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Potential of artificial neural networks to predict thermal sensation votes

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HIGHLIGHTS

- We used neural networks (NN) to predict thermal sensation votes on the ASHRAE scale.
- We tested a number of different predictors to optimize the performance of the NN.
- Prediction of mean vote and vote distribution under given conditions is excellent.
- Prediction outperforms the classical PMV.
- Prediction yields far more information than the classical PMV.

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ABSTRACT

If occupants of buildings are offered possibilities to interact with the building's equipment elements – such as with windows – in order to optimize their individual environment, these interactions will influence the energy consumption of the building. Therefore, during the design of the building, e.g. by building simulations, these interactions need to be predicted if the energy consumption of the building is to be optimized.

These interactions are partly motivated by the need for thermal comfort. A precondition for the prediction of interaction is therefore the prediction of the individual evaluation of the thermal environment. Although 'sensation' is not an optimal conceptualization of 'satisfaction with the thermal environment', it is frequently used as a measure for the evaluation of thermal comfort. However, the prediction of thermal sensation is currently not satisfactorily possible. Therefore, this article examines the potential of artificial neural networks to improve the predictability of thermal sensation. The data base used for this research derives from the RP-884 Adaptive Model Project.

Results show that the designed neural network performs excellently in the prediction of the distribution of individual ASHRAE votes under defined conditions, and that it outperforms the classical PMV index in terms of prediction quality and the range of information contained in the prediction.

1. Introduction

In modern building design, building occupants are offered a number of possibilities to interact with the equipment elements of the building, such as the heating or cooling systems, the windows or shading devices. They interact in order to optimize their local environment according to their multiple needs. For example, they switch on the desk light to obtain lighting conditions that better support their work task, or they close the shading device to improve the privacy situation, or they may turn on the heating system to optimize thermal comfort. These actions influence the energy balance of the building; they are energy-relevant human interactions with the building, and they serve to satisfy a set of energy-relevant needs. Examples of such needs, with reference to the introductory examples for interaction include: the need to implement a specific task; the need for privacy; or the need for comfortable environmental conditions [1].

The present article concentrates on the need for thermal comfort (a subtype of the need for comfortable environmental conditions). Specifically, it demonstrates that artificial neural networks (NN) have great potential to predict the entire scope of thermal sensation votes if they are trained with sufficient data. Why can this be considered to be helpful and necessary? Research in recent decades has shown that temperatures in which occupants perceive conditions as thermally neutral on the ASHRAE thermal sensation scale ("neutral temperature") can be predicted if a difference is made between naturally ventilated and mechanically cooled

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Nomenclature

$\bar{x}$	normalized feature of feature vector X
μ	mean
0 (on the ASHRAE scale)	"neutral"
1 (on the ASHRAE scale)	"slightly warm"
−1 (on the ASHRAE scale)	"slightly cool"
2 (on the ASHRAE scale)	"warm"
−2 (on the ASHRAE scale)	"cool"
3 (on the ASHRAE scale)	"hot"
−3 (on the ASHRAE scale)	"cold"
a	activation of neuron
ACC	accuracy
AGE	age of the subject
C	costs, error
CLO	clothing
CVDS	cross-validation dataset
day15_ta	outdoor temperature at 3 p.m. on day of survey
day15_vp	outdoor vapor pressure at 3 p.m. on day of survey
fNN	feedforward neural network
GENDER	gender of the subject
H	hypothesis vector
h	element of hypothesis vector H
I	size of feature vector (w/o bias unit)
INSUL	insulation
J	size of hidden layer (w/o bias unit)
K	size of hypothesis vector
L_1, L_2, L_3	input, hidden and output layer
M	size of dataset
MET	metabolic rate
n	neuron
PMV	predicted mean vote
relH	relative humidity
relV	relative air velocity
R_{MM}	monthly mean of horizontal total solar radiation
R_{YM}	yearly mean of horizontal total solar radiation
s	standard deviation
T_{AIR}	air temperature
TDS	training dataset
TestDS	test dataset
T_{MM}	monthly mean of outdoor temperature
T_{OP}	operative temperature
Tp_{MM}	monthly mean of outdoor wet bulb temperature
Tp_{YM}	yearly mean of outdoor wet bulb temperature
TRAD	radiant temperature
T_{YM}	yearly mean of outdoor temperature
VP	vapor pressure
w	weight (scalar)
W	weight (matrix)
X	feature vector
x	feature of feature vector X
Y	result vector
y	element of result vector Y
z	input to neuron

Subscripts

(m)	m-th element of dataset
0	bias unit of the layer
i	i-th neuron in the input layer
j	j-th neuron in the hidden layer
ji	between j-th and i-th neuron
k	k-th neuron in the output layer
kj	between k-th and j-th neuron

Superscripts

$(L1)$	belonging to input layer
$(L1–2)$	between input and hidden layer
$(L2)$	belonging to hidden layer
$(L2–3)$	between hidden and output layer
$(L3)$	belonging to output layer

buildings and if the mean monthly outdoor temperature (or a comparable measure) is taken into account (e.g. [2–5]). If thermal neutrality is regarded as the thermal state that building occupants want to achieve, the prediction of the neutral temperature is a valuable orientation during the design of new buildings. For example, thermal building simulations are often performed during the design of a building, in order to determine the energy expenditure that will be necessary for future operations to achieve a particular thermal comfort level. In such cases, the predicted space temperatures can be compared to the neutral temperature, and the thermal performance of the building can be optimized according to this criterion.

However, as mentioned above, certain types of occupant behavior—namely, the energy-relevant interactions—influence the energy balance of the building. Therefore, if one is to predict the energy consumption and the comfort conditions of types of buildings, which allow the occupant a certain range of energy-relevant interactions—e.g. operable windows, shading devices and local heating, this interactive behavior must be taken into account. These behaviors are usually elicited by non-optimal conditions, and aim for the restoration of optimal conditions. Therefore, it is essential to be able not only to predict which thermal conditions are likely to be perceived as the optimum by the occupant (e.g. the "neutral temperature"), but also to what degree conditions that deviate from an optimum are perceived as undesirable, and have the potential to elicit an action.

An established scale that individuals can use to express their thermal sensation is the above mentioned ASHRAE 7-point thermal sensation scale. It is an ordinal scale that comprises the following categories: 3 (hot); 2 (warm); 1 (slightly warm); 0 (neutral); −1 (slightly cool); −2 (cool); and −3 (cold). It is often used in lab-based and field studies to capture the thermal sensation of individuals under varying conditions. For example, the RP-884 dataset that was used to derive the aforementioned "neutral temperature" is a compilation of a number of different field studies of thermal sensation that made use of the ASHRAE scale [6]. In addition, the Predicted Mean Vote index (PMV index), developed by Fanger [7], mathematically predicts the average ASHRAE thermal sensation vote of a large group of individuals, based on six predictors: air temperature; radiant temperature; relative air velocity; relative air humidity; clothing and metabolic rate. However, since the PMV represents a mean vote, individual votes deviate considerably from the PMV. For example, a mean vote of 0, i.e. "neutral," includes, according to Fanger's findings, 60% of individual 0 votes, around 35% individual 1/−1 votes and 5% individual 2/−2 votes (see Table 14 of [7] and Fig. 1 of [8]).

Even though it is a sensation scale, rather than a measure of acceptability, the ASHRAE scale is often used to approximate satisfaction with thermal environments. For example, based on the findings of Gagge [9], Fanger claimed that individuals that vote beyond −1/1 on the ASHRAE scale are dissatisfied with their thermal environment. Using this assumption and the experimental distribution of votes in his studies ([7], Table 14), he statistically correlated the PMV index with the percentage of dissatisfied individuals. This resulted in the PPD index (predicted percentage of dissatisfied). For the above example, this means that a thermal