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COMFORT INDEX CALCULATION USING ARTIFICIAL NEURAL NETWORKS

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Abstract: *Client comfort has been and still is one of the most important goals of respectable companies. The comfort is influenced by several factors, such as air temperature or noise. However, the factor influence differs sometimes dramatically. Based on statistical data collected using sensors the influence of each factor can be approximated. In this paper we propose a comfort index calculation based on a basic artificial neural network which uses an evolutionary algorithm for the training process.*
Key words: *comfort index, artificial neural networks, evolutionary algorithm*

1. INTRODUCTION

In the last decades there has been an impressive development of several technological domains whose main purpose is to increase consumer comfort. Consequently, mathematical models have been developed and statistical research has been conducted in order to define and express the so called comfort index. Moreover, special spaces with centralized control of environmental factors that influence the well-being, such as smart buildings, have been developed.

The comfort index has been defined with respect to several factors such as air temperature or humidity which are assigned different weights. A recent trend is to compute the comfort index using computational tools that predict the value of the index based on statistical data collected from the environment with respect to several factors. The calculation of the comfort index using artificial neural networks (ANN) is proposed in this paper.

2. ARTIFICIAL NEURAL NETWORKS

ANN work in a controlled loop, imitating the brain functions, but in a digital way, restoring the mechanism of learning, as the input of the loop. ANN does not require detailed information about the system or equipment and can learn the relationship between input and output based on data acquisition. ANN is a device with nonlinear information processing built from processing devices called neurons, which are interconnected. Each input of the device is multiplied by a connection weight. Being a controlled loop, the product and the biases are summed and transformed through a transfer function to generate the result (the output).

The most network architectures which are used in the RACHP (refrigeration, air conditioning and heat pump) field are: (i) multi-layer feed forward, (ii) radial biased function network, (iii) generalized neural networks and (iv) adaptive neuro fuzzy systems [1].

ANN devices have been applied to the advanced thermal control of buildings by using connectivity and transfer functions between inputs and outputs to calculate the optimal input. Different mathematical models can be used such as regression models and control methods as PID (proportional - integrative - derivative) controllers, so that ANN can have adaptability via a self-turning process, to be able to decide with accuracy without external intervention for returning model parameters. Studies proved the advantage of ANN based on predictive control over mathematical strategies, for thermal control, reducing overheating and overcooling, and for the improvement of energy efficiency [2].

3. WELL-BEING INDEX

The thermal comfort can be defined, according to international standards, as: „That condition of mind which express satisfaction with the thermal environment". The thermal comfort is influenced by various factors but more researches have proven that the comfort temperature chosen by people living in different climates and cultures but with similar conditions of clothing and activities is very similar [5].

Computing and data acquisition of thermal comfort in a certain environment has been studied, resulting with models in this field area. One of this indexes is PMV (Predicted Mean Vote), developed by Fanger during the 70's, which predicts or anticipate the response based on statistics, for thermal sensation of an sample of people in laboratory conditions: thermic and time control. The value of PMV index is a seven point thermal sensation scale. In order to maintain the thermal comfort, it is recommended that the PMV index to be at level 0 with a tolerance of ±0.5. There are six variables that define the PMV index: metabolic rate, clothing insulation, air temperature, mean radiant temperature, air velocity and air relative humidity. From all these six variables, clothing insulation and metabolic rate can be measured only in laboratory controlled environment, because it depends on the situation of each user at a certain point of time. The value of these two variables can be found in manuals and standards. Another variable, mean radiant temperature which can be defined as the uniform temperature of an imaginary enclosure, where, the radiant heat transfer from the human body is the same as the one from the actual non-uniform enclosure, can be estimated by other methods [3, 4].

The PMV index is widely adopted as the main index, containing many adaptions for different cases. The thermal comfort indices include predicted mean vote (PMV), the model of simplified thermal comfort and the neural computing thermal comfort index. The developers, Fanger and Toftum took further away the PMV index to non-air-conditioned buildings in worm climates. The PMV model was used by Kul Karni and Hong to evaluate the level of comfort in transient pull downs. Also, Brager de Dear concluded that during winter, is needed a small positive adjustment when there is applied the original PMV index to the office buildings in San Francisco [6].

So far, in HVAC (heating, ventilation, and air conditioning) systems and prediction of cooling/heat load in buildings, the neural network models (NNM) are successfully implemented. However, the number of studies of applications using NNM in thermal comfort evaluation is limited. A proposal regarding the evaluation of PMV index of thermal comfort via neural computing in a wide range of human and environmental variables for HVAC systems has come from Atthajariyakul and Leephakpreeda with a practical approach, with a thermal comfort model but more developed for colony, or more individuals, not for individual [8].

Here, a neural network evaluation model (NNEM) of indoor thermal comfort is made in order to be available for individual thermal comfort: on the back propagation algorithm (BP neural network). The most important feature of BP neural network is the prediction of nonlinear systems and fast convergence rate and strong false compatibility. So, when it is applied to a thermal comfort domain, it will automatically learn and evaluate the level of comfort keeping in mind the variations of indoor environment [7].

4. INSTRUMENT DESCRIPTION

A computational model of a single neuron, also called perceptron, has been modeled and implemented in MATLAB R2009b. The perceptron has *m* inputs which are used to predict the output (see Fig. 1). At first *m* random weights, one for each input, are generated. Then, the best values of the weights are obtained by training the perceptron.

The training process is extremely important for ANN in general. Many conducted researches have shown that genetic algorithms improve the computational performance if they are used instead of a back propagation algorithm. In this paper we suggest a similar substitution: the instrument developed for comfort index calculation uses an evolutionary algorithm.

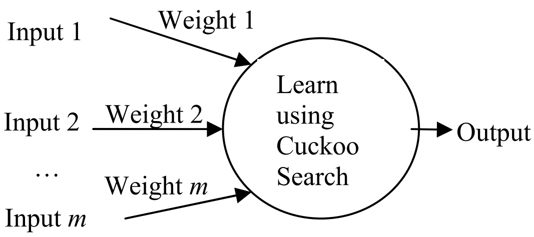

Fig. 1. Basic structure of the perceptron

An important characteristic of the evolutionary algorithms is the fact that they mimic the best elements of the biological systems that have evolved over so many years through natural selection. Two main features that stand out are environmental adaptation and survival of the best. One of these algorithms is Cuckoo Search developed in 2009 by Xin-She Yang and Suash Deb [9] and based on the so-called Lévy flights. This algorithm was used to conduct the training process.

Cuckoo Search based on Lévy flights was also implemented in MATLAB R2009b and can be described using the three rules mentioned in [9].

The program starts with generating an initial population of *n* random cuckoos within the limits of the search space representing the possible weights. A cuckoo is a vector of *m* variables whose values are necessary for generating the output. For every generation each cuckoo is evaluated using the objective function and the best cuckoo is found.

The migration of the cuckoos towards the area with the best values of the weights that minimize the sum of the modules of the differences between the output and the real value of the output for a certain input data set is implemented in a repetitive structure. The migration is based on the three already mentioned rules. It has to be mentioned that each new cuckoo chick which was obtained by laying an egg in a nest, replaces its parent in the population only if it is better than its parent.

The migration ends when the maximum allowed number of evaluations of the objective function *Nmax* is reached and the optimal weights are returned as solution.

5. INSTRUMENT VALIDATION

The instrument developed using an evolutionary algorithm for training has been tested on an example from the open literature.

The global comfort index has been defined as the weighted sum of the values of several parameters that influence the comfort [10]:

$$I = 1{,}24 + 0{,}39 \cdot S_t + 0{,}16 \cdot S_{ma} + 0{,}12 \cdot S_u + 0{,}05 \cdot S_i + 0{,}13 \cdot S_z + 0{,}36 \cdot S_{ca} \quad (1)$$

where S_t is the satisfaction code for the temperature, S_{ma} for the air motion, S_u for the humidity, S_i for the lighting, S_z for the noise, and S_{ca} for the quality of the air. The satisfaction code is a number {0,1,2} that has been atributted as follows: total dissatisfaction is coded using ”0”, dissatisfaction or marginal satisfaction is coded using ”1”, and satisfaction using ”2”.

Table 1

Instrument parameters

Parameter	Significance	Value
m	Number of weights	7
n	The number of cuckoos	25
Nmax	The maximum allowed number of objective function evaluations	50,000
pa	The discovery probability	0.25

Based on the formula given by (1) an input data set consisting in 30 7-dimensional points has been generated. The first 6 dimensions of each point represent the values of the 6 satisfaction codes while the last one represents the value of the comfort index computed using (1). The purpose of the input data set is to train the ANN. The training is conducted using the implemented Cuckoo Search which finds the optimal weights for each satisfaction code. The parameters required by the program are provided in Table 1.

The ANN was trained based on the already mentioned input data set. Even allowing only 50,000 evaluations of the objective function the weights given in (1) were obtained in less than four seconds.

6. CONCLUSION

The factors that influence the well-being and the comfort of people, as well as the extent of their influence have been the subject of many studies. Researchers have tried to develop certain models, such as the one for comfort index, to measure the comfort.

The approach proposed in this paper for comfort index calculation consists in using an instrument based on an ANN that handles the training process with an evolutionary algorithm. It has been shown that the developed instrument is fast and reliable with respect to basic comfort index models. Further research will be conducted for more complex models.

7. REFERENCES

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CALCULAREA INDICELUI DE CONFORT FOLOSIND RETELE NEURONALE

Rezumat: *Confortul clienților a fost și încă este unul dintre cele mai importante țeluri a companiilor care se respectă. Confortul este influențat de mai mulți factori, cum ar fi temperatura aerului sau zgomotul. Influența acestor factori diferă adeseori în mod dramatic. Pe baza unor date statistice colectate cu ajutorul unor senzori se poate aproxima influența fiecărui factor. În această lucrare propunem calcularea indicelui de confort bazată pe o rețea neuronală de bază care folosește un algoritm evolutiv ca proces de antrenare.*

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