

Individual thermal comfort models based on optimized BP neural network algorithms

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Abstract. Thermal comfort plays an important role in human life and it affects occupant satisfaction, health, and productivity. Individual differences are not considered in traditional control strategies based on temperature setpoints. The reality is that operators often expend more energy to maintain the indoor environment and the thermal satisfaction of occupancy is not as well as expected. Thus, individual thermal comfort models based on physiological parameters and environmental parameters were presented using the back-propagation (BP) neural network. Moreover, we used three training algorithms including Levenberg-Marquardt (L-M), Bayesian Regularization, and Scaled Conjugate. We observed that using the L-M algorithm resulted in slightly better performance ($R=0.96$) than other algorithms. The precision results suggest that the BP network algorithm is an effective approach for real-time predicting thermal comfort. In the follow-up study, we would focus on feature engineering (feature selection) and introduce appropriate variables (e.g., heart rate) to improve the model's accuracy.

1 Introduction

With the development of national science and technology, the thermal comfort level of interior personnel needs to be further improved. Thermal comfort plays an important role in human well-being while it affects occupant satisfaction, health, and productivity [1]. A traditional control strategy based on temperature setpoints does not take into account individual differences, and the satisfaction of building users often fails to achieve the desired result. A field study shows that 80% of the indoor occupants is hard to feel satisfaction located in China [2]. It noticed that individual differences are not considered in traditional control strategies based on temperature setpoints [3]. The reality is that operators often expend more energy to maintain the indoor environment and the thermal satisfaction of occupancy is not as well as expected. The traditional predicted mean vote (PMV) model is suitable for the assessment of a uniform steady environment with low airspeed [4]. Thus, the traditional control mode and function cannot meet the needs of intelligence. The back-propagation (BP) neural network is one of the more mature neural network algorithms, which has good adaptability, robustness, and generalization ability [5].

Up to now, BP neural network models were successfully applied in predicting energy utilization, thermal comfort, and indoor air quality [6,7]. Several studies have therefore combined ANN with predicting thermal comfort to save energy. Zhang et al. employed two neural network algorithms, which not only predicted the thermal expectation of the elderly but also compared the accuracy of those models [8]. Similarly,

Xue et al. proposed a BP model to predict the energy performance, predicted mean vote and indoor air quality, and draft rate [9]. In addition, Thongkhome et al. proposed a feed-forward back-propagation artificial neural network, which was used to realize the adaptive adjustment [10].

This paper presents an efficient thermal comfort framework that creates a great indoor environment. There are only a few studies about individual differences. To solve the above problems, individual thermal comfort models based on physiological parameters and environmental parameters were presented.

2 Optimized BP neural network algorithms

BP neural network is one of the most mature neural networks algorithms, with good adaptability, robustness, and generalization ability. Three layers BP neural network can easily approach any nonlinear function indefinitely [11]. It is widely used in image processing, data compression, and other fields. However, the convergence speed of the BP neural network is slow, it's difficult to find the global minimum value, and it can't deal with complex or missing information. To overcome these shortcomings, researchers introduce numerous optimization algorithms in the neural network framework. These optimization algorithms can significantly improve the performance of the BP neural network.

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According to the researchers, Levenberg-Marquardt (L-M) algorithms require more memory but less computation time. The mean square error of the validation sample was improved [12]. Bayesian regularization algorithms require more time but can produce good generalizations for difficult, small, or noisy datasets [13]. Similarly, a scaled conjugate gradient algorithm requires less memory. Training automatically stops when generalization stops improving, as shown by a decrease in square error in the validation samples [14].

The development of new technology (e.g., Computer Vision, Machine Learning, Internet of Things) provides a basis for creating data-driven models. The neural network algorithm was applied in the field of thermal comfort. Many studies have shown that using data-driven models resulted in slightly better accuracy than the PMV model. The selection of an algorithm is one of the key factors affecting the prediction model. Therefore, based on the environment data and physiology data, the study used a three-layered back-propagation network.

3 Building thermal comfort models

3.1 Experiment set

The experiment was conducted in a climate chamber in Xi'an during winter. Xi'an has a warm temperature semi-humid continental monsoon climate. According to previous studies, many factors might affect a human's thermal sensation. Therefore, Skin temperature, ambient temperature, relative humidity, and black bulb temperature were integrated as features. The outputs of personal thermal comfort models were thermal sensation, thermal preference, and thermal satisfaction votes. All the data was pre-processed for normalization because the factors were measured in different units. Two performance metrics were used to evaluate the training results, including the mean squared error (MSE) and Maximum value of the Coefficient of determination (R^2).

3.2 Data pre-processing

This section corrects and checks missing or inaccurate samples in the dataset. Before training the model, characteristics and voting data were integrated into a two-minute interval. All data should be pre-processed for normalization to remove the limitation of the unit and improve the efficiency of the BP neural network.

3.3 Building and evaluating thermal comfort models

Thus, we used three training algorithms including (L-M), Bayesian Regularization, and Scaled Conjugate. BP network had three components including output layer, hidden layer, and input layer. In addition, the

hidden layer of all thermal comfort models is 10 and the maximum training times are 1000, see in Fig.1.

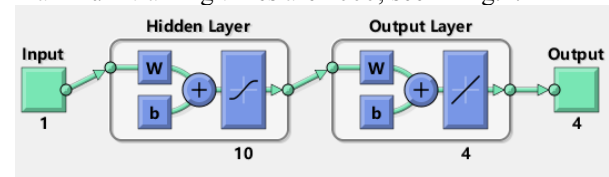


Fig. 1. Neural network framework.

All data sets are divided into three sets, namely training set, validation set, and test set. In each experiment, validation is the process that measures the generalization of the BP network. The training process automatically stops when generalization stops improving, as seen in Fig.2. It shows the performance of the BP neural network. It can be also seen that the training process stops when the best validation performance is found at epoch 2.

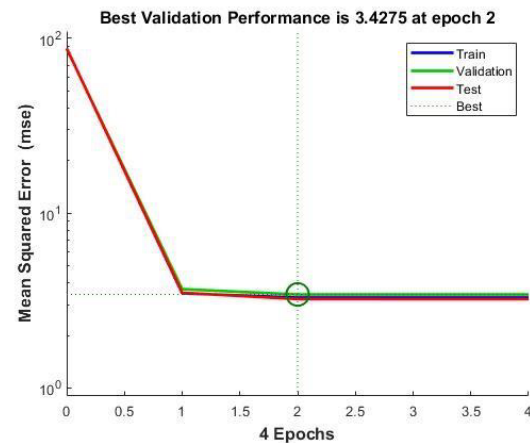


Fig. 2. Neural network training performance.

3.4 Data analysis

To conduct the statistical comparisons between the predictions and observations, MSE and R^2 .

$$MSE = \frac{1}{n} \sum_{t=1}^n |F_t - A_t| \quad (1)$$

Where F is the true value, A is the predicted value, n is the number of samples [15].

The test set performance of the personal thermal comfort prediction models is shown in Table 1. The parentheses represent the performance of the model based on data from female subjects. The optimum structure and statistical parameters of the BP neural network using different raining algorithms was given in Table 1 and Fig. 3

Unlike the two optimization algorithms (i.e. scaled conjugate and Bayesian regularization), based on the L-M training algorithm thermal comfort models with two subjects layer had the best performance of MSE.

Table 1. MSE, R with three algorithms.

L-M	Scaled Conjugate	Bayesian Regularization
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MSE	3.22611 (0.221679)	3.74593 (0.497819)	3.41885 (0.272301)
R	0.967016 (0.92925)	0.958976 (0.840376)	0.966636 (0.924614)

It is apparent that the L-M algorithm hand the highest speed compared. The regression graphs represent the relationship between measured and predicted values of the BP neural network, in the training, validation, test, and all sets are shown in Fig.3. In the test sets, the predicting results are very close to the results in the training sets. This proves that the selection of 11 features as inputs for predicting thermal comfort could achieve great performance.

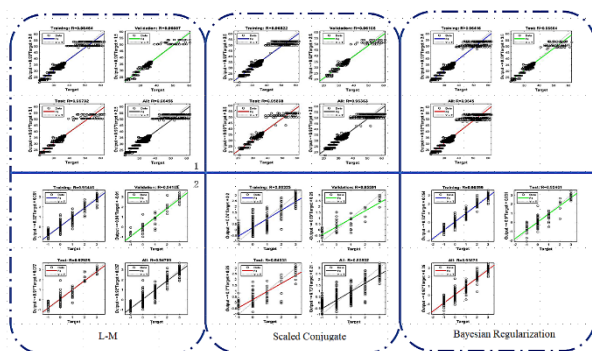


Fig. 3. Regression graphs of measured and output values of thermal comfort for training.

4 Conclusion

This study represents one effective model for estimating thermal comfort including three optimization algorithms and then compared with each other. BP neural networks with three different training algorithms were obtained to be proper for predicting personal thermal comfort. It is noticed that the BP neural network with L-M training algorithms with one hidden layer presented better accuracy ($R=0.96$), followed by Bayesian Regularization and Scaled Conjugate. Results showed that the neural network can learn the relationships between the input parameters and thermal comfort votes and provided relatively better prediction results for each subject. Thus, BP neural network can be suggested to predict personal thermal comfort because of fast, accurate, and reliable results effectively.

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