Prediction Model of Thermal Comfort Based on Tabu Genetic Neural Network

Zhehua Du¹*, Xin Lin²

¹Wuhan Second Ship Design and Research Institute, Wuhan, Hubei, 430205, China
²Hubei Province Engineering Consulting Co., LTD., Wuhan, Hubei, 430071, China

*Corresponding author’s e-mail: Jackydhz@163.com

Abstract. The calculation process of thermal comfort index has the characteristics of nonlinearity and high computational complexity, so that the real-time controller of air conditioning can’t be used directly. To solve this problem, based on the thermal comfort equation provided by professor Fanger, an improved tabu genetic neural network (TGA-BPNN) is proposed to generate a prediction model for PMV index. The improvements include: training the initial population using train( ) function and using tabu tables to optimize selection, crossover, and mutation. The simulation experiment shows that, compared with the traditional BP network and the genetic neural network, TGA-BPNN can quickly find the global optimal solution and make the prediction model more accurate under the condition of maintaining the diversity of the population. Of course, there are still deficiencies in the simulation experiment. The deficiencies include that initial population needs to be trained repeatedly, which increases algorithm’s running time compared to random population. The algorithm spatial complexity is increased, so that the efficiency of TGA-BPNN algorithm is not as high as that of GA-BPNN algorithm.

1. Introduction

Air conditioning also brings higher energy consumption while adjusting indoor environment. In order to balance the relationship between comfort and energy saving, the researchers proposed to adjust the operation mode of air conditioner in real time using thermal comfort as an indicator. Studies have proved that this index can effectively reduce energy consumption of air conditioners by about 20% while maintaining comfort. The calculation process of this index has the characteristics of nonlinearity and high computational complexity. This results in air conditioner controller can not be used directly. For this reason, we need to establish a set of simplified calculation models instead. Researchers have begun to introduce neural network technology into the field of PMV prediction and have achieved fruitful research results [1, 2]. As is known to all, the initial values of weights and thresholds in BP neural network are randomly assigned. The principle of network training is to reduce output error gradually by adjusting weights and thresholds until it converges to a target range. Therefore, the initial values of weights and thresholds directly affect the convergence speed and prediction effect of the network in the later period.

In this paper, tabu genetic algorithm is used to optimize the weights and thresholds of neural network. Then PMV prediction model is established through improved network.
2. Overview

Predicted average evaluation PMV index represents the feeling of most people in the same environment, and its value is mostly between [-3, 3]. -3 means very cold, -2 means cold, -1 means a little cold, 0 means neutral, +1 means a little hot, +2 means hot, +3 means very hot. Recommended PMV value of ISO7730 is between -0.5 - +0.5. PMV value is calculated iteratively from the following formula. $M$ is human metabolic rate. $T_a$ is air temperature. $t_r$ is average radiation temperature. $I_{cl}$ is clothing thermal resistance. $\psi_a$ is air relative humidity. $v_a$ is air velocity

$$PMV = f(M, t_a, t_r, I_{cl}, \psi_a, v_a)$$

3. Tabu genetic neural network

3.1. BP neural network

BP neural network, also known as Error Backpropagation Network, which is the most complete and widely used algorithm model in the current theoretical system. Its characteristic is that during the training of network, according to the error of output result, weights and thresholds are corrected layer by layer from output layer to reduce the error. BP neural network used in this paper has a three-layer structure. The first layer is input layer, containing 6 neurons, which respectively represent human metabolic rate, air temperature, average radiation temperature, clothing thermal resistance, air relative humidity and air velocity. The second layer is hidden layer, which contains 16 neurons, and training function is $\text{logsig}(\cdot)$. The third layer is output layer, including 1 neuron, which represents PMV index, and the training function is $\text{purelin}(\cdot)$.

3.2. Tabu genetic algorithm

Tabu genetic algorithm (TGA) is an improved algorithm based on genetic algorithm, which integrates tabu search. First, the algorithm randomly generates an initial population of a certain size, whose individuals are all possible solutions to the problem. Then, the selection, crossover (i.e. mating) and mutation behaviors in nature are simulated to optimize individuals, and optimal individuals are found through repeated iterations [3]. Genetic algorithm has been widely used because of their strong robustness and parallelism. However, the algorithm also has some defects, such as lack of memory, poor local search ability, and easy to fall into local extremum. Tabu genetic algorithm adds memory function to genetic algorithm [4]. According to the idea of tabu search, TGA algorithm adds tabu table structure to the coding of genetic individuals. Tabu table is used to record crossover behavior of each individual, so as to prevent the phenomenon of strengthening local extremum point due to repeated crossover of similar individuals. The main improvement points of TGA algorithm based on genetic algorithm include: optimizing initial population, modifying individual structure, adjusting crossover operation and mutation operation.

3.2.1. Initial population. In existing genetic neural networks, the initial population is generally randomly generated. However, simulation experiments show that the fitness of the randomly generated initial population is very low. It takes hundreds of genetic iterations to improve, which greatly reduces the efficiency of the algorithm. In order to improve the efficiency of algorithm and the prediction accuracy of neural network, the initial population used in this paper is trained by BP neural network. In simulation experiment, training function train( ) will be used to train N randomly generated BP neural networks. Thus, N groups of different combinations of weights and thresholds are obtained to form the initial population of genetic neural network, whose size is N [5].

3.2.2. Individual structure. Information bit $F$ and tabu table $T$ are added after genome $S$ of individual $X$, then the structure of any individual $X_i$ is shown as follows. Genome $S$ is a binary string, whose content is the combination of weights and thresholds to be optimized, and the length $L_i = (I_n \times H_n + O_n \times H_n + O_n) \times P$. $I_n$, $H_n$ and $O_n$ are the number of neurons in input layer, hidden layer and output layer respectively, and $P$ is binary digit of weight and threshold. Information bit $F$ is a decimal integer that
is randomly assigned a unique value by the system when new individuals are created. Tabu table $T$ is a set of decimal strings used to record the information of individuals who have ever crossed and mutated with themselves. Its length is $L_t = \text{int}(0.1 \times L_s)$.

$$X_i = [S, F, T]$$

3.2.3. Crossover operation. Individuals use a single point of intersection to achieve gene fusion. TGA algorithm will record the value of each other's information bits in the individual tabu table $T$. When the next cross behavior occurs, the individuals will check whether the contraindication tabu table $T$ contains the value of counterpart information bit. If it is included, the crossover is canceled, otherwise the crossover operation is performed. Since tabu table $T$ has a limited length, the recording of the information is performed in a first-in, first-out manner.

3.2.4. Mutation operation. Individuals of population perform mutation operations with a probability of $p_m = 0.7/L_{\text{ind}}$. $L_{\text{ind}}$ is the length of genome $S$, and specific operation method is discrete mutation. When an individual mutates, it is equivalent to forming a new individual, for which TGA algorithm will assign a new value of information bit $F$ and clear the tabu table $T$.

3.3. Tabu genetic algorithm – BP neural network (TGA – BPNN)

The essence of tabu genetic algorithm-BP neural network (TGA-BPNN) is to use global search ability and high parallelism of tabu genetic algorithm to solve the problem that neural network easily falls into local extreme points and slow convergence. The specific steps of TGA-BPNN algorithm are as follows.

1. 700 combinations of PMV parameters are randomly generated. PMV values are calculated according to PMV formula, which are used as the training and test sample of neural network.
2. The topology of BP neural network is determined.
3. A combination of weights and thresholds of trained network constitutes a population of initialization size $N$.
4. Relevant parameters of genetic algorithm are set, including max genetic iteration number $\text{MAXGEN} = 500$, genetic iteration variable $G = 1$, generation gap $G_p = 0.9$, crossover probability $P = 0.7$, and mutation probability $p_m = 0.7/L_{\text{ind}}$.
5. Individual fitness is calculated. BP neural network is constructed by using weights and thresholds in individuals. The network is then used to predict PMV values of training samples. Finally, mean square error between predicted result and actual result is taken as the individual's fitness.
6. Selection, crossover, and mutation operations are performed. Selection operation uses a random traversal sampling function to eliminate the individuals with lower fitness in the population by generation gap value $G_p$. Crossover and mutation operations are then performed on the remaining individuals according to tabu criteria.
7. A new generation of population is generated. Due to generation gap $G_p = 0.9$, the population size of the offspring is only 90% of that of the parent. In order to keep the population size constant, the optimal maintenance strategy should be used. A new generation population is formed by combining 10% of the individuals with higher fitness in the parent population with the offspring population.
   - Let genetic iteration variable $G = G + 1$. Then, it should be determined whether $G$ is greater than the maximum genetic algebra, and if so, end the iteration; otherwise, move to step 5.

4. Simulation experiment and result analysis

4.1. Sample data

The prediction accuracy of BP neural network is greatly affected by the size of training data. For this reason, within the specified parameter value range, 700 sets of parameter combinations were randomly generated. PMV values were calculated according to Professor Fanger's thermal comfort equation,
which were used as network sample data after normalization. Among them, 600 groups were used as training samples and 100 groups were used as test samples.

4.2. Simulation experiment and data analysis
The simulation experiment platform of this paper is MATLAB R2015a. In order to verify the superiority of TGA-BPNN algorithm, a total of four types of algorithms were set up as experimental objects. The first type is the neural network trained using \textit{train( )} function (Error Back Propagation Neural Network, BPNN). The second type is genetic neural network which initial population is randomly generated and optimized using genetic algorithm (Random Population Genetic Algorithm-BP Neural Network, RGA-BPNN). The third type is genetic neural network that uses genetic algorithm to optimize initial population (Genetic Algorithm-BP Neural Network, GA-BPNN). The fourth type is tabu genetic neural network optimized by tabu genetic algorithm (TGA-BPNN).

Figure 1 shows the result of BPNN network after 500 times random trainings using \textit{train( )} function, which took a total of 15.58 minutes. Because weights and thresholds of each network are randomly generated, there is a large difference between the results. The largest mean square error is 3.5401 and the smallest mean square error is 0.041. It can be seen that training results of network have great randomness due to the values of weights and thresholds. Repeated training does not guarantee that the network model with the highest prediction accuracy can be found.

![Figure 1. Training process of BPNN](image)

Figure 2 and Figure 3 respectively describe the change of mean square error of the best individual in the population with the number of iterations in 500 times iterations of RGA-BPNN and GA-BPNN network. Due to the difference in initial population, the training situation is very different. The initial population of RGA-BPNN network is randomly generated, and its initial mean square error is 648.1845. After the rapid optimization of the first 100 generations, the population evolution rate gradually slowed down. At the end of the 500th generation, the minimum mean square error is 8.8427 and training time is 36.58 minutes. The training time of the 500th generation GA-BPNN network is 37.24 minutes. Because the algorithm is basically the same and the population used by the GA-BPNN network has been trained beforehand, training time is similar to RGA-BPNN network. The initial population of GA-BPNN network is trained by \textit{train( )} function, so its initial mean square error is 0.00414. After 500 generations of genetic algorithm optimization, the best prediction mean square error is 0.0348. Mean square error represents the average error of all samples in the population. It can be seen that the overall prediction accuracy of GA-BPNN network population has been greatly improved.
Figure 4 shows how the minimum mean square error of TGA-BPNN network changes with the number of iterations. The training time of the network's 500 generations is 40.52 minutes. It takes longer time than GA-BPNN network because family characteristic bits and tabu tables are added to the individual structure of TGA-BPNN network. This leads to the increase in spatial complexity of algorithm, which affects calculation efficiency. TGA-BPNN network uses the same initial population as GA-BPNN network. After 500 genetic iterations, the minimum mean variance is 0.0352. Mean square error of TGA-BPNN network is slightly larger than that of GA-BPNN network. This indicates that TGA-BPNN network effectively maintains the diversity of population under the condition of ensuring prediction accuracy through tabu table technology. Figure 5 shows the comparison between the results predicted by the optimal network model of TGA-BPNN and the actual results for 100 test data. As can be seen from Figure 5, the network prediction effect is good, with the optimal prediction accuracy reaching $1.2\times10^{-4}$, while the network optimal prediction accuracy of GA-BPNN is $2.3\times10^{-4}$. It indicates that the prediction accuracy of TGA-BPNN network is improved by nearly one time on the basis of GA-BPNN network.

5. Conclusion
In this paper, based on the thermal comfort equation provided by professor Fanger, an improved tabu genetic neural network (TGA-BPNN) is proposed to generate a prediction model for PMV index. The improvements include: training the initial population using \textit{train( )} function and using tabu tables to optimize selection, crossover, and mutation. The above improvements enable TGA-BPNN network to find the global optimal solution more accurately under the condition of maintaining population diversity. Of course, there are still deficiencies in the simulation experiment, which need to be improved in later research. The deficiencies include that initial population needs to be trained repeatedly, which increases algorithm's running time compared to random population. In addition, because the individual needs to include all weights, thresholds, information bits and tabu tables, the
length of individual after conversion to binary reaches 3326 bits. Thus, the algorithm spatial complexity is increased, so that the efficiency of TGA-BPNN algorithm is not as high as that of GA-BPNN algorithm. Therefore, in the subsequent research, it is necessary to further improve the efficiency of algorithm on the basis of ensuring the algorithm accuracy, so that it can efficiently and accurately find the best network prediction model for PMV index.

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