vote of users is shown in Fig. 4.

Fig. 5 shows the controller behaviour, integrated with the neural network that computes the PMV by adapting its weight according to the real thermal comfort sensation. The PMV stays within the acceptable range of thermal comfort (-0.5 / +0.5). When $\Delta Users$ is zero, the values of $PMV_{calculation}$ and PMV_{values} given by the network coincide with one another. In addition, the figure shows the variation of the temperature set point.

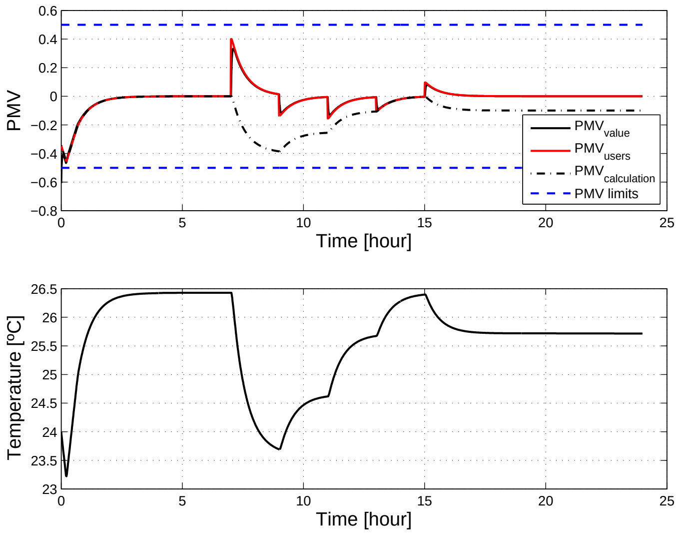

Fig. 5. System performance under propose thermal comfort control. The origin on the time axis corresponds to 00:00 AM.

7 Conclusions

The work has proposed a control strategy for an HVAC acclimatizing equipment to regulate the thermal comfort of an office space using a simple neural network.

With the proposed controller, the NN control is in charge of automatically modifying the setting temperature of the equipment, by adapting it to the six parameters considered in the thermal comfort study. The proper selection of the t_{sp} value for the PI controller is enough for such an aim. But this selection is not simple to do, because of the interrelationship between t_a and the remaining parameters involved in computing the PMV.

The incorporation of the NN PMV into the control system allows the acclimatization equipment adapt itself to the real needs of the users. This allows the system "to learn" the thermal satisfaction of users, which needs only to perform a single initial stage of learning. After this first stage, the user vote, or PMV_{users}, can be eliminated without affecting the proposed control scheme.

Besides is possible to ensure that, regardless the difference existing between the $PMV_{calculation}$ and the PMV_{users}, the controller will always yield a response within the acceptable limits for user comfort (-0.5/+0.5).

Studies like the one made here are of growing importance to increase the energy savings in HVAC thermal acclimatization equipments. These control techniques integrated with artificial intelligence are a proper option when needing to apply the concept of thermal comfort to the acclimatization control of work spaces.

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