RESEARCH ARTICLE

Evaluation of the effect of the main processes of leaf beating and retorting on the processing quality of tobacco homogenization

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This study focuses on the leaf roasting process in the field of tobacco processing. Leaf roasting is an important part of the process to adjust the moisture content of tobacco to the appropriate level, which has a significant impact on the homogenization and processing quality of tobacco. The study focused on the control of key parameters such as temperature, humidity and time in the leaf roasting process and their effects on tobacco quality. The study aimed to provide an in-depth assessment of the impact of the leaf roasting process on the homogenization and processing quality of tobacco. This study provides a scientific basis for optimizing the process parameters and control methods so as to enhance the processing quality of tobacco and the sustainable development of the tobacco industry. In this paper, an evaluation model was constructed to study the effect of leaf beating and re-firing process on tobacco quality by using a combination of BP neural network and genetic algorithm. Tobacco leaf homogenization processing quality indicators, such as moisture, temperature, and chemical composition, were analyzed, and how these factors play a role in the leaf beating and re-roasting process. Meanwhile, principal component analysis and typical correlation analysis were used to identify the main influencing factors, and a comprehensive evaluation model was constructed. The results of the study showed that the key parameters in the leaf beating and roasting process have a significant impact on the quality of tobacco processing. The combined model optimized by BP neural network and genetic algorithm can effectively predict and evaluate the effects of these process parameters on tobacco quality. The evaluation model developed in this study, which is used to analyze and improve the leaf roasting process, helps to improve the processing quality of tobacco leaves and the overall quality of tobacco products. In addition, this study provides a new analytical method and theoretical support for the field of tobacco processing.

Keywords: leaf beating and re-firing; homogenization; tobacco processing; BP neural network; genetic algorithm.

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Introduction

In today's tobacco processing field, the application of leaf roasting process is getting more and more attention. Leaf roasting is an important part of tobacco processing, and its main purpose is to restore the moisture content of tobacco from its natural state to a suitable level for subsequent processing and use [1]. This process has an important impact on the quality of homogenized tobacco processing and plays a key role in improving the quality and consistency of tobacco products [2]. The development of the leaf roasting process has gone through several stages. The early leaf roasting process was mainly focused on improving the drying efficiency of tobacco to reduce the impact on the quality of tobacco during the drying process. With the progress of technology and the development of the tobacco industry, the leaf roasting process gradually developed in the direction of refinement and homogenization. At present, researchers at home and abroad have made important progress in the control of key parameters such as temperature, humidity and time in the leaf beating and roasting process [3-5]. At the same time, new processing equipment and technologies have also emerged, providing more possibilities for improving the quality of tobacco homogenization and processing. In the existing research, the influence of the main process of leaf roasting on the quality of tobacco homogenization mainly involves the following aspects: (1) temperature: temperature is one of the most critical parameters in the leaf roasting process. Appropriate control of temperature can ensure that no caramelization reaction occurs during the drying process and maintain the color and aroma of the tobacco. Research shows that the appropriate temperature range is usually between 100-130℃, in which the inner quality of the tobacco can be retained to the maximum extent. (2) Humidity: Humidity is an important factor affecting the drying effect of tobacco. In the process of leaf roasting, the control of humidity is essential to maintain the integrity and intrinsic quality of the tobacco. Research shows that the appropriate humidity range is usually between 8% and 12%, within this humidity range can effectively reduce the loss of tobacco in the drying process and quality changes. (3) Time: Time is another key parameter in the leaf roasting process. Studies have shown that the appropriate drying time can ensure that the tobacco is fully dried, while avoiding the impact of over-drying on the quality of tobacco. In general, the drying time can be adjusted between 10-30 minutes depending on the variety and thickness of the tobacco. However, existing studies have mainly focused on the effects of individual process parameters on the quality of tobacco processing, and there is a lack of evaluation and study of the overall process. In view of this, this study aims to assess the effects of the main processes of leaf beating and reoiling on the quality of tobacco homogenization processing, provide scientific basis for optimizing process parameters and control methods, further improve the quality of tobacco homogenization processing, and realize the sustainable development of the tobacco industry.

Materials and methods

Backpropagation (BP) neural network

Backpropagation (BP) Neural Network is a multilayer feedforward network trained by backpropagation algorithm with good self-learning, self-organization and adaptability. Its core idea is to make the network able to automatically model the relationship between inputs and outputs by learning sample data, so as to make predictions on unknown data [6-8]. The topology of BP neural network includes an input layer, a hidden layer, and an output layer, which can be seen in Figure 1. Among them, the input layer is responsible for receiving data from external inputs, the hidden layer transforms the inputs into meaningful features through nonlinear transformation, and the output layer transforms the result of the hidden layer into the actual output. During the training process, the network will backpropagate according to the error between the actual output and the desired output, so as to adjust the weights and biases of each layer and make the prediction results of the network gradually close to the actual results [9].

The learning algorithm for BP neural networks consists of the following steps:

(1) Randomly initialize the weights and biases of the network, usually choosing smaller values to avoid the problem of vanishing or exploding gradients, given the range of connection weights (-1, 1), and set up the error function e, the computational precision ε , and the maximum number of learning times M according to the requirements.

(2) The kth input sample is randomly selected and computed to obtain its desired output:

$$x(k)=\left(x_1(k),x_2(k),\mathrm{K}\ ,x_{\mathrm{n}}(k)\right) \quad (1)$$

(3) Calculate the input and output of each neuron in the hidden layer:

$$hi_h(k)=\sum_{i=1}^{n} w_{ih}x_i(k)-b_h \qquad \text{h=1, 2,K , p} \quad (2)$$

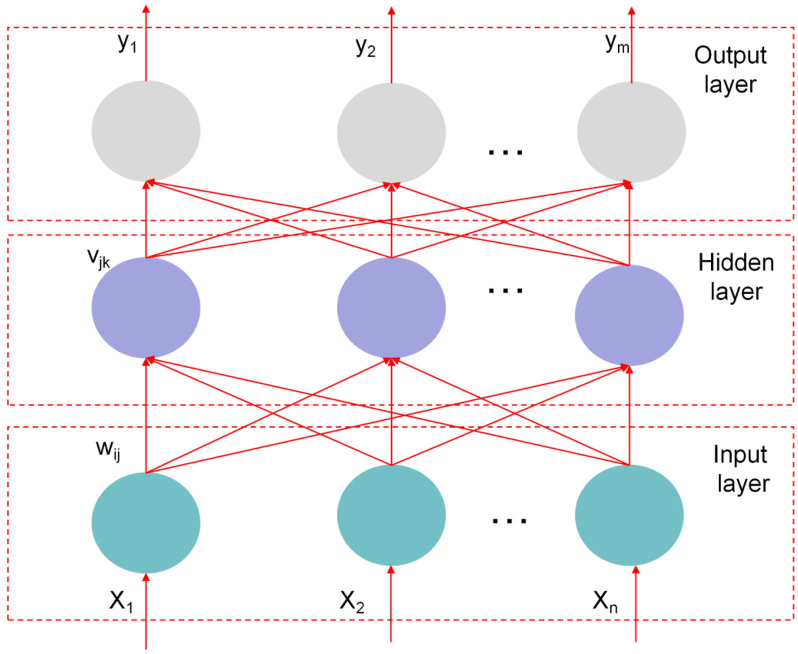

Figure 1. BP neural network topology.

$$ho_h(k) = f\left(hi_h(k)\right) \qquad h=1, 2,K , p \qquad (3)$$

$$yi_o(k) = \sum_{h=1}^{P} w_{ho} ho_h(k) - b_o \qquad o=1, 2,K , q \qquad (4)$$

$$yo_o(k) = f\left(yi_o(k)\right) \qquad o=1, 2,K , q \qquad (5)$$

(4) Calculate the partial derivatives of the error function with respect to each neuron in the output layer according to the obtained desired and actual outputs of the network $\delta_o(k)$

$$\delta_o(k) = \left(d_o(k) - yo_o(k)\right) yo_o(k)\left(1 - yo_o(k)\right) \qquad o=1, 2,K , q \qquad (6)$$

(5) The partial derivatives of the error function with respect to each neuron in the hidden layer are obtained using the connection weights from the hidden layer to the output layer, the $\delta_o(k)$ of the output layer and the output of the hidden layer $\delta_h(k)$:

$$\delta_h(k) = -\left(\sum_{o=1}^{q} \delta_o(k) w_{ho}\right) f'\left(hi_h(k)\right) \qquad (7)$$

(6) Use $\delta_o(k)$ for each neuron in the output layer and $w_{ho}(k)$ for the output-corrected connection weights of each neuron in the hidden layer:

$$\triangle w_{ho}(k) = -\eta \frac{\partial e}{\partial w_{ho}} = \eta \delta_o(k) ho_h(k) \qquad (8)$$

$$w_{ho}^{N+1} = w_{ho}^{N} + \eta \delta_o(k) ho_h(k) \qquad (9)$$

where η is the learning rate.

(7) Use $\delta_h(k)$ for each neuron in the hidden layer and $w_{ho}(k)$ for the output-corrected connection weights for each neuron in the input layer:

$$\triangle w_{ih}(k) = -\eta \frac{\partial e}{\partial w_{ih}} = \delta_h(k) x_i(k) \qquad (10)$$

$$w_{ih}^{N+1} = w_{ih}^{N} + \eta \delta_h(k) x_i(k) \qquad (11)$$

(8) Calculate the global error for all samples in the training set:

$$E = \frac{1}{2m}\sum_{k=1}^{m}\sum_{o=1}^{q}\left(d_o\left(k\right) - y_o\left(k\right)\right)^2 \qquad (12)$$

(9) Judge whether the error has reached the preset requirements. If the error has reached the set accuracy or the number of learning times has reached the set value, the learning is terminated. If the above conditions are not met, a new learning sample and the corresponding desired output are selected and return to step (3) to continue the learning [7].

The learning algorithm of BP neural network has the following advantages: (1) it is suitable for multidimensional and complex nonlinear problems; (2) it can automatically extract the relationship between inputs and outputs without human intervention; (3) it can be autonomously learned and organized; (4) it has good generalization ability and robustness. However, BP neural networks also have some drawbacks: (1) it is easy to fall into local minima and cannot guarantee to find the global optimal solution; (2) the learning speed is slow and requires a large amount of sample data for training; (3) improper selection of parameters can easily lead to overfitting or underfitting problems; (4) for large-scale neural networks, the computational complexity is high and requires efficient optimization algorithms for acceleration. To solve these problems, researchers have proposed many improvement methods, such as momentum term, regularization term, stochastic gradient descent and so on. These methods improve the training efficiency and generalization ability of the network by introducing additional optimization terms or changing the optimization strategy. In addition, with the continuous development of deep learning technology, new neural network structures, such as convolutional neural networks and recurrent neural networks, have been widely used, and have shown higher performance and robustness in processing complex tasks such as image, speech, and natural language.

Genetic algorithms

Genetic algorithm is an optimization algorithm based on the principles of biological evolution for solving search and optimization problems. It searches for the optimal solution of a problem by modeling the genetic mechanisms involved in biological evolution, such as gene mutation, crossover, and selection. Genetic algorithms are universal and can be applied to a variety of different problems such as function optimization, machine learning, image processing and production scheduling. Genetic algorithms mainly consist of three basic operations: selection, crossover, and mutation [10, 11]. The selection operation is to evaluate the current population according to the fitness function and select the individual with higher fitness for the next generation population. Crossover operation is to exchange the genes of two individuals to produce a new individual. Mutation operation, on the other hand, randomly changes a part of the genes of an individual to increase the diversity of the population.

The optimization process of genetic algorithms can be viewed as a continuous iterative process, where each step evaluates the current population according to the fitness function and selects individuals with higher fitness into the next generation of the population [12, 13]. This process gradually eliminates the individuals with lower fitness and eventually converges to the optimal solution. The process of genetic algorithm is as follows (Figure 2):

(1) Initialization: randomly generate an initial population with a population size of N.

(2) Adaptation assessment: each individual's adaptation is assessed according to a fitness function.

(3) Selection operation: the current population is selected according to the fitness function, and

individuals with higher fitness have a higher probability of being selected [10].

(4) Crossover operation: two individuals are randomly selected for crossover to generate a new individual.

(5) Mutagenic manipulation: a number of individuals are randomly selected for mutation to change some of their genes.

(6) Update the population: add the newly generated individuals to the population, keeping the population size N.

(7) Termination conditions: judge whether the algorithm converges according to certain termination conditions. If the maximum number of iterations has been reached or the adaptability of the population has reached the preset threshold, the algorithm ends; otherwise, return to the second step.

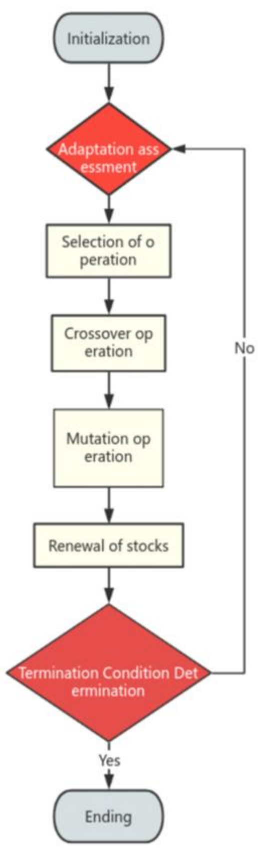

Figure 2. Flowchart of genetic algorithm.

Genetic algorithm optimization of BP neural networks

Genetic algorithm is an optimization algorithm based on the principle of biological evolution, which can automatically find the optimal solution and is suitable for solving complex nonlinear problems. BP neural network is a kind of multilayer feed-forward neural network, which is trained by back propagation algorithm, and it has strong self-learning and self-adaptive ability. Combining genetic algorithm and BP neural network can play their respective advantages and improve the optimization efficiency and accuracy. First, the process of genetic algorithm optimization of BP neural network is as follows:

(1) Initialization: a set of individuals are randomly generated as the initial population, and each individual represents a combination of parameters of a BP neural network.

(2) Adaptation assessment: for each individual, simulation is performed using a BP neural network to calculate its output value on the objective function, and its adaptation is assessed based on the objective function.

(3) Selection operation: based on the results of the fitness assessment, the individual with higher fitness is selected as the parent.

(4) Crossover operation: two parents are randomly selected for genetic recombination to generate new offspring.

(5) Mutation operation: for newly generated offspring, a portion of the genes is randomly altered to increase the diversity of the population.

(6) Update the population: add the newly generated offspring to the population and update the population size.

(7) Termination condition: according to the preset number of iterations or the objective function satisfies the condition, stop iteration and output the optimal solution.

The following points need to be taken into account in the realization process:

(1) Encoding method: the parameter combinations of BP neural networks are converted into binary codes to represent individuals.

(2) Fitness function: design a fitness function based on the objective function to assess the strengths and weaknesses of each individual.

(3) Selection operation: a roulette selection method or other selection strategy is used to ensure that individuals with a higher degree of adaptation have a higher probability of being selected.

(4) Crossover and mutation operations: random genetic recombination and mutation operations to increase population diversity based on crossover and mutation probabilities.

(5) Early stopping strategy: after reaching a preset number of iterations, iterations can be terminated early to prevent overtraining and overfitting.

Through experimental comparisons, it is found that using genetic algorithm to optimize BP neural network can significantly improve the performance and generalization ability of the network. When dealing with complex nonlinear problems, the genetic algorithm can automatically find the optimal combination of parameters and avoid the trouble of manually adjusting the parameters [14-17]. At the same time, the BP neural network has a strong adaptive ability, can automatically learn and adjust the parameters to improve the prediction accuracy.

Quality indicators of tobacco leaf homogenization processing

The quality of the leafing and roasting tobacco is influenced by physical, chemical, and structural factors. During leaf roasting, each piece of processed tobacco must meet certain requirements. Physical parameters include the moisture content, temperature, tightness, roasting speed, and ungluing rate of the tobacco [18]. Chemical composition is mainly reflected in nicotine, total sugar, reducing sugar, total nitrogen, potassium, and chlorine [19]. Tobacco structure, on the other hand, is reflected in the proportion of tobacco in the leaf. This study focuses on the homogenized processing quality of tobacco leaf after leaf beating and re-firing, so the main content of the study is the structure of the tobacco leaf after processing through the methods of tobacco wetting, leaf beating process and re-firing process. Considering that the effects of leaf beating and re-firing methods on the chemical composition of tobacco leaves are well established in related studies, it is proposed that the quality of tobacco leaf processing is based on leaf structure [20]. Leaf structure can be considered from two aspects, one part refers to the quality of tobacco before leaf beating and roasting, i.e., the quality of tobacco after de-stemming and before roasting; the other part refers to the structure of tobacco after leaf beating and roasting. The corresponding indexes include large slice rate (> 25.4 mm × 25.4 mm, %), medium slice rate (≤ 25.4 mm × 25.4mm > 12.7 mm × 12.7mm, %), small slice rate (≤ 12.7 mm × 12.7 mm > 6.35 mm × 6.35 mm, %), fragmentation rate (≤ 6.35 mm × 6.35 mm > 2.36 mm × 2.36 mm, %), fragmentation rate (≤ 2.36 mm × 2.36 mm, %), large and medium flakes (> 12.7 mm × 12.7 mm, %), and leaf peduncle rate (> 1.5 mm, %), and the leaf structure of tobacco leaves after leaf beating and re-froasting is shown in Figure 3. Tobacco leaf homogenization processing quality (leaf structure) indicators are organized as shown in Table 1.

Figure 3. Blade structure.

Table 1. Quality indexes of tobacco leaf homogenization processing.

Pre-baking		After baking	
Indicator No.	**Indicator name (%)**	**Indicator No.**	**Indicator name (%)**
P1	Pre-bake blockbuster rate	A1	Post-bake flake rate
P2	Pre-roast center flake rate	A2	Medium flake rate after baking
P3	Rate of small flakes before baking	A3	Rate of small flakes after baking
P4	Pre-bake fragmentation rate	A4	Post-bake fragmentation rate
P5	Pre-roast crumble rate	A5	Post-roasting crumble rate
P6	Pre-roasting large and medium slices	A6	Post-roasting large-medium flake rate
P7	Pre-roast leaf peduncle content	A7	Post-roast leaf peduncle content

Results and discussion

Indicator system construction and score analysis

According to the research of related scholars, the main processes of leaf beating and re-roasting include leaf wetting process, leaf beating and de-stemming process and re-roasting process. These processes have a total of 50 influencing factors on the quality of tobacco leaf homogenization, which are mainly divided into four categories: moisture factor, temperature factor, pressure factor, and other factors. These influencing factors vary in different processes and are of great significance to the control of tobacco leaf homogenization quality. Among them, the moisture factors include first-run moisture (%), second-run moisture (%), and cooling zone moisture content (%). Temperature factors include first wetting temperature (℃), second wetting temperature (℃), drying zone 2 temperature (℃), drying zone 3 temperature (℃), drying zone 4 temperature (℃), cooling zone temperature (℃), and return zone 2 temperature (℃). The pressure factors include first-run inlet steam pressure (mpa), first-run air pressure (mpa), first-run heater steam pressure (mpa), first-run rear nozzle steam pressure (mpa), first-run pure steam nozzle pressure (mpa), second-run inlet steam pressure (mpa), second-run air pressure (mpa), second-run pre-nozzle steam pressure (mpa), second-run rear nozzle steam pressure (mpa), second-run pure steam nozzle pressure (mpa), and return zone steam pressure (mpa) [16]. Process factors include the first run cylinder speed (r/min), the first run hot air circulating motor frequency (Hz), the second run cylinder speed (r/min), the second run hot air circulating motor frequency (Hz), the speed of the first dozen of one hit rollers (r/min), the speed of the first dozen of two hits rollers (r/min), the speed of the first dozen of three hits (r/min), the speed of the second dozen of rollers (r/min), the speed of the third dozen of one hit hitting rollers (r/min), three dozen two-connected hitting rollers (r/min), four dozen rollers (r/min), one wind fan frequency (Hz), two wind fan frequency (Hz), three wind fan frequency (Hz), four wind fan frequency (Hz), five wind fan frequency (Hz), seven wind fan frequency (Hz), eight wind fan frequency (Hz), wind sorting fan frequency (Hz), mesh belt frequency (Hz), thickness of tobacco laying (cm), drying zone 1 fan frequency (Hz), drying zone 2 fan frequency (Hz), cooling zone fan frequency (Hz), moisture return zone 1 M10 fan frequency (Hz), moisture return zone M9 fan frequency (Hz), moisture return M8 fan frequency (Hz), M6 fan frequency (Hz).

Through the principal component analysis, the cumulative contribution to the variance of the first 12 indicators was obtained, which is shown in Table 2. According to the data in Table 2, the total variance occupied by the eigenvalues of the 12 principal components reached 85.603%, so these 12 principal components can be extracted for further analysis and processing, and the specific values of the eigenvalues of the 12 principal components corresponded to 13.126, 7.371, 4.853, 3.691, 2.738, 2.222, 2.093, 1.875, 1.497, 1.430, 1.286, and 1.186. With these data, we can evaluate the comprehensive score of the

Table 2. Cumulative contribution of variance (top 12).

Ingredient	Initial eigenvalue			Extract the sum of squares and load			Rotate the sum of squares to load		
	Add up the total	% of variance	Cumulative %	Add up the total	% of variance	Cumulative %	Add up the total	% of variance	Cumulative %
1	13.126	26.141	26.141	13.126	26.141	26.141	11.639	23.167	23.167
2	7.371	14.630	40.771	7.371	14.630	40.771	6.356	12.601	35.768
3	4.853	9.795	50.566	4.953	9.793	50.564	5.610	11.108	46.876
4	3.691	7.270	57.836	3.691	7.270	57.834	3.169	6.226	53.102
5	2.738	5.364	63.200	2.738	5.364	63.198	3.156	6.200	59.302
6	2.222	4.333	67.533	2.222	4.333	67.531	2.337	4.564	63.866
7	2.093	4.075	71.608	2.093	4.075	71.606	2.243	4.374	68.240
8	1.875	3.639	75.247	1.875	3.639	75.245	2.001	3.890	72.130
9	1.497	2.883	78.130	1.497	2.883	78.128	1.915	3.718	75.848
10	1.430	2.750	80.880	1.430	2.750	80.878	1.793	3.474	79.322
11	1.286	2.462	83.342	1.286	2.462	83.34	1.680	3.249	82.571
12	1.186	2.261	85.603	1.186	2.261	85.601	1.660	3.030	85.601

final constructed index system and further extract the key information through principal component processing.

Based on the regression method, we derive the component score coefficient matrix according to $B=\left(A^{*}\right)^{T} R^{-1}$. Through in-depth analysis, the factor scores of the 12 principal components were precisely calculated according to the factor score function model. Then, referring to the data in Table 2, we constructed a model for calculating the comprehensive score F of the evaluation factors of the impact of the main processes of leaf beating and re-roasting on the processing quality of tobacco leaf homogenization.

$$F=(23.167F_1+12.601F_2+11.108F_3+6.226F_4+6.200F_5+4.564F_6+4.374F_7+3.890F_8+3.718F_9+3.474F_{10}+3.249F_{11}+3.030F_{12})/85.601 \quad (13)$$

According to the above formula of the evaluation factor composite score model F, the composite score of this evaluation index can be calculated. Since the calculation of the comprehensive score of the evaluation factors may carry a negative number, which is not of practical significance, it is necessary to carry out standardization processing so that the processed score is between 0 and 1. Standardized processing can be done in the following way:

$$Q=\frac{F-\min F}{\max F-\min F} \quad (14)$$

Evaluation modeling

After leaf roasting, the tobacco is categorized into three grades: superior, medium, and inferior. According to this classification, we can classify the evaluation of the influence of the main process of leaf roasting on the quality of tobacco leaf homogenization into three levels: top grade tobacco (score between 0 and 0.5), medium grade tobacco (score between 0.5 and 0.8) and lower grade tobacco (score between 0.8 and 1). Secondly, we obtained the score of the evaluation index of the impact of the main processes of leaf beating and retorting on the processing quality of tobacco leaf homogenization, F. In order to standardize this score, we processed it to obtain Q. This processed score corresponds to the results of the three levels of impact evaluation mentioned above. The leaf structure of tobacco leaves after leaf beating and re-roasting is most significantly affected by the leaf wetting process, leaf beating and de-stemming process and re-roasting process, while the other processes have a relatively small impact on the quality of tobacco leaf homogenization and processing. In the three main processes, there were 50 main influencing factors, which interacted and combined with each other to affect the leaf after tobacco leaf beating and re-roasting [21-23]. Therefore, when evaluating the influencing factors, it is necessary to consider each factor comprehensively and not focus on a single factor only. A BP neural network consists of an input layer, a hidden layer, and an output layer, where the hidden layer can have one or more intermediate layers. In existing research, most problems are solved using only a single hidden layer. Therefore, in this paper, a neural network with a three-layer architecture, i.e., each layer is an input layer, an implied layer, and an output layer, respectively, is used for BP neural network analysis. Such an architecture is relatively simple but can fulfill the need of problem solving.

BP neural network structure

(1) Input layer design

According to the index system of main influencing factors, combined with the method of modeling, the neurons in the input layer of the BP neural network were constructed as 50 main influencing factors, namely, W1, W2, W3, W4, W5, W6, W7, W8, W9, W10, W11, W12, W13, and W14 ......H48, H49, H50.

(2) Output layer design

Based on the multi-indicator assessment described above, we classified the evaluation results of the degree of influence of the main processes of leaf beating and re-firing on the processing quality of tobacco leaf homogenization into three levels: top grade, medium grade and bottom grade. In order to make the output results more intuitive, we selected the comprehensive score Q of the evaluation indicators as the output results.

(3) Implicit layer design

According to the relevant literature, there are various empirical formulas for determining the number of hidden layer units of a BP neural network, as shown below:

$$n_1 = \log_2 n \tag{15}$$

$$n_1 = n - 1 \tag{16}$$

$$n_1 = \sqrt{n+m} + \alpha, (1 < a < 10) \tag{17}$$

$$n_1 = \sqrt{0.43mn + 2.54m + 0.77n + 0.35 + 0.51 + 0.12n^2} \tag{18}$$

where n_1 is the number of implicit layer cells, n is the number of input layer cells, m is the number of output layer cells, and α denotes the tuning parameter.

In the study of this paper, the number of input variables (input layer) in the model is 50, and the number of output variables (output layer) is 1, then the number of input layer units is n=50, and the number of nodes in the output layer is m=1. According to the above four empirical formulas the number of units in the implied layer can be calculated, and the number of nodes in the implied layer should be selected from the set [8-17, 15, 19, 49], and analyzed by comparing several experiments. Through the comparison and analysis of many experiments, the number of nodes in the implied layer is 17 which is more effective. The model in this study has 50 units in the input layer and 1 node in the output layer, and the number of units in the output layer is 50. Based on this information, we can use four empirical formulas to calculate the number of units in the implied layer [24]. Based on these calculations, we need to select the number of nodes of the implicit layer in the set [8-17, 15, 19, 49]. After several experiments and comparative analysis, we find that the model performs better when the number of nodes in the implied layer is 17. In order to improve the performance of the trained individual network in terms of generalization ability and to ensure that it converges quickly during the training process, the model decided to use a hyperbolic tangent S-shaped function as the excitation function for each layer [25]. Also, in order to optimize the training process, we used gradient descent with momentum for training. During the network training process, 50 sets of sample data should be randomly sorted, and the test set should be

Table 3. Sample data used for integrated learning modeling.

Serial number	W1	W2	W3	W4	W5	...	H48	H49	H50	Q
1	65	0.4	0.5	0.4	0.3	...	45	45	8	0.044
2	65	0.4	0.5	0.4	0.4	...	45	45	8	0
3	70	0.5	0.4	0.4	0.6	...	45	44	8	0.231
4	70	0.5	0.5	0.4	0.6	...	46	45	9	0.563
5	75	0.5	0.4	0.4	0.6	...	45	45	8	0.606
6	75	0.5	0.5	0.5	0.5	...	45	44	8	0.685
7	75	0.5	0.4	0.5	0.6	...	45	45	8	0.702
8	75	0.5	0.5	0.6	0.5	...	45	45	6	0.712
9	75	0.6	0.5	0.6	0.5	...	44	46	8	0.719
...	...	...	...	...	...	...	...	...	...	...
50	75	0.5	0.5	0.4	0.4	...	45	45	7	0.756

selected with a 10% ratio, that is, 5 sets of sample data are selected as the test set while the remaining 45 sets of sample data are used as the training set (Table 3). An important step that we should perform before applying the sample data is normalization. Normalizing the data can significantly increase the speed of network training and avoid large output value errors due to excessive data fluctuations. Normalization is the process of converting raw sample data into decimal values between 0 and 1. This process is performed in a specific way [22]. Once the normalized data is used as input data, its output cannot be used as the desired prediction data. Therefore, in order to obtain the desired predicted values, we have to perform the inverse normalization process. In this paper, we will use MATLAB software to implement the normalization and denormalization process. The sample data is normalized using MATLAB software and the normalized sample data is stored between 0 and 1. The normalization process is completed using the mapminmax function, and the program is written as P = mapminmax (X, TMIN, TMAX), where X represents the sample data, TMIN represents the minimum value of each row, TMAX represents the maximum value, T represents the normalized data, and P represents the structure stored after normalization. In the MATLAB software environment, we took the following steps to normalize the sample data:

(1) Normalize the sample data using the mapminmax function. The parameters of this function include the input data X, and the minimum value TMIN and maximum value TMAX for each row.

(2) The mapminmax function normalizes the sample data to between 0 and 1.

(3) The normalized data is stored in the structure P.

By performing the above steps, we are able to achieve the normalization of the sample data and store the normalized data between 0 and 1. This processing method can improve the comparability and analyzability of the data.

We used a BP neural network to construct the model and focused on the selection of functions in the design process. For the transfer function, we used Sigmoid function, and there are two commonly used Sigmoid functions: tansig function and logsig function. Since our input data is normalized and the data values are between [0,1], we chose the logsig function as the hidden layer transfer function. For the training function, we provide several learning algorithms in MATLAB: variable learning rate gradient descent algorithm (traingda), momentum gradient descent algorithm (trainm), gradient descent algorithm (traingd), and variable learning rate momentum gradient descent algorithm

Table 4. Parameter settings for BP neural network.

Typology	Parameters	Parameter value
BP neural network	Number of training samples	38
	Number of test samples	5
	Maximum number of training sessions	10000
	Number of nodes in the hidden layer	17
	tolerance (allowed error)	10^{-2}

(traingdx) [26]. In this paper, traingda is chosen as the gradient descent training function for adaptive lrBP. In addition, by training the research model several times and comparing the results of several simulations, we finally chose the clearngdm function as the learning function. The performance function chosen in this paper is mse, and we set the training objective to 0.01 and the number of training times to 10000 times. A summary of the relevant descriptions of the parameter settings was shown in Table 4. Considering that individual BP networks are more sensitive to the selection of baseline and threshold values, this paper decides to use genetic algorithm for the optimization of BP neural networks. Genetic algorithm has the performance of global search and can calculate the value of fitness function to optimize the weights and thresholds of BP network. The optimized weights and thresholds will be used as the initial weights and thresholds of the BP network, aiming to improve the accuracy and stability of prediction. During evolution, if an individual is highly adapted to its environment, the probability that it will pass on the corresponding function to the next generation will increase significantly. Conversely, if the individual is not well adapted to its environment, the probability that the function will be copied to the next generation will be significantly reduced. This is the result of the mechanism of natural selection, which tends to retain traits that help individuals survive and reproduce. During natural evolution, recombination of two pairs of chromosomes can produce a new chromosome. This recombination involves recombining certain genes of the chromosomes in some way to produce a new individual. This method is also consistent with the principle of evolution, which is to pass on the good genes from both parents to their offspring through continuous evolution. In the process of evolution, we do not want too many good genes to be destroyed, because these genes could potentially lead to the creation of a new, better individual. In the process of biological evolution, errors due to certain factors may occur, and these errors may further trigger changes in biological characteristics, resulting in the creation of new biological characteristics. Although the likelihood of this happening is relatively small, it still has a role to play in individual change and should therefore not be ignored. Mutation is the process by which certain genes on two different chromosomes are replaced to form a new individual, and it is the most important and indispensable auxiliary method to produce a new individual. When designing the mutation operator, two issues need to be considered: the method of replacing gene values and the location of the mutation point.In this paper, we chose to use the fitness subfunction fitness.m for the independent variable screening optimization analysis. gabp Eval.m and gadecod.m involved in this paper are the fitness and coding subfunctions used for weight and threshold correction and optimization. There is no fixed learning rate due to the use of genetic algorithm to optimize the BP neural network where the learning rate is variable. The population size is set to 20 and the population evolution frequency is set to 50 times to ensure that the optimal result is found. The values of crossover probability and mutation probability are determined by comparing the results of several experiments. The contents of the relevant parameter settings are shown in Table 5.

Table 5. Relevant parameter settings of genetic algorithm.

Typology	Parameters	Parameter value
Genetic algorithm	Maximum number of iterations	50
	population size	20
	crossover probability	0.3
	probability of mutation	0.1

Results and discussion

After in-depth analysis, we have successfully determined the parameters and functions to initialize the network. After this, we imported 40 sets of test data out of 50 sets of sample data into a predefined grid for training. After training in this grid, we obtained the results as shown in Figures 4, 5, and 6. According to Figure 4, we can observe a gradual decrease in the network error value. After 8 iterative runs, the error value reaches the lowest point and stabilizes.

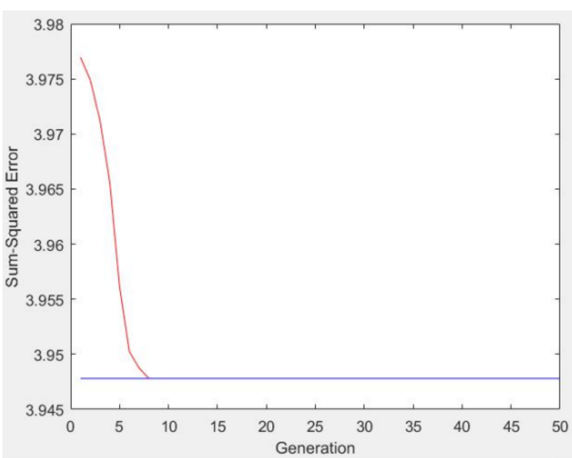

Figure 4. Error sum of squares curve.

Meanwhile, Figure 5 shows that the network fitness value reaches the highest point and remains stable. In Figure 6, the network converges after 121 times of training, which indicates that the performance of our constructed BP network has reached the expected level. After the BP network reached the desired level, we imported sample data from the test set to this network model for testing. After 10 valid experiments, we calculated the average relative error and organized the test results into Table 6.

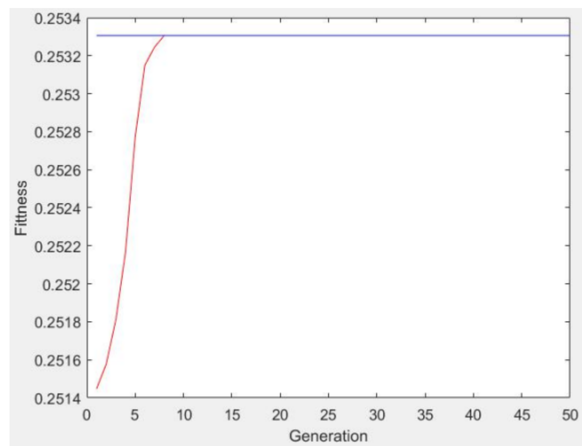

Figure 5. Adaptation curve.

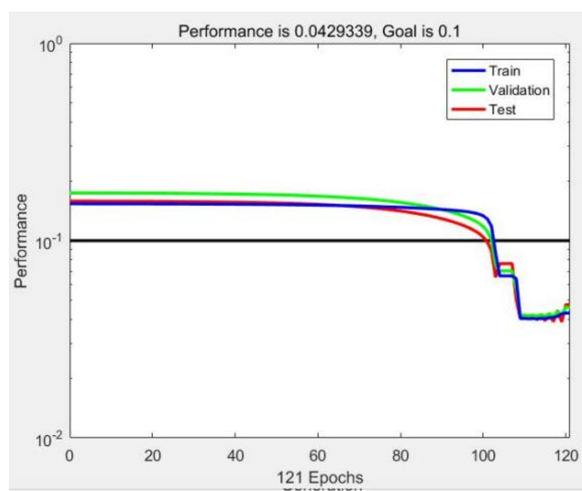

Figure 6. Performance curve.

After standardization, the value of score Q between 0 and 0.5 corresponds to superior

Table 6. Mean relative error.

Sample No.	Hierarchy	Desired output	Actual output	Average relative error (%)	Blade structural grade
39	moderate	0.7930	0.7695	3.0565	moderate
40	moderate	0.7860	0.7763	1.2584	moderate
41	Highest quality	0.8050	0.8449	4.8575	highest quality
42	moderate	0.7560	0.7645	1.0845	moderate
43	moderate	0.7570	0.7449	1.4523	moderate

smoke; between 0.5 and 0.8 corresponds to medium smoke; between 0.8 and 1 corresponds to inferior smoke. For superior cigarettes, the proportion of pre-roasting blade structure larger than 25.4 mm x 25.4 mm should be greater than or equal to 47%, and the proportion larger than 12.7 mm x 12.7 mm should be greater than or equal to 83%. For medium cigarettes, the proportion of pre-roasting blade structure that is greater than 25.4 mm x 25.4 mm should be greater than or equal to 45%, and the proportion that is greater than 12.7 mm x 12.7 mm should be greater than or equal to 81%. For lower grade tobacco, the proportion of pre-roasting blade structure that is larger than 25.4 mm x 25.4 mm should be greater than or equal to 41%, and the proportion that is larger than 12.7 mm x 12.7 mm should be greater than or equal to 77%. In addition, for top grade, medium grade and lower grade cigarettes, the proportion of pre-roasting blade structure that is greater than 6.35 mm x 6.35 mm should be greater than or equal to 94%, the proportion that is greater than 2.36 mm x 2.36 mm should be greater than or equal to 99.2%, and the proportion that is greater than 2.36 mm x 2.36 mm should be less than 0.8%. After 10 valid experiments, we obtained the predicted results. The maximum relative error between the actual output and the expected value on the prediction of the composite influence factor score was 4.96%. The relative errors derived from the five sets of test data were all controlled within 5%. In addition, the quality grade of tobacco leaf homogenization processing predicted by the evaluation model is basically consistent with the quality grade of tobacco leaf homogenization processing to which the original sample belongs. The prediction effect has reached 100% correct rate, which verifies the effectiveness of the evaluation model.

Conclusion

In this study, through in-depth analysis of the impact of leaf beating and re-grilling process on the processing quality of tobacco leaf homogenization, a comprehensive evaluation model was successfully established, and the construction and optimization of the model was carried out by using a combination of BP neural network and genetic algorithm. The results of the study show that the key parameters such as temperature, humidity and time in the leaf beating and roasting process have a significant effect on the processing quality of tobacco leaf homogenization. After several experiments, the established evaluation model can effectively predict the processing quality of tobacco leaf blade homogenization and control the prediction error within 5%, showing good accuracy and stability. This result not only provides a new analytical tool for the field of tobacco processing, but also provides a scientific basis for optimizing the parameters of the leaf beating and roasting process, which can help to improve the quality of tobacco processing and thus promote the sustainable development of the tobacco industry.

Acknowledgments

This study was supported by Hongyun Honghe tobacco (Group) Co., Ltd. Science and Technology Plan Project "Research and application of stacking of high-end cigarette raw materials of group Yunyan brand" (HYHH2019YL04).

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