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Dynamic Control Method of Improving Extreme Learning Machine Algorithm in Wood Spinning Process

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Abstract. The precise control of the feed system of the rotary cutting machine is the key to achieving uniform thickness rotary cutting of wood on the log-core veneer lathe. The application of Improving the Extreme Learning Machine Model in the feed system can effectively solve the problem of unstable feed rate matching in traditional control methods. This study analyzed the working mechanism of log-core veneer lathe and established a kinematic model of its feed system. Using the thickness and thickness variation of the wooden board as the control results of Improving the Extreme Learning Machine Model, in order to solve the optimal weight and threshold of Improving the Extreme Learning Machine Model, this paper uses an improved particle swarm optimization algorithm to solve. Finally, in the Matlab software environment, log-core veneer lathe motion model and control model are written, and simulation experiments are conducted to verify. The results show that Improving the Extreme Learning Machine Model effectively improves the control performance of the system, with stable feed rate changes, good real-time performance, fast convergence, high control accuracy, and strong adaptability.

Keywords: extreme learning machine, log-core veneer lathe, particle swarm optimization

1 Introduction

China is the world's largest exporter and consumer of wood trade and wood products. Due to the sharp decline in global forest resources, the supply of wood has significantly decreased, and the supply-demand contradiction is becoming increasingly prominent. From the current technological development perspective, synthetic wood boards are the best solution to replace raw wood materials and address the global shortage of wood resources. In the production process of artificial wood boards, rotary cutting machines are the main cutting equipment [1].

The uniformity of wood processing reflects the quality of wood processing, and the quality of wood depends on the processing equipment and the precision control of the processing equipment. It can be said that the performance of the rotary cutting machine control system directly determines the quality of artificial board processing. Therefore, studying high-performance control algorithms for rotary cutting machine control systems has important theoretical and practical significance [2].

The rotary cutting machine can be divided into log-core veneer lathe and Rotary cutting machine with card shaft according to its structure. Due to the better quality of finished products, higher work efficiency, and less remaining wood waste, log-core veneer lathe has become the main equipment used in China's wood processing industry.

This article conducts research on the common problems of log-core veneer lathe used in the current wood processing industry. After investigation and research, it is found that there are the following problems in the current non card axis rotary cutting process and control strategies:

1) Due to the structural characteristics of log-core veneer lathe itself, there is no axial clamping effect on the log during the rotary cutting process. At the same time, due to the uncertainty of the log shape, the large size and weight of the log, and the processing accuracy of the processing equipment not meeting the standard, log-core

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veneer lathe rotary cutting wood often experiences axial movement. When the axial movement distance exceeds the effective processing range of the rotary cutting tool, it can cause tool blockage or log splitting, and in severe cases, it can lead to motor blockage and circuit damage.

2) In terms of control strategies and optimization algorithms, existing control strategies have slow convergence speed and local optima when solving, resulting in suboptimal solutions.

Therefore, the research on log-core veneer lathe machining control process in this article is mainly reflected in the following aspects:

1) Analyzed the composition and working principle of the rotary cutting machine, established a kinematic model for the rotary cutting machine to facilitate the construction of optimization equations.

2) An intelligent algorithm for solving the model was proposed, and the improvement process of the algorithm was described in detail.

3) A simulation experimental environment was established, appropriate simulation experimental parameters were set, and the feasibility and scientificity of the control algorithm proposed in this paper were verified through simulation experiments.

The chapter composition of this article is as follows: Chapter 1 introduces the purpose and research background of this study, Chapter 2 analyzes some typical research results of relevant personnel, providing ideas and methods for this study, Chapter 3 constructs the kinematic model of the rotary cutting machine, Chapter 4 is the optimization and improvement process of the control algorithm, Chapter 5 is the experimental simulation stage, builds the experimental environment to verify the feasibility of the proposed method, Chapter 6 is the conclusion section, summarizes the content of this article, and points out the further research direction of this article.

2 Related Works

There is not much research on log-core veneer lathe, and due to the large domestic market for wood processing and use, domestic experts and scholars have relatively more research on log-core veneer lathe. Therefore, this chapter mainly describes the research results of some domestic scholars.

Changqing Ren conducted research on the working back angle and cutting trajectory of A, calculated the theoretical parameters such as tool loading height and working back angle, and finally obtained relevant change curves through MatLab simulation and fitted polynomial equations to achieve reasonable control of the cutting tool [3].

Zhiyang Gao mainly improved the structure of the rotary cutting machine, taking timeliness of detection, rotary cutting position, and incorrect operation of the reset mechanism as factors to determine the installation position and optimal reset lead of the detection device. He designed an interlock between the detection and reset devices and the rotary cutting machine to ensure that the reset mechanism will not malfunction during the rotary cutting process [4].

Kangqiao Zhou established a dynamic programming optimization model for maximizing the utilization rate and profit of two-dimensional wooden boards under various product cutting requirements, and solved it based on the knapsack algorithm. MATLAB software was used for simulation, and the cutting plan with the highest utilization rate and maximum product profit under cutting multiple product requirements was obtained. The plan is replicable for flat material processing [5].

Weiling Ma proposed a control system based on feedforward neural network to address the issues of the log-core veneer lathe variable speed feed system being unable to compensate for system uncertainty and susceptibility to interference under open-loop control, as well as the complexity and difficulty in determining parameters of traditional closed-loop control. The system is efficient and reliable [6].

Suzhen Yang established a kinematic model of rotary cutting thickness control for the precise speed matching control problem of its variable speed feed system with overall uncertainty. Further, by introducing new control variables, a closed-loop error control model of the uncertain system was obtained. Finally, based on Lyapunov theory, the controller was designed, and the designer improved the stability of the model [7].

Hongjie Sun from Qingdao University of Technology improves the control of wood thickness during the rotary cutting process by improving the mechanical device and improving the detection accuracy of wood thickness [8].

3 Establishment of Kinematic Model for Rotary Cutting Machine

Log-core veneer lathe is mainly composed of three wheels, two of which are fixed driving wheels called wheel I and wheel II, respectively. The fixed wheels rotate synchronously to drive the log to rotate at a constant speed. The other wheel is the feed wheel, called Wheel III. The feed wheel and the cutter form the feed system, and the function of the feed wheel is to provide pressure to compress the round wood, and the cutter cuts the wood [9]. The feed system drives the cutting tool to feed at a matching speed in the direction of the feed wheel based on the cutting conditions and thickness of the processed log. Assuming that the feed system has sufficient structural rigidity, while ignoring the sliding between the feed wheel and the cutting tool, a uniformly thick wooden board can be obtained through rotary cutting machine processing. In order to obtain uniformly thick wooden boards, the feed system requires real-time variable speed adjustment, which is usually achieved by using a speed regulating motor to drive the ball screw. In order to analyze the rotary cutting process and achieve control optimization of the rotary cutting machine, it is necessary to establish a kinematic model of log-core veneer lathe. The schematic diagram of log-core veneer lathe's structure is shown in Fig. 1.

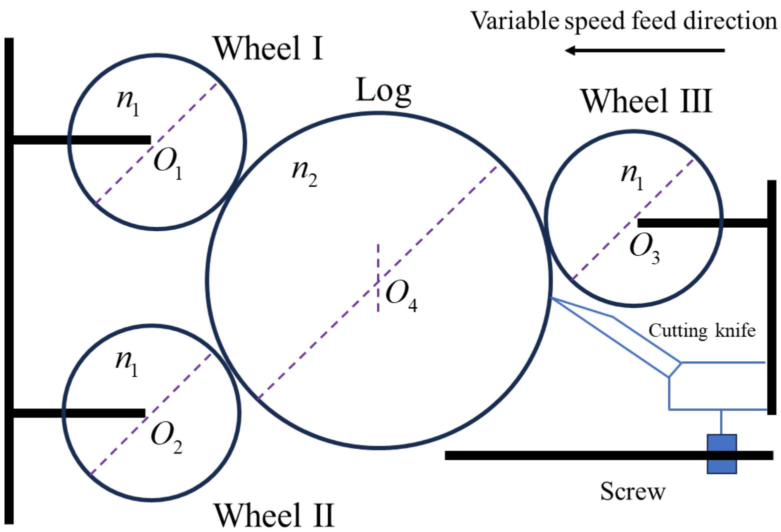

Fig. 1. Structural schematic diagram of log-core veneer lathe

Based on the action characteristics and schematic diagram of the rotary cutting machine, the mathematical model of the rotary cutting machine can be derived. Assuming that the thickness of the wooden board is h, the initial radius of the log is R_4, the hardness is H, the density is ρ, the rotary cutting force is F_x, the feed wheel radius is R_{III}, the angular velocity is ϕ_{III}, the diameter of the drive wheel is D_q, the center distance of the drive wheel is l, the feed speed of the drive wheel is v_{III}, and the horizontal displacement coordinate of the blade in the plane coordinate system is x. Here, we assume that there is no relative sliding between the two drive rollers and the log. Among the three drive rollers, wheel I and wheel II are fixed. During the operation of the rotary cutting machine, the drive rollers are driven by hydraulic cylinders and perform self rotation motion on one side to provide the log. The frictional force of rotation drives the log to move in a straight line while performing feed motion [10].

There is a linear relationship between the hardness and density of round wood, and the linear expression for hardness and density is:

$$H = k\rho + a. \tag{1}$$

If there is a positive linear relationship between the cutting force of the rotary cutter and the density of the round wood, the expression for the rotary cutting force is:

$$F_x = m\rho + b. \tag{2}$$

Transform Formula 1 and Formula 2 to obtain the expression for shear force:

$$F_x = \frac{m}{k}\left(H - a\right). \tag{3}$$

In the formula, H is the hardness of the log, k is the coefficient of the relationship between hardness and density, m is the coefficient of the relationship between shear force and density, and a and b are constants in linear expressions, respectively. Assuming the diameter of the feed wheel is R_{III}, the torque received by the feed wheel from the round wood during the machining process is:

$$T_{\mathrm{III}} = \frac{1}{2} \cdot R \quad F_x. \tag{4}$$

The angular velocity of the feed wheel is expressed as:

$$\phi_{\mathrm{III}} = \frac{\pi v_{\mathrm{III}}}{30}\left(rad \cdot s^{-1}\right). \tag{5}$$

In the formula, ϕ_{III} represents the rotational angular velocity of the feed wheel, and v_{III} represents the rotational linear velocity of the feed wheel. The slip characteristics of three asynchronous motors are expressed as:

$$T_{\mathrm{III}} = 2T_{\max} / \left(\frac{s}{s_m} + \frac{s_m}{s}\right). \tag{6}$$

In the formula, $T_{\max}$ is the maximum torque of the motor. Therefore, by organizing the above formulas, it can be concluded that:

$$F_x = 2T_{\max} \cdot \eta \cdot j / \left[\frac{1}{2} R_{\mathrm{III}} \left(\frac{s}{s_m} + \frac{s_m}{s}\right)\right]. \tag{7}$$

Assuming that there is no slippage between the wheel and the log during rotation, the linear speed between the optional installation of the log and the feed wheel is equal. Assuming that the motor operates at rated power and the motor speed is at rated speed, the thickness of the cut plate is expressed as:

$$h = \frac{V}{n_{\mathrm{III}} R \quad / j}. \tag{8}$$

According to formula (6), it can be concluded that:

$$s = \frac{T_{\max} \cdot s_m \pm \sqrt{T_{\max}^2 \cdot s_m^2 - T_{\mathrm{III}}^2 \cdot s_m^2}}{T_{\mathrm{III}}}. \tag{9}$$

The change in thickness of the wooden board is expressed as:

$$\Delta h = \left[\frac{s^2 + s_m^2}{ks\left(1 - s\right)} \cdot \frac{F_x}{F_x - \Delta F_x} - 1\right] \cdot \frac{V}{n_{\mathrm{III}} R \quad / j}. \tag{10}$$

The mechanical characteristic curves of the three asynchronous motors are shown in Fig. 2.

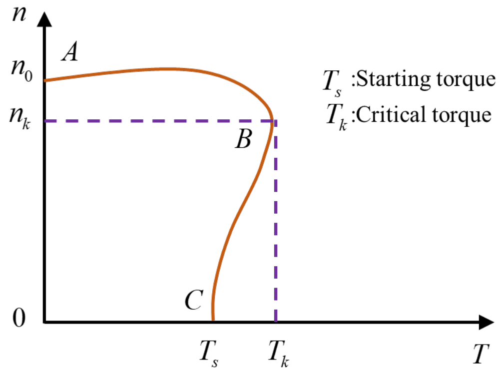

Fig. 2. Motor torque characteristics

As shown in the figure, the BC segment curve represents the unstable operating range of the motor. Due to the self adjustment effect of the motor, the rotary cutting machine generally operates in the AB segment [11]. When the motor operates within this range, the expression of slip rate is as follows:

$$s = \frac{T_{\max} \cdot s_m - s_m \sqrt{T_{\max}^2 - T_{\mathrm{III}}^2}}{T_{\mathrm{III}}}. \tag{11}$$

The expression for the thickness of the wooden board after sorting is:

$$h = \left[\frac{1}{k_0} \cdot \frac{4\eta^2 j^2 \left(T_{\max} \cdot s_m - s_m \sqrt{T_{\max} \cdot s_m - \frac{R_{\mathrm{III}}^2 \left(F_x + \Delta F_x \right)}{4\eta^2 j^2}} \right)}{T_{\max} - s_m \sqrt{T_{\max}^2 - \frac{R^2{}_{\mathrm{III}} F_x^2}{4\eta^2 j^2}}} \right] + \delta. \tag{12}$$

The process of round wood cutting contains a lot of uncertainty, therefore, in the algorithm model of this article, δ is used to replace the overall uncertainty in the rotary cutting process.

The linear speed of the driving roller is equal to the linear speed of the log,

$$2 \times R_4 \times n_2 = D_q \times n_1. \tag{13}$$

The cutting blade is fixedly connected to the driving roller III, and on the horizontal center plane of the driving rollers I and II, we obtain the coordinates of the blade from the figure as:

$$x = R_4 + \sqrt{\left(R_4 + R_{\mathrm{II}} \right)^2 - \left(l/2 \right)^2}. \tag{14}$$

To obtain the feed rate of the blade, taking the derivative of the two sides of the above equation yields:

$$v = \frac{dx}{dt} = \frac{1}{2} \times \left[1 + \frac{R_4 + R_{\mathrm{II}}}{\left(R_4 + R_{\mathrm{II}} \right)^2 - l^2} \right] \times \frac{d_{R_4}}{dt}. \tag{15}$$

According to formula (13), after differentiation transformation, it can be concluded that:

$$\frac{d_{R_4}}{dt} = -h \times n_2. \tag{16}$$

Therefore, by organizing the formula, it can be concluded that the feed rate of the tool is:

$$v = \frac{dx}{dt} = -\left[1 + \frac{R_4 + R_{\mathrm{II}}}{\left(R_4 + R_{\mathrm{II}}\right)^2 - l^2}\right] \times h \times n_2. \tag{17}$$

According to the mathematical model formula of the rotary cutting machine mentioned above, program in Matlab as follows [12]:

Algorithm.

```
clear all
  i=1;
    for d=0,150;
    v(i)=(1+(d+87)/(sqrt((d+87)^2-86^2)))*(0.6*87*63/d);
    i=i+1;
    end
     d=0,150;
    plot(R, n)
    grid
    xlabel('d(s)');
    ylabel('v(mm/min)');
    title
    map(n,R).
```

After Matlab simulation, the relationship between the feed rate of the cutting tool and the radius of the round wood is shown in Fig. 3.

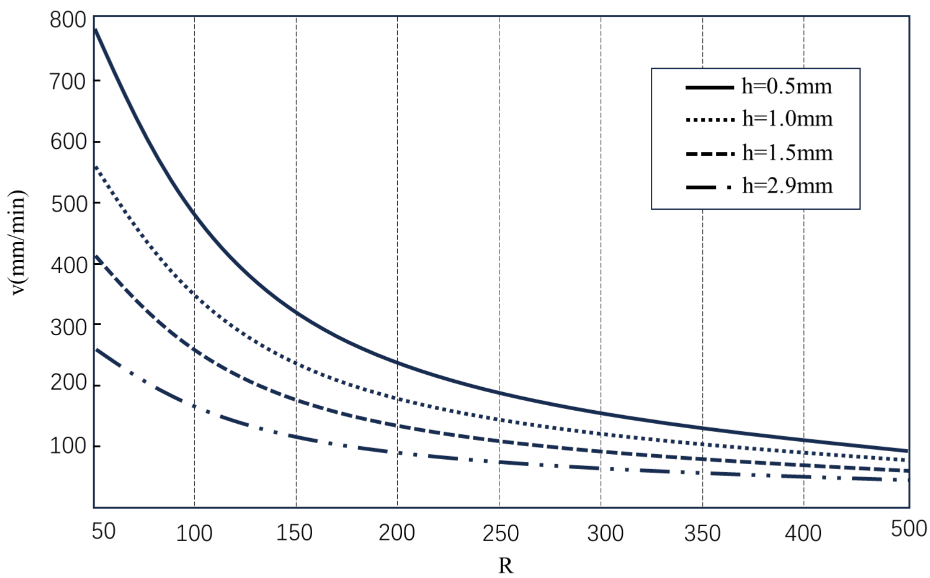

Fig. 3. Speed and radius relationship diagram

From the above figure, it can be seen that under the condition of determining the radius and the center distance of the driving roller, the feed rate of the cutting edge is closely related to the thickness of the round wood. During the rotary cutting process, the smaller the radius of the round wood, the greater the change in feed rate, and the greater the numerical value of the thickness of the cut wood. The feed rate of the cutting edge of the rotary cutting machine also changes faster.

When the wood rotates for one cycle, it is equivalent to two thickness displacement changes on the horizontal displacement. Therefore, the calculation formula for the change in rotary cutting time corresponding to the feed rate is as follows:

$$R \times dR = h \times n_2 \times R_{\text{II}} \times d_t. \tag{18}$$

Perform integration on both sides to obtain the integration result:

$$\int_{R_0}^{R_4} R \times dR = \int_0^t h \times n_2 \times R_{\text{II}} \times d_t. \tag{19}$$

After integral operation, the following results are obtained:

$$R_4^2 - R_0^2 = -8 \times h \times n_2 \times R_{\text{II}} \times t. \tag{20}$$

By organizing the above formulas, it can be concluded that:

$$t = \frac{R_0^2 - R^2}{8 \times h \times n_2 \times R_{\text{II}}}. \tag{21}$$

According to the above formula, simulate in Matlab, and the simulation code is as follows:

Algorithm.

```
clear all
 i=1;
   for d=0,150;
   v(i)=(1+(d+87)/(sqrt((d+87)^2-86^2)))*(0.6*87*63/d);
   i=i+1;
   end
    d=0,150;
    d=0,150;
     plot(t,v)
     grid
    xlabel('t(s)');
    ylabel('v(mm/min)');
    title(Speed changes over time)
```

After running in Matlab, the variation curve of the blade feed rate v with time t is shown in Fig. 4.

From Fig. 3 and Fig. 4, it can be seen that with the determination of the diameter of the round wood, the distance between the center of the driving roller, the speed of the feed wheel, and the thickness of the wooden board, the feed speed of the cutting edge gradually increases over time. The reason is that the diameter of the round wood decreases, resulting in a decrease in the time required for one revolution, and thus the tool speed continues to increase. The thicker the wooden board, the faster the feed rate of the rotary cutting machine's blade increases, and the less time it takes. This is because during the operation of the rotary cutting machine, the speed of the driving roller remains constant. Therefore, as the diameter of the log decreases due to cutting, the speed of the log continuously increases. In order to ensure the uniformity of sheet thickness, it is required that we accurately control the feed rate of the cutting tools. It can be seen that as time increases, the tool speed becomes faster and faster. In order to ensure the quality of veneer rotary cutting, it is required that the extension speed of the hydraulic cylinder can track its changes well.

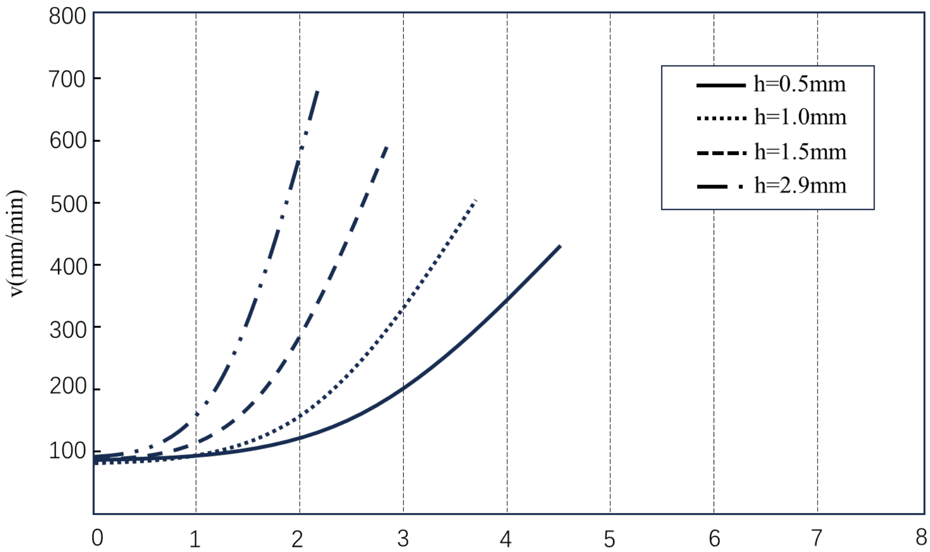

Fig. 4. The relationship curve between cutting tool feed rate and time

4 Design of Improved Extreme Learning Machine Model

The thickness change of the log depends on the feed amount generated by the cutter with the change of the log diameter, as well as the roughness of the log surface and whether the feed force is balanced. In order to control the thickness of the wooden board, the thickness of the wooden board is taken as the control objective, and an improved algorithm is used to obtain an accurate value of uniform thickness, avoiding the randomness of the cutting process. Traditional prediction algorithms face problems such as computational complexity, long time consumption, large fluctuations, and low accuracy in controlling the thickness of logs and predicting uncertainties. This paper proposes an improved model based on the Extreme Learning Machine algorithm.

4.1 Principle of Extreme Learning Machine Algorithm

Compared with other neural algorithms, extreme learning machines only need to set the number of hidden layer neurons and obtain a unique optimal solution by solving equations [13]. The neural network model is shown in Fig. 5.

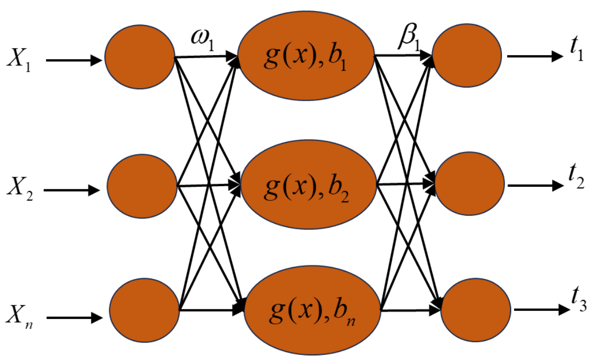

Fig. 5. Extreme learning machine network model

Assuming there are M arbitrary samples (Y_i, l_i), where $Y_i = \left[y_{i1}, y_{i2}, \cdots y_{im}\right]^T \in \phi^m$ and $l_i = \left[l_{i1}, l_{i2}, \cdots, l_{in}\right]^T \in \phi^n$ can be used as:

$$\begin{aligned} &\sum_{i=1}^{R} \beta_i g\left(\omega_i \cdot Y_j + b_i\right) = o_i \\ &j = 1, 2 \cdots M. \end{aligned} \tag{22}$$

In the formula, $g(x)$ is the activation function, ω_i is the weight of the input layer, β_i is the weight of the output layer, b_i is the i-th hidden layer, and $\omega_i \cdot X_j$ is the inner product of the operation.

To reduce the output error of the neural network, the learning objective function is represented by a permanent matrix as follows:

$$W\beta = K. \tag{23}$$

$$W = \begin{bmatrix} g_i\left(\omega_1 \cdot x_1 + b_1\right) & g_i\left(\omega_k \cdot x_1 + b_k\right) \\ g_i\left(\omega_1 \cdot x_M + b_1\right) & g_i\left(\omega_k \cdot x_N + b_k\right) \end{bmatrix}_{M \times K}. \tag{24}$$

W is the output matrix of the hidden layer of the neural network, β is the weight between the hidden layer and the output layer, and K is the expected vector output by the neural network. By arbitrarily determining the connection weights of the hidden layer and the threshold of the hidden layer neurons, the optimal solution can be obtained by setting the number of hidden layer neurons. The connection weight β can be obtained by solving a system of least squares equations:

$$\min \left\| W\beta - K \right\| = 0. \tag{25}$$

In the traditional modeling process, the number of hidden layer nodes is usually smaller than the number of training sets, and the extracted sample data is highly likely to have multicollinearity problems. The problem of multicollinearity leads to the singularity of the random matrix during the solving process, resulting in multiple hidden layer weights and non unique output weights.

4.2 Improving the Particle Swarm Extreme Learning Machine Model

Integrating kernel functions into extreme learning machines can compensate for the shortcomings of extreme learning machine algorithms and make learning machines more robust and stable [14]. The representation method of kernel function is as follows:

$$\begin{cases} H_{ELM} = A \cdot A^T \\ H_{ij} = g\left(x_i\right) \cdot g\left(x_j\right) = E\left(x_i, x_j\right) \end{cases}. \tag{26}$$

The random parameter matrix $A \cdot A^T$ is replaced by a kernel function H, which reduces computational complexity and obtains a higher dimensional projection with better properties. After setting the parameters related to the kernel function, the parameters of the random matrix $A \cdot A^T$ are uniquely determined by calculating formula (26), where $g(x)$ is the output function of the hidden layer node. For the ELM neural network algorithm, the RBF Gaussian kernel function is applied, which is:

$$E(x, y) = \exp\left[\frac{-(x-y)^2}{2\sigma^2}\right]. \tag{27}$$

In the formula, σ is the radial parameter and (x, y) is the input vector. On the basis of kernel function, ridge regression constant [15] and Gaussian kernel function [16] are introduced,, and the constant α is added to $A \cdot A^T$ to form the diagonal of the unit diagonal matrix, cleverly avoiding the singularity problem of the random matrix. According to the generalized inverse theory, a unique solution can be obtained for the weight vector at this time. The output weight calculation result is:

$$\beta = A^T \left(\alpha + A \cdot A^T\right)^{-1} T. \tag{28}$$

$$\alpha = \frac{M}{N}. \tag{29}$$

In the formula, M represents the diagonal identity matrix $A \cdot A^T$ generated through kernel function sample mapping, and N is the penalty factor used to adjust the proportion of structured risk and empirical risk. Therefore, the training mode of extreme learning machines is represented as:

$$X_{ELM} = \frac{1}{2}\beta^2 + N\frac{1}{2}\sum_{s=1}^{T}\varsigma_s^2. \tag{30}$$

Among them, $s = 1, 2, 3, ..., T$ and $\frac{1}{2}\beta^2$ represent structural risk, $\frac{1}{2}\sum_{s=1}^{T}\varsigma_s^2$ represents empirical risk, and X_{ELM} represents loss function. By adjusting the penalty factor N to adjust the loss function, it is possible to adjust the error of the extreme learning machine by adjusting the penalty factor, making the model run more accurately. In addition, the penalty factor also corrects the problem of matrix singularity during the solving process, making the weights uniquely determined. After determining the Gaussian kernel function $E(x, y)$, N is the unique value. Once the penalty factor H is determined, the weight of the output layer is obtained. Therefore, extreme learning machines are simpler, more convenient, and more efficient due to the inherent randomness of kernel mapping stability and the fluctuation of model output caused by randomness.

4.3 Improving the Particle Swarm Extreme Learning Machine Model

Traditional extreme learning machine algorithms have large fluctuations and are prone to falling into local optima. In order to enable the extreme learning machine algorithm to efficiently complete the solving task of this article, an improved particle swarm optimization algorithm is used to solve the weights and thresholds of the extreme learning machine model [17].

Particle swarm optimization algorithm is an intelligent evolutionary algorithm based on mutual cooperation and information sharing among individuals in the population. The basic idea of this algorithm is to design a mass free particle to simulate a flock of birds, with each particle having a position and velocity, where position represents the particle's position and direction of movement in parameter space, and velocity represents the particle's speed of movement in space. Each particle independently searches for the optimal solution in the parameter space and records individual information. Each particle shares individual information, including extremum information, with other particles in the population, and uses the found extremum as the optimal solution for the entire particle swarm. This article aims to optimize the thickness of the wooden board, so the optimization process based on particle swarm optimization algorithm is as follows [18]:

The algorithm is initialized as a group of random particles, and then iteratively finds the optimal solution. In each iteration, the particles update themselves by tracking individual extremum. Assuming that the velocity and position of particles in the PSO algorithm are $V_i = (v_{1d}, v_{2d}, ..., v_{3d})$ and $X_i = (x_{1d}, x_{2d}, ..., x_{3d})$, respectively, the velocity has a significant impact on the global convergence of the algorithm. When the particles approach the optimal solution, the control and constraints corresponding to the particles will weaken, and the corresponding local search ability will also decrease. Therefore, by introducing the inertia factor w to solve the above problems, the updated strategy is:

$$v_{id}^{(k+1)} = \omega \cdot v_{id}^{(k)} + c_1 r_1 \left(p_{id}^{(k)} - x_{id}^{(k)} \right). \quad (31)$$

$$x_{id}^{(k+1)} = x_{id}^{(k)} + v_{id}^{(k+1)}. \quad (32)$$

In the formula, k represents the current number of iterations, i = 1, 2, ..., S, D = 1, 2, ..., D, and S represent the population size, usually set to 30-40, D is the problem dimension to be optimized, $p_{id}^{(k)}$ is the individual and global optimal solution of the particle in the k-th iteration, c_1 is the positive learning factor, usually set to $c_1 = 2$, $r_1 \in (0,1)$. The algorithm solving process is as follows:

1) To initialize a particle swarm, the parameters that need to be initialized include the particle swarm size value S, learning factor c_1, inertia weights $w_{\max}$ and $w_{\min}$. The maximum number of iterations is $k_{\max}$, and the initial values of particle velocity v_{id} and position x_{id}.

2) Taking the difference in thickness and the change in thickness during wood processing as optimization objectives, an improved extreme learning machine algorithm is used for training and learning to obtain predicted values.

3) Using the fitness value of particles as the basis for particle updates, first calculate the fitness value of any particle, then calculate the fitness value of the second particle, and then update the position of the second particle. Then, based on the obtained optimal solution, obtain the fitness value of the third particle, and update the individual optimal extreme and global optimal extreme using the same operation method as above.

4) Check the termination conditions of the PSO algorithm. If the maximum number of iterations or optimal solution is met, output the best fitness value and corresponding particle optimal solution. Otherwise, return to step 2)

5) Construct a reflection spot offset prediction model based on the sample training set and the optimal solution obtained from training. On this basis, validation is conducted using a sample test set.

The schematic diagram of the dynamic control process of the improved algorithm for the rotary cutting process is shown in Fig. 6.

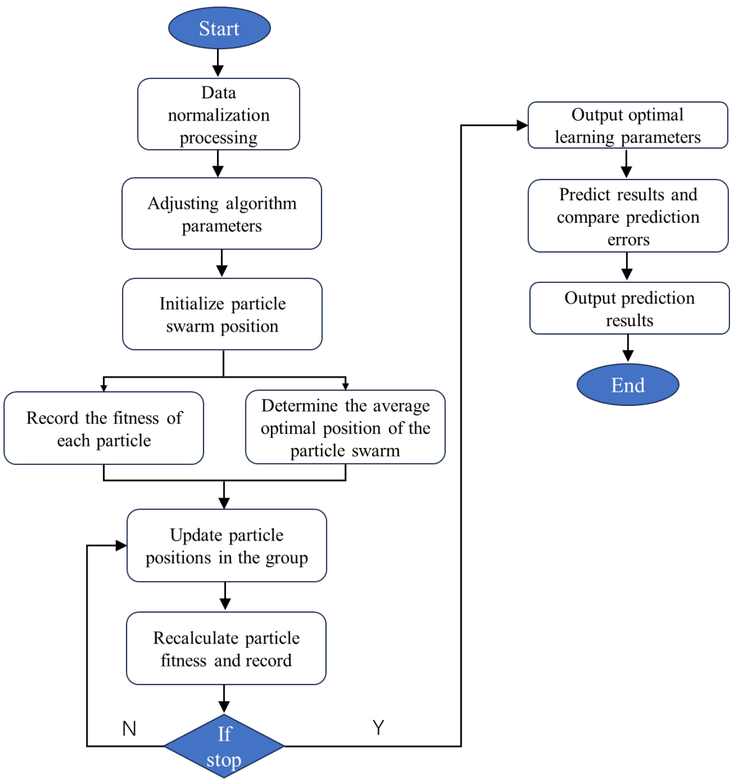

Fig. 6. Extreme learning machine network model

The algorithm process is represented by pseudocode:

```
Algorithm.
Start:
   Setup:
   Data normalization processing;
   Adjusting algorithm parameters;
   Initialize population position;
   Return value:
       The fitness of each particle;
       Average optimal position;
   Update the position of particles in the group;
   Recalculate the fitness of each particle;

   If (Stop)
      {
           Output the optimal learning parameters and solve the learn-
            ing machine prediction model;
           Calculate prediction error;
           Output prediction results;
      }
   Else if
      {
           Update the position of particles in the group;
            Recalculate the fitness of each particle;
      }
   End
```

5 Experimental Simulation and Result Analysis

This article uses Matlab to write an improved Extreme Learning Machine algorithm program, and the parameter settings in the improved Extreme Learning Machine algorithm are as Table 1:

Table 1. Improving the setting of parameters in extreme learning machine algorithms

Name	Symbol	Number
Particle swarm size	S	90
Positive learning factor	c_1	2.1
Dimension	D	3
The minimum value of inertia weight	$w_{\min}$	0.4
The maximum value of inertia weight	$\omega_{\max}$	0.9
Maximum number of iterations	$k_{\max}$	100
Activation function	Sigmoid	-
Hidden layer nodes		20

As shown in Fig. 7, as the number of iterations increases, the fitness function value gradually decreases.

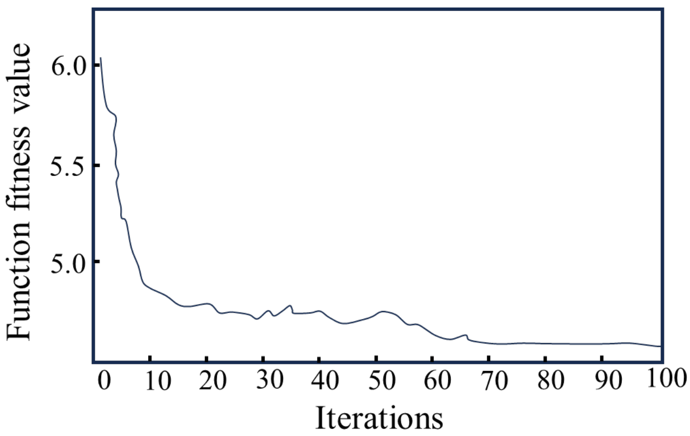

Fig. 7. Algorithm optimization curve

As shown in Fig. 4, after 68 iterations, the thick algorithm reaches a stable state, and each particle is near the optimal solution. The actual thickness variation curve of the rotary cutting veneer is shown in Fig. 8, and the feed rate variation curve of the rotary cutting blade is shown in Fig. 9. Simulation graphics show that the improved extreme learning algorithm can quickly respond and stably and accurately follow the expected single board thickness value, and the tuning speed is very fast with small steady-state errors. As the diameter of the rotary cut log decreases, the feed rate of the rotary cutting blade also increases nonlinearly, showing a rapid and variable speed feed process. In the experiment, it was also found that in order to achieve better rotary cutting quality and uniform thickness of the veneer, the rotary cutting angle between the blade and the contact surface of the logs of different tree species needs to be adjusted separately when rotary cutting the logs; When rotary cutting veneer with different thicknesses, different constant linear speeds should be used. The thicker the rotary cutting veneer, the smaller the constant linear speed should be.

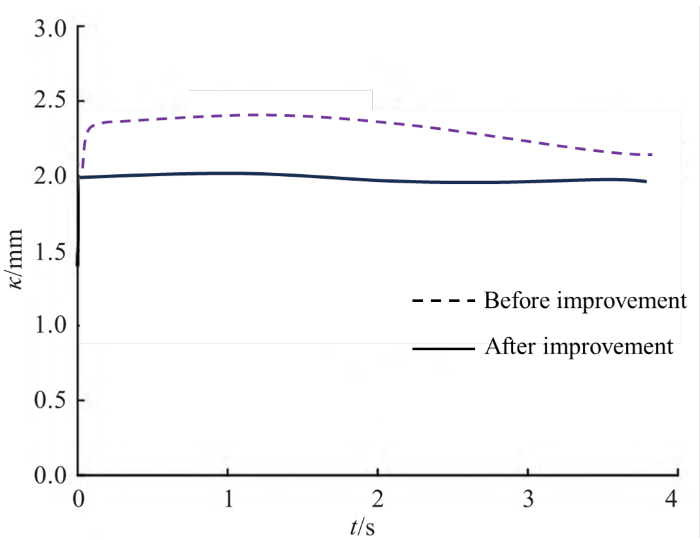

Fig. 8. Wood thickness variation curve

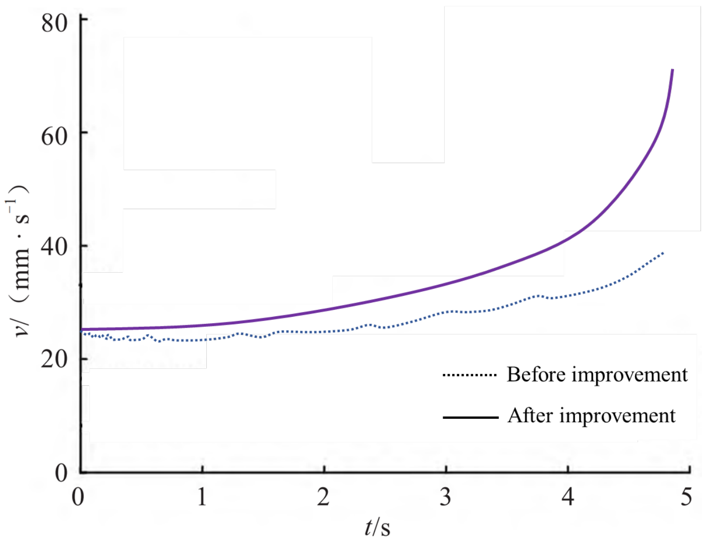

Fig. 9. Feed rate variation

After the above analysis of the nuclear model simulation solution process, the number of model iterations and the optimization results of the rotary cutting process were obtained. From the optimization results, it can be seen that the method proposed in this paper is effective and can achieve dynamic control of the rotary cutting machine, and the control results are stable, achieving the design goals.

6 Conclusion

On the basis of establishing the kinematic model and extreme learning machine model of system A, this article designs an extreme learning machine model based on improved particle swarm optimization algorithm and conducts simulation experiments. The experimental results of rotary cutting of wood boards show that in order to achieve uniform thickness rotary cutting of A, its rotary cutting feed system is a nonlinear variable speed feed. The smaller the rotary cutting thickness, the smaller the required feed rate and the smaller the range of variation. At the same time, the designed extreme learning machine control model controls the thickness error of the rotary cut wood board to converge to zero, with fast dynamic response and high control accuracy, which has engineering application value.

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References

[1] J. Zhao, Z.-Y. Gao, Y.-S. Shen, Y. Song, Automatic Grading and Stacking System for Rotary Veneer Manufacturing, Chinese Journal of Wood Science and Technology 35(5)(2021) 66-71.
[2] Y. Liu, Z.-L. Zhuang, M. Tang, Research progress on deep learning in wood processing, Journal of Forestry Engineering 8(4)(2023) 1-9.
[3] C.-Q. Ren, Z.-H. Xu, P. Song, Research on the working orthogonal clearance and rotary-cutting locus of new log-core veneer lathe, Forestry Machinery & Woodworking Equipment 51(9)(2023) 16-20.

[4] Z.-Y. Gao, G.-Y. Meng, Y. Song, Y.-S. Shen, Structural Design of Log Axial Detecting and Resetting Device for Spindle-Less Rotary Lathe, Chinese Journal of Wood Science and Technology 35(3)(2021) 71-76.
[5] K.-Q. Zhou, P.-X. Yan, G.-Q. Pang, Design of board cutting scheme based on Knapsack algorithm, Heilongjiang Science 11(4)(2020) 29-31.
[6] W.-L. Ma, K.-R. Hao, PIDNN-based Control of A Constant Linear Velocity Spindleless Veneer Lathe Feed System, Forestry Machinery & Woodworking Equipment 44(1)(2016) 13-16.
[7] S.-Z. Yang, Variable Speed Feed Sliding Mode Control of the Uncertain Log-core Veneer Lathe Modern Manufacturing Technology and Equipment 59(10)(2023) 112-114.
[8] H.-J. Sun, G.-Y. Meng, Z.-H. Wang, B. Guo, Design of Metal Detection Devices in Log Conveyors for Rotary Veneer Production Line, Chinese Journal of Wood Science and Technology 34(3)(2020) 56-58.
[9] H.-Y. Wu, H.-Y. Zhang, Design and analysis of the feed control system of electrical frequency conversion log-core veneer lathe, Journal of Minxi Vocational and Technical College 15(2)(2013).
[10] B. Yang, Z.-X. Liu, H.-K. Liu, X.-W. Li, Parameter Identification of Bridge Crane Dynamics Model and Design of Its Anti-swing Controller, Machine Tool & Hydraulics 48(10)(2020) 193-196+200.
[11] Z.-Y. Chen, J.-Y. Zhang, Z.-C. Lv, H. Liu, Modeling and Analysis of Machine Tool Feed System Based on Ball Screw Drive, Machine Tool & Hydraulics 51(13)(2023) 166-171.
[12] G.-P. Liu, Z.-Y. Lin, Optimization Design of Cross Feed Servo System of Machine Tool Based on MATLAB, Machine Building & Automation 44(1)(2015) 168-170.
[13] Y.-F. Rao, Y. Liu, L.-L. Li, Z. Fang, L.-N. Qu, Power prediction of photovoltaic power generation system based on improved bird swarm and extreme learning machine model, Renewable Energy Resources 38(10)(2020) 1318-1325.
[14] W.-W. Wang, D.-R. Kong, A comparison of two estimation methods for probability density's derivatives, Journal of Qufu Normal University (Natural Science) 48(4)(2022) 14-21.
[15] Z.-W. Chen, J. Chang, Application of Integrated Ridge Regression and SARIMA Methods in the Analysis of Bridge Health Monitoring Data, Science Technology and Engineering 23(20)(2023) 8846-8853.
[16] Z. Tian, F. Li, Y.-S. Luo, R.-R. Liu, Y. Gu, Identification of Hammerstein Nonlinear System Based on Gaussian Kernel Functions, Control Engineering of China 29(11)(2022) 2034-2041.
[17] Y.-F. Tian, S. Wang, Z. Wang, Y. Liu, Z.-X. Xing, Short Term Prediction of Wind Power Based on Nuclear Improvement to Reduce Particles of Learning Machines, Electrical & Energy Management Technology (3)(2022) 39-44+76.
[18] P.-Y. Shi, Y. Du, S. Liu, L.-L. Cui, Analysis of Photovoltaic Maximum Power Point Tracking Strategy Based on Improved Particle Swarm Optimization, Electronic Technology 52(2)(2023) 78-80.