Pengpeng Cheng[1,2*],
Jianping Wang[1],
Xianyi Zeng[2],
Pascal Bruniaux[2],
Daoling Chen[3]

Intelligent Prediction Model of the Thermal and Moisture Comfort of the Skin-Tight Garment

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[1] **Donghua University, College of Fashion and Design,** Shanghai, China,
* e-mail: cppcdl3344@163.com

[2] **Gemtex, Ensait, Centrale Lille,** F-59000 Roubaix, France

[3] **Minjiang University, Clothing and Design Faculty,** Fuzhou, China

Abstract
In order to improve the efficiency and accuracy of predicting the thermal and moisture comfort of skin-tight clothing (also called skin-tight underwear), principal component analysis(PCA) is used to reduce the dimensions of related variables and eliminate the multicollinearity relationship among variables. Then, the optimized variables are used as the input parameters of the coupled intelligent model of the genetic algorithm (GA) and back propagation (BP) neural network, and the thermal and moisture comfort of different tights (tight tops and tight trousers) under different sports conditions is analysed. At the same time, in order to verify the superiority of the genetic algorithm and BP neural network intelligent model, the prediction results of GA-BP, PCA-BP and BP are compared with this model. The results show that principal component analysis (PCA) improves the accuracy and adaptability of the GA-BP neural network in predicting thermal and humidity comfort. The forecasting effect of the PCA-GA-BP neural network is obviously better than that of the GA-BP, PCA-BP, BP model, which can accurately predict the thermal and moisture comfort of tight-fitting sportswear. The model has better forecasting accuracy and a simpler structure.

Key words: *sportswear tights, thermal and moisture comfort, principal component analysis, intelligent prediction model.*

Introduction

The evaluation of thermal and moisture comfort has always been a hot spot in the study of clothing comfort, which is a result of the harmonious interaction between physiological and psychological factors of the human body and garments under different motions. The factors affecting thermal and moisture comfort are complex, which not only cover fabric properties but also involve human body characteristics, movement state and clothing size, even style, colour, seam technology and other factors. Therefore, the thermal and moisture comfort of clothing is the result of the interaction and comprehensive influence of the above factors. However, at present, most of the researches on clothing comfort focus on single or multiple factors. such as fabric or fiber properties, to analyse thermal and moisture comfort [1-3], and few researchers comprehensively and systematically analyse and study the effects on thermal and moisture comfort. Such studies can easily cause information loss, and cannot effectively or truly describe subjective comfort and its influencing factors; and the repeatability of experiments is also low. In addition, there are complicated relationships among these parameters, which are difficult to be handled well by common neural network models or linear theoretical models.

As sportswear favoured by sports enthusiasts, tight-fitting sportswear can be worn as underwear (also called tight-fitting underwear), and can also be used as outdoor sportswear, such as tight-fitting running sportswear. However, there is little research on the thermal and moisture comfort of tight-fitting sportswear. Scholars at home and abroad mainly study the many functions of tight-fitting sportswear, such as protection [4-6], drag reduction [7-9] and improving sports performance [10-12].

Due to the different occasions of wearing clothing, the functional requirements of clothing vary widely, but for thermal and moisture comfort, it must be considered for any kind of garment. As clothing that closely adheres to human skin, the thermal and moisture comfort of tight-fitting sportswear is also a key performance indicator that cannot be ignored. In this paper, evaluation of the thermal and moisture comfort of tight-fitting sportswear was assessed by human sensory perception, where the process of analysing comfort information is extremely complicated, which is related to whether the clothing and human body meet a series of requirements. How to integrate multi-domain knowledge to build a spatial form model representing comfort is a problem to be solved.

In order to analyse the thermal and moisture comfort of tights, 10 subjects were selected in this paper. According to the average size of the subjects, 5 tight tops and 5 tight trousers were purchased, all of which can be worn as underwear. Among them, three sets had the same pattern but different fabrics, while the other two sets had different patterns but the same fabric, and the colors were mainly black, dark blue and grey. Through wearing experiments, the influencing factors of thermal and moisture comfort were analyzed comprehensively and systematically from multiple dimensions, which provides reference for the design of tights.

To improve the efficiency of research on the thermal and moisture comfort of sportswear tights, this paper proposes to establish a prediction model. However, because there are too many factors affecting thermal and moisture comfort and the relationship between some parameters is complicated, it is difficult for a general mathematical model to deal with the relationship, and it is easy to fall into a local optimum, which ultimately leads to unsatisfactory prediction results of the comfort model. In view of this, this paper proposes a new prediction model: a principal component analysis-genetic algorithm-BP neural network. By designing a new experimental scheme, principal component analysis (PCA) is used to reduce the dimension of feature parameters, remove irrelevant indexes and related indexes, and avoid the redundancy of input indexes, thus reducing the calculation workload of the GA-BP model and simplifying the network structure. At the same time, the simplified data still retain most of the information of the original

Table 1. *Subjects' body parameters.*

No.	Age	Bust girth, cm	Waist girth, cm	Height, cm	Shoulder girth, cm	Thigh girth, cm	Arm girth, cm	Upper hip girth, cm	Lower hip girth, cm	BMI
M1	26	95.9	80.9	176.8	41.9	55.5	33.1	91.3	97.6	21.1
M2	28	100.1	88.8	178.2	42.9	57.1	32.8	95.0	100.5	22.7
M3	28	99.7	88.4	176.5	42.6	56.8	33.3	94.4	99.9	21.2
M4	26	96.5	84.7	177.0	42.1	55.7	32.9	91.8	98.0	21.7
M5	27	98.3	86.7	176.7	42.4	56.3	33.0	93.2	99.0	22.4
M6	25	97.8	86.2	175.3	42.1	56.1	32.8	92.6	98.4	20.8
M7	26	99.6	88.2	177.6	42.7	56.9	33.1	94.5	100.1	22.8
M8	27	98.7	87.2	176.4	42.4	56.5	32.9	93.5	99.2	22.2
M9	25	97.3	85.6	176.1	42.1	55.9	33.0	92.3	98.3	21.6
M10	25	103.1	89.2	178.8	43.2	57.9	33.4	96.8	101.5	23.5
BMI = Weight, kg ÷ Height, m^2										

Table 2. *Size of tights.*

No.	Bust girth, cm	Waist girth, cm	Shoulder girth, cm	Thigh girth, cm	Arm girth, cm	Upper hip girth, cm	Lower hip girth, cm	Sleeve length, cm	Trousers length, cm
T1	90	*	33	*	26	*	*	55	*
T2	91	*	36	*	28	*	*	56.5	*
T3	91	*	36	*	28	*	*	56.5	*
T4	89	*	31	*	25	*	*	55	*
T5	88	*	31	*	25	*	*	55	*
P1	*	67	*	48	*	76	82	*	92
P2	*	62	*	46	*	75	80	*	90
P3	*	67	*	48	*	76	82	*	92
P4	*	66	*	47	*	78	84	*	90
P5	*	64	*	46	*	75	81	*	90

data. The genetic algorithm (GA) has strong global search ability [13-17], and the BP neural network has strong nonlinear fuzzy approximation ability [18-21]. The GA algorithm combined with the BP neural network can better deal with the intricate relationship between indexes, obtain reliable and credible prediction results, and finally establish an objective quantitative model for thermal and moisture comfort evaluation.

Experiment

Subjects

10 healthy young men of similar age, size and hobbies were selected. They had long-term running experience, were all graduate students majoring in clothing, and had sufficient knowledge of ergonomics. For the convenience of research, the subjects are numbered as M1, M2,... M10. See ***Table 1*** for the body shape parameters.

According to the "2020 China Runner Sports Big Data Report" jointly released by ANTA and GUDONG, runners aged 22-30 account for 30% of the total runners. Besides running, runners also like sports such as gym activities and walking. Most people aged 22-30 have strong sports vitality and are energetic. According to the research report of the Forward Industry Research Institute, this age group is also the main one to buy tight-fitting sportswear, which may be related to their monthly income, because this age group works, being at a medium level and having strong purchasing power. Therefore, male youths aged from 25 to 28 years old were selected as experimental subjects.

Experimental clothing

According to the average body shape of the 10 subjects, 5 tight tops (T1,T2,...,T5) and 5 tight trousers (P1,P2,...,P5) were purchased (see ***Table 2*** for the size of tights). In order to analyse the influence of the pattern, fabric composition and colour on thermal and moisture comfort, 2 sets of them with the same pattern but of different fabrics, and 3 sets with different patterns but of same fabric were selected. 25 sets of experimental tights were formed by the free combination of tops and trousers, which were named T1P1, T2P2, T3P3, T1P2, T2P3, T3P1, T1P3, T2P1, T3P2, ..., . During the whole experiment, the 10 subjects wore the 25 sets of experimental tights in turn.

Experimental requirements

(1) All the experiments were conducted in an artificial climate room at constant temperature and humidity, environment temperature (25±2)°C, relative humidity (65±5)% and wind speed ≤ 0.1 m/s.
(2) Before participating in the experiment, the subjects maintained a good mood and emotion.
(3) Before the experiment, it was ensured that all experimental tights were restored to their original state and placed in the artificial climate room for 24 h.
(4) Testers randomly selected and tried them on in turn without being told about the fabric of the tights.
(5) Before the experiment, all subjects were given a comprehensive explanation of the questionnaire, so as to ensure that all subjects had the same understanding of the questionnaire content and scale, and eliminate systematic error of the experiment as much as possible.

Experimental content

The whole testing process was divided into 7 test stages, and the total duration of the experiment was 90 minutes (in-

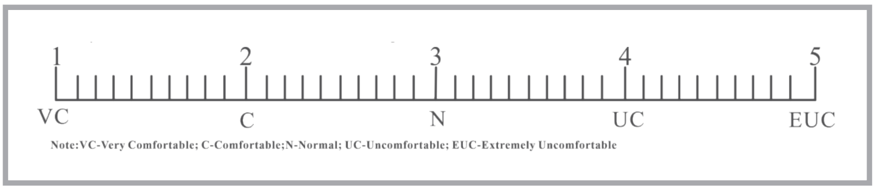

Figure 1. *Overall thermal and moisture comfort evaluation scale.*

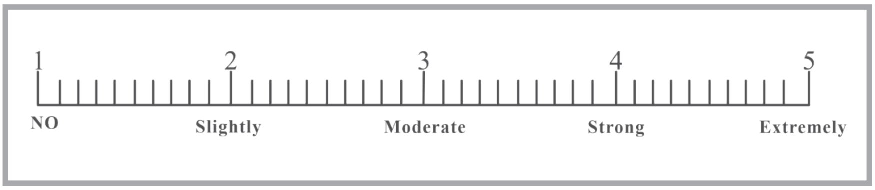

Figure 2. *Thermal and moisture comfort feeling evaluation scale.*

cluding the preparation before the experiment): prepare (20 min, adapt to the test environment) → standing (10 min) → jumping (10 min) → squat (10 min, 1 min as a group, rest 0.5 min individually) → jogging (10 min, average speed: 5.5 km/h) → walking (10 min, average speed: 4.3 km/h) → lifting legs (10 min, left and right legs raised alternately, 1 min as a group, rest 0.5 min individually) → rest (10 min) → experiment end. During the standing process, all the subjects undertook limb movements, such as bending over, lifting their arms horizontally, lifting their arms vertically, and lifting their arms laterally at 45°. At the end of each testing stage, the staff recorded the subjective thermal comfort evaluation values of the partcipant under different motions.

Evaluation scale

Overall thermal and moisture comfort was evaluated subjectively according to ISO 10551-2001 "Ergonomics of Thermal Environment Assessing the Influence of Thermal Environment by Subjective Judgment Scale", which means very comfortable, comfortable, normal, uncomfortable and extremely uncomfortable, shown in ***Figure 1***.

Sensory comforts such as thermal sensation, moisture sensation and cold sensation all adopt the five-level scale of semantic difference, that is, no feeling, slight feeling, moderate feeling, strong feeling and extremely strong feeling. The evaluation scale is shown in ***Figure 2***.

And then, according to the comfort evaluation scale, the thermal-moisture comfort under different motions conditions was evaluated where the thermal-moisture comfort evaluation of each set of tight-fitting sportswear is the average value of the thermal-moisture comfort evaluation of that set of tight-fitting sportswear by the 10 subjects.

Data acquisition of fabric parameters

For data collection for the performance of the tights fabric, the main testing instruments were as follows: a fabric density mirror, an air permeabilimeter (EMI-Developpement), KES-FB system, an LCK-800 textile capillary effect tester, a Thermo Labo II (Kato Tech Co., Ltd.), a sweat hot plate tester (Northwest Testing Technology Company of the United States), a digital fabric thickness meter (Sodemal Co., Ltd.), and an EY60 MMT automatic liquid water management tester (Standard International Group (HK) Limited), related data of which are shown in ***Table 3***.

Pretreatment of experimental data

Encode and transform non-numeric data

In this study, there are some non-numerical variables, such as fiber content, colour, tissue structure, and seam process, and we often dealt with numerical variables in many studies. All the non-numerical variables involved in this paper can be regarded as disordered characteristic variables. For these kinds of non-numerical variables, most researches often give 1, 2, 3, 4, etc. From a numerical point of view, after assigning values such as 1, 2, 3, 4, etc., they have a certain order relationship from small to large. In fact, these variables do not have so much of a size relationship and should be equal and independent of each other. Therefore, it is not reasonable to assign values according to values such as 1, 2, 3 and 4. In order to solve the problems above, this paper adopted One-Hot Encoding to encode these kinds of non-numerical features.

The coding process of One-Hot is to design the corresponding coding vector length according to the value space of features, which also plays a role in expanding features to a certain extent. Its values are only 0 and 1, and different types are stored in different spaces [22-25].

One-Hot coding realises the mapping from feature to coding space. If the value space of a feature is V, the coding result of the i-th element v_i in the order-preserving feature space is $r = (r_1, \ldots, r_{|V|})$, $r_j = 1_{j=i}$, $j = 1, 2, \ldots, |V|$. At any time, there is the only significant part of the result of One-Hot coding, whose value is 1, and the rest are all 0.

Normalisation of transformed non-numerical data and numerical data

Because the input parameter values and output parameter values of the model are different in magnitude and dimension, there will be great differences between the data, hence they should be standardised before establishing the model. In this paper, ***Equation (1)*** is directly adopted to normalise or standardise the input parameters and output parameters of the prediction model.

$$x_{ij}^{*} = \frac{2\times(x_{ij} - x_{i\min})}{x_{i\max} - x_{i\min}} - 1 \qquad (1)$$

Where, x_{ij} is the value before normalisation of the j-th column of the i-th row sample, x_{ij}^{*} the normalised value of the jth column of the i-th row sample, and $x_{i\max}$ and $x_{i\min}$ are the maximum and minimum values before normalisation, respectively.

Intelligent model

On the basis of the BP neural network, the genetic algorithm (GA) is used to optimise the weights and thresholds of the BP neural network and improve the accuracy of the BP neural network. The initial input parameters of the GA-BP neural network model are given in ***Tables 1, 2*** and ***3***, with a total of 38 parameters, which are the fiber content, colour, fabric structure, seam process, thickness, grammage, longitudinal fabric density, horizontal fabric density, moisture regain, air permeability, moisture permeability, wet resistance, heat resistance, heat preservation rate, heat transfer coefficient, porosity, wicking height, evaporation rate, liquid water diffusion rate, maximum wetting radius, tights size (bust girth, waist girth, shoulder girth, thigh girth, arm girth, upper hip girth, lower hip girth, sleeve length, trouser length), and human body size (bust girth, waist girth, height girth, shoulder girth, thigh girth, arm girth, upper hip girth, lower hip girth, BMI), while the output parameters are the evaluation values of thermal and moisture comfort under different motions. However, there are too many input parameters and there may be a complex correlation, which may lead to network redundancy. Multi-collinearity between input variables will lead to strange changes in network parameters, reducing the general performance of the network. Therefore, PCA is used to reduce the dimension of parameters as well as eliminate some irrelevant factors and multicollinearity among the variables to improve the accuracy of the GA-BP model.

Dimension reduction of input parameters

The purpose of dimension reduction mainly includes: reducing the number of predicted variables; making these variables independent of each other; thereby removing noise. Through principal component analysis, some representative input parameters are selected. The specific process is as follows:

(1) 38 input parameters (all parameters are normalised data according to ***Equation (1)***) are grouped into a matrix by columns: $J = (j_1, j_2, ..., j_P)$ $(p = 38)$,

(2) Then all indexes are linearly transformed to form a new comprehensive variable, which is expressed by Y, that is, the new comprehensive variable can be linearly expressed by the original variable as follows,

$$\begin{cases} Y_1 = \mu_{11} j_1 + \mu_{12} j_2 + \cdots + \mu_{1p} j_p \\ Y_2 = \mu_{21} j_1 + \mu_{22} j_2 + \cdots + \mu_{2p} j_p \\ \vdots \\ Y_q = \mu_{q1} j_1 + \mu_{q2} j_2 + \cdots + \mu_{qp} j_p \end{cases} \quad (2)$$

Where, to meet $\mu_i' \mu_i = 1$, Y_i and Y_j are independent of each other. Then Y_1, Y_2, ..., Y_q are the first, second, ..., q-th principal components of the original variables, $2 \le q \le 38$.

Through ***Equation (2)*** to determine the principal components affecting thermal and moisture comfort, and finally extracting the characteristic index of each

Table 3. *Data of fabric parameters.*

No.	Fiber content	Colour	Fabric structure	Seam process	Thickness, mm	Grammage, g·m^{-2}	Longitudinal fabric density, coil number·(5 cm)$^{-1}$	Horizontal fabric density, coil number·(5 cm)$^{-1}$	Moisture regain, %	Air permeability, L·m^{-2}·s^{-1}	Moisture permeability, g/(m^2·h)	Wet resistance, Pa·m^2·W^{-1}	Heat resistance, °C·m^2·W^{-1}	Heat preservation rate, %	Heat transfer coefficient, W·m^{-2}·K^{-1}	Porosity, %	Wicking height, cm/30 min	Evaporation rate, g·h^{-1}	Liquid water diffusion rate, mm·s^{-1}	Maximum wetting radius, mm
T1	91%Polyester, 9%Spandex	Gray	Jersey stitch	Sewing	0.94	153.3	136.5	88.5	0.39	189.2	173.76	3.963	0.316	28.756	23.98	75.36	1.52	0.12	2.9	19.4
T2	75%Polyester, 25%Polyamide fibre or nylon	Dark blue	Warp plain stitch	Sewing	0.60	181.1	99.0	103.5	1.32	981.8	261.64	3.395	0.243	20.879	28.51	80.15	0.26	0.05	5.1	16.0
T3	70%Polyester, 26%Nylon, 4%Spandex	Gray	Jersey stitch	Bonding	0.66	230.8	178.0	93.5	1.78	638.6	289.52	2.792	0.212	18.558	30.26	79.61	0.28	0.02	4.8	16.6
T4	91%Polyester, 9%Spandex	Black	Jersey stitch	Sewing	0.91	215.5	153.5	111.5	0.47	364.2	221.16	2.819	0.304	27.325	19.73	71.23	0.35	0.10	4.9	19.1
T5	91%Polyester, 9%Spandex	Dark blue	Interlock stitch	Bonding	0.88	232.6	125.5	100.5	0.53	412.6	226.47	3.108	0.257	24.088	26.36	83.55	0.30	0.11	3.1	18.8
P1	91%Polyester, 9%Spandex	Black	Warp plain stitch	Sewing	0.99	305.7	180.5	116.0	0.44	218.4	223.83	3.652	0.325	30.104	17.88	78.12	1.19	0.14	3.8	19.9
P2	72%Polyester, 28%Spandex	Black	Warp plain stitch	Bonding	1.14	334.2	143.5	96.0	0.61	279.4	252.25	3.306	0.236	23.235	29.67	85.31	0.25	0.06	4.3	21.1
P3	87%Polyester, 13%Spandex	Gray	Interlock stitch	Sewing	0.98	237.5	129.5	110.0	0.58	177.6	247.82	2.178	0.207	20.269	30.19	77.64	0.32	0.09	4.0	19.8
P4	91%Polyester, 9%Spandex	Dark blue	Jersey stitch	Bonding	0.47	312.5	165.5	123.5	0.45	83.2	215.86	3.521	0.213	23.616	27.81	81.57	0.29	0.07	3.4	14.7
P5	91%Polyester, 9%Spandex	Gray	Jersey stitch	Bonding	0.61	264.7	109.0	88.5	2.31	616.6	258.64	3.357	0.086	15.364	53.611	78.51	3.73	0.13	1.3	16.1

Table 4. *Evaluation value of thermal and moisture comfort.*

Tights	Posture	Thermal sensation	Moisture sensation	Cold sensation	Cool sensation	Sticky body sensation	Overall thermal and moisture comfort
T1P1	standing	1.0	1.0	4.3	3.5	1.0	1.2
	jumping	1.3	1.2	4.0	3.3	1.1	2.2
	squat	2.1	1.7	3.7	3.3	2.2	2.4
	jogging	3.6	4.2	2.2	2.1	4.0	2.7
	walking	4.2	3.9	2.5	2.3	3.8	3.1
	lifting legs	4.5	3.6	3.5	1.3	3.3	2.8
	rest	3.9	4.1	4.0	1.3	3.2	2.8
T3P5	standing	1.0	1.1	4.2	3.2	1.0	1.1
	jumping	1.3	1.2	4.0	3.2	1.2	1.8
	squat	2.4	1.8	3.6	3.1	2.3	2.5
	jogging	4.0	4.2	2.1	2.7	4.0	3.3
	walking	4.3	4.4	2.5	2.3	4.1	3.3
	lifting legs	4.3	3.8	3.3	1.5	3.9	3.0
	rest	4.3	4.1	4.1	1.3	3.9	3.8
T2P2	standing	1.1	1.0	4.1	3.5	1.1	1.1
	jumping	1.3	1.3	4.1	3.5	1.1	2.1
	squat	2.5	1.6	3.8	3.4	2.5	2.6
	jogging	4.2	4.5	2.3	2.5	4.3	3.8
	walking	4.4	4.3	2.4	2.4	4.2	3.5
	lifting legs	4.4	3.9	3.6	1.6	4.0	3.6
	rest	4.5	4.4	4.3	1.5	4.1	4.1

type of factor using formula ***Equation (3)*** and professional knowledge, the calculation formula of the characteristic index is as follows:

$$\bar{\mathrm{E}}_{\mathrm{h}}^{2} = \left[\sum c^{2}\right] \times N_{h} \tag{3}$$

Where, $\bar{\mathrm{E}}_{\mathrm{h}}^{2}$ is the characteristic value of input parameter h, c the correlation coefficient between the input parameter and other input parameters, and $\mathrm{N_h}$ is the index number of input parameters. If the $\bar{\mathrm{E}}_{\mathrm{h}}^{2}$ value is larger, it indicates that the parameter is representative in this category and can reflect the information of this classification; hence, this parameter can be used as the characteristic index of this classification.

Through the calculation of ***Equation (3)***, the characteristic indexes affecting the thermal and moisture comfort parameters finally obtained are as follows.

Fibre content ($\bar{\mathrm{E}}_{j}^{2}$= 0.772), fabric structure ($\bar{\mathrm{E}}_{j}^{2}$= 0.8160, seam process ($\bar{\mathrm{E}}_{j}^{2}$= 0.735), porosity ($\bar{\mathrm{E}}_{j}^{2}$ = 0.851), horizontal fabric density ($\bar{\mathrm{E}}_{j}^{2}$ = 0.753), evaporation rate ($\bar{\mathrm{E}}_{j}^{2}$ = 0.808), heat transfer coefficient ($\bar{\mathrm{E}}_{j}^{2}$= 0.766), moisture regain ($\bar{\mathrm{E}}_{j}^{2}$= 0.803), maximum wetting radius ($\bar{\mathrm{E}}_{j}^{2}$= 0.659), air permeability ($\bar{\mathrm{E}}_{j}^{2}$ = 0.729), bust girth of tights ($\bar{\mathrm{E}}_{j}^{2}$ = 0.845), thigh girth of tights ($\bar{\mathrm{E}}_{j}^{2}$= 0.682), BMI ($\bar{\mathrm{E}}_{j}^{2}$= 0.798), arm girth of human body ($\bar{\mathrm{E}}_{j}^{2}$= 0.811), bust girth of human body ($\bar{\mathrm{E}}_{j}^{2}$ = 0.638), hip girth of human body ($\bar{\mathrm{E}}_{j}^{2}$ = 0.7600.

Therefore, after principal component analysis and 16 input parameters having been preliminarily obtained, mainly the fiber content, fabric structure, seam process, porosity, horizontal fabric density, evaporation rate, heat transfer coefficient, moisture regain, air permeability, maximum wetting radius, bust girth of tights, thigh girth of tights, BMI, arm girth of human body, bust girth of human body, and hip girth of human body, it can be preliminarily judged from the non-numeric parameters that the fiber content, fabric structure, and seam process have a certain impact on the thermal and moisture comfort of tight-fitting sportswear, while pattern and colour have little effect.

Among them, different from other types of clothing, such as loose clothing, pattern design has little influence on the thermal and moisture comfort. The main reason may be that tight-fitting sportswear, as body-fitting clothing, has no obvious influence on the thermal and moisture comfort, or it may be because there are fewer patterns of experiment clothing used in this study, and the influence of patterns needs to be verified by more patterns. To determine the final input parameters of the prediction model, it is necessary to further optimise the parameters selected by principal component analysis through the GA-BP model.

GA-BP neural network model design

(1) The hidden layer $l = \sqrt{m+n+a}$, where m is the number of input layer variables (i.e. the number of input layer nodes or neurons), n the number of output layer variables (i.e. the number of output layer nodes or neurons), and a is a constant between 1 and 10. In addition, the maximum number of times of this training is 1000; the learning rate is 0.1, and the minimum learning error is 0.0001. The additional momentum factor is net.trainParam.mc = 0.95, the minimum performance gradient net.trainParam.min_grad = 1e-6. Genetic algorithm parameter evolution algebra is iteration times maxgen = 100, the population size sizepop = 50, the cross probability pcross = 0.4, and the mutation probability pmutation = 0.05.

(2) Transfer function: the transfer function from the input layer to the hidden layer and the transfer function from the hidden layer to the output layer all use the log-sigmoid function.

$$\log sig(x) = \frac{1}{1+e^{-x}} \tag{4}$$

The sigmoid function is suitable for the neural network model of forward propagation, which can compress data and ensure that there is no problem with data amplitude. The sigmoid function is smooth and differentiable. In addition, the transfer function of the BP network must be differentiable, hence the transfer function of perceptron, such as hardlim/hardlims function, is not applicable. The differentiability of the sigmoid function makes it possible to use the gradient descent method. In the output layer, if the sigmoid function is used, the output value will be limited to a small range. Therefore, the typical design of a BP neural network is that the sigmoid function is used as the transfer function in the hidden layer, while a linear function is used as the transfer function in the output layer.

(3) Determination of the fitness function. The fitness function F(r) optimised by the GA algorithm for the BP neural network is determined by the learning error of sample (i.e., tight-fitting sportswear) data on population training, whose expression is as follows,

$$F(r) = \sum_{\mathrm{n}} \sum_{m} \left(e_m - a_m\right)^2 \tag{5}$$

Where, r represents the number of chromosomes, m the number of network output nodes, n the number of training samples; and e_m & a_m ,respectively, represent the expected and actual values of thermal-moisture comfort perception of the m-th tights.

The purpose of BP neural network training in this paper is to ensure that the sum of error squares between the expected value and the actual value is the smallest; thus, the fitness function f(r) of the GA algorithm should be expressed by the reciprocal of the sum of error squares, expressed by:

$$f(r) = \frac{1}{F(r)} \tag{6}$$

Results and discussion

Analysis of thermal and moisture comfort data of each part and whole body

In this paper, T1P1, T3P5 and T2P2 are taken as examples, and the thermal and moisture comfort values of these three sets of tight-fitting sportswear are the test samples of the intelligent prediction model, while the rest are training samples, shown in ***Table 4***.

It can be seen from ***Table 4*** that in a static state of the human body, the sense of coldness and coolness is obvious, because in a static state the energy generated by the human body's metabolism alone is far from enough to maintain human body temperature. However, there is no obvious difference in other senses, and hence the thermal and moisture comfort of tight-fitting sportswear should be analysed in an exercise state. The results obtained can better reflect the thermal and moisture comfort of wearing, and thus the research is more convincing. When running, the humidity and sticky feeling are stronger. When running stops, the evaluation of the humidity and sticky feeling of T1P1 and T2P2 is ceased, while that of the humidity and sticky feeling of T3P5 is increased, which indicates that a higher polyester content is beneficial with respect to humidity and a sticky feeling. This is mainly because polyester has better moisture conductivity, and fabric with a higher polyester content can quickly transfer sweat adsorbed on the skin to the outer surface of the fabric, resulting in the subject being wet. Under sports conditions, the overall thermal and moisture comfort of T1P1 is

Table 5. *Prediction value of thermal and humidity comfort.*

Tights	Posture	Thermal sensation				Moisture sensation				Cold sensation				Cool sensation				Sticky body sensation				Overall thermal and moisture comfort			
		PCA-GA-BP	GA-BP	PCA-BP	BP	PCA-GA-BP	GA-BP	PCA-BP	BP	PCA-GA-BP	GA-BP	PCA-BP	BP	PCA-GA-BP	GA-BP	PCA-BP	BP	PCA-GA-BP	GA-BP	PCA-BP	BP	PCA-GA-BP	GA-BP	PCA-BP	BP
T1P1	standing	0.9573	0.9638	1.1624	1.2259	1.1052	1.1734	1.0386	1.4192	4.2262	4.1383	4.3434	4.6492	3.4310	3.3842	3.2026	3.1219	1.0182	1.0359	1.3272	1.4567	1.1521	1.4583	1.5219	1.3168
	jumping	1.2682	1.3514	1.4273	1.7131	1.2231	1.1105	1.0348	1.2053	3.9967	4.0456	4.1137	4.2752	3.3886	3.3483	3.7834	3.1915	1.0582	1.3872	1.2476	1.4307	2.2101	2.3656	2.1128	2.3511
	squat	2.1396	2.1472	2.0482	2.0354	1.8152	2.2353	2.0559	2.3374	3.6812	3.3355	3.5530	3.7529	3.2898	3.4007	3.4425	2.8357	2.1013	2.4131	2.5032	2.4836	2.4012	2.3839	2.1139	2.5766
	jogging	3.5925	3.3733	3.5150	3.4737	4.2908	3.8296	3.2056	3.0917	2.2003	2.1381	2.1176	2.9593	2.2140	2.4465	2.3823	2.5747	4.0226	4.1408	4.4562	4.5144	2.7003	2.1058	2.1062	2.7444
	walking	4.2046	4.3262	4.4900	4.5178	4.0193	4.2846	4.1602	4.3177	2.4155	2.9564	3.0585	2.1306	2.2918	2.4796	2.4094	2.1962	3.7455	3.9812	3.4177	3.6448	3.2156	3.3744	3.4020	2.7623
	lifting legs	4.4625	4.4025	4.7745	4.1631	3.4962	3.6695	3.8729	3.2376	3.3083	3.8299	4.1534	3.2362	1.2131	1.3384	1.4522	1.8116	3.2731	3.0646	3.3541	3.4235	2.8709	2.9615	2.8179	3.1264
	rest	3.7926	3.3905	3.5883	3.8364	3.9506	3.6466	3.7716	3.0292	4.1426	3.9375	3.7276	3.3987	1.1231	1.2398	1.3752	1.7659	3.1754	3.2882	3.5418	3.1573	2.7144	2.9972	3.0198	2.6351
T3P5	standing	1.1231	1.2554	1.2468	1.1054	1.1231	1.0042	1.3863	1.061	4.3116	3.9854	3.5269	4.7962	3.1257	3.1751	3.4233	3.7361	1.0165	1.1352	1.1714	1.1466	1.0670	1.4353	1.7424	1.2122
	jumping	1.2142	1.3230	1.6037	1.6918	1.1214	1.5602	1.2316	1.0289	4.1312	3.9551	3.9285	4.4576	3.3145	3.5233	3.3584	3.4028	1.1719	1.2878	1.1581	1.1749	1.7518	1.5755	1.2479	1.0955
	squat	2.4273	2.3278	2.4429	2.2746	1.9133	2.1991	2.1507	2.1871	3.5694	3.8828	4.0408	4.2699	3.0429	3.2117	3.5123	3.3857	2.2551	2.6065	2.3857	2.4028	2.6506	2.0923	2.2952	2.3256
	jogging	4.0532	3.9522	3.4361	3.4634	4.0755	4.2065	3.9276	3.7126	2.1679	2.3659	2.4656	2.4918	2.6837	2.6681	2.3681	2.9709	4.1786	4.0527	4.3735	3.6376	3.1286	2.9006	3.6918	3.2317
	walking	4.5059	4.0351	4.2527	4.3542	4.2128	4.0971	3.9843	4.0594	2.6052	2.8147	2.2482	2.5018	2.4944	2.1038	2.3026	2.5211	4.2303	4.0252	3.9907	3.7906	3.3313	3.1469	3.2450	3.5906
	lifting legs	4.4134	3.7136	4.4895	4.1472	3.9079	4.4898	4.1692	4.0311	3.1803	3.7798	3.6959	3.7741	1.5965	1.1249	1.2015	1.0983	4.1756	3.7985	3.5050	3.7533	3.0159	2.7124	3.3661	3.2856
	rest	4.4421	3.6304	4.5203	4.2728	4.1242	4.1562	4.5206	4.0864	3.9769	4.0995	4.3917	4.4319	1.3469	1.2433	1.4840	1.7149	4.0049	3.7335	3.8269	3.1783	3.8567	3.2066	3.9554	3.1191
T2P2	standing	1.1725	1.3688	1.4882	1.0187	1.1245	1.0324	1.0107	1.4619	3.9368	4.1390	4.2851	3.9103	3.3346	3.9564	3.0638	3.1749	1.0260	1.3857	1.0176	1.8793	1.2773	1.3688	1.5754	1.2188
	jumping	1.2179	1.0812	1.7693	1.6395	1.1332	1.0359	1.5183	1.8763	4.0589	4.3517	4.4224	4.5834	3.4615	3.1814	3.9291	2.9917	1.2094	1.4028	1.6957	1.4781	2.0440	2.3426	2.5919	2.4473
	squat	2.3778	2.1428	2.1932	2.0519	1.6313	1.6053	1.0162	1.1407	3.7657	4.0493	3.1817	3.6028	3.6132	3.2497	3.0246	2.9874	2.5773	2.3667	2.4408	2.6230	2.6325	2.4809	2.9867	2.5547
	jogging	4.1158	3.8136	4.5404	4.7314	4.4748	4.6687	4.4357	4.5721	2.4273	2.2776	2.9212	2.1312	2.3515	2.2744	2.1486	2.0192	4.4872	4.3952	4.4028	4.3667	3.9068	3.5558	3.4575	3.6547
	walking	4.6052	4.0689	3.9829	3.8011	4.4292	4.2944	4.0261	4.924	2.5059	2.1715	2.5737	2.0227	2.2568	2.4156	2.5023	2.1714	4.1549	4.2858	4.3857	4.3951	3.4634	3.3332	3.2778	3.8047
	lifting legs	4.3197	4.5335	4.9202	4.2309	4.0784	4.1638	4.0104	3.8652	3.8765	3.2409	3.1658	3.1402	1.8185	1.3012	1.4836	1.5144	4.1123	4.0902	4.3753	4.8092	3.5082	3.5375	3.2593	3.1531
	rest	4.4134	4.8839	4.9787	4.1269	4.375	4.1131	4.9315	4.2325	4.1908	4.0717	4.7993	4.5256	1.4701	1.5527	1.4177	1.1573	4.0436	4.4385	4.6356	4.9332	4.2913	4.4486	3.7554	3.8676

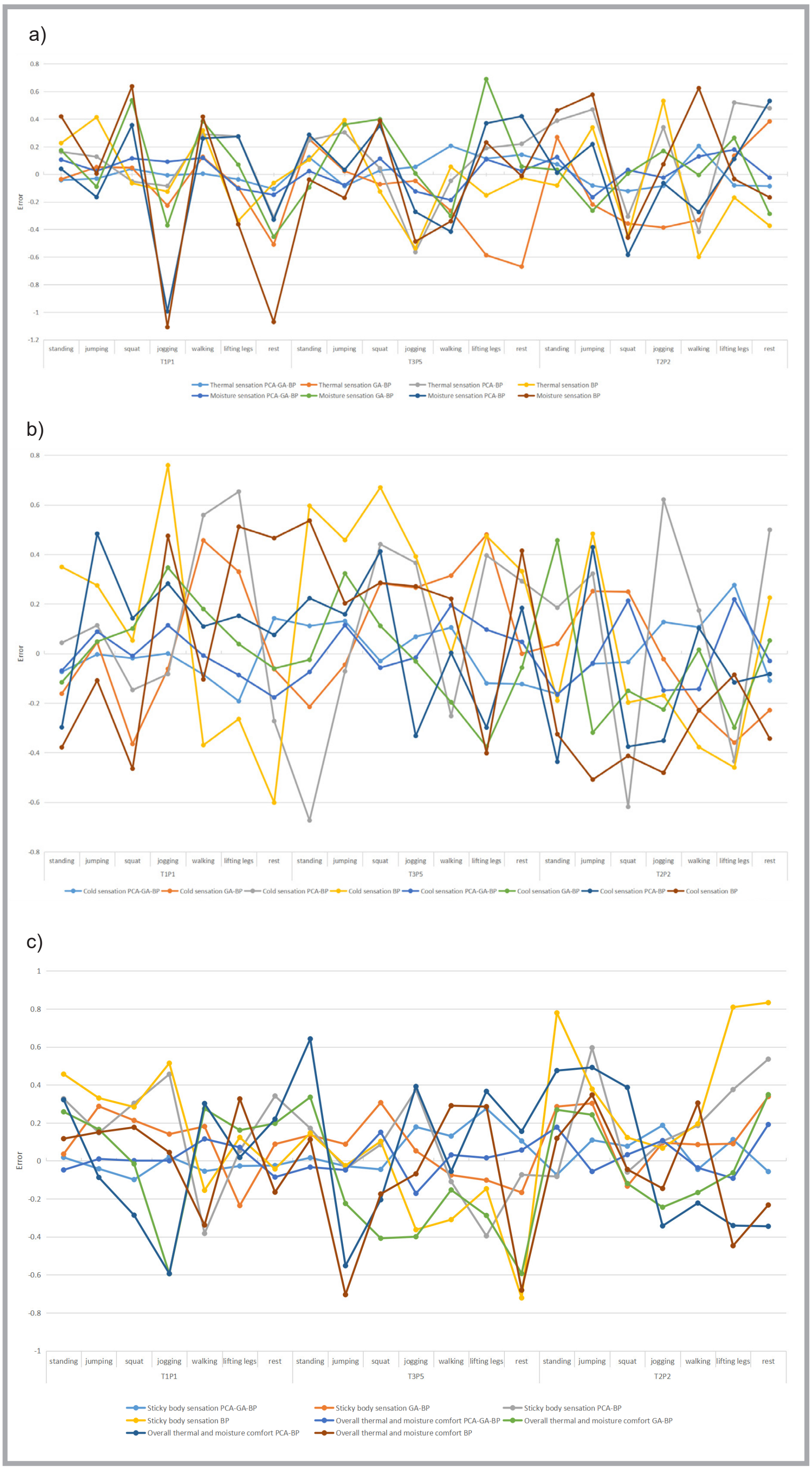

Figure 3. *Prediction errors of various models.*

better than that of T3P5 and T2P2, with T2P2 being the worst, which indicates that the higher the polyester content, the better the overall thermal and moisture comfort. When the subject is at rest, the cold and moisture feeling are strong, because the whole experiment causes the subject to produce a lot of sweat, and the evaporation thereof takes away part of the body heat, with the heat generated by the metabolism not being able to completely supplement the lost heat in time. For thermal sensation, there is little difference among T1P1, T3P5 and T2P2, which shows that the combination of polyester and spandex has no obvious effect on regulating human thermal sensation.

Parameter index optimisation

There are 16 input parameters after dimension reduction, thus the number of input parameter indexes in this paper is set to N(N = 16). When the indexes are optimised and screened by the genetic algorithm, the coding length of this paper is designed to be N, with each bit of chromosome corresponding to an index and the gene value of each bit being "1" or "0" (such as 101101101). If a certain bit of chromosome is "1", on the contrary, it means that the index corresponding to "0" is not used as the one to finally participate in the modeling. N indexes and corresponding thermal and humidity comfort evaluation values are used as the input and output parameters of the BP neural network, respectively.

The genetic algorithm is used to optimise the thermal and moisture comfort index, and it is concluded that the most representative evaluation factor of thermal and moisture comfort is I = [1 0 1 1 0 1 1 0 0 0 0 1 1 0 0 1], that is, the indexes corresponding to these chromosome numbers: the fiber content, seam process, porosity, evaporation rate, heat transfer coefficient, thigh girth of tights, BMI, and hip girth of the human body, being the main indexes that affect the thermal and moisture comfort of tight-fitting sportswear.

It shows that the factors affecting thermal and moisture comfort are not only fabric properties but also clothing size and human body shape characteristics. Therefore, in order to evaluate the wearing comfort of clothing more comprehensively and effectively, it should be analysed from multiple dimensions, otherwise it will often lead to a lack of information, which will eventually lead to wide differences in thermal and moisture comfort analysis, which may also be the main reason why the research cannot be repeated. In addition, when designing tight-fitting sportswear, we should pay more attention to the thigh circumference, BMI and the hip circumference of the human body.

Prediction results and verification

After training the optimized GA-BP model through learning samples, the optimized GA-BP neural network model is verified by T1P1, T3P5 and T2P2 test samples. For verifying the superiority of the PCA-GA-BP model, the prediction results are compared with those of GA-BP, PCA-BP and BP models, respectively, as shown in ***Table 5***, ***Figure 3*** and ***Table 6***.

According to ***Table 5*** and ***Figure 3***, the maximum absolute error of the PCA-GA-BP model is 0.2052, and the absolute error of thermal prediction is almost within 0.15 when wearing T2P2 in a walking state and other sports motion states, which shows that the PCA-GA-BP model has high accuracy of thermal sensation prediction. The absolute error of the PCA-GA-BP model for other perceptions is smaller than that of the other models, and the maximum absolute error is 0.2765. Through comparative analysis, the prediction accuracy of the PCA-GA-BP model is obviously higher than that of the other models. According to the overall analysis, the PCA-GA-BP model has the best effect on thermal and moisture comfort perception and overall thermal and moisture comfort perception, followed by the GA-BP and PCA-BP models, which shows that there is a complex relationship between the parameters affecting thermal and moisture comfort, and that the parameters must be optimised before the prediction model is established.

With respect to the average absolute error (see ***Table 6***), that of the PCA-GA-BP model is less than 0.10, with the average value of absolute error being only 0.0892, while the maximum absolute error of GA-BP model is only 0.2629, with the average absolute error being 0.2148. The prediction effect of the BP neural network is the worst, which shows a strong correlation and nonlinearity between the input parameters without dimension reduction, and the weakness that the BP is easy to fall into a local optimal solution The maximum average absolute error and average absolute error of the PCA-BP and BP models are close to each other, being higher than that of the PCA-GA-BP and GA-BP models, which shows that although PCA has fewer output parameters to a certain extent and achieves the effect of dimension reduction, its effect on the BP neural network is not obvious. Therefore, PCA should be combined with other neural networks to optimize the BP model and achieve higher prediction accuracy. The results show that the PCA-GA-BP model is reliable in predicting the sensory evaluation value of thermal and moisture comfort.

Table 6. *Average absolute error of each model.*

Sensation	PCA-GA-BP	GA-BP	PCA-BP	BP
Thermal sensation	0.0836	0.2426	0.2780	0.2611
Moisture sensation	0.0974	0.2387	0.3026	0.3851
Cold sensation	0.0982	0.2126	0.3436	0.3665
Cool sensation	0.1005	0.1680	0.2403	0.3440
Sticky body sensation	0.0823	0.1637	0.2476	0.3289
Overall thermal and moisture comfort	0.0729	0.2629	0.3238	0.2512
Mean absolute error	0.0892	0.2148	0.2893	0.3228

Through the above analysis, it can be stated that the GA algorithm can deal with the correlation and nonlinear problems among the influencing factors well and that the combination of the GA-BP model has strong robustness and can accurately obtain a global optimal solution, which reduces the possibility of BP falling into a local extremum. At the same time, the PCA-GA-BP model has higher prediction accuracy than the GA-BP model, which shows that PCA has improved the prediction accuracy of the GA-BP model to a certain extent.

Conclusions

There have been many researches on thermal and moisture comfort, but there are some limitations due to various reasons. In this paper, a new experimental scheme was designed and a prediction model of thermal and moisture comfort sensation established. The results show that the performance of a GA-BP neural network based on principal components analysis is better than that of other models in predicting thermal and moisture comfort, and it has higher accuracy and adaptability, which can better satisfy the application of the GA-BP neural network in multi-dimensional and multi-factor thermal comfort sensation evaluation, screening out the factors affecting thermal comfort. It can be seen from the indexes' contents that the factors affecting thermal and moisture comfort are multi-dimensional and diverse, in which fabric properties should not only be considered but also comprehensively and systematically analysed in order to reflect the thermal and moisture comfort effect more truly.

There are many influencing factors of thermal and moisture comfort, and the relationship between them is highly nonlinear and complex. Before establishing the prediction model, the parameter indexes should be preprocessed or optimised, the representative and independent parameters (that is, there is no mutual influence between the parameters) screened out, and the intelligent algorithm or the combination of linear analysis and intelligent algorithm be adopted to deal with them. It is difficult for the general algorithm to deal with such complicated relationships. The PCA-GA-BP model used in this paper can handle this relationship well, and the predicted value of thermal and moisture comfort is close to the real thermal and moisture comfort sensation evaluation, which shows that the model is universal and can be popularised.

The sports motion state has a great influence on thermal and moisture comfort, and the combination of different fabrics has a significant influence on thermal and moisture comfort. Therefore, when designing tight-fitting sportswear, we should pay attention to the matching of different fabrics according to sports type, especially when running, analyse which part has the most obvious comfort state in the running state, and increase the design of that part.

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