Thermal Sensation Modeling and Experiments for Liquid-Cooled Garments

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***Abstract*— Liquid-cooled garment (LCG) is a promising personal thermal management (PTM) technique that satisfies the individual thermal comfort requirement by creating a microclimate around the human body. Thermal sensation, which is defined as "the wearer's sense of temperature between hot and cold," is a helpful target for designing an LCG with good thermal comfort. There are just a few methods to predict the thermal sensation of the LCGs. In addition, the previous prediction methods related to the conventional heating, ventilation, and air conditioning (HVAC) systems cannot be directly applied to the LCG, due to the lack of consideration of some dominating characteristics of the LCG and the human body. To solve this problem, a neural network model was proposed to predict the thermal sensation of wearers of LCGs, taking physiological parameters [heart rate (HR), skin temperatures, and tympanic temperature] and physical parameters [ambient temperature (AT) and relative humidity (RH)] including water inlet temperature of LCGs into consideration. Experiments were carried out to obtain the model training data under various conditions. After optimization, the neural network model performs excellently, which shows the potential to predict the thermal sensation for LCGs. The correlation analysis indicates that water inlet temperature is the most correlated parameter to thermal sensation in LCGs.**

***Index Terms*— Liquid-cooled garments (LCGs), neural networks, personal thermal management (PTM), thermal sensation.**

I. Introduction

THE conventional heating, ventilation, and air conditioning (HVAC) systems contribute to approximately 15% of total U.S. energy consumption [1]. Such large energy consumption is caused by creating a uniform thermal environment for extensive areas, e.g., the whole buildings and rooms. In contrast to HVAC systems, personal thermal management (PTM) is superior and efficient, which could achieve the individual thermal comfort requirement by creating a microclimate around the human body [2]. PTM leads to higher energy efficiency since it only cools or heats a single human body and its microclimate rather than the extensive areas. To achieve PTM, five personal cooling garments have been developed according to the type of cooling sources: air-cooled garment [3], [4], evaporative cooled garment [5], [6], phase-change garment [7], [8], radiative cooled garment [9]–[11], and liquid-cooled garment (LCG) [12]–[14]. Relatively, the LCG is a kind of active cooling way with the advantages of higher cooling efficiency, adjustable capacity, and reliability [15].

As a special garment, wearing comfort is of particular importance. Thermal sensation, which is defined as "the wearer's sense of temperature between hot and cold," is a helpful target for designing an LCG with good thermal comfort [15], [16]. It can be quantified using ordinal scale: 3 (hot); 2 (warm); 1 (slightly warm); 0 (neutral); −1 (slightly cool); −2 (cool); and −3 (cold), which is known as the seven-point American Society of Heating, Refrigerating and Air-conditioning Engineers (ASHRAE) thermal sensation scale [17]. For example, the wearers of LCGs will vote 3 when they feel hot. In order to keep the wearers thermally comfortable, neutral temperature (0) is desired. The thermal sensation is usually measured after the LCGs have been designed and fabricated, which is the post-assessment parameter to feedback the design of LCGs in the next round. Such trial-and-error design cycle for the development of LCGs is rather inefficient and costly. So, it is urgent to establish a thermal sensation predictive model to guide the design of LCG. To tackle this issue, several thermal sensation predicting models were developed by researchers, such as the predicted mean vote (PMV) model [18] and standard effective temperature ∗ (SET∗) [19]. Although these models reflect the average thermal response of a standard person, they cannot be applied to PTM because they mainly rely on empirical recommendations or predefined formulas without taking the individual's physiological characteristics into consideration. A better model should take consideration of the individual's physiological characteristics and the dominating characteristics of the LCG, such as water inlet temperature.

To address these concerns, in this study, a neural network (NN) model based on thermal sensation votes was proposed to analyze and predict the thermal sensation of LCGs, taking physiological parameters [heart rate (HR), local skin temperatures, and tympanic temperature] and physical parameters [ambient temperature (AT) and relative humidity (RH)] including water inlet temperature of LCGs into consideration. The establishment process of the neural network for predicting the thermal sensation of LCG is introduced, followed by the experimental validation. Finally, the influence of relevant features, training data set size, and regularization on the accuracy of the neural network was investigated.

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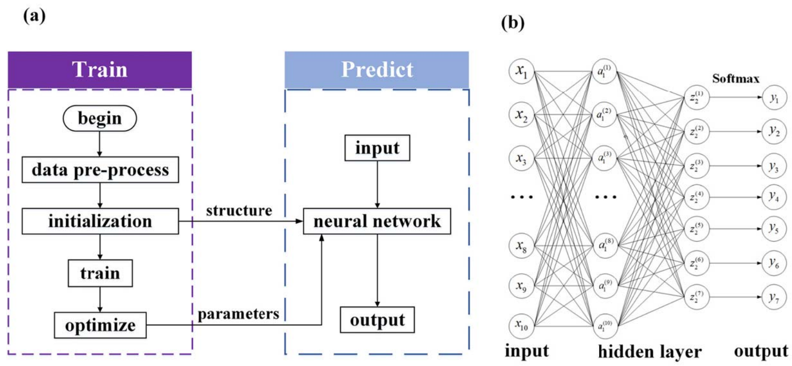

Fig. 1. (a) Flowchart of neural network training and prediction. (b) Neural networks structure.

II. Modeling

What makes neural networks a suitable tool for the prediction of thermal sensation is their ability to learn highly nonlinear hypotheses through adequate training [20]. The basic principle is to optimize the weight parameters of neural networks in the iteration process so that the neural network model can better fit the data set. The training process of the neural network includes a forward process and a backpropagation process. The forward process calculates the output value according to the input parameters of the neural network. The backpropagation process spreads reversely the difference (that is, the error) between the output value and the real value in the network, calculates the derivative of the error to each parameter of the neural network, and optimizes the parameters according to the optimization algorithm.

Predicting the thermal sensation of LCG is a classification problem, which means that we want to use the neural network to transfer the input parameters into an ASHRAE vote on the seven-level scales (−3, −2, −1, 0, 1, 2, and 3). The number of neurons in the output layer is corresponding to one vote scale, so the output layer consists of seven neurons. Fig. 1(a) shows the flowchart of neural network training and prediction. After data preprocess and initialization, the weight parameters of the neural network are optimized in the iteration process, so that the neural network model can better fit the data set. The neural network structure used in this article is shown in Fig. 1(b), only including three layers: L1 (input layer), L2 (hidden layer), and L3 (output layer). The training data can be well fitted through increasing the numbers of hidden layers in a complex neural network. However, it increases the more computational costs and the highest risk of overfitting, which results in a worse prediction of cross-validation data set. Three layers included are enough in this problem [20].

The number of neurons in the input layer and output layer is determined by the research problem, while the choice of the number of neurons in the hidden layer needs to be tested repeatedly to achieve the best effect. The numbers of neurons in the hidden layer recommended by some previous research studies [21], [22] are

$$2 \cdot \sqrt{I} + K \leq J \leq 2 \cdot I + 1 \tag{1}$$

where I represents the size of feature X, K represents the size of the hypothesis vector, and J is the size of the hidden layer.

Neurons $n_i(L1)$ in the input layer $L1$ are linked with each neuron $n_j(L2)$ in the hidden layer $L2$. The Jth neuron in the hidden layer $L2$ is computed by using the following equation:

$$z_j^{(L2)} = \sum_{i=1}^{I} w_{ji} \cdot x_i + b = \sum_{i=1}^{I} w_{ji} \cdot x_i + w_{j0} \cdot x_0 = \sum_{i=0}^{I} w_{ji} \cdot x_i \tag{2}$$

where the subscript 0 usually denotes the bias unit.

In order to increase the ability of NN to express nonlinear problems, neurons need to be activated. It maps the resulting values into the desired range, such as between 0 and 1 or −1 and 1, etc. (depending upon the choice of activation function). The activation $a_j^{(L2)}$ of each neuron $n_j^{(L2)}$ in the hidden layer will be obtained based on the calculated input $z_j^{(L2)}$. The activation function of neurons in the hidden layer here is rectified linear unit (ReLU) function, as shown in the following equation:

$$a_j^{(L2)} = \max\left(0, z_j^{(L2)}\right). \tag{3}$$

The softmax function instead of ReLU function is often used to calculate the activation in the output layer for classification problems. Given the input features, the softmax function will show the probability of each ASHRAE votes to the correct one. For example, the activation $a_1^{(L3)}$ of neuron $n_1^{(L3)}$ is calculated by using the following equation:

$$h_1 = a_1^{(L3)} = \frac{e^{z_1^{(L3)}}}{\sum_{k=1}^{K} e^{z_k^{(L3)}}}. \tag{4}$$

The average cross-entropy error as the cost function overall is computed according to the following equation:

$$C(Y, H) = -\frac{1}{M} \cdot \sum_{m=1}^{M} Y_{(m)} \cdot \log(H_{(m)}). \tag{5}$$

Then, error (cost) C is backpropagated through the neural network to get the partial derivatives of the error C. Then the error C was minimized through the obtained partial derivatives in the optimization process, with certain numerical optimization algorithms, such as Newton's descent method, Adam optimizer, etc. The optimization algorithm used here was Adam optimizer.

Before the start of the iteration process, the variables W and b of the neural network need to be randomly initialized. It might make a slight difference in the iteration speed and minima due to different initialization. Therefore, the final results were averaged of ten iterations. In this article, Xavier initialization method is used to initialize the variables in the neural network.

III. Experiments

To obtain a large training data set used in the neural network model, the experiment was conducted to record the parameters, which include both data about the relevant conditions and individual sensation votes that correspond to these conditions. The whole experiment has been conducted inside a climate chamber. The experimental setup includes an air-conditioning, a thermostatic water bath, and a data acquisition instrument. The air-conditioning is used to control the AT and RH. A thermostatic water bath is used to control the inlet water temperature of LCG. Six subjects with a range of height from 170 to 183 cm and weight from 57 to 67 kg have participated in the experiments voluntarily and all of them are students. The subjects sit quietly in the experiment and the estimated metabolic rate (M) was approximately 1 met according to ISO-EN 7730 [23]. The subjects of similar weight and height wear typical summer clothing consisting of a T-shirt, a pant, and a liquid-cooled vest in the experiments. The liquid-cooled vest incorporated with a network of fine hoses (the diameter of the hose is 0.5 mm, and the distance between every two adjacent hoses is 2.5 mm) sandwiched between two-layer polyester mesh fabrics, which was made of flexible spandex and polyester mix fabric.

All subjects have not been informed any information before about the exposure conditions during the experiments without initial psychological interference, so it increases the accuracy. Fig. 2 shows the schematic of the test setup for LCG and the thermocouples arrangement on the human body. The thermocouples arrangement on the human body is referred to [17]. In this study, the water temperature is investigated while the flow rate is set at 800 mL/min. The flow rate needs to be set higher to reduce the temperature difference between inlet and outlet for avoiding local discomfort of wearers. However, the flow rate shows little improvement in cooling when the flow rate exceeds a certain value, which depends on the cooling system [12], [15]. Hence, we fixed the flow rate as 800 mL/min based on practical considerations. Wind speed was kept under 0.05 m/s and mean radiant temperature was close to AT during the experiments. AT and RH were measured by temperature and humidity instrument (testo605). Wind speed was recorded by an anemometer (testo425, range 0.01–20 m/s). The water inlet temperature of LCG was measured by the k-type thermocouple (TT-K-30, accuracy 0.4%, Omega, United States) as a potential feature parameter related to the thermal sensation of LCG. Among many human physiological indices, skin temperature (five sensors of the k-type thermocouple, the arrangement is shown in Fig. 2), and HR (Yuwell, YX303) were measured while the experimental condition stabilized (every 5 min). The tympanic temperature was measured using an infrared tympanic Thermometer (Braun, IRT6520). In the experiments, we placed the infrared probe in the ear canal and measured the temperature each 5 min, as shown in the inset of Fig. 2(b). Psychological measurements include the ASHRAE thermal sensation votes [17] by direct questionnaires.

As shown in Fig. 3(a), the experimental procedures are as follows.

1) At the beginning of each experiment, subjects wear LCG and then take rest for 20 min (for adaptation and preparation time), and the environmental parameters are measured before the test.
2) After the ensembles reached a steady state, we turn on the data recorder and activate the LCG. The skin temperature will decrease and the ensembles would reach another equilibrium condition. All data are continuously recorded.
3) During the experiment, the water inlet temperature gradually changes from 5 °C to 30 °C. We keep it consistent with the actual work. Because the water inlet temperature usually changes from 5 °C to 30 °C during the whole working process [13], [14]. The subjects answer questionnaires and are asked to continue this survey every 5 min.
4) Repeat the procedure 1–3 after adjusting the AT (range of 23.1 °C–30.9 °C) and RH (range of 36%–77%).

Fig. 3(b) shows the photograph of subject experiments.

IV. Results and Discussion

Neural network data set was obtained through the above experiment results, which contained 467 groups of data. It is noted that T_{skin} is calculated by averaging the temperature of the five points while all five sites of skin temperatures have been used in the model training.

The scale of each feature parameter in the original data is not consistent. To give equal attention to each feature in the neural network, all feature parameters X were normalized by using the following equation:

$$X_{\text{norm}} = \frac{X - \mu}{\sigma} \tag{6}$$

where μ represents the mean of feature X overall the whole data set, and σ is the corresponding standard deviation. Preparation of data set is imperative in the same way before the neural network is tested on any other data.

It is necessary to divide the entire data into subsets because complex neural network tends to over-fit the training data. Cross-validation data set and test data set are usually used to achieve a more reliable result of the accuracy for validation. In this study, the entire data set obtained from experiments is divided into three parts, including the training subset (70%), the cross-validation subset (20%), and the test subset (10%).

The quality of the neural network is always strongly determined by factors, such as the size of the training data set, regularization, and relevant features. To achieve a better performance of the neural network, we analyzed the influence of these parameters on the accuracy of the model.

The selection of appropriate features for training is an important aspect of the neural network. The neural network

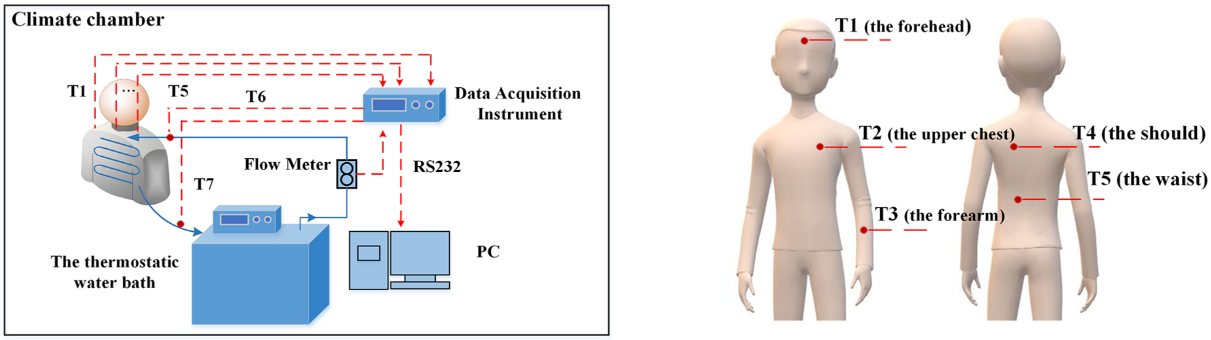

Fig. 2. Schematic of the test setup for LCG and the thermocouples arrangement on the human body.

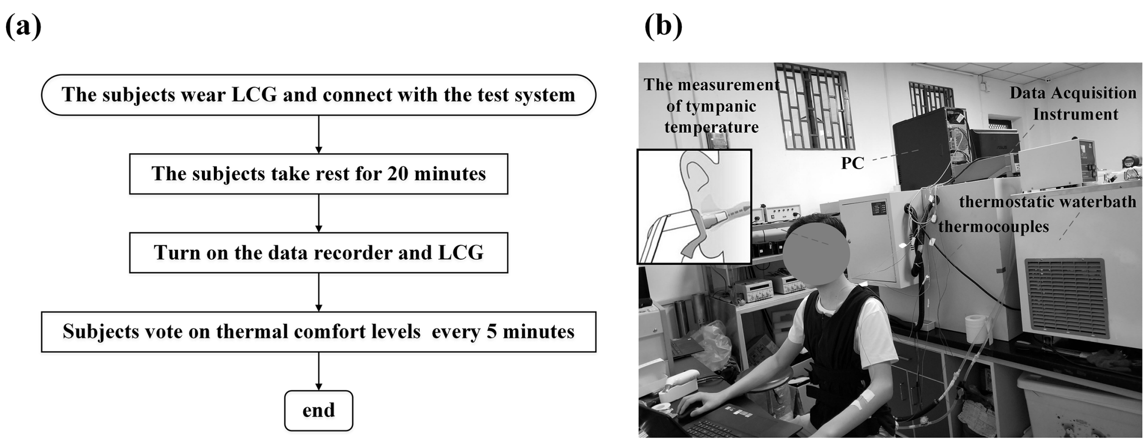

Fig. 3. (a) Experimental procedures. (b) Photograph of subject experiments.

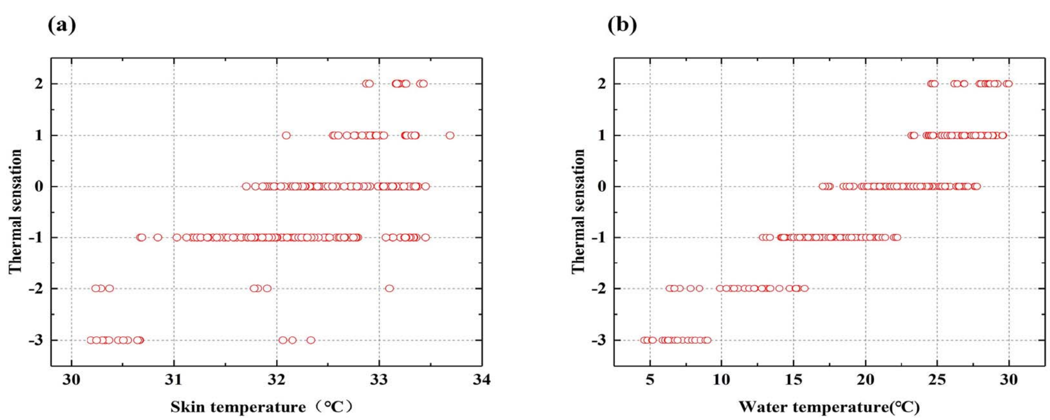

Fig. 4. Thermal sensation distribution with (a) skin temperature and (b) water temperature.

model cannot work well if the features are not enough, no matter how to adjust the parameters of the NN or enlarge the data set size. However, more computational cost and additional noise will be caused, if the irrelevant features are selected. Therefore, we analyzed the effect of the different feature parameters on thermal sensation.

The Pearson correlation coefficients between different factors and thermal sensation are shown in Table I. It can be seen that water inlet temperature and skin temperature are more correlated with thermal sensation. Fig. 4 shows the thermal sensation distribution with skin temperature and the water inlet temperature. It indicated that the water inlet temperature is more relevant to the thermal sensation than skin temperature. The Pearson correlation coefficient reached at 0.910, which indicated the water inlet temperature is the most important factor in the thermal sensation of LCG. Different from the conventional clothes, the water inlet temperature, as a potential feature parameter related to thermal sensation, has to be considered in the LCG system.

Fig. 5 shows the accuracy of prediction with the addition of features. It can be easily seen that the accuracy is significantly improved with an increasing number of features. It shows that only using the AT and RH achieves an accuracy of 46.26% in the training data set. The accuracy gradually increases to 99.97% in the training data set and 92.04% in the cross-validation data set by adding the tympanic temperature, HR, skin temperatures, and the water inlet temperature. It is noted that the accuracy of the cases "+$T_{tympanum}$" and "+HR"

TABLE I
PEARSON CORRELATION COEFFICIENT BETWEEN DIFFERENT FACTORS AND THERMAL SENSATION VOTES

Factors	AT	RH	$T_{tympanum}$	HR	T_{skin}	T_{water}
Correlation coefficient	0.187	-0.094	0.213	0.292	0.691	0.910

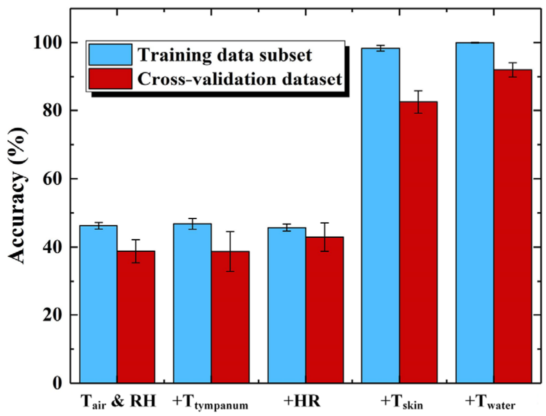

Fig. 5. Accuracy with the addition of features.

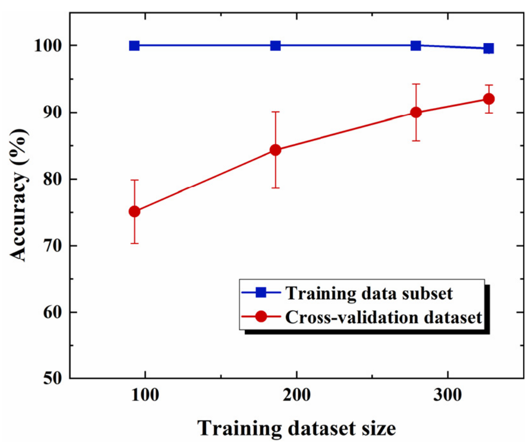

Fig. 6. Accuracy with the variation of training data set size.

did not increase. This is because the subjects sit quietly all the time in the experiment, so the "$T_{tympanum}$" and "HR" of the subjects rarely changed. Hence, the accuracy of the cases "+$T_{tympanum}$" and "+HR" did not increase. According to the aforementioned correlation analysis, skin temperature shows a certain correlation with the thermal sensation; therefore, the accuracy of prediction has achieved 82.47% after skin temperature is added. However, the water inlet temperature is more correlated with the thermal sensation than skin temperature. Hence, the accuracy of prediction has improved from 82.47% to 92.04% in the cross-validation data set when the water inlet temperature is added. With the addition of features, the training accuracy and cross-validation accuracy of neural network increase accordingly, indicating that increasing the number of effective features can significantly improve the performance of the neural network.

In order to investigate the influence of training data set size on the accuracy of the neural network model, the model was trained using data from 20%, 40%, 60%, and 70% of

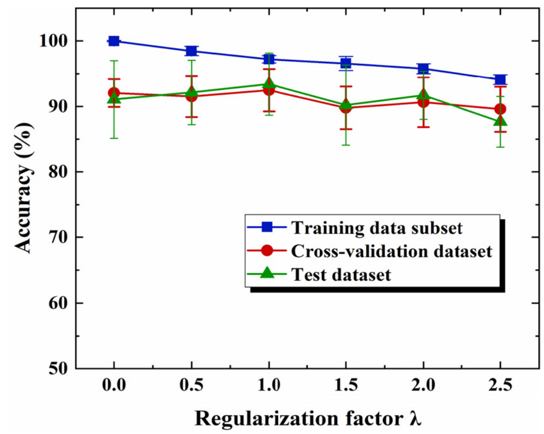

Fig. 7. Effect of regularization on the accuracy.

the whole data set (using all features). Fig. 6 shows the accuracy of prediction with the variation of training data set size.

The results show that the accuracy of the training data set decreases slightly from 100% to 99.57% when the training data set increases. However, the accuracy of the cross-validation data set is improved significantly from 75.11% to 92.04% with the increase in training data. This makes sense because it is more arduous for the neural network to fit well since the random noise increases with the training data size. Therefore, the learned weights are less specific while the neural network has a better performance in the cross-validation data set. This is a positive effect, as the ultimate aim is to learn general weights that are not specific to the training data [20]. At the same time, error bars narrow down, indicating that increasing data set size improves the accuracy of prediction. Variation of accuracy shows a slow trend, which is expected eventually to come stable. Therefore, a better quality of neural networks can be achieved by enlarging training data set. Here, the accuracy of the training data set achieves nearly 100% because the size of the training data set is not enough big. However, a larger data set is not available at present limited to the existing test condition.

The training data can be well fitted through increasing the numbers of hidden layers in a complex neural network. However, it increases the more computational costs and the highest risk of over-fitting. Over-fitting means that the neural network does not generalize well from our training data to unseen data. Regularization can be used to prevent the overfitting of random noise by using the following equation:

$$C' = C + \lambda \cdot \sum_{i}^{i} \sum_{j}^{j} w_{ji}^{2}. \quad (7)$$

Regularization factor λ needs to be selected appropriately for cross-validation data set of the best performance. However, since this is another optimization process, more representative accuracy can be obtained when the trained model structures are tested in the test subset. Fig. 7 shows the effect of regularization on the accuracy of the prediction. The accuracy of the training subset apparently decreases when the regularization

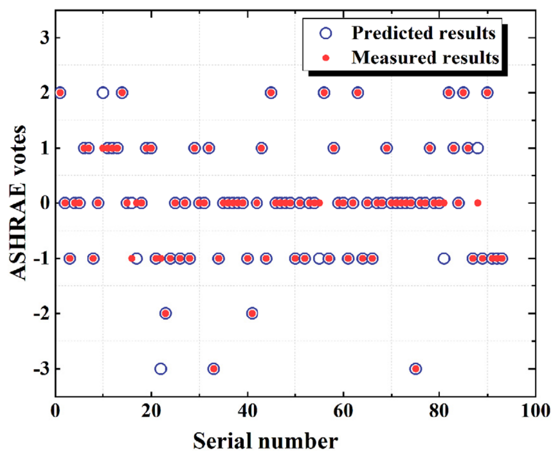

Fig. 8. Comparison of predicted ASH-votes and measured ASH-votes with various samples.

factor λ increasing from 0 to 2.5. Meanwhile, the accuracy of the cross-validation data set also drops off with a slight fluctuation, meaning that regularization factor λ does affect the performance of the neural network. The results show that the optimal size of λ is 1.0 when test accuracy achieves the highest accuracy of 92.47%.

The neural networks have to be appropriately designed and sufficiently trained for better prediction; in other words, the neural network needs to be trained with a lot of data with proper regularization. Based on the above analysis, the accuracy of the model achieves the highest of 92.47% while the regularization λ is 1.0 and the size of the data set is largest. By comparing the predicted ASHRAE thermal sensation vote and measured ASHRAE thermal sensation vote with various samples, the accuracy of the model has been verified.

Fig. 8 shows the measured results (red dots) and the predicted results of the NN (blue circles) over the different samples. It shows that the agreement between the predicted ASHRAE votes and the measured ASHRAE votes. The prediction is right if the predicted result is equal to the measured result, and the accuracy is the ratio of the right numbers in the total numbers of samples. Finally, we get an accuracy of 92.47% from the comparison of the predicted results and measured results, which indicated that 92.47% of the individual votes are predicted correctly with the NN prediction model.

V. Conclusion

In this article, we presented a NN model to predict and analyze thermal sensation of LCG. The data for the analysis was derived from the experiments that contain 467 groups of relevant data. After the experimental data training, a predicting model based on the neural network method has achieved an accuracy of 92.47% in the test. With a given set of inputs, the developed model can predict the thermal states of wearers. The conclusions are summarized as follows: Enlarging the size of the data set and choosing an optimal size of λ are extremely important for improving the performance of neural networks. More relevant features might be considered to further improve the model, which are not available at present. The water inlet temperature as a most import feature parameter related to the thermal sensation should be considered in the LCG system. Prediction of thermal sensation for LCGs by using neural network model can provide guidance for comfort research of other wearable devices.

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