International Journal of Innovative Computing, Information and Control
Volume **13**, Number **4**, August **2017**
ICIC International ©2017 ISSN 1349-4198
pp. 1323–1333

RESEARCH ON INDOOR ENVIRONMENTAL COMFORT BASED ON COMPLAINTS

Fuzhong Nian[1,*], Ke Wang[1] and Qianchuan Zhao[2]

[1]School of Computer and Communication
Lanzhou University of Technology
No. 287, Langongping Road, Lanzhou 730050, P. R. China
*Corresponding author: gdnfz@lut.cn; wklutwk@163.com

[2]Department of Automation
Tsinghua University
No. 1, Qinghuayuan, Haidian Dist., Beijing 100084, P. R. China
zhaoqc@tsinghua.edu.cn

Received December 2016; revised April 2017

Abstract. *Aiming at these shortcomings that traditional node model had unreasonable points, ignoring the difference of different individuals' comfort and PMV (Predictive Mean Vote) predictors with multiple parameters, nonlinearity and static properties failed to dynamically and timely measure and predict the human comfort, an approach was proposed in this paper with only choosing temperature and relative humidity as indoor environment parameters. By people complaining the hot and cold feeling, recording the current temperature and humidity as hot and cold complaint points, adopting BP (Back Propagation) neural network training the hot and cold complaint points, the uncomfortable region was decided. Then removing the uncomfortable zone from the whole testing temperature and humidity area, the comfortable zone would be confirmed. At last, using the MATLAB simulation platform, the relationship between the indoor environmental temperature and humidity and human comfort feeling was verified effectively, real-timely and dynamically.*
Keywords: Complaint, BP neural network, Indoor, Comfort

1. Introduction.

More than 85% time of human are indoors in modern life, and many a modern professional staff will even work no less than 22 hours in the artificial environment. Therefore, a growing number of people have put forward much higher requirements for the more suitable indoor environment, the good indoor environment not only is conducive to human health, but also improves work efficiency, and the appropriate thermal environment can increase productivity by 18% [1]. In order to create the comfortable indoor environment, a lot of researches have been done by a host of scholars at home and abroad. The traditional research mainly focuses on node-based control. These control systems are either limited to the satisfaction of the single individual or limited to the unreasonable indoor node settings. Peeters et al. [2] pointed out that unreasonable node settings can not only destroy the performance of the control system, but also increase the energy consumption. To this problem, Fanger et al. [3,4] proposed the predictive mean vote (PMV), which took account of factors that affected the thermal comfort of the human body, representing the evaluation of thermal comfort by most of people. Humphreys and Nicol [5] used ASHRAE (American Society of Heating, Refrigerating and Air-conditioning Engineers) database, analyzed people's bias against PMV and thus confirmed the advantages of PMV. Wu and Sun [6] integrated the parameters of housing architecture into the PMV specification. Y. Cheng et al. [7] used Bayesian estimation from both laboratory and field settings to predict acceptability and modifed the PMV curve. Although PMV predictor overcame node-based limitations, attempting to establish a link between people's comfort senses and indoor environmental parameters, such as the typical ASHARE 7-scale model [8], which played an important role in the indoor environment design and estimation, it ignored the whole staff indoors. Federspiel [9] proposed a stochastic process model to describe a group of people's complaining frequency; however, the model is on condition that everyone had same complaints against the indoor environment, neglecting the difference of people indoors, and lack of instantaneity.

With the rapid development of information technology and its extensive application in the construction industry, people have come up with much higher demand for the indoor environment, the traditional node-based model with unreasonable node settings and limited prediction of individual comfort degree cannot fulfill people's requirements for comfortable indoor environment [10]. The PMV got over the unreasonable node settings of the node-based model, fully taking consideration of the four indoor environment variables: air temperature, air relative humidity, air velocity and average radiation temperature and two body parameters: human metabolism and the function of clothing's heat resistance, but it is its nonlinear, complex iterations and static properties that made it difficult to measure and predict human comfort degree dynamically and timely [11]. Motivated by this, an approach with two parameters: indoor temperature and relative humidity (because indoor temperature and relative humidity are two basic problems that people closely pay attention to) was presented in this paper.

In this paper, the BP neural network algorithm is used to model the indoor environment comfort. BP neural network has the following two directions: theoretical research and application research. Theoretical research is mainly studied by neurophysiology and cognitive science research on human thinking and intelligence mechanism, using mathematical methods to improve neural network model and algorithm, the performance of the neural network is superior, in-depth study and performance of neural network convergence. The research of application field is mainly about the application of neural network in various fields, such as pattern recognition, information processing, expert system, optimization combination, robot control and other fields [12]. Calvino et al. [13] proposed a new simple approach that focused on the application of an adaptive fuzzy controller that avoids the modelling of indoor and outdoor environments. Kim et al. [14] developed two types of adaptive PMV models based on the black-box theory and the adaptive thermal comfort theory in air-conditioned buildings. Castilla et al. [15] and Atthajariyakul and Leephakpreeda [16] proposed an indoor comfort algorithm based on BP neural network which can reduce the complexity of network training and prediction error. In this paper, the BP neural network was applied to modelling indoor thermal comfort based on complaints, avoiding the complexity of the traditional calculation model of indoor environment thermal comfort. Besides, the BP neural network has strong capability of nonlinear approximation, so that it can judge and predict the indoor environment comfort well.

People complaint about hot and cold feelings, which was recorded as hot and cold complaining points. BP neural network was used to train the hot and cold complaining points, and then remove the uncom recorded as hot and cold complaining points ortable area from the testing indoor environment temperature and relative humidity area; as a result, the rest was just the comfort areas which people can feel well at this range of temperature and relative humidity. Finally, the proposed method was proved by MATLAB simulation, and it turned out effectively that there was certain relationship between the human comfort degree and the indoor environment temperature and relative humidity.

2. **PMV Indicator.** Indoor environmental comfort is generally expressed by the thermal comfort, which is about the subjective evaluation and perception for the indoor thermal environment [17]. Indoor environment is a fuzzy system with multi-parameter. There are many factors affecting the indoor environmental comfort, such as temperature, relative humidity, wind speed, environmental radiation temperature and other physical parameters, including personal subjective feelings [18]. In the aspect of the thermal comfort evaluation, Professor Fanger's PMV index is a representative, synthetically taking account of all the factors that influenced the human thermal comfort, on behalf of the majority of people's evaluation to the thermal comfort. The PMV index has four environmental variables: air temperature, air relative humidity, air flow rate and average radiation temperature and two human parameters: the body's metabolic rate and the function of clothing's heat resistance, and PMV index represents people's thermal sensation. The PMV index is calculated as follows [19]:

$$\begin{aligned} PMV = {} & \left(0.303e^{-0.036M} + 0.028\right) \times \big\{ (M - W) \\ & - 3.05 \times 10^{-3} \times [573 - 6.99\,(M - W) - P_a] - 0.42\,[(M - W) - 58.15] \\ & - 1.72 \times 10^{-5} \times M\,(5867 - P_a) - 0.0014M\,(34 - t_a) \\ & - 3.96 \times 10^{-8} \times f_{cl}\left[(t_{cl} + 273)^4 - (t_r + 273)^4\right] - f_{cl}h_c\,(t_{cl} - t_a) \big\} \end{aligned} \tag{1}$$

M is human's energy metabolism rate, W/m^2; W is the mechanical work to the outside world by people, W/m^2; P_a is water vapor pressure around the human body, Kpa; t_a is the air temperature around the human body, °C; t_r is the average environmental radiation temperature, °C; f_{cl} is the ratio of body surface area to naked body surface area.

$$f_{cl} = \begin{cases} 1.00 + 1.290 \times I_{cl}, & I_{cl} < 0.078\ \mathrm{m^2 \cdot {}^\circ C} \\ 1.05 + 0.645 \times I_{cl}, & I_{cl} > 0.078\ \mathrm{m^2 \cdot {}^\circ C} \end{cases} \tag{2}$$

It should be noted that I_{cl} refers to the thermal resistance, m^2 · °C/W; t_{cl} refers to clothing outer surface temperature, °C;

$$\begin{aligned} t_{cl} = {} & 35.7 - 0.028 \times (M - W) - I_{cl} \times \big\{3.96 \times 10^{-8} \\ & \times f_{cl}\left[(t_{cl} + 273)^4 - (t_r + 273)^4\right] - f_{cl}h_c\,(t_{cl} - t_a) \big\} \end{aligned} \tag{3}$$

h_c is surface heat transferring coefficient, W/(m^2·K);

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

v_a is air flowing rate, m/s.

In the actual calculation process, the simplified PMV indicators can be used as follows. When general adults meditate and light labor, human metabolic rate M is 69.8 W/m^2; the mechanical work to the outside world by people W is 0; the garment area coefficient is 1.1; human clothing thermal resistance in summer is 0.5 Clo, and human clothing thermal resistance in winter is 1.5 Clo; wind speed indoors in summer is 0.2 m/s; wind speed indoors in winter is 0 m/s [20].

f_{cl} and t_{cl} can be decided by I_{cl}, and h_c is the function of wind speed. Thereby, under above assumptions, the PMV index is related to air temperature, humidity, wind speed, average radiation temperature, clothing thermal resistance and human metabolic rate. Average radiation temperature is equal to the air temperature generally.

$$PMV = f\,(t_a, h_a, v_a, t_r, I_{cl}, W) \tag{5}$$

The PMV index uses the 7-level scale, respectively representing −3-3, corresponding to the body's cold, cool, cooler, neutral, warmer, warm, hot [21], which are shown in Table 1.

Table 1. PMV's 7-level scale

Thermal sensation	cold	cool	cooler	neutral	warmer	warm	hot
PMV indicators	−3	−2	−1	0	+1	+2	+3

3. **Indoor Environmental Comfort Based on Hot and Cold Complaints.**

3.1. **BP neural network.** There are two stages for learning BP neural network.

1) Input known learning samples, and calculate each neuron output from the first layer of the network by setting the network structure and preciously iterated weights and thresholds.

2) Modify weights and thresholds, and calculate the influence (gradient) that each weight and threshold have made to the total error from the last layer.

Repeat above two phases alternately until the convergence is reached. This convergence means that the result of BP neural network training error accuracy reaches the set value or the number of learning times reaches the maximum value. The specific BP neural network algorithm's implementation is as follows [22]:

(1) Initialize each parameter and give each neuron random values in interval $(-1, 1)$;
(2) Supply as many training sets as possible to establish the network, that is input quantity X and expected value y';
(3) Calculate the network output y_t, according to the established network model;

$$y_t = f\left(\sum w_{ij} x_j\right) \tag{6}$$

Note: the $f(x)$ is sigmoid function:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{7}$$

(4) Adjust the weight according to the principle of BP neural network, and transfer the network error reversely to the middle layer by Formula (8):

$$W_{ij}(t+1) = W_{ij}(t) + \eta \delta_j y_j \tag{8}$$

Note: η is the added value greater than 0. This η is a value we set. We set η is 1.653, δ_j is node j's error. The error values of nodes in different forms are calculated by Formula (9):

$$\delta_j = \begin{cases} y_i\left(t - y_i\right)\left(y_i' - y_i\right), & j \text{ is input node} \\ y_i\left(1 - y_i\right)\sum \delta_j W_{jk}, & j \text{ is output node} \end{cases} \tag{9}$$

(5) Go back to step (2). Calculate the next round until the network convergence. The initial value of BP neural network weights and threshold values are randomly generated.

3.2. **Introduction of indoor environmental comfort based on hot and cold complaints.** There exist complex non-linear relationships among the various factors of human thermal comfort. Many parameters cannot be directly detected, only get results indirectly by complicated iterative calculation according to the detected indoor air temperature, humidity, air flow velocity and other parameters. As a result, it is not easy to satisfy real-time control of HVAC systems via traditional methods to determine the PMV indicator [23]. Because of this, an indoor environmental comfort forecasting model was proposed in this paper. Record people's hot and cold complaints in the current temperature and relative humidity, which denotes an uncomfortable complaint about the indoor environmental comfort, that is to say, if you feel too cold, complain the cold and record as a cold complaint, on the contrary, if you feel too hot, complain the heat and record as a hot complaint, Firstly, regard the recorded hot and cold complaint samples as BP neural network's training sets. Secondly, use BP neural network algorithm to classify hot and cold complaining regions. Finally, removing hot and cold complaining regions from the whole region, then the rest of the range of temperature and relative humidity was the comfort region; thus the indoor environmental comfort region will be determined. Eventually, predict whether the indoor environmental relative humidity and temperature meet the requirements of human comfort in a future certain moment, recording the human comfort at this very moment. Whether predicted results are the same as the real recorded data will be verified. Therefore, detecting effect factors (relative humidity and temperature) of human comfort, BP neural network will be applied to modelling the indoor environmental comfort based on complaints. Intelligent prediction of indoor environmental comfort will create favorable living conditions [24].

3.3. **Design of indoor environmental comfort based on hot and cold complaints.** BP neural network algorithm is widely used in practical control systems such as pattern recognition, function approximation, and prediction with its strong non-linear approximation ability. In this paper, BP neural network was used to model indoor comfort based on hot and cold complaints, and indoor people's hot and cold complaints were real-time recorded in the computer database by hot and cold complaint software through a group of experiments. The temperature and relative humidity were recorded as hot and cold complaints point when people complain about hot and cold, a part of which is regarded as the training set of BP neural network, the other part of which is regarded as the validation set verifying that the identified hot and cold complaining intervals are correct, if so, determine the hot and cold complaint region. Because the site of experimental environment is located in the summer of a university laboratory in Lanzhou, people generally feel comfortable temperature of 24 °C to 28 °C and relative humidity of 44% to 56%, the temperature was set for per 0.1 °C from 24 °C to 28 °C and relative humidity was set for per 0.1% from 44% to 56% as the test set. From the tested temperature and humidity region, to exclude hot and cold complaining area, it is the comfort region. When the comfort region of the indoor environment is determined, it is just determined that the relative closed room environment is almost comfortable with the temperature and humidity range. The indoor environment temperature and humidity were adjusted, so that the indoor environment temperature and humidity in the BP neural network prediction of the comfort region. The comfort of the people in the comfort region is recorded again, and the accuracy of the comfort region is verified.

The hot and cold complaint software is shown in Figure 1.

The indoor environment comfort model based on the hot and cold complaints point is shown in Figure 2.

FIGURE 1. The mobile client interface of indoor environmental comfort complaining

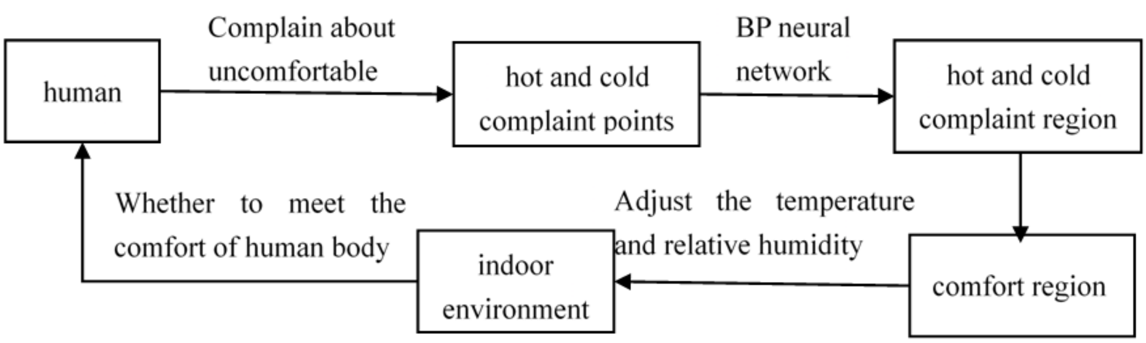

FIGURE 2. The model diagram of indoor environmental comfort

The selection of initial weight of BP neural network is related to whether the network can train effectively and reach convergence. The initial weights are usually randomly generated in a small range, the input sample after the normalization process, the greater of which falls on the transfer function gradient place, so as to ensure that earning process of each neuron will be where the activation function becomes the greatest. If the input is very large or very small, the slope of the output function is close to 0, and the gradients of the multi-layer network will be very small when applying the gradient descent method. So the adjustment range of weights and thresholds is reduced, even if the optimum value is not reached, the result of training stop will be formed. Elastic gradient descent can eliminate this effect. When the BP neural network is trained by the elastic gradient descent method, the weight correction depends on the sign of the derivative of the performance function, but the magnitude of the derivative has no effect on the weight correction [25].

In this paper, the indoor environment comfort model was designed to train the BP neural network by elastic gradient descent method. When the BP neural network algorithm was designed, the input layer of BP neural network was two-dimensional because the indoor environment model was based on the two parameters of temperature and relative humidity. For the selection of the hidden layer of BP neural network, this paper chooses the double hidden layer under the premise of accuracy and efficiency. The number of neurons in the hidden layer selection often needed to be determined according to the designer's experience and multiple experiments. Excessive number of neurons in the hidden layer can lead to too long learning time, but the error is not necessarily the best, and will lead to poor fault tolerance, and cannot identify previously not seen samples. Therefore, the number of neurons in the double hidden layer was 3 and 2, respectively. For the output layer, there were 2 neurons in the output layer, as the result was hot and cold complaint of the cold complaint output and the hot complaint output.

3.4. **Innovation and features.** The traditional method of comfort evaluation is stick to the iteration and calculation of formula; besides it is not conducive to the timely evaluation and reflection of indoor comfort, and cannot meet the needs of real-time control of HVAC system. In this paper, learning function of BP neural network is used to explore a fast and credible method of thermal comfort evaluation. Because of the complex nonlinear relationship between the PMV index and the thermal comfort of human body, many factors cannot be directly detected as well, and the traditional method to determine indoor comfort is difficult to achieve in the reality. The proposed method of comfort evaluation based on indoor environment temperature and relative humidity using BP neural network effectively overcomes the limitations of the traditional formula in terms of data acquisition. The traditional collection and evaluation of indoor environment are mainly based on the acquisition of environmental parameters, which often ignores the influence factors of the human body and individual experience. In this paper, the cold and hot complaints by people were collected and used BP neural network to determine the range of temperature and humidity to ensure the comfort of the human body.

4. **Experiments and Simulation.** In order to verify the actual effect of the indoor environment model, a laboratory in a university in Lanzhou (about 30 square meters) was as the experimental location. Two indoor environmental parameters, namely air temperature and relative humidity, can be measured by the environment quality sensor placed in the laboratory. The sensor is shown in Figure 3.

The experimental simulation took the use of newff function to generate BP neural network by Matlab platform. The indoor environment comfort model based on BP neural network is shown in Figure 4. Experimental computer is a Lenovo notebook of CPU 2.6G clock speed, 4G memory, 500G hard drive, Win 7 of the operating system.

Figure 3. Indoor environment temperature and humidity monitoring sensor box

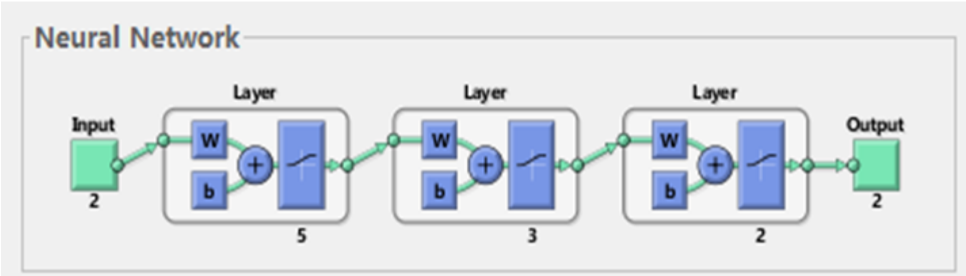

FIGURE 4. The BP neural network design of indoor environment comfort model

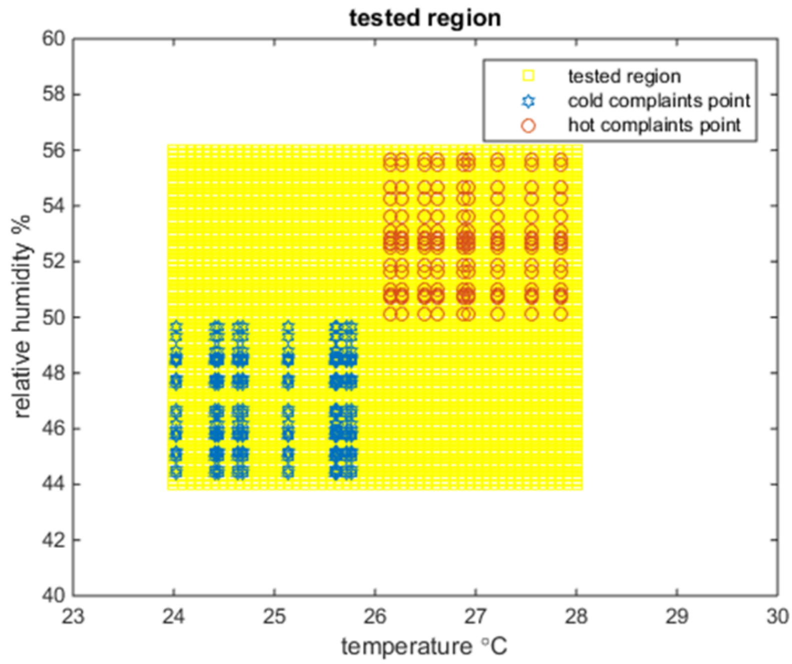

FIGURE 5. Tested indoor environmental region

In this experiment, we collected 200 groups of hot and cold complaining points of human comfort including 100 hot complaint points and 100 cold complaint points, among which the former 180 sets of data were used as the training set of BP neural network. Because human generally feels comfortable temperature of 24 °C to 28 °C, relative humidity of 44% to 56%, the temperature was set for per 0.1 °C from 24 °C to 28 °C and relative humidity was set for per 0.1% from 44% to 56% as the test set in this paper, as shown in Figure 5. The test set was outputted by BP neural network to determine the hot and cold complaining region, and further, the comfort region was determined. The output prediction results are shown in Figure 6. The result in the $(0, 1)$ interval is the comfort point, the result that equals 1 is the cold complaint point, and the result that equals 0 is the hot complaint point. The horizontal coordinates represent the number of samples in the test environment, and each sample point represents the set point of temperature and relative humidity, for example, it represents (24.1 °C, 44.1%) when the sample point is 1, that is to say, the test point is that the temperature is 24.1 °C and the relative humidity is 44.1%. The result of the comfort area is shown in Figure 7. As can be seen from Figure 7, the result in the $(0, 1)$ of comfort region is located in blue portion. By comfort region determination, adjust the indoor temperature and relative humidity, which can ensure people of the indoor environment comfort requirements. Compared with

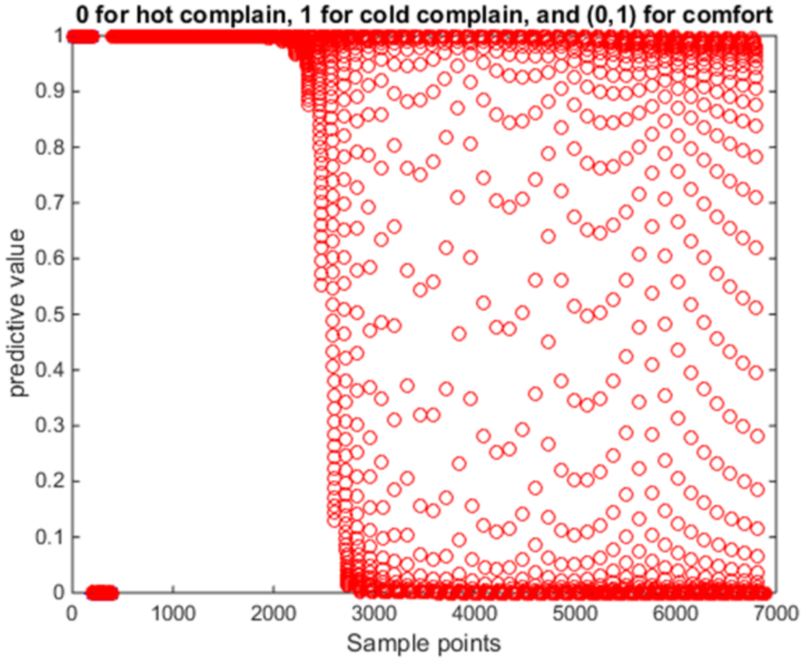

Figure 6. Trained BP neural network and predicted results

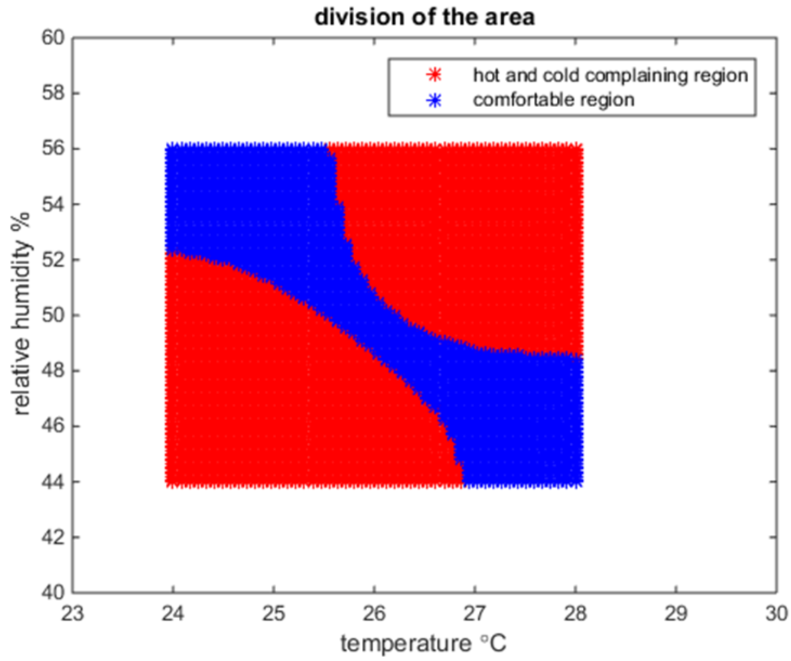

Figure 7. Indoor comfort region

the recorded cold and hot feeling of human body at the same time, it can be concluded that the comfort region predicted by the BP neural network can meet people comfort requirements in the experimental environment.

From the above results it is not difficult to see, the comfort model used in this paper can determine the relationship between indoor environment temperature, humidity and human comfort feeling in real time, effectively and dynamically, which avoids the traditional PMV index of parameters, static, nonlinear and need complex iterations that can be obtained, and cannot be dynamic measurement and prediction of human comfort and other shortcomings. The establishment of thermal comfort zone can effectively meet the comfort of the human body feeling, more precisely predict and control the comfort of the human body.

False negative rate (FNR) can be a good comparison of the performance of machine learning algorithms [26]. Compared with other classification algorithms, such as the traditional linear classifier SVM (Support Vector Machine), some samples from experiment were extracted by FNR comparison. Experiments a, b, c, d were selected from the database of four times of indoor comfort experiments. Equal number of hot and cold complaints points were randomly extracted, the number of them is 100, and SVM and BP neural network were used to FNR comparison. The FNR comparison is as Table 2.

Table 2. False negative rate for SVM model and BP neural network model

experiment	SVM model	BP neural network model
a	0.52	0.06
b	0.36	0.07
c	0.45	0.09
d	0.32	0.05

It can be seen from Table 2, the BP neural network has low FNR. It can be found that the BP neural network applied in the indoor environment model based on complaint has the low possibility of complaint point misjudgment, so that it can accurately identify and predict the indoor environment of people complained about discomfort, so as to control the environmental factors to meet human comfort.

5. **Conclusions.** Due to the traditional method based on node model that has unreasonable nodes setting and limitation of personal comfort predictions, and PMV index of multi-parameter and nonlinear required complex iterations to obtain, which is a static indicator that cannot be dynamic measurement and prediction of human comfort and other shortcomings, this paper proposes a method that only needs to measure the two parameters of indoor temperature and relative humidity, records the current complaints about the temperature and humidity as a hot and cold complaints point through people complaining about hot and cold feeling, and uses BP neural network to train the hot and cold complaining points to determine the uncomfortable region and comfortable region. Finally, the simulation results of MATLAB show that the method proposed in this paper can determine the relationship between the indoor environment temperature, relative humidity and human comfort feeling in real time, effectively and dynamically.

Although the results of the paper are due to the limited experiment, it is still a promising method to implement intelligent indoor environment. Much more work is going to be done such as the intensive experiment investigation, and comparison with the classic control. The model and learning algorithm also have many possible extensions such as extension to other larger environment and other algorithm can make the comfort prediction more accurately.

Acknowledgment. This research is supported by the National Natural Science Foundation of China (No. 61263019), Program for International S&T Cooperation Projects of Gansu Province (No. 144WCGA166) and the Doctoral Foundation of LUT.

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