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Forecasting of Wood Moisture Content Based on Modified Ant Colony Algorithm to Optimize LSSVM Parameters

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ABSTRACT Wood moisture content (WMC) is an important technical index used in the wood drying process, and assessing its change accurately and reliably is the key to improving wood drying quality. In order to improve the accuracy and reliability of WMC forecasting, a modeling method is proposed that uses a modified ant colony algorithm (MACA) to optimize the least square support vector machine (LSSVM). The MACA combines the large-step size global search with the small-step size local fine search to obtain the optimal parameter combination automatically and are tested by five standard functions. Then the MACA-LSSVM model is proposed to predict the WMC and compared with back propagation neural network (BP-NN), LSSVM model, and ant colony optimization LSSVM (ACO-LSSVM). The drying data from a small-sized wood drying kiln independently developed by Northeast Forestry University are taken as the samples for analyzing. The results indicate that the root mean square relative error (*RMSRE*) obtained by the proposed method (MACA-LSSVM) is only 1.82%, which is 0.77%, 0.50%, and 0.20% less than those of the BP-NN, LSSVM, and ACO-LSSVM models. The forecasting time are 0.0070 s, 0.0030 s, and 0.0010 s shorter, respectively. The relative error (*RE*) and the mean absolute error (*MAE*) are also lower than those of the latter three models. The MACA-LSSVM shows the characteristics of low computational complexity, fast convergence speed, high prediction accuracy and strong generalization ability, and the prediction effect is ideal. This model can provide the theoretical support for intelligent control of the wood drying process.

INDEX TERMS Ant colony algorithm, least square support vector machine, parameter optimization, wood moisture content.

I. INTRODUCTION

Wood is a kind of green material which is renewable and recyclable. Wood products belong to a basic industry in national economy and occupy an important position. In recent years, the deterioration of environment leads to the gradual decrease of forest resources, environmental and ecological problems become more and more obvious. How to protect the existing forest resources, improve the wood product quality and reduce the energy loss of wood drying process becomes quite important.

Wood drying is the most important process in wood processing and comprehensive utilization. Correct and

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reasonable drying treatment of wood is not only the key to improving the utilization rate of wood and ensuring the quality of wood product, but also an important method of saving energy and reducing costs [1]. As one of the important indexes for the selection of drying schedule and the evaluation of drying stage, the accurate forecasting of wood moisture content (WMC) in drying process is a necessary condition for the regulation of drying control parameters and for the guarantee of drying quality [2]. In order to improve the precision and reliability of WMC forecasting, it is of great practical significance to establish an effective forecasting model of WMC for improving the technical level of intelligent control of wood drying.

In recent years, scholars at home and abroad have done lots of studies on the forecasting model of wood drying process.

Cronin *et al.* [3] gave the theoretical formulas for the mean and standard deviation of water content of board versus time. At the same time, they compared it with the Monte Carlo model and determined an optimum double set point schedule. Fortin *et al.* [4] proposed the concept of water potential in wood drying process and established a two-dimensional model of wood drying. The model was useful for optimizing the kiln schedules according to the drying time, energy consumption, and wood quality. Carlsson and Tinnsten [5] established a two-dimensional anisotropic drying benchmark model and optimized it with a gradient-based program. Ding *et al.* [6] studied the multiple regression prediction model of wood drying quality and realized the prediction of WMC and stress. Fan *et al.* [7] studied the soft measurement modeling method of SVM and realized the soft measurement of water content in the timber drying process. Liu *et al.* [8] established an online prediction model for WMC by using BS-PLS regression model. In this method, the temperature and the humidity values are taken as the model inputs, and the WMC is taken as the model output. The experiment results indicated that the model had better generalization ability and higher forecasting accuracy. In recent years, the artificial neural network (ANN) has a widespread application on nonlinear prediction, and some achievements have been made in the prediction of moisture content [9], [10]. Zhang *et al.* [11] used the neural network method to identify the wood drying system and established the neural network model of the wood drying process. However, ANN, based on the assumption of infinite amount of sample and empirical risk minimization principle, has some defects such as difficult to determine the network structure, over learning, easy to fall into the local optimal value, unsuitable for high dimension and small sample prediction, which seriously affect its application effect [12]. Based on the statistical learning theory and the principle of structural risk minimization, support vector machine (SVM) effectively avoids the defects of ANN [13]. It can approximate any function with arbitrary accuracy and has been widely used in the fields such as regression analysis and pattern recognition [14].

The least square support vector machine (LSSVM) is an improvement and extension of SVM. It has low computational complexity and strong robustness. The prediction accuracy and generalization ability of the LSSVM model largely depend on the penalty factor and kernel function parameter [15]–[17]. Therefore, determining the appropriate parameters is the key to the modeling and forecasting by LSSVM. Jiang *et al.* [18] employed LSSVM to establish a soft measurement model of moisture content in wood drying process and used PSO algorithm to optimize its parameters. The PSO algorithm converges fast, but it is easy to fall into the local optimal solution [19]. Chappelle *et al.* [20] proposed the method of gradient descent to solve the optimal value of the SVM model parameters. The running efficiency of the algorithm has been improved obviously, but the initial point is strictly required and it's easy to fall

into local optimization. Fernandez-Lozano *et al.* [21] proposed the genetic algorithm to optimize the LSSVM parameters. Although it is independent of the mathematical model of the problem, its genetic operation is relatively complex and the late convergence speed is slow [22]. Ant colony optimization (ACO) algorithm has the features of heuristic search, distributed computing, information positive feedback, etc., [23]. It has high solution precision and strong robustness and is very suitable for combinatorial optimization problems [24]. However, ACO is an intelligent algorithm for discrete optimization problems at the beginning, and some details of the algorithm must be improved when solving continuous optimization problems by it [25]. In view of this, on the basis of previous researches, a modified ant colony algorithm (MACA) is proposed to optimize the penalty factor and the kernel function parameter of LSSVM, it combines the large-step size global search with the small-step size local fine search to obtain the optimal parameter combination. A nonlinear relationship model between the temperature, humidity and WMC is built in the wood drying kiln with the best parameter combination. The MACA-LSSVM is applied to forecast the WMC to improve the prediction accuracy and operation efficiency, which can ensure the quality of wood product, save energy, and reduce the cost.

The specific objectives are as below: (1) Five test functions are selected to test the optimization ability of the algorithms in the contrast literatures and the MACA proposed in the paper, the convergence accuracy and convergence stability are compared among the algorithms. (2) The MACA-LSSVM model is constructed and the prediction accuracy and the prediction stability are verified. (3) The BP-NN, LSSVM, ACO-LSSVM, and MACA-LSSVM models are tested by using the actual data of *Fraxinus mandshurica* drying process. The prediction effects are compared among the four models.

The main contributions of the paper are as below: (1) The MACA-LSSVM model is put forward to forecast the WMC. The results show that the model can well fit the nonlinear relationship between the drying medium and the WMC. (2) The MACA-LSSVM model has a higher forecasting accuracy than other three models (BP-NN, LSSVM, and ACO-LSSVM) and can meet the actual needs. (3) This model can provide the accurate and reliable data for the wood drying process. It is beneficial to improve the wood drying quality and the intelligent control technology level of wood drying process.

The rest of this paper is organized as follows. Section II introduces the principle and the parameters of LSSVM model. Section III mainly completes the optimization ability test of MACA. Section IV mainly establishes the WMC forecasting model based on MACA-LSSVM and discusses the forecasting results of the BP-NN, LSSVM, ACO-LSSVM, and the MACA-LSSVM models. The conclusion, contributions, limitations, and future studies are given in Section V.

II. LEAST SQUARE SUPPORT VECTOR MACHINE

A. PRINCIPLE OF LSSVM

The SVM algorithm is an important part of statistical learning theory. Its basic idea is to map the input space samples to a high-dimensional feature space and transform the problem into a quadratic programming problem with inequality constraints through a nonlinear mapping function. It can be well used to solve the actual problems of small samples, high dimensionality and complex nonlinear systems [13], [26]. The model has a high precision but its speed is low [27].

The LSSVM is an improvement and expansion of the standard SVM. It can change the inequality constraints of a standard SVM into equality constraints, taking the loss function and error square as empirical losses of training samples. At the same time, the quadratic planning problem is transformed into a problem for solving linear equations [28]. When solving problems, compared with the original method, the complexity of the model is reduced effectively, and the operation efficiency and convergence accuracy are improved [29].

For a given training sample set $S = \{(x_i, y_i), i = 1, 2, \dots, l\}$, $x_i \in R^n$ and $y_i \in R$ are the n -dimensional input vector and one-dimensional output vector of the system, respectively, and l is the size of the sample set. In the LSSVM regression algorithm, the nonlinear function $\varphi(\cdot)$ is used to map the sample to a high-dimensional feature space (Hibert). In this way, we transform the nonlinear function estimation problem in the input sample space into a linear function estimation problem in the high-dimensional feature space. The regression estimation expression is (1):

$$f(x) = \omega^T \varphi(x) + b \quad (1)$$

where $\omega = [\omega_1, \omega_2, \dots, \omega_l]^T \in H$ is the vector of weight coefficient; $b \in R$ is the offset quantity; and

$\varphi(\cdot) = [\varphi(\cdot)_1, \varphi(\cdot)_2, \dots, \varphi(\cdot)_l]^T$ is the nonlinear mapping from the input space (R^n) to the feature space (H). The optimization problem of function estimation using the LSSVM is as follows [30]:

$$\begin{cases} \min J(\omega, e) = \frac{1}{2} \|\omega\|^2 + \frac{C}{2} \sum_{i=1}^l e_i^2 \\ s.t. y_i = \omega^T \varphi(x_i) + b + e_i (i = 1, 2, \dots, l) \end{cases} \quad (2)$$

where J is the loss function; $e = [e_1, e_2, \dots, e_l]^T \in R^l$ is the error vector; and $C \in R^+$ is the penalty factor.

To solve the above constraint optimization function (2), the Lagrange polynomial function is established for dual problems, as shown in (3):

$$L(\omega, b, e, \alpha) = J(\omega, e) - \sum_{i=1}^l \alpha_i [\omega^T \varphi(x_i) + b + e_i - y_i] \quad (3)$$

where $\alpha = [\alpha_1, \alpha_2, \dots, \alpha_l]^T \in R^l$ is the Lagrangian multiplier. According to the KKT condition, equation set (4) can

be obtained by optimizing (3):

$$\begin{cases} \frac{\partial L}{\partial \omega} = 0 \rightarrow \omega = \sum_{i=1}^l \alpha_i \varphi(x_i) \\ \frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^l \alpha_i = 0 \\ \frac{\partial L}{\partial e_i} = 0 \rightarrow \alpha_i = C e_i \\ \frac{\partial L}{\partial \alpha_i} = 0 \rightarrow \omega^T \varphi(x_i) + b + e_i - y_i = 0 \end{cases} \quad (4)$$

The kernel function is defined according to the Mercer condition: $k(x_i, x_j) = \varphi^T(x_i) \cdot \varphi(x_j) = \Omega_{ij}$, ($i, j = 1, 2, \dots, l$). Equation (5) is obtained by eliminating ω and e_i of equation set (4):

$$\begin{bmatrix} 0 & 1 & \dots & 1 \\ 1 & k(x_1, x_1) + \frac{1}{\gamma} & \dots & k(x_1, x_l) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & k(x_l, x_1) & \dots & k(x_l, x_l) + \frac{1}{\gamma} \end{bmatrix} \times \begin{bmatrix} b \\ \alpha_1 \\ \vdots \\ \alpha_l \end{bmatrix} = \begin{bmatrix} 0 \\ y_1 \\ \vdots \\ y_l \end{bmatrix} \quad (5)$$

Equation (5) is abbreviated as follows:

$$\begin{bmatrix} 0 & Q_l^T \\ Q_l & \Omega + C^{-1}I \end{bmatrix} \times \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \quad (6)$$

where $Q_l = [1, \dots, 1]^T$, $y = [y_1, \dots, y_l]^T$, and I_l is an $l \times l$ dimensional unit matrix.

The estimation of parameters $[b, \alpha^T]^T$ can be obtained by the LS method. There are multiple kernel functions of the LSSVM that satisfy the Mercer condition, including the polynomial kernel function, linear kernel function, sigmoid kernel function and radial basis function (RBF). In this paper, the RBF is selected as the kernel function of the LSSVM model because of its fewer parameters, stronger generalization ability, and learning ability [31].

$$k(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \quad (7)$$

The decision function of the LSSVM can be obtained by solving (6):

$$f(x) = \sum_{i=1}^l \alpha_i \times k(x_i, x_j) + b \quad (8)$$

where x_i, x_j and α are the input sample vector, the kernel function centre of RBF, and the width parameter of the RBF kernel function, respectively.

B. PARAMETERS OF LSSVM

The parameter values of the LSSVM have a great impact on its learning ability and generalization ability, so determining the parameter values is a key problem of the LSSVM [32]. The LSSVM regression algorithm with the RBF kernel function includes two parameters: penalty factor (C) and kernel function width (σ). C is a compromise between the sample

error and the structural risk. The value of C is related to the tolerable error. A smaller value allows a larger error, whereas a larger value allows a smaller error. The value of σ is related to the input space width or range of the learning samples. If the input space width of the sample is smaller, the value will be smaller. In contrast, if the input space width of the sample is larger, the value will be also larger [33]. To improve the optimality of parameter selection, the modified ant colony algorithm is adopted in this paper to search for the optimal combination of C and σ in a certain area. To some extent, it can avoid the blindness based on the subjective experience selection so as to improve its prediction accuracy.

III. PARAMETER COMBINATION OPTIMIZATION OF LSSVM BASED ON MACA

The ant colony optimization (ACO) algorithm was proposed by Italian scholar Dorigo *et al.* [34] in the 1990s. It is a type of simulated evolutionary algorithm based on the bionics principle—a global search algorithm with advantages such as a good positive information feedback mechanism, distributed computing and greedy heuristic searching. However, the ACO is proposed originally for discrete optimization problem, if the continuous optimization problem of (9) is considered, some details of the algorithm need to be improved [35]. The pheromones of ants are distributed on the paths between discrete points in the basic ant colony algorithm. In the MACA, each ant in the population selects the next travelling mode according to the influence of the pheromones of a certain region on it. The pheromones are attached to the population individual, and represent the attraction degree of the individual to the ants. After the individual optimization guided by the ants, a local fine search in the optimal ant neighbourhood is performed to avoid skipping over a better solution, and then the pheromone is released on the optimal ant individual.

In this paper, the parameter selection process of the LSSVM model is regarded as a combination optimization problem of parameters. The objective function is constructed according to the random combination of parameters, and then the MACA is applied to search for the optimal objective function value. Finally, the optimal value of the combined parameters is output.

A. SELECTION OF OBJECTIVE FUNCTION

The minimum mean square error (MSE) is taken as the objective function (F) of the optimization problem in the paper. The optimal F value is searched for by MACA iteration to gain the optimal set of parameter combination (C, σ), and the objective function is established as follows [36]:

$$\begin{aligned} \min F = \min MSE &= \frac{1}{l} \sum_{i=1}^l (y_i - \hat{y}_i)^2 \\ \text{s.t. } C_{\min} &\leq C \leq C_{\max} \\ \sigma_{\min} &\leq \sigma \leq \sigma_{\max} \end{aligned} \quad (9)$$

where y_i and \hat{y}_i are the actual values of the training samples and the predicted values estimated by the LSSVM model regression, respectively.

B. OPERATING STEPS OF MODIFIED ANT COLONY SEARCH

The idea of the parameter optimization of LSSVM is to search for a set of parameters (C, σ) iteratively through MACA to minimize the F value. In this paper, a set of parameter sequences (C, σ) in the domain is defined as the position vector of the ants in the MACA. Then, the dynamic random extraction method is employed to determine the target individual, guide the ant colony for global search, and then perform a small-step local fine search in the neighbourhood of the optimal ant to find the optimal parameter of the model. After multiple iterations, the optimal forecasting model based on the MACA for optimizing the LSSVM (MACA-LSSVM) is obtained. The specific steps are as follows:

Step 1: Initialize the parameters. Setting the problem scale as l , the number of ants is n , the pheromone volatilization coefficient $\rho \in [0, 1]$, and t_{\max} is the maximum number of cycles. Within the range of $C \in [C_{\min}, C_{\max}]$ and $\sigma \in [\sigma_{\min}, \sigma_{\max}]$, taking a set of parameter sequences (C, σ) as the initial position vector $X_i = (X_{i1}, X_{i2}, \dots, X_{id})$ of the ants in the algorithm, $i = 1, 2, \dots, l$. n ants are placed randomly at position i of question l at the initial moment.

Step 2: The LSSVM model is learned and trained by the training sample set, the F value of each ant individual is calculated by (9), and the pheromone density of each ant is calculated by (10) [37]. If the F value is smaller, the σ value is larger; conversely, if the F value is larger, the σ value is smaller.

$$\tau(i) = e^{-F(X_i)} \quad (10)$$

where e is the base number of the natural logarithm.

Step 3: p ants are extracted from ant colony n at random, the ant with the smallest F value is selected as the head ant X_{obj} and whose position is X_{best} . The random extraction rules are as follows:

$$p = [r \cdot n] \quad (11)$$

$$r = \frac{t_{ter} + t_{\max}}{2t_{\max}} \quad (12)$$

where t_{ter} is the current iteration number, and r is the extraction rate of dynamic change.

Step 4: Other ants in the ant colony move to the position of the X_{obj} according to (13) and perform a large step global search [38].

$$X_i = (1 - \lambda) X_i + \lambda X_{obj} \quad \lambda \in (0, 1) \quad (13)$$

where λ is the adjustable coefficient and X_{obj} is the position of the head ant with the smallest F value.

Step 5: The head ant X_{best} generated during the last iteration performs a local fine search in its neighbourhood

according to (14) and (15).

$$X_{best} = \begin{cases} X'_i & F(X'_i) < F(X_{best}) \\ X_{best} & \text{others} \end{cases} \quad (14)$$

$$X'_i = X_{best} \pm \delta \cdot h \quad (15)$$

where X'_i is the position after local search of the head ant X_{best} . $\delta = 0.1rand()$, and the choice of “ \pm ” can be explained by the idea of “exploration” in pattern searching, as determined by (16):

$$X'_{best} = X_{best} \pm (X_{best} \cdot 0.01) \quad (16)$$

When $F(X'_{best}) \leq F(X_{best} + X_{best} \cdot 0.01)$, “+” is taken in (16); otherwise, “-” is taken.

h is the dynamic search step size, updated by (17):

$$h = \left(h_{max} - \frac{iter(h_{max} - h_{min})}{t_{max}} \right) \quad (17)$$

where h_{max} and h_{min} are the initial constants; generally, $h_{max} = 10h_{min}$ is taken. t_{max} is the maximum number of iterations. As the iterations increase, the search step will be adjusted dynamically to make the search process much more detailed so as not to skip the global optimal solution.

Step 6: During the iterative process, the concentration of the ant pheromone at each location is updated. The updating rule is as follows [39]:

$$\tau(i) = (1 - \rho)\tau(i) + \Delta\tau(i) \quad (18)$$

where ρ is the pheromone volatilization coefficient, $\rho \in (0, 1)$.

Step 7: Determining whether the termination condition of iteration is satisfied. If yes, terminate the iteration and output the optimal parameter combination (C, σ) , otherwise, go back to *Step 4* and continue. A flow chart of the LSSVM parameter optimization based on the MACA is shown in Fig. 1.

C. MACA PERFORMANCE TEST

In this section, the experimental method is proposed for evaluating the performance of MACA. In order to compare the parameter optimization performance with the other algorithms, we select five typical standard test functions commonly used in the literatures [40]–[44] to show the performance of each algorithm. The algorithm parameter settings in this paper are the same as those in the comparison literatures. The ant colony size is 20; convergence accuracy is 1.0×10^{-4} . In the proposed algorithm, pheromone volatilization coefficient ρ is 0.9; the minimum search step size h_{min} is 1 and the maximum search step size h_{max} is 10, respectively; adjustable coefficient λ is 0.1. Five test functions are all minimum value optimization, and the specific expressions are shown in Table 1.

We perform each test function 50 times by using the algorithm presented in the paper, the results are shown in Table 2. Where $G\%$ represents the proportion of the experimental results that satisfying the convergence accuracy to all the

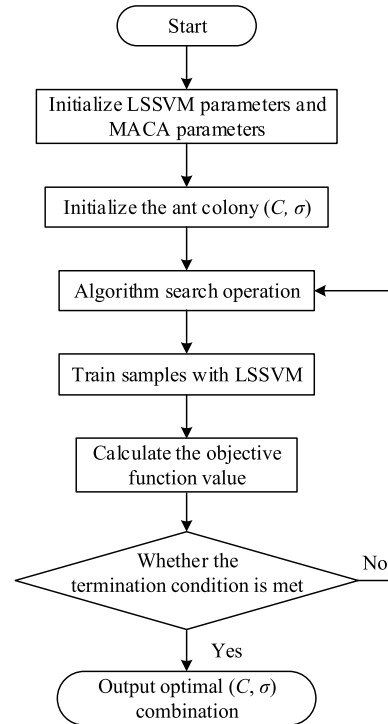


FIGURE 1. Flow chart of LSSVM parameter optimization based on MACA.

experimental results. The convergence accuracy is the absolute value of the difference between the actual solution value and the theoretical optimal value. Err is the solution error; $Time$ represents the running time; $Ave/Max/Min$ represents the average value, maximum value, and minimum value of the evaluation number; $iter$ is the number of iterations, which is determined by the allowable error range in formula (19) [40]. As the number of iterations in the algorithm proposed in this paper is proportional to the evaluation number ($Evals$), the $Evals$ is calculated according to the number of iterations: $Evals = iter \times n$, where n is the number of ants.

$$|v^\alpha - v^*| < \varepsilon_1 \cdot v^* + \varepsilon_2 \quad (19)$$

where v^α is the global optimal value found by the algorithm; v^* is the theoretical global optimal value of the objective function; ε_1 and ε_2 are the accuracy parameters, in all tests discussed in this paper, $\varepsilon_1 = \varepsilon_2 = 1.0 \times 10^{-4}$.

As shown in Table 2, each test function repeats 50 times, the optimization ratios of five test functions for MACA are all 100%. For the f_5 test function, the MACA can't reach the minimum value (0); for the other four test functions, the MACA can all reach the minimum value (0), but the solution accuracy for the f_5 test function is still high. The evaluation numbers of five test functions are mainly within 1000 times, and the average running time is less than 0.07s.

Table 3 represents the comparison of experimental results between the algorithm proposed in the paper and the algorithms mentioned in the comparison literatures, where the meaning of $G\%$ is the same as in Table 2; O_{MIN} represents the minimum value of Err ; O_{AVE} represents the average

TABLE 1. Test function.

Symbol	Name	Function (F)	Interval of x_i
f_1	Martin & Gaddy	$MG(X) = (x_1 - x_2)^2 + \left(\frac{x_1 + x_2 - 10}{3}\right)^2$	[-20, 20]
f_2	Griewangk's	$GR(X) = 1 + \sum_{i=1}^n \left(\frac{x_i^2}{4000}\right) - \prod_{i=1}^n \left(\cos\left(\frac{x_i}{\sqrt{i}}\right)\right)$	[-5, 5]
f_3	Sphere Model	$SM(X) = \sum_{i=1}^n x_i^2$	[-5, 5]
f_4	Rastrigin	$RA(X) = \sum_{i=1}^n (x_i^2 - 10 \times \cos(2\pi x_i)) + 10n$	[-5, 5]
f_5	Rosenbrock	$RS(X) = \sum_{i=1}^{n-1} \left[100(x_i^2 - x_{i+1})^2 + (x_i - 1)^2\right]$	[-5, 10]

TABLE 2. Test results of the MACA.

Symbol	G%	Err			Evals			Time		
		Ave	Max	Min	Ave	Max	Min	Ave	Max	Min
f_1	100	2.9084E-11	1.1725E-10	0	822.0	918	766	0.0469	0.0540	0.0422
f_2	100	0	0	0	655.2	720	603	0.0587	0.0662	0.0543
f_3	100	2.9007E-11	4.7907E-11	0	662.7	701	650	0.0583	0.0662	0.0537
f_4	100	6.3798E-11	4.8581E-10	0	675.3	743	610	0.0669	0.0776	0.0626
f_5	100	6.7072E-11	1.2487E-10	2.3678E-11	1371.2	1435	1310	0.0474	0.0536	0.0442

TABLE 3. Test results of different algorithms on five functions.

Symbol	Algorithm	G%	O_{MIN}	O_{AVE}	E_{AVE}
f_1	CIAC [40]	20	/	0.340	11751
	ACO [41]	100	0	4.9899E-11	807.1
	NFCACO [42]	100	7.2717E-08	7.2347E-07	1008
	MACA	100	0	2.9242E-11	806
f_2	CIAC	63	/	0.01	48402
	ACO	100	0	0	655.8
	DMCACO [43]	49	1.7825E-02	/	19626
	MACA	100	0	0	634
f_3	API [44]	/	/	0.00	10000
	ACO	100	2.2607E-11	3.0091E-11	657
	NFCACO	100	6.7764E-06	1.5960E-05	861
	MACA	100	0	2.8957E-11	653
f_4	ACO	100	3.2079E-11	1.4311E-10	674.3
	NFCACO	100	0	8.3957E-08	298.2
	DMCACO	100	0	0	549
	MACA	100	0	6.3696E-11	671.3
f_5	CIAC	100	/	3E-03	11797
	ACO	100	4.8710E-11	1.0188E-10	1388.1
	NFCACO	100	1.3444E-07	6.5040E-07	1507.8
	MACA	100	4.7780E-11	6.7041E-11	1371.9

value of *Err*; E_{AVE} represents the average value of *Evals*. We repeat each function 10 times which is the same as the comparison literatures so as to compare with the CIAC,

ACO, NFCACO, DMCACO, and API algorithms. Each function takes the corresponding dimension in the comparison literature.

As shown in Table 3, the optimization ratios of five test functions for MACA are all 100%. The f_2 and f_4 are multimodal functions, there are about 10^n local minima in definition domain. For the f_2 test function, the evaluation number of MACA reduces greatly compared with those of CIAC and DMCACO, and the solution accuracy is obviously better than that of CIAC and DMCACO. Although MACA has the same solution accuracy as ACO, the evaluation number of MACA is less than ACO. For the f_4 test function, the average value of error and the evaluation number of MACA are slightly worse than DMCACO. However, the MACA itself can reach a higher solution accuracy, and which is higher than those of ACO and NFCACO.

For the f_1, f_3 and f_5 test functions, the solution accuracy of MACA is better than those of the comparison algorithms, and the evaluation numbers are relatively little. Although the test result of f_5 test function can't reach the minimum value (0), the solution accuracy is still high.

On the basis of above analysis, the test results of the MACA algorithm for five functions show high solution accuracy and excellent global optimization ability, and the test results are satisfactory.

IV. FORECASTING OF WMC BASED ON MACA-LSSVM

A. ESTABLISHMENT OF WMC FORECASTING MODEL BASED ON MACA-LSSVM

During the wood drying process, due to the influences of temperature, humidity and air velocity on the wood surface, the WMC is a non-stationary data sequence that changes with time and decreases nonlinearly. In the wood drying experiment of this paper, the fan will keep running at full speed after starting, and the air velocity on the wood surface in the drying kiln is approximately constant. Therefore, the state data of the fan are not taken into account when establishing the forecasting model. The structure of the WMC forecasting model of the optimized LSSVM based on MACA in the drying process is shown in Fig. 2.

The input sample data are mapped to a high-dimensional feature space by the LSSVM through nonlinear functions, so the data sequence needs phase space reconstruction processing to construct suitable input and output vectors [18]. The structure of the moisture content forecasting model during the wood drying process based on the MACA-LSSVM is shown in formula (20), where $T(t)$ is the current temperature input in the wood drying kiln; $T(t-1) \cdots T(t-p)$ are the temperature inputs in the historical state of the system; $H(t)$ is the current humidity input; $H(t-1) \cdots H(t-p)$ are the humidity inputs in the historical state; $y(t)$ is the current system output of WMC; $y(t-1) \cdots y(t-q)$ are the system outputs of WMC in the historical state; and $y^*(t)$ is the current predicted output value of the model.

$$y^*(t) = f[T(t) - T(t-p), H(t) \cdots H(t-p), y(t) \cdots y(t-q), \theta] \quad (20)$$

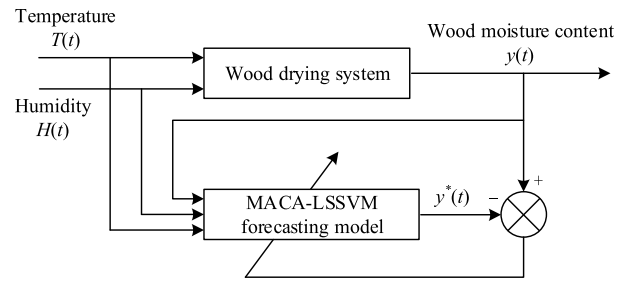


FIGURE 2. Structure of forecasting model of WMC.

where p and q represent the time delay and θ is the parameter set of the forecasting model. It is very important to determine the time delay. If the time delay is too large, the model structure will become complex and the computation amount will increase; however, if the time delay is too small, the dynamic characteristics of the system can't be reflected, and the precision of the model will become poor. In this paper, the time delay can be determined on the basis of the fitting precision of the model in simulation experiments.

The specific implementation steps of establishing a moisture content forecasting model (MACA-LSSVM) for the wood drying process are as follows:

Step 1: Select the data of the wood drying process to form the training samples and predicting samples. Set a delay time and reconstruct a phase space with q groups of data.

Step 2: Initialize the LSSVM parameters and MACA parameters, then construct the LSSVM forecasting model with the training samples.

Step 3: Adopt the MACA for automatic search; then, the best parameter combination (C, σ) of LSSVM is selected.

Step 4: C and σ are substituted into (6); then, b and α_i are solved.

Step 5: Substitute $\sigma, b,$ and α_i into (8), and the function expression of LSSVM regression estimation is obtained; then, the WMC is predicted, and the result is output.

B. EVALUATION INDEX OF THE FORECASTING MODEL

In this paper, we choose the root mean square error (RMSE), the relative error (RE), the root mean square relative error (RMSRE), and the mean absolute error (MAE) as evaluation indexes and use them to evaluate the performance of the WMC forecasting model. The calculation methods are shown in formulas (21)-(24).

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (21)$$

$$RE = \frac{y_i - \hat{y}_i}{y_i} \times 100\% \quad (22)$$

$$RMSRE = \sqrt{\frac{1}{N} \sum_{i=1}^N \frac{(y_i - \hat{y}_i)^2}{y_i^2}} \quad (23)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (24)$$

where N is the number of forecasting samples; y_i is the actual value; and \hat{y}_i is the forecasting value.

The $RMSE$ is used to evaluate the prediction accuracy of MACA-LSSVM model. The smaller the error, the higher the prediction accuracy.

In order to better evaluate the performance of the prediction models, reasonable and comprehensive error analyses are necessary. Among the comparison of the prediction performance of the models (BP-NN, LSSVM, ACO-LSSVM, and MACA-LSSVM), the RE is used to evaluate the prediction stability; the $RMSRE$ and the MAE are selected to evaluate the accuracy of the prediction model.

C. SIMULATION RESEARCH AND PREDICTED RESULTS ANALYSIS

In the study, *Fraxinus mandshurica* is used as the experimental tree specie. During the decreasing drying phase of the actual drying process of *Fraxinus mandshurica*, we collect 123 sets of data as simulation experiment samples, including the temperature and humidity in the drying kiln and the WMC under the corresponding states. Each set of data is measured under the same condition and has the same composition structure.

In the 123 samples, the temperature ranges from 49.4°C to 64.7°C, the humidity ranges from 10.9% to 15.8%, the WMC ranges from 33% to 7.3%, and there is a nonlinear and strong coupling relationship among them. Using the first three sets of data to reconstruct the phase space of the LSSVM model and then using the middle 100 sets of data to establish the WMC forecasting model, the penalty factor C and the kernel function parameter σ of the LSSVM are automatically optimized through the MACA algorithm. Finally, the temperature and humidity of the last 20 groups of data are input to the forecasting model, and the predicted values of the WMC are obtained, which are compared with the corresponding actual values. Then, the deviations are obtained.

MATLAB 2017b and the LSSVM labv1_8 toolbox are used to write the WMC forecasting program of the MACA-LSSVM. The algorithm is initialized as follows: ant colony size $n = 20$; pheromone volatilization coefficient $\rho = 0.9$; the minimum and maximum search step sizes are $h_{min} = 1$ and $h_{max} = 10$, respectively; adjustable coefficient $\lambda = 0.1$; and maximum iteration number $t_{max} = 100$; $1 \leq C \leq 10000$, $1 \leq \sigma \leq 1000$. The optimal parameter combination of the LSSVM is searched by the MACA and is substituted into the MACA-LSSVM model to predict the WMC. The convergence process of F is shown in Fig. 3.

From Fig. 3, we can see that the objective function F of the MACA converges rapidly with the increase of iterations; at the 36th iteration, $F = 0.0200$, which tends to be stable. Finally, the optimal parameter combination of LSSVM is obtained at $C = 3110.2429$, $\sigma = 717.9204$. The results indicate that the MACA is suitable for the optimization selection of LSSVM model parameters with fast convergence speed and high computational efficiency.

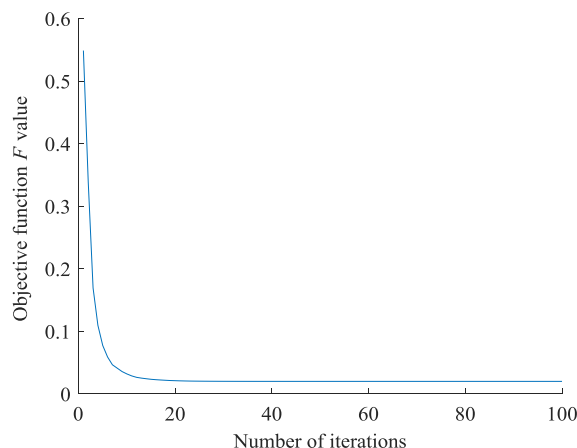


FIGURE 3. Convergent curve of F .

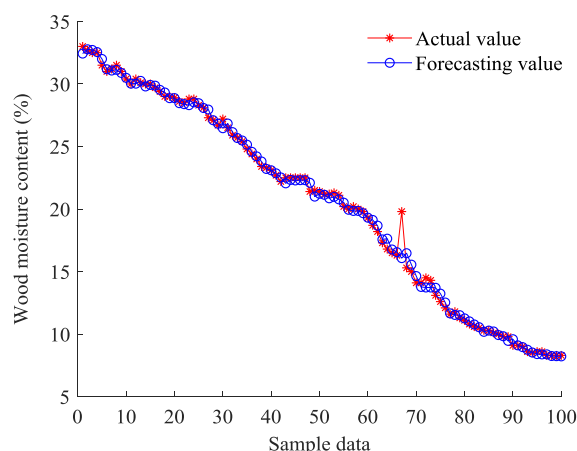


FIGURE 4. Training process curve of MACA-LSSVM.

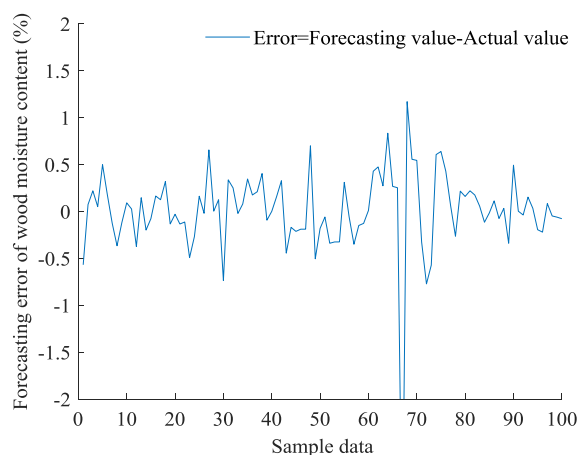


FIGURE 5. Training process error curve of MACA-LSSVM.

The building process curve and error curve of the moisture content forecasting model of *Fraxinus mandshurica* are shown in Fig. 4-Fig. 7. The training process curve and the error curve are shown in Fig. 4 and Fig. 5, respectively; Fig. 6 and Fig. 7 are the forecasting process curve and the error curve, respectively; the abscissas from Fig. 4 to

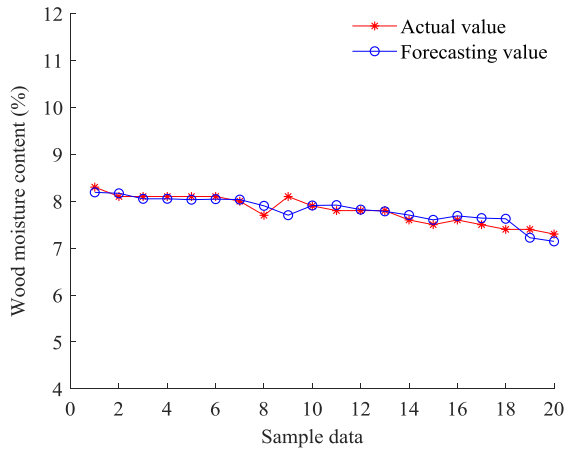


FIGURE 6. Forecasting process curve of MACA-LSSVM.

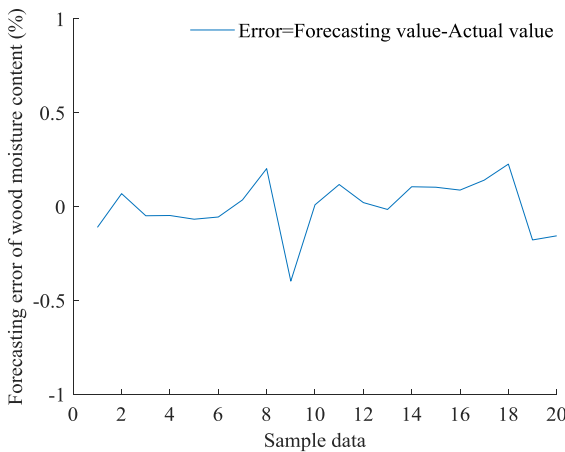


FIGURE 7. Forecasting process error curve of MACA-LSSVM.

Fig. 7 represent the number of samples; and the ordinates of Fig. 5 and Fig. 7 represent the errors between the forecasting values and the actual values of WMC during the drying of *Fraxinus mandshurica*.

As can be seen from Fig. 4 and Fig. 6 that the output curves of the training process and the prediction process can better approximate the actual values. For the discontinuous sample point (No. 67) in the training process which is shown in Fig. 4 and Fig. 5, its forecasting error of WMC is larger. This is because the output disturbance appears in the temperature and humidity of the wood drying kiln, and the historical data before the current forecasting time of the system should be considered in the modeling of the MACA-LSSVM method. This disturbance is still included in the subsequent sample training, which affects the forecasting accuracy and makes the model have a large error near the discontinuous point. However, it can be seen from Fig. 5 that after several steps of training with disturbance, the forecasting error is significantly reduced, the model gradually tends to be stable, and the WMC variation in the drying process is better predicted. The forecasting model based on MACA-LSSVM

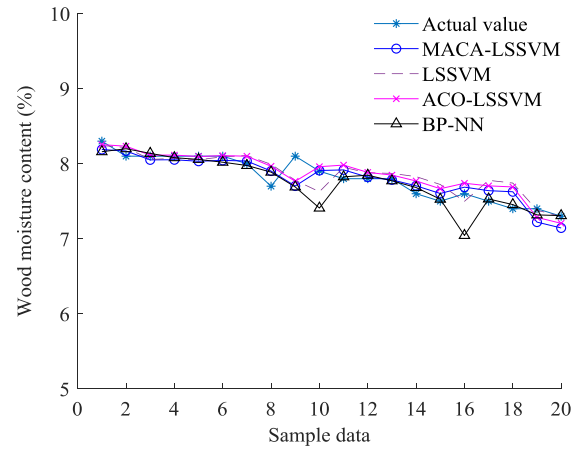


FIGURE 8. Forecasting process curves of BP-NN, LSSVM, ACO-LSSVM and MACA-LSSVM.

of the wood drying process has strong generalization ability and certain robustness.

The total running time of the MACA-LSSVM is 16.1940 s, $RMSE = 0.4586$; the training time of the middle 100 groups is 0.0040 s, $RMSE = 0.4984$; the forecasting time of the last 20 sets of samples is 0.0020 s, $RMSE = 0.1415$; and the error of the forecasting process is within ± 0.5 . The simulation results show that the MACA-LSSVM has small $RMSE$ and high prediction accuracy. It can accurately predict the WMC in the drying process and meet the actual process requirements.

To verify the prediction performance of the model in this paper, the forecasting results of the MACA-LSSVM model are compared with those of the BP-NN, LSSVM, and ACO-LSSVM models. The model structure of the BP-NN is 5-7-1; the learning factor is $\mu = 0.9$; and the maximal allowable error is $\varepsilon = 1.0 \times 10^{-4}$. The penalty factor of the LSSVM model is $C = 10000$; and the kernel function parameter is $\sigma = 1000$; ant colony size n is 20; M is the maximum number of iterations; h is the dynamic search step size; p is the number of ants extracted randomly from ant colony n ; r is the extraction rate of dynamic change. The parameters of each model are set in Table 4.

Fig. 8 shows the simulation results of the BP-NN, LSSVM, ACO-LSSVM, and MACA-LSSVM models for the prediction of the moisture content of the last 20 groups of samples. It can be found that the WMC forecasting model based on MACA-LSSVM can well fit the nonlinear relationship between drying medium and WMC. The fitting effect of the forecasting curve and the actual value is better than that of the other three forecasting models.

The RE curves between the forecasting value and the actual value of the four models are shown in Fig. 9. The RE , $RMSRE$, MAE , and the forecasting time of four models are shown in Table 5. The actual values and forecasting values of moisture content are expressed in A_V and F_V , respectively.

Table 5 shows that the RE between the forecasting value and the actual value of WMC fluctuates between -2.44% and

TABLE 4. Model parameter settings.

Algorithm	Parameters
BP-NN	$\mu = 0.9, epochs = 1000, show = 50$
LSSVM	$C = 10000, \sigma = 1000$
ACO-LSSVM	$n = 20, M = 100, \rho = 0.9, h_{min} = 1, h_{max} = 10, \lambda = 0.1, C_{min} = 1, C_{max} = 10000, \sigma_{min} = 1, \sigma_{max} = 1000,$
MACA-LSSVM	$n = 20, M = 100, \rho = 0.9, h_{min} = 1, h_{max} = 10, \lambda = 0.1, C_{min} = 1, C_{max} = 10000, \sigma_{min} = 1, \sigma_{max} = 1000,$ $p = rand\ r, n$

TABLE 5. Simulation results and relative errors.

Samples	Moisture Content	BP-NN		LSSVM		ACO-LSSVM		MACA-LSSVM	
	$A_V / \%$	$F_V / \%$	$RE / \%$	$F_V / \%$	$RE / \%$	$F_V / \%$	$RE / \%$	$F_V / \%$	$RE / \%$
104	8.3	8.1595	1.69	8.2419	0.70	8.2534	0.56	8.1889	1.34
105	8.1	8.1991	-1.22	8.2151	-1.42	8.2329	-1.64	8.1687	-0.85
106	8.1	8.1375	-0.46	8.0562	0.54	8.1138	-0.17	8.0507	0.61
107	8.1	8.0799	0.25	8.0702	0.37	8.1146	-0.18	8.0521	0.59
108	8.1	8.0568	0.53	8.0522	0.59	8.0953	0.06	8.0323	0.84
109	8.1	8.0196	0.99	8.0917	0.10	8.1079	-0.10	8.0441	0.69
110	8.0	7.9760	0.30	8.1086	-1.36	8.0996	-1.24	8.0351	-0.44
111	7.7	7.8875	-2.44	7.9912	-3.78	7.9661	-3.46	7.9018	-2.62
112	8.1	7.6899	5.06	7.7786	3.97	7.7656	4.13	7.7023	4.91
113	7.9	7.4087	6.22	7.6263	3.46	7.9601	-0.76	7.9089	-0.11
114	7.8	7.8249	-0.32	7.9514	-1.94	7.9812	-2.32	7.9172	-1.50
115	7.8	7.8462	-0.59	7.8789	-1.01	7.8840	-1.08	7.8209	-0.27
116	7.8	7.7721	0.36	7.8707	-0.91	7.8481	-0.62	7.7843	0.20
117	7.6	7.6826	-1.09	7.8277	-3.00	7.7697	-2.23	7.7053	-1.39
118	7.5	7.5267	-0.36	7.7227	-2.97	7.6667	-2.22	7.6027	-1.37
119	7.6	7.0439	7.32	7.4986	1.33	7.7393	-1.83	7.6875	-1.15
120	7.5	7.5300	-0.40	7.7780	-3.71	7.7048	-2.73	7.6405	-1.87
121	7.4	7.4550	-0.74	7.7421	-4.62	7.6900	-3.92	7.6259	-3.05
122	7.4	7.3178	1.11	7.3814	0.25	7.2845	1.56	7.2218	2.41
123	7.3	7.3080	-0.11	7.2953	0.06	7.2057	1.29	7.1438	2.14
	<i>RMSRE</i> / %	2.59		2.32		2.02		1.82	
	<i>MAE</i>	0.1237		0.1397		0.1237		0.1097	
	Forecasting time / s	0.0090		0.0050		0.0030		0.0020	

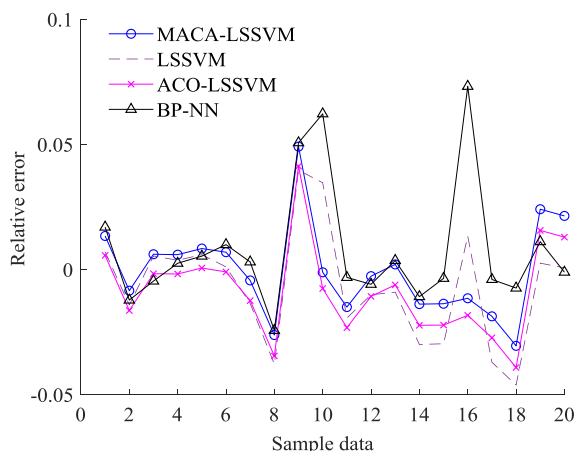


FIGURE 9. Relative error of each model.

7.32% of the BP-NN model; the *RE* between the forecasting value and the actual value of the LSSVM model fluctuates between -4.62% and 3.97%; the *RE* between the forecasting

value and the actual value of the ACO-LSSVM model fluctuates between -3.92% and 4.13%; the *RE* between the forecasting value and the actual value of the MACA-LSSVM model fluctuates between -3.05% and 4.91%. The *RE* between the forecasting value and the actual value of the BP-NN model fluctuates greatly, which shows that the prediction stability of the BP-NN model for WMC is poor and the prediction stability of the MACA-LSSVM model is relatively good.

In addition, as shown in Table 5 the *RMSRE* obtained by the MACA-LSSVM method is only 1.82%, which is 0.77%, 0.50%, and 0.20% lower than those obtained by the BP-NN, LSSVM, and ACO-LSSVM models, respectively. The *MAE* of the MACA-LSSVM is 0.1097, which is also lower than those of the other three models. The forecasting time of the MACA-LSSVM is 0.0070 s, 0.0030 s, and 0.0010 s shorter than that of the BP-NN, LSSVM, and ACO-LSSVM, respectively. The results indicate that the running speed of the MACA-LSSVM model improves effectively. According to the above analysis, we can see that the MACA-LSSVM forecasting model proposed in this paper has higher prediction

accuracy and operation efficiency than the BP-NN, LSSVM, and ACO-LSSVM models.

V. CONCLUSION

With the decrease of global forest resources and the continuous emergence of environmental protection and ecological problems, great attention has been brought on how to effectively use the existing wood resources, improve the utilization rate of wood and improve the quality of wood products. Wood drying is the most important part in processing and comprehensive utilization. Wood drying quality can impact on the utilization ratio of wood and the quality of wood products directly. Wood moisture content is an important parameter to judge the wood drying degree and the quality of wood products. Exploring a scientific and effective method to predict the wood moisture content accurately is helpful to adjust the drying process and improve the drying level. Therefore, the research combines the MACA with the LSSVM model, and puts forward the MACA-LSSVM model to predict the water content of wood drying process. The purpose of this study is to provide the accurate data of wood drying process by improving the prediction accuracy of forecasting model, so as to implement the accurate regulation and improve the intelligent control level of wood drying system.

The main findings are as follows:

a) The MACA algorithm is proposed to optimize the LSSVM model parameters and get the optimal parameter combination (C , σ) automatically.

b) For continuous domain optimization problem, in order to test the optimization ability of MACA, five standard test functions are selected to test MACA algorithm, respectively. Then we compared the results with CIAC, API, ACO, NFCACO, and DMCACO algorithms and the test results show that the optimization rate of MACA is 100%, the solution accuracy is higher than the comparison algorithms.

c) Based on the actual data of the wood drying process of *Fraxinus mandshurica*, the MACA-LSSVM forecasting model of wood moisture content is built. In the process of training and prediction, the convergence rate of the objective function is fast, the *RMSE* and the *MAE* values are small, and the prediction error is of within ± 0.5 . Moreover, the model could restore the stability quickly after the discontinuous sample point and show a better prediction effect.

d) In this study, the BP-NN, LSSVM, ACO-LSSVM, and MACA-LSSVM models are used to predict the moisture content of *Fraxinus mandshurica*, respectively. The results show that the *RMSRE* of MACA-LSSVM is only 1.82%, which is 0.77%, 0.50%, and 0.20% lower than that of BP-NN, LSSVM, and ACO-LSSVM; the *MAE* is only 0.1097, which is 0.0140, 0.0300, and 0.0140 lower than that of BP-NN, LSSVM, and ACO-LSSVM, respectively. The running time is also shorter than the other three models. The experimental results indicate that the prediction accuracy and the running speed of MACA-LSSVM are all better than the other three models.

The main contributions of the paper are as follows: (1) The MACA-LSSVM model is proposed to forecast the moisture content of wood drying process. The results indicate that the model can satisfy the actual needs; (2) Compared with the BP-NN, LSSVM, and ACO-LSSVM models, the MACA-LSSVM model has a higher prediction accuracy and computational efficiency. (3) By improving the prediction accuracy and prediction stability of the forecasting model, the intelligent control level of the wood drying system is improved.

In this study, despite the MACA-LSSVM model has a high prediction accuracy, certain research work is required to be supplemented and perfected. For example, the MACA-LSSVM model belongs to the offline modeling. In the future, we will study the online pre-processing of sample data to realize the online modeling and forecasting of wood drying process. In addition, the forecasting of water content in the drying process of multiple tree species should be carried out to improve the generalization performance of the forecasting model.

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