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The Tobacco Leaf Redrying Process Parameter Optimization Based on IPSO Hybrid Adaptive Penalty Function

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Abstract: In the tobacco redrying process, process parameter settings are greatly influenced by ambient temperature and humidity, and the moisture content of the tobacco leaf. In the face of complex and variable tobacco leaf characteristics, it is difficult to accurately adapt the process parameters to fluctuations in the incoming material characteristics by manual experience alone. Therefore, an improved optimization method combining an improved particle swarm optimization algorithm (IPSO) and an adaptive penalty function is proposed, which can adaptively recommend the best combination of process parameters according to the dynamic incoming characteristics of the tobacco leaf, to reduce the deviation in the outlet moisture and temperature of the roaster under different processing standards of the tobacco leaf. Firstly, the Radial Basis Function (RBF) Neural Network is used to fit the relationship between process parameters and roaster exit moisture content and temperature. Then, taking the standard tobacco leaf redrying export quality as the optimization goal, the optimization algorithm is used to search for the optimal solution. From the high-dimensional nature of the process operating conditions, the difficulty of this study lies in searching for the optimal solution under complex nonlinear constraints of multiple processes. To improve the convergence speed and accuracy of the searching algorithm, the position update method of the particle swarm optimization algorithm is improved, and the adaptive penalty function is combined to search for the optimal global solution to the optimization problem. Redrying experiments are conducted using the method proposed in this paper. Compared with the manual regulation of outlet moisture and temperature, the fluctuation range values are reduced by 7.5% and 11.8%, respectively, which has good application prospects and promotion value.

Keywords: RBF neural network; IPSO; adaptive penalty function; roaster exit moisture content and temperature

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1. Introduction

The tobacco redrying process is the last process before shredding and a vital part of producing high-quality tobacco. The main objective is to achieve the standard export moisture and temperature after the redrying process. Suitable redrying process parameters can effectively prevent late mold and provide the necessary conditions for long-term storage and mellowing of the tobacco leaf.

In actual production, the values of the initial process parameters for the tobacco leaf with different incoming characteristics are usually set by technicians based on experience. As the tobacco redrying process is a nonlinear, strongly coupled, and complex system, it is difficult for even experienced staff to precisely regulate the process parameters according to the incoming characteristics of the tobacco leaf. As a result, tobacco redrying usually works at low efficiency. Therefore, providing a theoretical research method for a parameter regulation scheme for the tobacco redrying process is important. The scheme can provide stable tobacco redrying process parameters in response to the changes in dynamic incoming characteristics of tobacco leaves, thus solving the problems of imprecise regulation and low production efficiency.

In the tobacco leaf redrying process, the moisture content and temperature of the tobacco leaf are usually used as measuring standards for the quality of redrying [1]. To obtain the required product quality, some scholars have investigated process control by combining the mechanistic models of industrial production. Pakowsk et al. [2] set the process variables by establishing theoretical models based on the heat and mass balance of the material in the drying process. Budman et al. [3] investigated the effect of different process parameter settings on the product quality of alfalfa at different inlet moisture contents, ambient temperatures, and humidities by establishing dynamic heat balance, material balance, and heat and humidity transfer equations. As tobacco redrying involves complex processes such as heat and mass transfer, gnostic mechanistic modeling is complicated, and artificial intelligence technology provides an effective way to model complex processes and process technology control [4–8].

Currently, to obtain the product quality that meets the demand, some studies have sought the optimal process parameters under the process parameter constraints [9,10]. The method is usually divided into two steps. First, a nonlinear relationship between process parameters and process criteria is established to determine the mathematical optimization model of the objective function. Then, the mathematical optimization model is used with an intelligent algorithm to search for the optimal solution of the process parameters. The commonly used intelligent algorithms include the genetic algorithm (GA) [11], particle swarm optimization (PSO) algorithm [12], and differential evolution algorithm (DE) [13]. Zhao et al. [14] used a combination of the Artificial Neural Network (ANN) and GA to provide process parameter values for header mining using coal production per minute as the optimization objective. The coal yield obtained by manual control of process parameters was compared with the process parameters provided by the optimization algorithm. The results showed that using the process parameters recommended by the optimization algorithm can increase efficiency and improve the automation of the mining work. Babu et al. [15] used the Back Propagation (BP) neural network combined with GA to optimize the process parameters of aluminum alloy. The experiments showed that the resulting combination of process parameters was better than the results of orthogonalization. The above studies used the historical data of industrial production to learn the relationship between process parameters and product quality autonomously through neural networks, solving the problem of the difficulty in establishing complex process mechanism models. Under different processing standards of tobacco redrying quality, it is still difficult to precisely regulate the process parameters according to the dynamic incoming characteristics of the tobacco leaf. Therefore, this paper adopts a data-driven approach to establish the complex relationship between process parameters and tobacco regrind quality, then combines the optimization algorithm to dynamically recommend the optimal combination of process parameters according to the variation in incoming characteristics of the tobacco leaf.

To adapt the provided optimization scheme to the dynamic incoming variation in tobacco leaves, this paper is based on the historical data of a tobacco factory in Yunnan Province, and the quality of tobacco leaves after redrying is the optimization target. First, the Radial Basis Function (RBF) neural network is used to fit the relationship between process parameters and tobacco leaf exit temperature and moisture content, and then it is combined with the improved particle swarm optimization (IPSO) algorithm searching for the optimal global solution to the optimization problem [16]. As the tobacco quality is affected by the high-dimensional process parameters, a change in one process parameter may lead to a difference in the tobacco redrying exit moisture and temperature during the solution update of the optimization algorithm. In addition, it is difficult to fully utilize the information of infeasible solutions. Therefore, this paper uses the improved particle swarm optimization algorithm combined with the adaptive penalty function (IPSOAPF), adaptively adjusts the constraint violation degree of infeasible particles, and speeds up the convergence speed of the algorithm [17,18]. Using the optimization model proposed in this paper to carry out tobacco redrying experiments, the results show that the method can be used to recommend the optimal process parameters for different incoming tobacco leaves adaptively, solving the problem of the initial parameters having difficulty adjusting the redrying process and improving the production efficiency.

2. Process Description

The workflow of the tobacco griller is shown in Figure 1. The tobacco leaves are well mixed by a bin feeder and fed evenly into the griller by a conveyor belt through vibration under an electronic flow scale monitoring. Based on the physical properties of the tobacco leaf, the redrying process can be divided into three stages [19], the drying section, the cooling section, and the rewetting section. The drying section consists of six zones, and the hot air temperature in drying zones one to six directly contacts the tobacco leaf and transfers heat to them by convection. The higher the hot air temperature in the drying zone, the more moisture the air can hold and the faster the moisture diffusion in the tobacco leaf. The cooling area is after the drying zone, and the purpose is to lower the temperature of the tobacco under the cooling airflow to meet the process requirements of the rewetting section. The rewetting area is divided into four zones. The tobacco leaf in the first two stages is heated and humidified by adjusting the saturated water vapor temperature in each zone of the rewetting, so the tobacco leaf reaches the standard export moisture content and temperature. In the drying and rewetting areas, there is a separate set of tide discharge systems, which takes away the moisture in the re-expansion oven through the tide discharge fan.

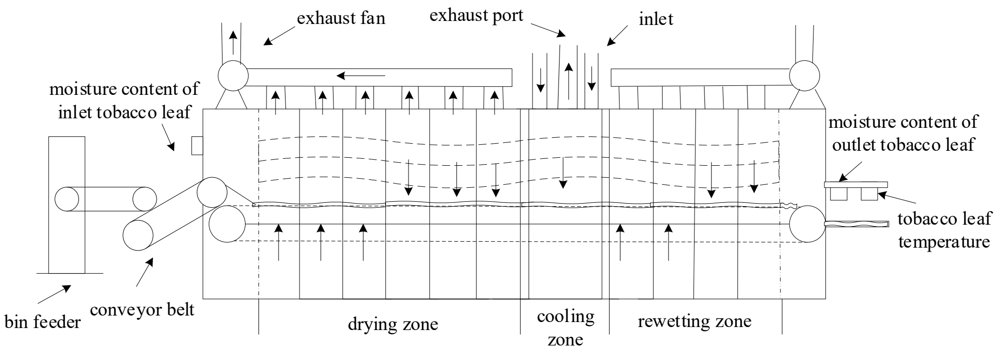

Figure 1. Schematic diagram of tobacco leaf redrying process.

Before the tobacco leaf enters the redrying process, a moisture detector can effectively detect the moisture and temperature at the entrance of the roaster. The quality of the tobacco leaf after redrying depends on the values of the process parameters. The proper tobacco leaf export moisture and temperature guarantee the subsequent processing and storage of the tobacco leaf.

Upon investigation, in most of the processing plants in Yunnan, the redrying process parameters are mainly adjusted manually based on production experience. According to the manually adjusted process parameters, the system then uses PID for feedback adjustment internally [20]. For the situation where the set target value deviates from the real-time detection value, the feedback adjustment mechanism of PID control is laggy and poor in time [21]. In addition, factories have a high turnover and few experienced technical workers. For tobacco leaves with varying characteristics of incoming material, the control of process parameters is intensively subjective, and the quality of tobacco leaf redrying cannot be guaranteed.

Generally, the tobacco grades processed in the factory are top-grade and medium-grade. According to the redrying tobacco standards, the export moisture is usually controlled between 11.5% and 13.0%, and the export temperature of roaster flake tobacco is generally maintained at 45 °C–55 °C. As different customers have different quality requirements for grilled tobacco and the incoming characteristics of different batches of tobacco vary, it is difficult to establish a predictive and accurate multi-output model based on the physical properties of the tobacco leaf.

Due to the strong coupling and complexity of the tobacco redrying process compared with other procedures, it is essential to use deep learning combined with intelligent algorithms to adaptively select the best process parameters for different incoming characteristics of tobacco leaves. To obtain a stable quality of tobacco leaves and reduce the dependence of manual control on the parameters of the redrying machine, it is necessary to use the method of deep learning and intelligent algorithms to optimize the adjustable parameters in the tobacco leaf redrying process, to provide initial parameter recipes for the redrying tobacco production.

3. Mathematical Model for Optimization of Process Parameters

The optimization of tobacco redrying process parameters is based on the constraint of the historical process parameters range and customer-required tobacco quality standards as the target. A mathematical model combined with an optimization algorithm adaptively recommends the initial process parameters for tobacco redrying based on the incoming characteristics of the tobacco leaf. This section specifies the optimization objectives and solutions.

3.1. Selection of the Decision Variables

In the redrying process, to reduce the complexity of process parameter control in the redrying process, some process variables are usually set to be controlled automatically by the upper-class computer, and the critical process parameters are manually regulated to ensure the export quality of tobacco redrying. Combined with the analysis of the redrying process, the critical process parameters that affect the export quality of tobacco redrying can be defined as:

$$x = [r_k, \mathrm{g}, z_m]_{1\times 11} \tag{1}$$

where x is the solution to the optimization problem, $r_k(k = 1, 2, \ldots, 6)$ denotes the temperature of drying zone one to zone six, g denotes the temperature of the leaf roasting and cooling zone, and $z_m(m = 1, 2, \ldots, 4)$ denotes the temperature of moisture regaining zones one to four. Compared with the traditional manual experience setting of process parameters, this paper can seek the best combination of process parameters adaptively according to the tobacco leaf with different incoming characteristics, improve the efficiency of tobacco processing, and ensure the export quality of tobacco redrying.

3.2. Objective Function

As different customers have different standards for tobacco processing requirements, the value of the fitness function will change with different processing ranges. Within the process parameter constraint range, the smaller the absolute value of the difference between the predicted value and the target value, the closer the process parameter can be to the customer processing requirements. The objective function of this paper can be defined as:

$$\begin{gathered} \mathrm{minf}(x_i) = |y_1(x_i) - tar_1| + |y_2(x_i) - tar_2| \\ s.t.\begin{cases} |y_1(x_i) - tar_1| \leq 0.5 \\ |y_2(x_i) - tar_2| \leq 1 \end{cases} \end{gathered} \tag{2}$$

where x_i denotes the position of the i-th particle; y_1 and y_2 denote the moisture and temperature predicted by the neural network, respectively. As the values of export moisture and temperature of tobacco redrying have a greater impact on the subsequent processing of tobacco, the fluctuation range values of export moisture and temperature are controlled within (0, 1) and (0, 2), respectively. Among them, tar_1 and tar_2 denote the target values of tobacco export moisture content and temperature, respectively. As the criteria for tobacco export moisture and temperature are a range of values, the specific values can be selected according to the following definitions.

$$tar_1 = \frac{(w_{a,\min} + w_{a,\max})}{2} \tag{3}$$

$$tar_2 = \frac{(t_{a,\min} + t_{a,\max})}{2} \tag{4}$$

3.3. Constraints

A predictive model connecting decision variables and process quality is required for process manipulation optimization [22]. The decision variables are defined in this paper as process variables in the tobacco redrying process, and the range can be determined based on historical process parameters. In this paper, the constraints of the optimization problem and the range of process parameters can be expressed as:

$$\begin{cases} w_{a,\min} \leq w_a \leq w_{a,\max} \\ t_{a,\min} \leq t_a \leq t_{a,\max} \\ r_{k,\min} \leq r_k \leq r_{k,\max} \\ g_{\min} \leq g \leq g_{\max} \\ z_{m,\min} \leq z_m \leq z_{m,\max} \end{cases} \tag{5}$$

where w_a and t_a denote the moisture content and temperature of the tobacco leaf, respectively, and the range size is determined according to the customer's processing requirements. $t_{a,\min}$ and $w_{a,\min}$ denote the minimum outlet temperature and moisture, respectively. $t_{a,\max}$ and $w_{a,\max}$ denote the maximum temperature and moisture at the outlet of the tobacco leaf redrying exit, respectively. r_k, g, and z_m denote the decision variables of the drying zone, cooling zone, and moisturizing zone in the redrying process, respectively. The range of decision variables $[r_{k,\min}, r_{k,\max}]$, $[g_{\min}, g_{\max}]$, and $[z_{m,\min}, z_{m,\max}]$ is determined by historical process parameters, where the values of k and m are the same as in Equation (1).

3.4. Unconstrained Optimization of Process Parameters

The essence of an optimization algorithm is still an unconstrained processing method, and choosing a suitable constraint processing mechanism can effectively improve the convergence speed of the algorithm [23]. The penalty function method is a common constraint processing method widely used due to its simplicity [24].

To speed up the convergence of the optimization algorithm, this paper uses the penalty function method to transform the constrained optimization problem into an unconstrained optimization problem, constructs the penalty term by constructing the individual constraint violation degree, and increases the penalty on the infeasible particles in the population to reduce the probability of being selected for recombination, improving the proportion of feasible solutions. To improve the robustness of the algorithm, the objective function and the penalty function are normalized. The individual normalized objective function $f(x)_{norm}$ and penalty function $g(x)_{norm}$ are defined as:

$$f(x)_{norm} = \frac{f(x) - f_{\min}}{f_{\max} - f_{\min}} \tag{6}$$

$$G(x)_{norm} = \frac{G(x)}{G_{\max}} \tag{7}$$

$$s.t. G(x) = \max(0, |y_1(x) - Tar_1| - 0.5) + \max(0, |y_2(x) - Tar_2| - 1)$$

where $f_{\min}$ and $f_{\max}$ are the maximum and minimum values of the particle objective function in the population, respectively; $G_{\max}$ is the maximum value of the constraint violation in the population.

To measure the degree of deviation of individuals from the target value, this paper introduces the distance value $N(x)$, given by Equation (8). When there are no feasible individuals in the population, the distance value of individual particles is the constraint violation value of the target. In contrast, a smaller constraint violation value is beneficial to guide the particles closer to the feasible individuals. If there are only some possible individuals in the population, both the value of the objective function and the degree of constraint violation are considered.

$$N(x) = \begin{cases} G(x)_{norm} & \text{if } \mathrm{r}_f = 0 \\ \sqrt{f(x)_{norm}{}^2 + G(x)_{norm}{}^2} & \text{otherwise} \end{cases} \tag{8}$$

As the above distance values are the values after normalization, the increased penalty value for infeasible individuals is small, resulting in little change in the value of the fitness function. Therefore, a double penalty method is proposed for infeasible individuals. This method can dynamically adjust the size of the penalty value according to the proportion of particles in the feasible solution. By mining the information of infeasible solutions of better quality in the population, the particles are brought closer to the possible solutions. The adaptive penalty function of this paper can be defined as:

$$\begin{gathered} P(x) = (1 - r_f)X(x) + r_f Y(x) \\ s.t. \\ X(x) = \begin{cases} 0 & r_f = 0 \\ \mathrm{G(x)}_{norm} & \text{otherwise} \end{cases} \\ Y(x) = \begin{cases} 0 & \text{for feasible individual} \\ f(x)_{norm} & \text{for infeasible individual} \end{cases} \end{gathered} \tag{9}$$

where r_f denotes the proportion of feasible particles. The penalty function given by Equation (9) shows that for the first penalty term, with fewer feasible solutions, individuals with more extensive constraint violations are penalized more than those with more minor constraint violations. Similarly, for the second penalty term, in the case of more feasible solutions, individuals with larger normalized fitness functions will be punished more than those with smaller ones. The fitness function in this paper can be defined as:

$$\begin{gathered} \min : F(x) = N(x) + P(x) \\ \text{find} : x = [r_k, \mathrm{g}, z_m]_{1\times 11} \end{gathered} \tag{10}$$

4. Data and Methods

4.1. Dataset Introduction and Processing

The data used in this paper are from a tobacco factory in Yunnan Province from 1 January 2021 to 30 December 2021, with a sampling frequency of 15 Hz. In the actual tobacco redrying production, to ensure the quality of tobacco redrying, the roaster needs to be preheated in advance before the tobacco leaf can enter the roaster. In addition, there will be an unstable inlet flow for a while when the tobacco leaf is entering the redrying machine, but the PLC is still collecting data, and the data collected at this moment are abnormal working data. It is necessary to clean the collected data in advance and select the data of regular operation of the roaster, and the specific parameter screening range can be determined according to the range of historical experience process parameters.

Controlling the tobacco export moisture and temperature within the set range is the purpose of the redrying process, and the plant technicians maintain the tobacco redrying export quality by operating the critical process variables defined in Equation (1). The reasonable exploration of other factors affecting the process variables of tobacco redrying operation is essential to improve the quality of tobacco redrying. Generally, many factors affect the setting of process parameters for tobacco leaf drying. However, tobacco leaf environmental temperature, humidity, and moisture content are key factors [25]. According to the survey, tobacco factories produce in fixed seasons each year, such as January–April and October–December. By analyzing the historical ambient temperature and humidity data of the production plant in Yunnan Province in 2021, as shown in Figure 2, the ambient temperature and humidity are constantly changing every day, and the changes in ambient temperature and humidity in a month are more than 10 and 20, respectively. In addition to seasonal changes that can cause changes in ambient temperature and humidity, once the baking machine is started, it will carry out 24 h uninterrupted production, and the temperature difference between day and night will also lead to a significant change in ambient temperature and humidity. When the room's humidity is high or the temperature is too high, the moisture content and temperature of the tobacco leaf will also change. To achieve the standard export moisture and temperature, the process parameters for conducting tobacco drying should also be adjusted. The magnitude of ambient temperature and humidity will directly affect the setting of process parameters by influencing the physical characteristics of the tobacco leaf, such as moisture and heat absorption. Therefore, this paper considers ambient temperature, humidity, and tobacco leaf inlet moisture content as the key factors affecting the regulation of process parameters.

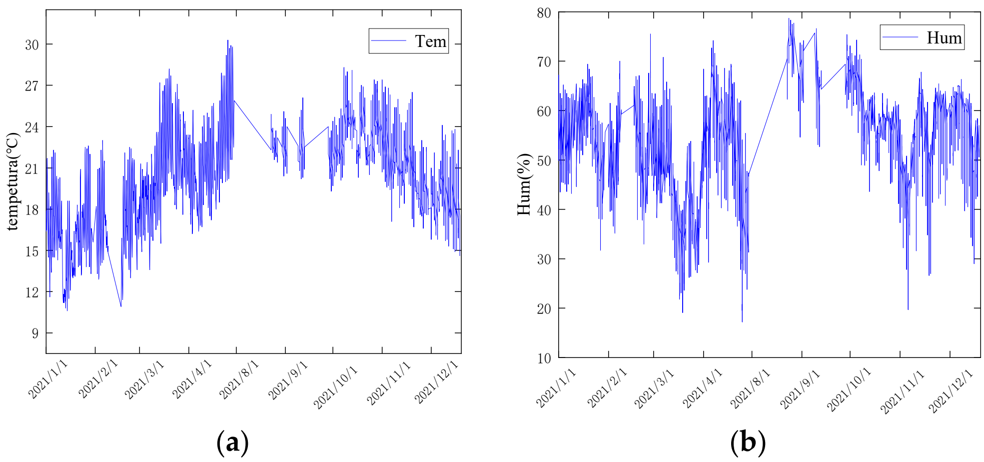

Figure 2. Changes in ambient temperature and humidity: (**a**) indoor temperature; (**b**) indoor humidity.

4.2. Methods

This paper proposes the RBF neural network hybrid IPSOAPF parameter optimization method, and the specific flow chart can be seen in Figure 3. First, the RBF neural network fits the nonlinear relationship between the redrying process parameters and the tobacco quality, and the well-trained tobacco leaf quality prediction model is saved. Then, IPSOAPF is used to calculate the fitness function and output the process parameters corresponding to the minimum value of the fitness function. As the relationship between process parameters and the quality of tobacco is obtained through neural network training, it is difficult to establish the relationship between the neural network and fitness function. In addition, the fitness function may be multiple locally optimal nonconvex functions [26]. Finding the process parameter combination that minimizes the fitness function using the traditional gradient descent method is difficult. PSO is a method with high search efficiency and robustness [27], but it is easy to fall into the optimal local problem in the later stages of the search [28]. To improve the degree of combining the update process of the penalty function with that of the PSO algorithm, the IPSO is used to search for the optimal global solution to the optimization problem. The following subsections describe in detail the implementation details of each process.

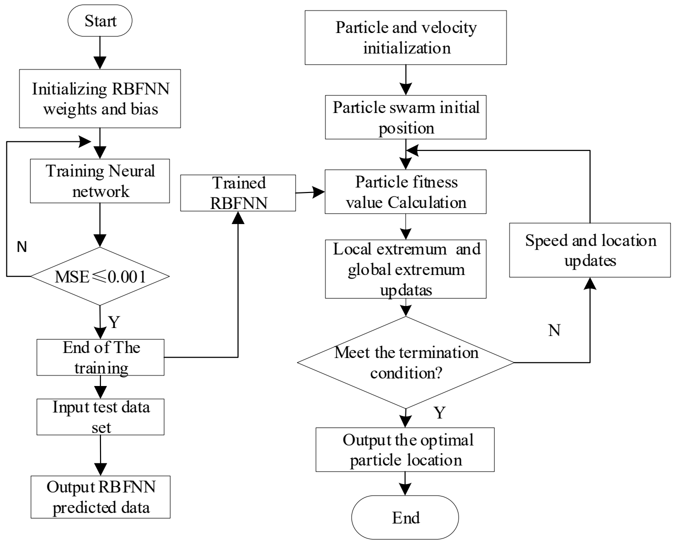

Figure 3. Flow chart of RBF neural-network-improved PSO hybrid adaptive penalty function.

4.3. RBF Neural Network

The RBF neural network is proposed by Broomhead [29]. It has been widely used for modelling and prediction because of its simple network structure and fast learning speed [30]. The network model is based on a three-layer topology, as shown in Figure 4. The number of neurons in the input layer of the RBF neural network is determined by the dimensionality of the operational variables affecting the export quality of tobacco redrying. The hidden-layer neurons are used to increase the nonlinearity of the model [31]. The process parameters are transferred from the input layer to the hidden layer. The data are mapped into a high-dimensional linear separable space by radial basis functions in the hidden-layer neurons. The radial basis function in the hidden layer uses the Gaussian function, and the closer the input vector is to the center vector of the neuron in the hidden layer, the larger the output value of the function. The output of the t-th neuron in the hidden layer can be expressed as:

$$\mathrm{h}_i = \exp\left(\frac{\|\xi - c_i\|}{2{\sigma_i}^2}\right) i = 1, 2, \ldots, n \tag{11}$$

$$\xi = [w_a, t, h, r_k, g, z_m]^T{}_{1\times 14} \tag{12}$$

where n denotes the number of hidden nodes; ξ denotes the input vector of the RBF neural network; w_a, t, and h denote the moisture content of the tobacco leaf, ambient temperature, and ambient humidity, respectively; r_k, g, and z_m denote the same as in Equation (1); c_i and σ_i denote the hyperparameters of the t-th neuron in the hidden layer, respectively. h_i denotes the Euclidean distance between the input vector and the t-th hidden neuron and the center value.

The neuron's output is obtained by linearly combining the outputs of the hidden nodes [32,33], and it is formulated as:

$$y_j = \sum_{i=1}^{n} w_{ij} h_i i = 1, 2, \ldots, n,\ j = 1, 2 \tag{13}$$

where y_1 and y_2 denote the moisture and temperature predicted by the neural network, respectively. w_{ij} denotes the connection weight between the t-th neuron of the hidden layer and the j-th output neuron.

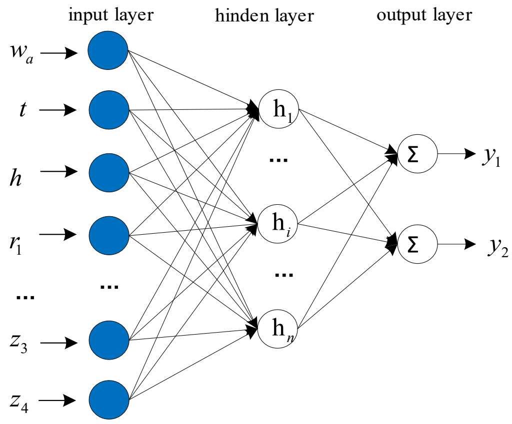

Figure 4. Architecture of RBF neural network to predict tobacco moisture content and temperature.

The collected historical dataset is trained by the RBF neural network to establish the relationship between the process parameters and the export quality of tobacco redrying. The RBF hyperparameters can be continuously updated using the gradient descent method, and the Mean Squared Error (MSE) is used to measure the prediction effect of the model, as in Equation (14). The target value of MSE is set to 0.01, and if MSE < 0.01, the RBF hyperparameters are updated and retrained. Otherwise, the iteration ends and the RBF hyperparameters will be saved. The model satisfying the requirements can be used to predict tobacco redrying export moisture and temperature.

$$MSE = \frac{1}{n}\left(\sum_{i=1}^{n}(y_1(x_i) - n(x_i))^2 + \sum_{i=1}^{n}(y_2(x_i) - m(x_i))^2\right) \tag{14}$$

where n denotes the number of training samples of the neural network. $y_1(x_i)$ and $y_2(x_i)$ denote the predicted values of moisture and temperature of the tobacco leaf, respectively. $n(x_i)$ and $m(x_i)$ denote the actual moisture and temperature of the tobacco leaf, respectively. x_i denotes the t-th sample.

4.4. Improved PSO Algorithm (IPSO)

The optimal solution to the process parameters can be obtained by combining the tobacco quality prediction model with the optimization algorithm that obtains optimal solutions. To improve the convergence speed of the penalty function combined with the update process of the particles, the IPSO algorithm is used to search for the optimal global solution, and the specific implementation steps are shown below:

(1) Initialize particles

In this experiment, the size of the population is set to 50, and the number of process parameters determines the particle dimension. The method of initial position production of particles is defined by Equation (16) to increase the randomness of the particle distribution. The initial position component of each particle can be determined by the constraints of the process parameters in Equation (2). The initial position component x and velocity v range of the particle can be expressed as follows:

$$v_j \in [v_{\min}, v_{\max}] j = 1, 2, \ldots, 50 \tag{15}$$

$$\begin{cases} x_{j,r1}(\mathrm{r}_k) = t_{a,\min} + r_0(t_{a,\max} - t_{a,\min}) \\ x_j(g) = g_{\min} + r_0(g_{\max} - g_{\min}) \\ x_{j,r2}(z_m) = z_{m,\min} + r_0(z_{m,\max} - z_{m,\min}) \end{cases} \tag{16}$$

where j denotes the size of the population, k and m denote the same values as in Equation (1), and r_0 denotes a random number in [0, 1].

According to Equation (1), there are 11 key parameters affecting tobacco quality, and the number of process variables determines the particle's dimension, so the particle's dimension is 11. The position and velocity of the j-th particle can be expressed as $x_j = \left(x_{j,1}, x_{j,2}, \ldots, x_{j11}\right)$ and $v_j = \left(v_{j,1}, v_{j,2}, \ldots, v_{j,11}\right)$, respectively. The position of each particle in the candidate solution represents the possible optimal solution for the process parameters. The particle position dimension component can be randomly initialized according to Equation (16). Then, the position and velocity of the particle after initialization can be expressed as follows:

$$\begin{cases} x_j(0) = \left(x_{j,r1}, x_{j,g}, x_{j,r2}\right) \\ v_j(0) = (v_{\min} + r_0(v_{\max} - v_{\min})) \end{cases} \tag{17}$$

(2) Fitness function calculation

The initialized particle position vectors are put into the trained RBF model to calculate the moisture content y_1 and temperature y_2, and the fitness value is calculated according to Equation (10). After the t-th iteration of the particle, the extreme individual value p_{jbest} and the global best position g_{jbest} of the whole population are recorded, where:

$$p_{jbest}(t) = [p_{j,1}(t), p_{j,2}(t), \ldots, p_{j,11}(t)] \tag{18}$$

$$g_{best}(t) = [g_1(t), g_2(t), \ldots, g_{11}(t)] \tag{19}$$

(3) Particle velocity and position update

In the traditional particle swarm search algorithm, the particle velocity and position can be updated according to the following equation.

$$\begin{cases} v_j(t+1) = w(t)v_j(t) + c_1 r_1[p_{jbest}(t) - x_j(t)] + c_2 r_2[g_{best}(t) - x_j(t)] \\ s_j(t+1) = s_j(t) + v_j(t+1) \end{cases} \tag{20}$$

where $v_j(t+1)$ and $s_j(t+1)$ denote the velocity and position of the updated particle, respectively; c_1 and c_2 denote the learning factor within [0, 2], respectively, usually $c_1 = c_2$; it is set to 2.0 in this paper. r_1 and r_2 are random numbers uniformly distributed in [0, 1], which is used to increase the randomness of the search. $w(t)$ denotes inertia weight, which adjusts the search space range by controlling the degree of influence of the previous speed on the current speed. The individual optimum and the global optimum are updated by comparing the fitness function values.

$$\begin{cases} p_{jbest}(t+1)\begin{cases} p_{jbest}(t), Fit(p_{jbest}(t+1) \geq F(p_{jbest}(t))) \\ s_j(t+1), \text{ otherwise} \end{cases} \\ g_{best}(t+1) = \min\left[Fit(p_{jbest}(t+1))\right] \end{cases} \tag{21}$$

In the traditional process of inertia weight update, the inertia weights are used to decrease gradually. It cannot make good use of the information of feasible solutions in the population after each iteration in the particle swarm. To improve the degree of combining the penalty function with the update process of particles and accelerate the convergence speed of the optimization algorithm, the position update method of the particles is improved in this paper.

$$s_j(t+1) = s_{j,pbest}(t) + (1 - \gamma_f)(s_{gbest}(t) - s_{j,pbest}(t)) + \lambda_{k+1}\alpha l \tag{22}$$

$$\lambda_{t+1} = \lambda_t \eta \tag{23}$$

where λ_{k+1} denotes the random decay rate of the particle and η represents the random decay factor, set to 0.2 and 0.95, respectively; λ_{t+1} decreases with the increase in iterations. l and γ_f denote the range of process parameters and the proportion of feasible particles, respectively, and α is a random number within (0, 1). In Equation (22), the first term is the position of the local optimum of the particle after the t-th update. The $s_{gbest}(t) - s_{j,pbest}(t)$ in the second term denotes the difference between the optimal position and the optimal local position of the k-th update; it can dynamically update the size of the particles moving toward the optimal solution according to the proportion of feasible particles in the population. The third term can be used to increase the diversity of particle search in the population and improve the convergence accuracy of the algorithm.

(4) Algorithm termination condition judgment

The termination condition of the algorithm is set as 300 iterations. When the set number of iterations is reached, the optimal particle position information corresponding to the adaptation function can be output. If the maximum number of iterations is gone and the value of the process condition that satisfies the constraint is not found, the following methods can be taken to deal with it: a: reinitialize the particle velocity; b: increase the number of iterations, until the optimal feasible solution is found.

5. Results and Discussion

Based on the historical data of the tobacco redrying process in a tobacco factory in Yunnan, the collected historical data are divided into the training set, test set, and prediction set according to the ratio of 7:2:1, and the network error is set to 0.01. The relationship between process parameters and tobacco quality is established by using the RBF neural network, in which the number of hidden-layer neural networks has a significant influence on the prediction effect of the model. It is found that the prediction effect is better when the number of neurons in the hidden layer is 60. The MSE is used to evaluate the model, and the change in MSE during the training process is shown in Figure 5. As shown in the figure, the error of the model eventually oscillates smoothly around 0, indicating that the model has excellent fitting performance and satisfies the set net error value.

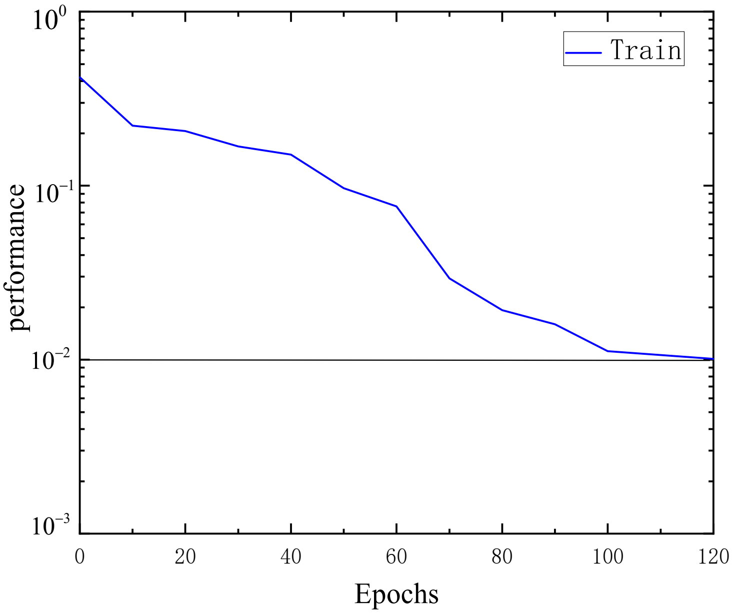

Figure 5. RBF neural network error curve.

As the prediction value significantly influences the optimization search result, the prediction effect of the model should be ensured to meet the prediction accuracy requirement first. To verify the reliability and superiority of the model prediction, the trained RBF neural network model is used to predict the moisture and temperature of tobacco redrying export, and the results are shown in Figure 6. As we can see from the figure, the predicted values are very close to the actual values of the samples. The experiments showed that the relationship between redrying process parameters and tobacco quality could be well fitted using the RBF neural network.

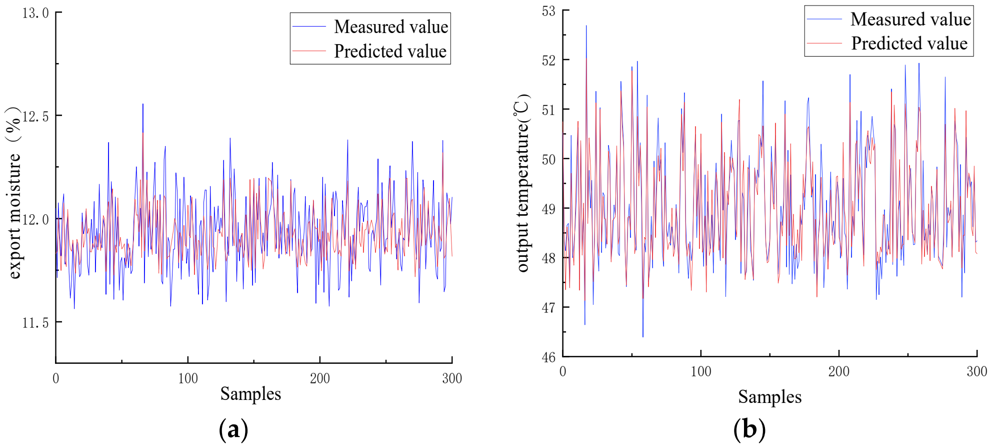

Figure 6. Predicted values of the RBF model on the test set: (**a**) moisture content and (**b**) temperature.

Comparative experiments are conducted to verify the effectiveness of the IPSOAPF method used in this paper. The tobacco quality prediction model satisfying the accuracy requirements is combined with other standard optimization algorithms, such as DE [34], traditional PSO [35], and the IPSO algorithm [36]. The convergence plots of the obtained optimization results are shown in Figure 7. The convergence speed of the IPSOAPF is the fastest. The IPSOAPF algorithm can reach full convergence at 43 steps due to adding a constraint handling mechanism to IPSO, which improves the convergence speed of the algorithm. The convergence speed of the traditional PSO algorithm and DE algorithm is affected by the problem of falling into local optimality.

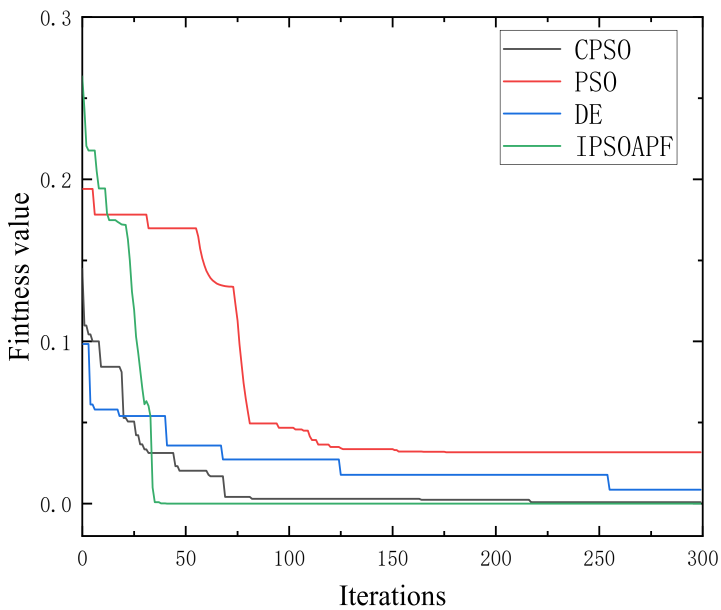

Figure 7. Iterative process of each algorithm.

The trained RBF neural network prediction model is combined with the optimization algorithm for optimization calculation, and the obtained process parameters can be used for redrying tobacco production. The redrying experiment is carried out for a batch of tobacco leaves in April 2022, in which the tobacco leaf grade is medium tobacco, the moisture content is 17.3%, the ambient temperature is 20.9 °C, and the ambient humidity is 63.7%. The target moisture content and temperature values for tobacco redrying export are 11–12.5% and 48 °C–54 °C, respectively. The optimal combination of initial process parameters obtained by the method in this paper is shown in Table 1. It can be seen from the table that the optimized process parameters x_{opt} are between the constrained upper bound x_{up} and the constrained lower bound x_{lb}. This proves the feasibility of the optimization algorithm.

Table 1. The optimal values and boundary values of decision variables.

Operation Variables	r_1	r_2	r_3	r_4	r_5	r_6	g	z_1	z_2	z_3	z_4
x_{lb}	55	60	62	63	62	58	35	53	63	70	70
x_{opt}	64.1	65.3	79.1	65.4	66.3	61.5	37.3	57.8	71.3	73.6	78.5
x_{up}	68	75	85	84	83	68	45	66	75	76	80

The process parameters obtained by the above optimization algorithm are applied to the redrying experiment, using sensors to detect the values of moisture content and temperature at the exit of the roaster in real time over a while, and comparing them with the quality of tobacco obtained by manual adjustment of the process parameters, as shown in Figure 8. The figure shows that the values of moisture content and temperature obtained using the RBF neural network combined with the CPSOAFP method to guide the redrying experiments are less fluctuating than the values of the manual regulation. Based on the range of export moisture content and temperature expected by the customer, it is clear that the values of tobacco export moisture content and temperature obtained using the optimization algorithm should fluctuate around 12.1% and 51 °C, respectively. It can be seen from the figure that the export quality of tobacco leaves after retorting meets the requirements. Figure 8b shows that in the preliminary stage of manual adjustment, moisture content and temperature after redrying could not meet the required range of 11.5–12.5% and 48 °C–54 °C, respectively. After several experiments conducted manually, the moisture and temperature of tobacco leaves exported from the roaster could reach within the standard export range, but the fluctuation range is extensive. The fluctuation ranges of tobacco export moisture and temperature obtained using the method in the paper are 11.7–12.5% and 49.8 °C–51.5 °C, respectively, which are 7.5% and 11.8% smaller than the fluctuation range values of manual regulation, respectively, and improved the stability of tobacco redrying export quality.

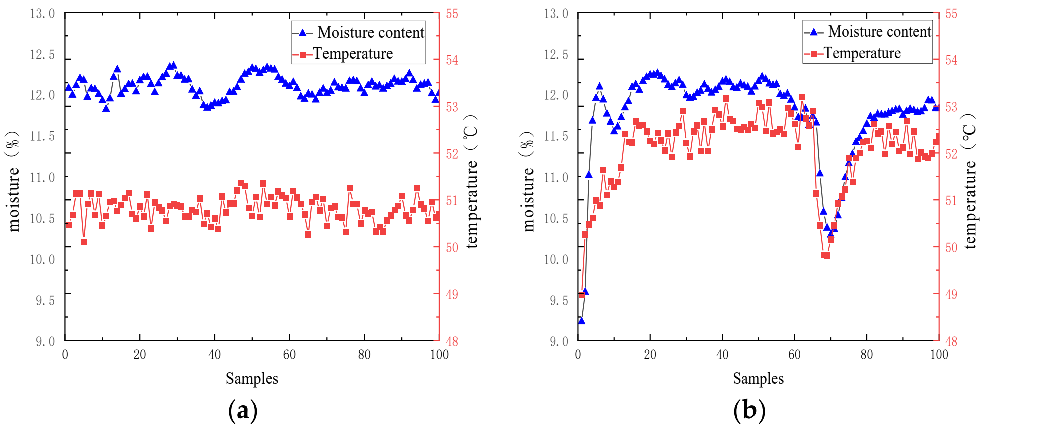

Figure 8. Moisture and temperature at the outlet of the oven: (**a**) Optimization algorithm; (**b**) manual control.

From the experiments, it can be seen that the values of moisture and temperature at the exit of tobacco redrying fluctuate within a certain range, which is because the values of critical factors affecting the quality of tobacco redrying, such as the moisture content at the entrance of tobacco, are not stable. In addition, the size of the tobacco leaf fragmentation rate, ambient temperature, and humidity also affect the drying rate and water absorption rate of the tobacco leaf during the redrying process. As the physical properties of tobacco leaves of the same grade do not change much and the ambient temperature and humidity change slowly, using the same process parameters for process control, the tobacco reheating moisture and temperature will fluctuate within a certain range. When the moisture content of the roaster outlet is detected to deviate from the set target value, the internal PID controller of the system will make feedback adjustments, reducing the dependence on manual labor and ensuring the quality of tobacco redrying. The experiment shows that the recommended process parameters can guide the production of tobacco redrying, reduce the time of manual adjustment of process parameters, and improve the automation of the griller.

6. Conclusions

(1) The key factors affecting the quality of tobacco based on the tobacco redrying process are analyzed. The process parameters affecting tobacco quality are taken as variables to be decided, and tobacco grade, tobacco moisture content, and environmental temperature and humidity are taken as characteristic physical parameters affecting the settings of tobacco process parameters. A nonlinear relationship model between the factors affecting tobacco quality and tobacco moisture content and temperature is established using the RBF neural network.

(2) In the parameter optimization process, to improve the convergence accuracy of the optimization algorithm, the improved IPSO algorithm is used. At the same time, to solve the problems of the complex boundary of the feasible area of process operation and slow convergence of the algorithm, an IPSOAPF algorithm for redrying tobacco leaves is proposed. The method in this paper is compared with the traditional PSO, IPSO, and DE. The experiments prove that the IPSOAPF algorithm is better in optimization speed and optimal search effect.

(3) The optimized process parameters are applied to a redrying tobacco experiment, and sensors are used to detect the moisture and temperature at the roaster outlet over a while. The results show that the initial process parameters recommended in this paper can guide the redrying production, reduce reliance on manual labor, and improve the redrying production efficiency. Moreover, it fills the theoretical deficiency in the inaccurate regulation of traditional parameters and realizes the sustainable development of the redrying process production in response to the dynamic incoming changes of tobacco leaves and variable tobacco quality processing standards.

(4) This study is the first attempt to optimize the parameters of the redrying process, which is difficult to control with the change in dynamic feed characteristics of tobacco leaves. The tobacco redrying quality standard is taken as the optimization objective in the paper, and the association of process parameters with processing energy consumption is not considered. Therefore, a multi-objective optimization model related to processing energy consumption will be further introduced to achieve energy saving and consumption reduction by regulating the process parameters.

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