

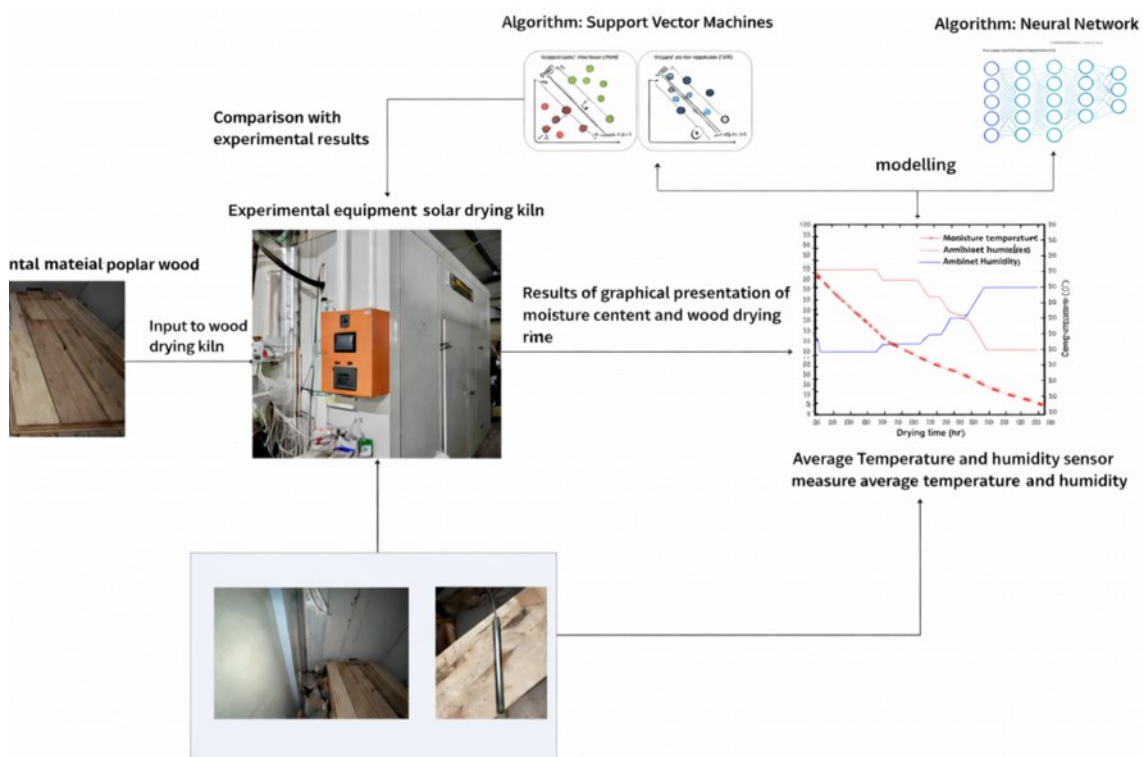
Predicting Combined Solar and Conventional Drying of Wood with an Algorithm Based on Support Vector Regression and Particle Swarm Optimization

Hongwei Wang,^{a,c} Rui Liu,^b Ying Zhou,^c and Hao Li^{d,*}

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GRAPHICAL ABSTRACT



Predicting Combined Solar and Conventional Drying of Wood with an Algorithm Based on Support Vector Regression and Particle Swarm Optimization

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Accurate prediction of wood-drying rates is essential for enhancing drying efficiency and product quality; however, reliable models remain scarce, particularly for solar drying systems. In this study, poplar wood was dried in a solar kiln, and moisture content was determined through periodic mass measurements. The drying rate was calculated from the moisture content reduction over time, while kiln temperature and relative humidity were continuously monitored using calibrated sensors. Experimental results showed that poplar wood with an initial moisture content of 73.2% required approximately 130 h to reach a final moisture content of 7.5% under solar drying conditions. Based on an analysis of key physical factors affecting the drying process, kiln temperature, relative humidity, and wood moisture content were selected as input variables, with the drying rate as the output variable. Several optimization algorithms were evaluated, and a particle swarm optimization–support vector regression (PSO-SVR) model demonstrated the best performance. The optimized model achieved a mean squared error of 0.00105 and a mean absolute error of 0.039, indicating high prediction accuracy. In addition, the training time was reduced to 0.275 s, reflecting excellent computational efficiency. These results confirm that the PSO-optimized SVR model can be both accurate and efficient, *i.e.*, practical industrial wood-drying applications.

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Keywords: Solar kiln drying; Drying rate prediction; Support vector regression; Particle swarm optimization

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INTRODUCTION

The process of wood drying is a crucial step in enhancing the efficiency of wood consumption. Ensuring consistent drying rates offers advantages in terms of reducing drying faults, minimizing downgrading, and enhancing drying efficiency (Ai *et al.* 2016). It is necessary to develop a model for drying rates to effectively regulate the process.

Innovative approaches are abundant in the field of wood drying, aimed at reducing energy consumption and enhancing efficiency. These include the adoption of new drying techniques, pre-drying treatments, and the development of drying process models. Owing to the strong intermittency and climate dependence of solar energy input, its coupling with conventional heat sources significantly increases the nonlinearity and

disturbance amplitude of the drying process. Consequently, advanced control and prediction tools (such as high-precision average temperature and humidity sensors and data-driven models) are required to guarantee a stable drying rate. This article considers the case of a combined in which solar energy is paired with conventional drying. The drying system consists of five main units, a drying chamber, a multi-pass solar air collector, a cylindrical parabolic solar collector, a thermal storage tank, and a closed feed air heater. The drying time decreases as the collector area increases and the boards thickness decreases (Khouya 2020).

The implementation of forced ventilation and a waste heat recovery system during kiln drying effectively captures waste heat from the exhausted moist air. This approach has been found to result in reductions of 18.9% in electrical consumption and 38.5% in overall energy usage (Khouya *et al.* 2021). The hybrid solar dryer model combines a heat pump and a concentrated photovoltaic thermal panel using air as a cooling fluid for the solar cells. The results showed that the combined system can reduce the drying time up to 18% (Phonetip *et al.* 2019). In the climate conditions of summer, spring, and winter in Epinal, France, a solar wood dryer made of wood planks was built, and the corresponding model was established.

The model yielded a mean absolute error of 2.33% and a mean relative error of 4.53%, both below 5%, respectively (Simo-Tagne *et al.* 2020). The solar dryer, which operates on forced convection, is constructed using wood and wood panels, and it includes a solar collector (Simo-Tagne *et al.* 2021). This experimental field solar dryer has been numerically simulated under the climatic conditions of both Yaoundé and Nancy. The role of the solar collector has been carefully analyzed, confirming its effectiveness as a dryer in temperate environments. The results show that in the tropical environment, the thermal efficiency exceeds 40% during the summer and spring, but falls below 30% during the winter and autumn seasons. The current research on solar drying models requires more modeling of physical processes, as well as more experimental and drying data support (Lamrani *et al.* 2023).

A variety of physical means are used to enhance drying efficiency and drying result. Ultrasound pretreatment applied before vacuum drying improves effective water diffusivity; To achieve equivalent pretreatment effects, higher ultrasonic power requires a longer pretreatment duration, whereas reduced absolute pressure shortens the overall drying time (He *et al.* 2013). Such a system was found to be especially beneficial when removing free water. The results showed that the effective water diffusivity of the specimens dried by the ultrasonic assisted vacuum drying at 0.05 or 0.08 MPa were higher than that of the samples dried without ultrasound. The ultrasound-vacuum drying method could be applied in the wood drying industry as a means of saving energy and minimizing product quality damage (He *et al.* 2013). The back propagation (BP) neural network algorithm was used to predict the change of wood MC during the drying process of a high frequency vacuum. Compared with the experimental measurements, the predicted values conformed to the variation law and size of experimental values, and the error was about 2% and the MC prediction error of measurement points along thickness direction was within 2% (Chai *et al.* 2018).

A fast online grading apparatus for sawn lumber based on near-infrared (NIR) spectroscopy has been developed. Additionally, predictive models for moisture content (MC) and modulus of elasticity (MOE) under various MC conditions were developed from the NIR spectra with the aid of partial least squares regression (PLSR) analysis. These experiments indicate that the developed device could be applied for the online

quality certification of sawn lumber in commercial sawmills (Kobori *et al.* 2015). The NIR spectra collected from the surface of wood chips were used to develop calibration models for moisture content and basic density predication, and various spectral preprocessing techniques were applied to improve the accuracy and robustness of the prediction models (Liang *et al.* 2019). An artificial neural network (ANN) model for predicting surface-released strain (SRS) was developed based on NIR spectra collected from the lumber during drying.

The SRS evolution during drying as predicted by the models showed a similar trend to the laboratory-measured one. The predicted elapsed times to reach maximum tensile SRS and stress reversal roughly coincided with the laboratory-measured times (Watanabe 2014). The PLSR regression models for predicting surface-released strain (ϵ) were developed using NIR spectra obtained from Sugi (*Cryptomeria japonica* D. Don) samples during drying. The PLS analysis identified the wavelengths around 2.035 mm as making significant contributions to the prediction of ϵ (Watanabe *et al.* 2017).

Wood's drying rate determines the quality of the product and efficiency of the process. The drying rate of western hemlock (*Tsuga heterophylla*) lumber has been found to depend on the basic density, the initial moisture content, the percentage and position of heartwood, the annual ring count, the number of rings from the pith, the growth ring angle, and the early wood and late wood coverage on board faces (Berberović and Milota 2011).

Despite the above achievements, three critical knowledge gaps remain: (i) no drying-rate model considers the transient disturbance of solar-air hybrid heating under fluctuating ambient conditions; (ii) the quantitative relationship between juvenile-wood fraction ($\geq 42\%$) and the rate drop in the fibre-saturation to end-use moisture interval is still unreported; and (iii) an explicit trade-off between optimisation accuracy and training time for SVR hyper-parameter selection has not been established for on-line industrial controllers.

To address these gaps, this work presents the first dynamic data set for fast-grown poplar dried in a solar-air hybrid kiln and introduces a juvenile-wood-aware PSO-SVR model that attains a MSE of $0.00105 (\%/h)^2$ with a training time of only 0.275 s—an order-of-magnitude acceleration over grid-search methods—thereby providing an immediately deployable tool for real-time drying-rate prediction

EXPERIMENTAL

The primary focus of this study was the investigation of fast-growing poplar wood as the central subject of research. The utilization of solar drying equipment and adherence to moisture content drying criteria are employed in the process of drying poplar wood and acquiring drying data, including average temperature, humidity, and moisture. The utilization of Support Vector Regression (SVR) was employed for the modeling of the wood drying rate.

The modeling technique utilized grid search, evolutionary algorithms, and PSO to identify the optimal hyperparameters for the SVR model. This study aims to evaluate and compare the performance of several training models to identify the most effective prediction model for future industrial applications. Figure 1 illustrates the experimental approach (He *et al.* 2017).

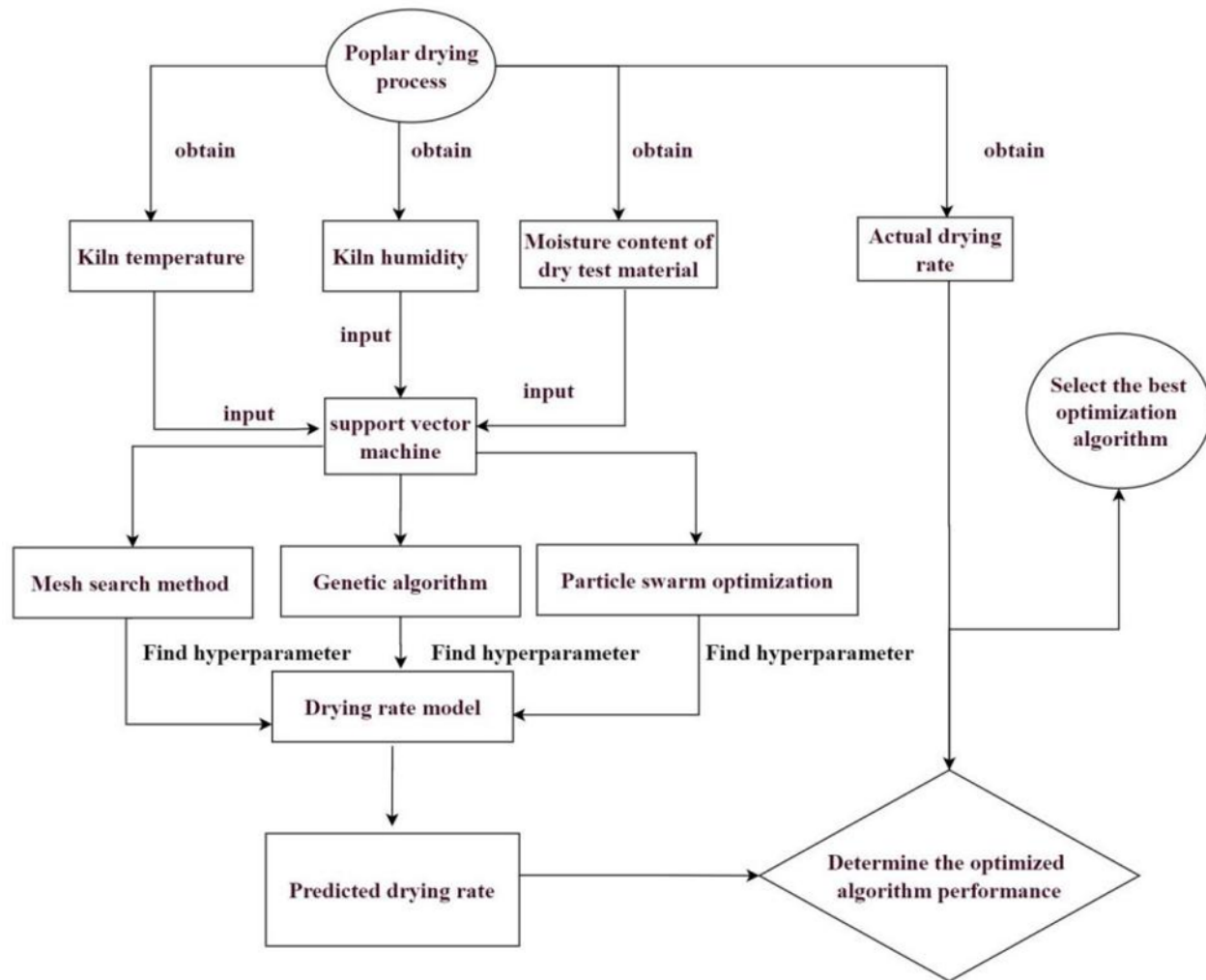


Fig. 1. Flowchart of wood drying rate experiment and model establishment

Wood Drying Experimental Equipment

1. Timber derived from rapidly growing poplar trees (500 mm × 200 mm × 35 mm) was obtained from Yilan County, Harbin City. The initial moisture content of the timber ranged from 60.63% to 80%.

2. The dimensions of the solar/air energy combination drying equipment were 3.5 m in length, 2 m in width, and 1.7 m in height. The wood chamber within the equipment has a volume of 3.3 m in length, 0.9 m in width, and 1.5 m in height (Nanjing Shenke, 020, shenke, Nanjing, China). The equipment utilized in the drying process is shown in Fig. 2.

3. The electronic balance used in this study was the YP15K-1 model (Shanghai Hengping, YP15K-1, Shunyu, Shanghai, China), which has a precision of 0.1 g.

4. A vernier caliper (Shangliang, Deep, Wangliang, Shanghai, China) with a precision of 0.01 mm was used.

5. The THD paperless (DAGA, HTS8, DAGASensor, Guangdong, China) recorder was used. It accepts 0 to 20 mA and 0 to 5 V input signals. This device can measure temperatures from -50 to 2400 °C and humidity levels from 0 to 100% relative humidity (RH).



Fig. 2. Flowchart of wood drying rate experiment and model establishment

Poplar Wood Drying Experimental Method

The poplar sawn lumber was introduced into the drying apparatus. Solar energy was utilized for heating purposes during periods of sunny weather, whilst during nights were characterized by inadequate sunshine. Therefore, a combination of solar and air energy was employed for heating (Meng *et al.* 2012). An electric convection drying oven with precise temperature and relative humidity control (model DHC-9070A, 101-2AB) was employed for the development of the intermittent drying schedule. A customized air energy–assisted solar wood drying system was used for the solar drying experiments. As shown in Fig. 1, the system mainly consisted of a solar collector, a hot water storage tank, an air-source heat pump, and a drying kiln. The effective volume of the drying kiln was $3.4 \times 1.7 \times 2.0 \text{ m}^3$. The lumber stack dimensions were $3.2 \times 0.9 \times 1.4 \text{ m}^3$, with a sticker thickness of 25 mm.

Solar radiation intensity during the experiments was recorded using a solar irradiation meter (HQJYFSV24VOC, range: 0 to 2000 W/m²). Multiple temperature and relative humidity sensors were installed, including Pt100 temperature sensors (range: –40 to 120 °C) and FG6010 humidity sensors (range: 0 to 100%), to monitor the air temperature and RH inside the kiln as well as the core and surface temperatures of the lumber during drying. A THD industrial paperless recorder was used for data acquisition at 1 min intervals.

Other instruments used in the experiments included a CM-303 woodworking planer, a YOTA-1442 drawbar saw, a YP15K-1 electronic balance with an accuracy of 0.1 g, and an LD210-2 electronic balance with an accuracy of 0.01 g. The electrical power consumption of the air energy–assisted solar drying system was continuously monitored using an industrial electricity meter with a resolution of 0.1 kWh. The air velocity inside the wood drying kiln was regulated by adjusting the operation of the top-mounted circulation fan and the exhaust fan. According to different stages of the drying process, the air velocity was controlled within the following ranges: Initial stage: 1.0 to 1.5 m/s, Middle stage: 1.8 to 2.5 m/s, and Final stage: 1.2 to 2.0 m/s.

The timber was organized using separators, and specifically chosen poplar sawn timber with favorable material quality, elevated moisture content, compact texture, and gradual drying characteristics, such as the edge material, tangential cut board, and tree

base material, was utilized as the poplar moisture content test board. The test board for measuring the moisture content of poplar was positioned at several locations on the timber stack, including the four corners, center, and one-third distance from the top. To mitigate water evaporation, the terminations of the test board were treated with a layer of impermeable waterproof material. The dimensions of each test board used for measuring moisture content were 500 mm × 200 mm × 35 mm. The initial moisture content of each board was determined through the process of weighing, resulting in values of 73.2%, 70.5%, 68.4%, 65.2%, and 66.7%.

The average temperature and humidity levels during specific stages of the drying process of poplar sawn timber were adjusted based on the moisture content and stress indicators of the poplar. This adjustment was guided by authoritative training data and aimed at ensuring optimal drying quality (Simpson 1999). The adjustment of average temperature and humidity levels was made in accordance with the set requirements for poplar moisture content drying, as outlined in LY/T 1068 (Lü *et al.* 2012) standard as shown in Table 1.

Table 1. Drying Criteria of Poplar Water Content

Moisture Content Stage	Dry Bulb Temperature (°C)	Wet Bulb Temperature (°C)	Equilibrium Moisture Content (%)
Preheating	45	1	20
Pretreatment	60	0.7	20
> 40	50	5	12.7
40 to 30	52	6	11.5
30 to 25	55	9	9.3
25 to 20	60	12	7.7
20 to 15	65	15	6.4
< 15	70	20	4.9
Equalization Treatment	75	10	8
Terminal Treatment	75	3	15

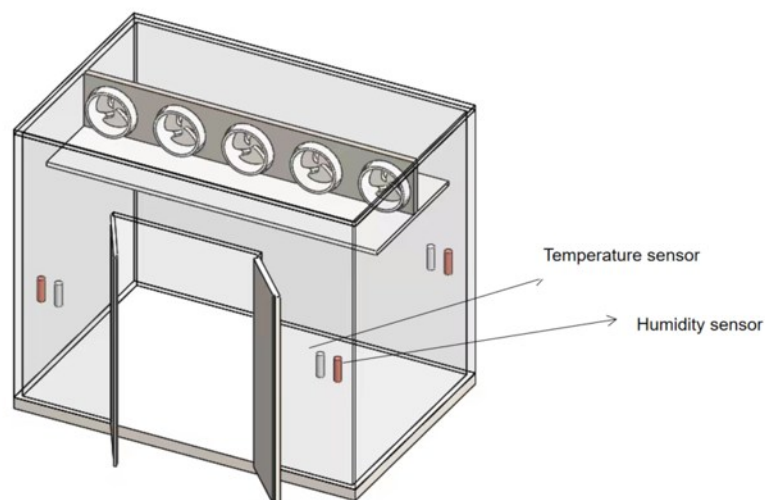


Fig. 3. Location diagram of average temperature and humidity sensor in drying kiln

RESULTS AND DISCUSSION

During the experiment, the drying rate of the wood was calculated by dividing the change in moisture content by the corresponding drying time for that change. The main methods for determining wood moisture content are the weighing method and the electrical method. To ensure the accuracy of the experimental data, this study adopts the weighing method, which can determine all moisture-content indicators of the dried poplar lumber.

Several kinds of data are retrieved from the test conducted on the moisture content of the test boards. The determination of moisture content is achieved by weighing, wherein the average moisture content is then derived from the collected data sets.

$$MC = \frac{W_c - W_d}{W_d} \times 100\% \quad (1)$$

In Eq. 1, MC is the moisture content of the test board (%); W_c is the weight of the test board (g); W_d is the oven-dry weight of the test board (g). The drying rate (DR) of wood indicates the speed at which the moisture content of the wood decreases due to drying over a certain time interval. The drying rate of wood can be calculated using Eq. 2,

$$DR = \frac{M_{n+1} - M_n}{n} \times 100\% \quad (2)$$

where M_{n+1} is the moisture content of the poplar lumber test board at the (n+1)-th measurement; M_n is the moisture content of the poplar lumber test board at the n-th measurement; and n is the time interval of the measurement.

Poplar sawn timber was loaded into the drying apparatus. During periods of sufficient sunlight, solar energy was employed as the primary heat source; during nighttime or conditions with inadequate solar radiation, a combined heating mode utilizing both solar energy and air energy was adopted. The timber stack was arranged with stickers according to the standard stacking method.

From the batch of poplar timber, boards exhibiting desirable attributes—such as high initial moisture content, sapwood characteristics, tangential-sawn orientation, dense texture, and slow-drying properties, typically originating from the butt-end of the log—were selected as moisture content test boards. These test boards were placed at key positions within the stack, including the four sides, the center, and one-third of the height from the top, to capture representative moisture distribution. Both ends of each test board were coated with a waterproof sealing material to prevent premature moisture evaporation. The placement strategy also ensured convenient access and reliable moisture measurement.

Each test board was periodically removed, weighed, and its moisture content recorded. Measurements were taken at three-hour intervals until the boards reached a state close to oven dryness. Multiple parallel experiments were conducted, and the datasets exhibiting the most stable and representative drying-rate patterns were selected as identification data for subsequent model training.

Based on the data derived from the moisture content analysis of the test boards, it can be observed that the solar drying procedure for poplar wood, initially possessing a moisture content of 73.2%, required roughly 130 h to reduce the moisture content to

around 7.5%. This trend is consistent with the widely accepted mechanism in which free water is initially transported to the surface by capillary forces, giving a high drying rate; once the surface film breaks and the evaporation front recedes below the surface, vapour diffusion becomes the rate-limiting step and the drying rate falls. The present data provided no evidence contradicting this classical explanation.

Figure 4 illustrates the fluctuations in moisture content during the drying process.

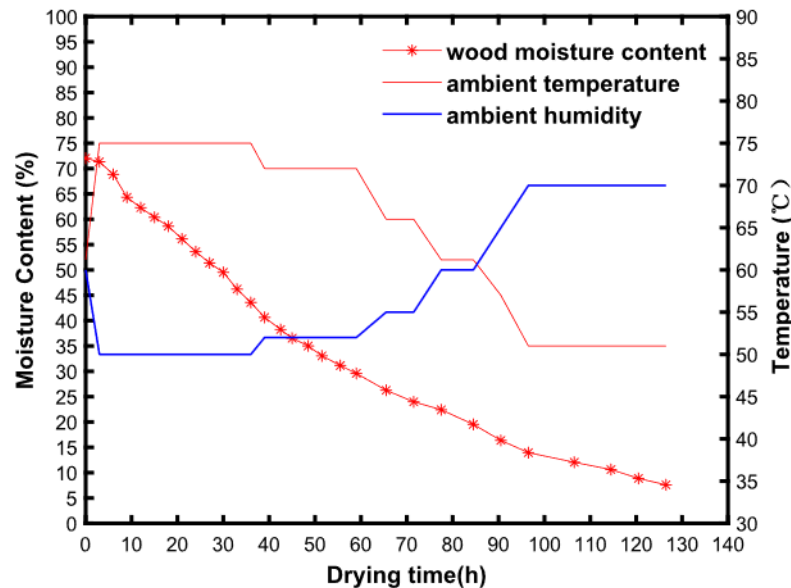


Fig. 4. Plot of moisture content and drying rate of wood

During the initial phases of the drying process, the rate of drying was comparatively elevated. This is depicted in Fig. 4, the graph illustrating the drying rate of wood. During the initial 40-h period, the drying process demonstrated a more rapid pace, characterized by an average drying rate ranging from 1.23% per hour to 0.35% per hour. The drying rate experienced a drop after a drying period ranging from 40 to 80 h. The drying rate observed within this time frame ranged from roughly 0.34% per hour, which represents the highest pace, to around 0.18% per hour, which represents the slowest rate (Alhijawi and Awajan 2024). Following a drying period of 80 h, the rate of drying exhibited a deceleration, with values ranging from 0.05% to 0.1% per hour. The drying rate exhibited modest fluctuations between 70 and 80 h, indicating the presence of anomalous data points. These fluctuations may be attributed to the moisture level nearing the fiber saturation limit, which has the potential to impact the drying rate. From the study *Using LSTM and PSO techniques for predicting moisture content of poplar fibers by impulse-cyclone drying*, it was found that when a multiple linear regression (MLR) model was used to predict wood moisture content, the mean squared error (MSE) ranged from as low as 0.025 to as high as 110. Considering that the prediction of wood drying rate is inherently more complex than that of moisture content, more advanced machine-learning and deep-learning models were therefore adopted in this work.

Support Vector Regression and Optimization Algorithm

The primary concept behind Support Vector Regression is to identify an ideal surface that minimizes the structural risk of the model (Vapnik 1998).

GridSearch CV is a method used to find the best parameters for support vector regression. It systematically explores a specific range of parameters by adjusting them in increments to find the parameter values that yield the maximum accuracy on a validation set (Kocak *et al.* 2024).

The genetic algorithm (GA) is another method used to find the best parameters for support vector regression. The GA is a computing model that simulates the biological evolution process as described by Darwin's theory of biological evolution. The process of identifying the most suitable parameter values as the ideal answer through heredity (Chen *et al.* 2023).

The PSO algorithm, the third method used to find the best parameters, has its roots in the study of avian foraging behavior. The update of particle velocity and location is determined by considering the global best particle and historical best particle within the feasible region to identify the optimal parameter (Zhang 2014).

Model Evaluation Metrics

When employing the predictive model for analysis, the primary considerations revolve on the complexity of the model and its predictive performance. The fundamental evaluation metrics encompass the subsequent metrics.

The MSE represents the mean squared error between the predicted values and the true values. A smaller MSE value indicates a smaller prediction error and better predictive performance. The MSE is calculated according to Eq. 3,

$$MSE\left(y, \hat{y}\right) = \frac{1}{m} \sum_{i=1}^m \left(\left| y_i - f\left(x_i\right) \right| \right) \quad (3)$$

The RMSE is the arithmetic square root of MSE. It measures the degree of deviation between predicted and actual values and is calculated according to Eq. 4,

$$RMSE\left(y, \hat{y}\right) = \sqrt{\frac{1}{m} \sum_{i=1}^m \left(\left| y_i - f\left(x_i\right) \right| \right)} \quad (4)$$

In Eqs. 3 and 4, m is the number of data points or observations, y_i is the actual or true value of the i th data point, $\hat{y}_i$ is the prediction result, x_i is the variable number, and $f\left(x_i\right)$ is the predicted value of the i th data point given by the model.

The MAE represents the average of the absolute differences between the predicted values and the actual values. A smaller MAE value indicates better predictive performance of the model. Equation 5 was used to calculate the MAE,

$$MAE = \frac{1}{n} \sum \left| y_i - \hat{y}_i \right| \quad (5)$$

The MAPE is the mean of percentage of the absolute errors between the predicted value and true value. A smaller MAPE indicates more accurate predictions. The MAPE was calculated according to Eq. 6,

$$MAPE = \frac{1}{n} \sum \left(\frac{|y_i - \hat{y}_i|}{y_i} \right) * 100\% \quad (6)$$

In Eqs. 5 and 6, n is the number of data points or observations, y_i is the actual or true value of the i th data point, $\hat{y}_i$ is the predicted value of the i th data point given by the model.

The above metrics reflect the predictive performance of the model. The smaller the error value, the higher the prediction accuracy.

The duration required for model training is indicative of the temporal resources allocated to the process. The efficiency of computation increases as the duration of model training decreases

Initial Parameter Setting

The primary determinants impacting the rates of wood drying are the established standards for wood drying and the moisture content maintained throughout the drying process (Bekkioui *et al.* 2023). This study examined the continuous nature of wood drying data, which is characterized by a relatively small amount in comparison to internet data. To effectively model wood drying data, it is advisable to establish distinct initial parameters for the radial basis function (RBF), which is known for its ability to effectively capture nonlinear relationships. Subsequently, employing cross-validation and grid search techniques would facilitate the exploration of hyperparameters within a certain range. This approach enables the analysis, comparison, and validation of the obtained outcomes (Duan *et al.* 2021). A full set of 326 datasets pertaining to the process of drying was developed during the training phase. For the purposes of this study, a total of 326 groups of poplar drying data were selected. Among them, 306 groups were randomly assigned for training the model, while the remaining 20 groups were used to evaluate the performance of the model. To enhance the simulation of industrial circumstances, the data underwent shuffling and random sampling on each occasion, resulting in a total of 16 iterations.

Grid Search CV

The optimal parameters of the RBF function can be found by the lattice search method, which requires setting the initial data for the different variables as in Table 2 (Dhiman *et al.* 2019). The RBF kernel function has the following initial parameters to be set, the penalty coefficient c and the initial kernel parameter, which control the tolerance of the model to misclassified samples. The margin error band p indicates the classifier's ability to accommodate errors when categorizing novel data instances. The $c(\min)$ and the $c(\max)$ specify the boundaries within which the penalty parameter is varied to optimize the model's performance (Awajan and Adeli 2023). The $g(\max)$ and the $g(\min)$ define the search space for the kernel parameter during hyperparameter optimization. The step controls the precision of the search for optimal hyperparameters through grid search (Sun *et al.* 2021).

Table 2. Parameter Settings of SVR Regression Model

	c	g	p	C(max)	C(min)	G(max)	G(min)	Step
Group1	0	0	0.01	10^1	10^{-1}	10^1	10^{-1}	1
Group2	0	0	0.05	10^1	10^{-1}	10^1	10^{-1}	1
Group3	0	0	0.1	10^1	10^{-1}	10^1	10^{-1}	1

Table 3. Training Results of Some Accuracy Metrics for SVR Training Under the First Set of Parameters

Number of Training Iterations	MSE	RMSE	R ²	MAE	MAPE (%)	Model Training Time (s)	MAPE (%)	Model Training Time (s)
1	0.0509	0.0616	29.8%	0.1784	21.3	3.516	21.3	3.516
2	0.0037	0.0612	85.1%	0.0696	9.89	3.294	9.89	3.294
3	0.0018	0.042	88.6%	0.0348	6.66	3.430	6.66	3.430
4	0.018	0.134	55.4%	0.136	12.5	3.735	12.5	3.735
5	0.0226	0.150	55.1%	0.15	23	3.246	23	3.246
6	0.014	0.118	62.9%	0.12	13.8	3.528	13.8	3.528
7	0.089	0.298	32.1%	0.1681	27.43	3.216	27.43	3.216
8	0.061	0.247	73.5%	0.17	19.5	3.240	19.5	3.240
9	0.0034	0.0583	77.8%	0.072	10.3	3.398	10.3	3.398
10	0.0132	0.114	70.5%	0.118	16.87	3.351	16.87	3.351

The model should be trained using the initial parameters from the first set. By iteratively conducting simulations, the objective is to search for the ideal model hyperparameters that yield the highest level of performance (Xu *et al.* 2021). The outcomes of each model training should be documented in Tables 3 and 4.

The model should be trained using the second set of initial parameters. By iteratively conducting simulations, one can search for the appropriate model hyperparameters to achieve optimal performance of the model. The outcomes of each model training should be documented in Tables 5 and 6.

The model should be trained using the third set of initial parameters. By iteratively conducting simulations, one can search for the appropriate hyperparameters of the model to achieve optimal performance. The outcomes of each model training were documented in following Tables 7 and 8.

Table 4. Training Results of Some Accuracy Metrics for SVR Training Under the Second Set of Parameters

Number of Training Iterations	MSE	RMSE	R ²	MAE	MAPE	Model Training Time
1	0.0034	0.0583	75.9%	0.057	8.27%	8.674 s
2	0.0041	0.0640	83.8%	0.076	11.29%	6.996 s
3	0.050	0.223	32.15%	0.175	32.15%	7.823 s
4	0.018	0.134	86.5%	0.129	13.7%	7.963 s
5	0.098	0.313	22%	0.22	31.4%	7.609 s
6	0.0612	0.247	77.8%	0.21	18.1%	7.656 s
7	0.00186	0.0431	88.3%	0.0481	6.94%	8.165 s
8	0.010	0.100	69%	0.47	15.7%	8.116
9	0.0222	0.149	51.4%	0.87	22.5%	7.620
10	0.040	0.200	34.2%	0.148	22%	7.849 s

Table 5. Training Results of Some Accuracy Metrics for SVR Training Under the Third Set of Parameters

Number of Training Iterations	MSE	RMSE	R ²	MAE	MAPE (%)	Model Training Time (s)
1	0.0041	0.0640	83.8%	0.076	11.28	7.669
2	0.0496	0.223	32.15%	0.1751	22.7	7.739
3	0.050	0.223	85.96%	0.1321	14.4	7.996
4	0.098	0.313	35.0%	0.22	30.7	7.855
5	0.0612	0.247	77.8%	0.21	18.1	7.224
6	0.0104	0.102	68.9%	0.11	15.7	8.260
7	0.022	0.148	51.4%	0.87	22.5	7.622
8	0.04	0.200	34.2%	0.47	15.7	7.709
9	0.013	0.114	63.8%	0.12	13.6	8.391
10	0.040	0.200	30.3%	0.168	27.7	7.873

Hyperparameters found with different RBF initial parameters and using the gradient search method were analysed by box-and-whisker plots for the median and mean of the results trained for each group. The results are shown in Figs. 5, 6, and 7.

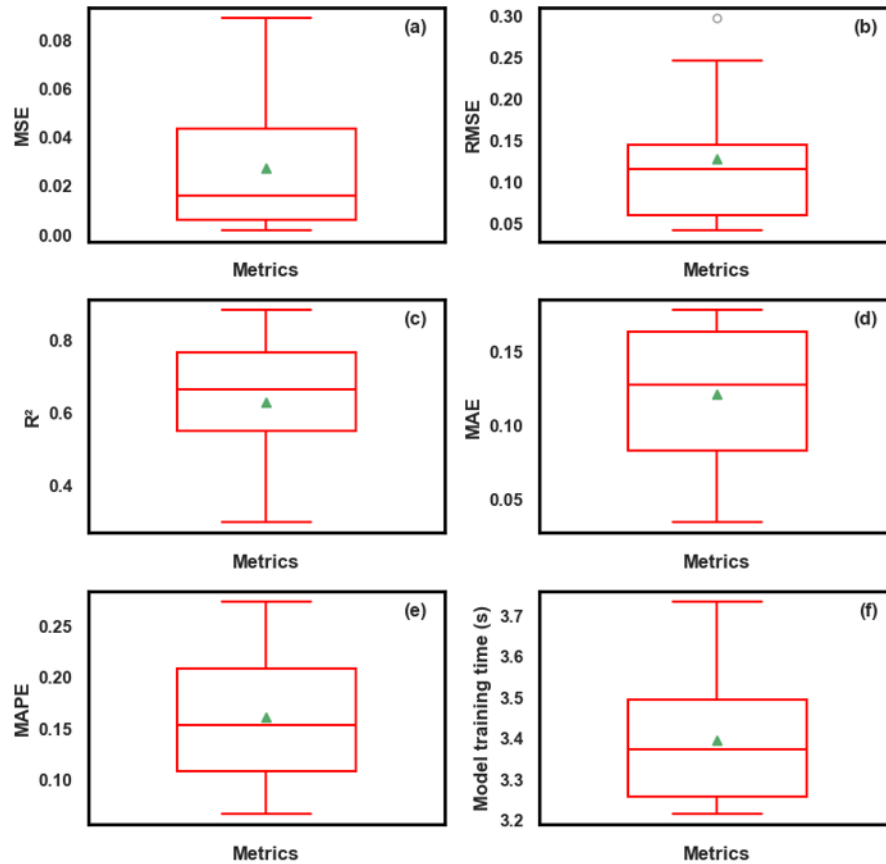


Fig. 5. Accuracy and time spent results under the first set of parameters training

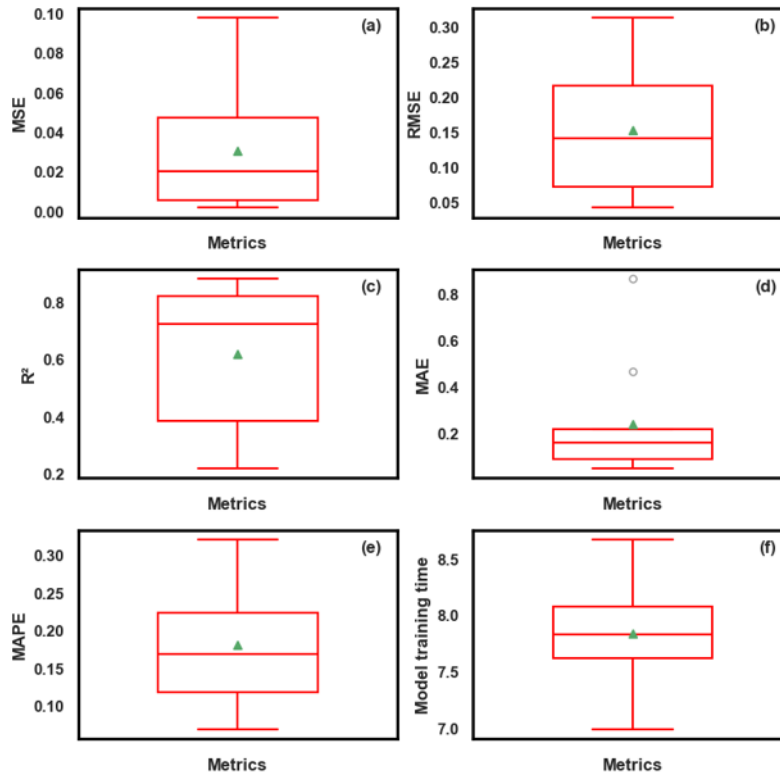


Fig. 6. Accuracy and time spent results under the second set of parameters training

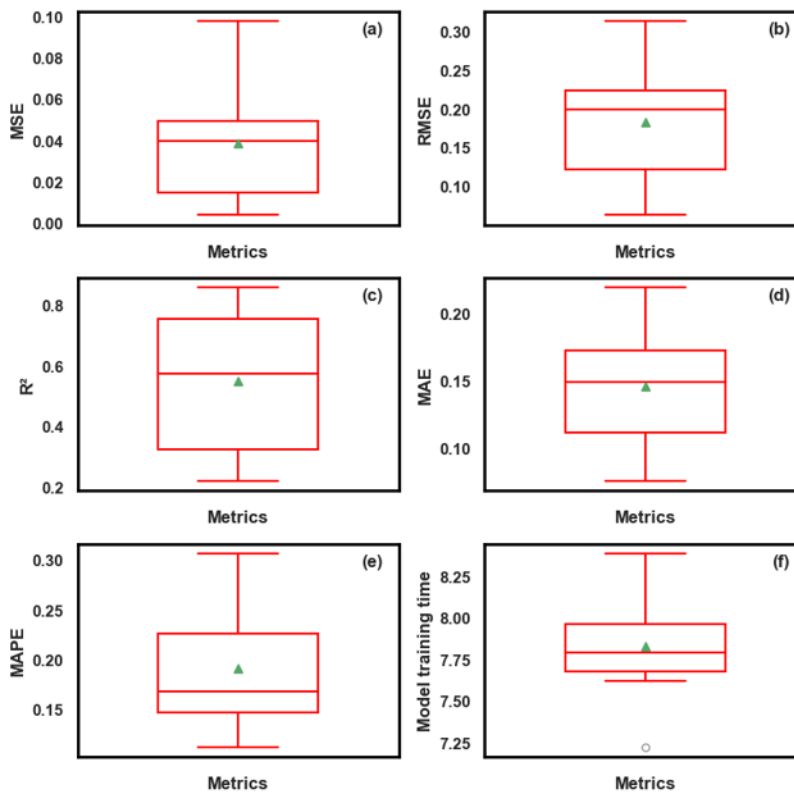


Fig. 7. Accuracy and time spent results under the third set of parameters training

Based on the data shown in Tables 5, 6, and 7, the average MSE was 0.028, the average RMSE was 0.128, the average R^2 was 63.08%, and the average MAE was 0.121; the average MAPE was 16.13%, with an average model training time of 3.285 s. For the second group, the average MSE was 0.031, the average RMSE was 0.153, the average R^2 was 60.36%, and the average MAE was 0.24; the average MAPE was 18.21%, and the average model training time was 7.868 s. For the third group, the average MSE was 0.0388, the average RMSE was 0.1834, the average R^2 was 56.33%, and the average MAE was 0.25512; the average MAPE was 19.24%, and the average model training time was 8.05 s (Li et al. 2021).

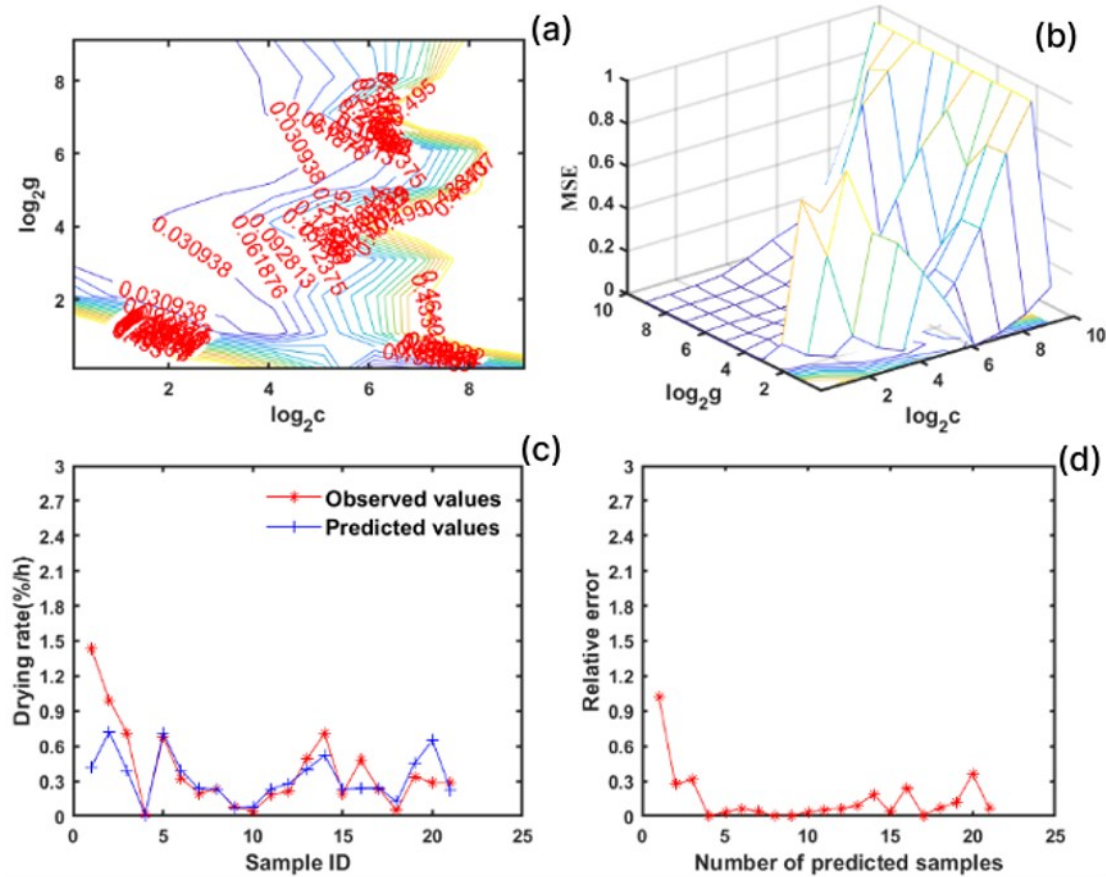
As can be seen from Figs. 5, 6, and 7, the average MSE was larger than the median MSE in the first and second groups, which indicates that there were outliers with relatively large errors under this group of parameters. The average MSE in the third group was far closer to the median MSE, which indicates that the error distribution fluctuated little in this group of parameters, and there were no outliers with large errors, and it also indicates that the model performance was more balanced in this group of parameters. The mean value of R^2 in the three groups was larger than the median, indicating the existence of outliers with smaller correlation degree.

Overall, the mean and median values of R^2 converge and were more evenly distributed. The second group of parameters of MAE had the distribution of outliers with larger error, and the remaining two groups were more uniformly distributed. The third group of MAPE had the appearance of outliers with smaller correlation coefficients. In terms of model training time, the mean and median of the training time used for the first, second, and third groups were consistent (Xu et al. 2021). Comparing the results of multiple trainings with different initial parameters, it can be seen that when the epsilon parameter was 0.01, the SVR model had the best overall performance. The MSE = 0.0018, RMSE = 0.042, R^2 = 88.6%, MAPE = 6.66%, MAE model training time 3.430 s, with hyperparameter c = 274.3, and g = 1.0718.

Through comparing the values of parameters c and g during multiple hyperparameter tuning processes, it was observed that during the hyperparameter tuning process, the penalty coefficient c changed while the kernel parameter g converged to the same value 1.0718. Therefore, the hyperparameter tuning process consisted of essentially the process of finding the optimal penalty coefficient c (Aghbashlo 2015).

The hyperparameter tuning visualization revealed that the MAE was variable within the range of 10^{-1} to 10^{-2} , eventually converging to a stable value of approximately 0.03, as depicted in Fig. 8-a's contour plot. Based on the 3D surface plot depicted in Fig. 8-b, it is evident that the MSE exhibited variations within the range of 0 to 1. Notably, there were multiple places characterized by valley bottoms, which correspond to the locations of the best hyperparameters.

In the visualization of model prediction performance, as depicted in Fig. 8-c, it is evident that the predicted values and true values exhibited a high degree of proximity. This close proximity suggests a minimal prediction error in the estimation of the drying rate. Based on the error visualization plot depicted in Fig. 8-d, it is evident that the error values predominantly hovered around zero, with occasional outliers observed over numerous samples, however, not surpassing a threshold of 0.3.



In this paper, the BP neural network's iteration count was set as 100, 200, 300, and 1000, the target error was set as 10^{-4} , and the iteration step size was set to 0.1 for training the model. The best training result was achieved when the iteration count was set to 1000 times. With 1000 iterations, the optimal training results were: MSE = 0.00739, RMSE = 0.086, MAE = 1.6230, $R^2 = 54.3\%$, MAPE = 16.62%, and training time = 4.974 s (Wang 2013).

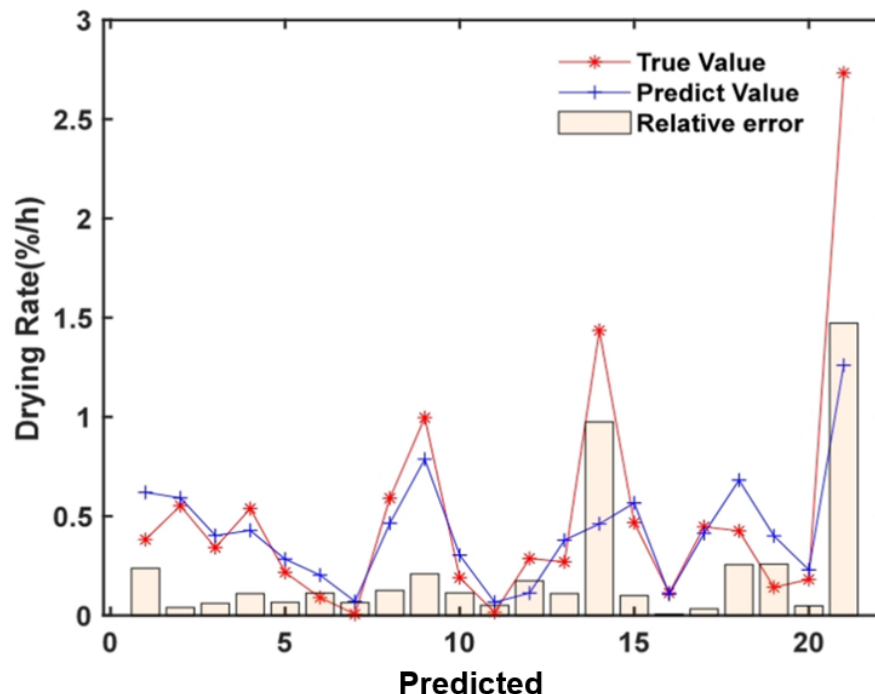


Fig. 10. The comparison chart of actual values and predicted values

From Fig. 10, around 35% of the predicted values showed an error of 0.2 or more, which is a large error compared to the results of the SVR. Compared with the prediction results of the support vector regression model, the accuracy and stability of the BP neural network were far inferior to that of the support vector regression model, which may be because the amount of data collected in the process of wood drying was relatively small, which cannot meet the large number of data samples required for neural network training (Nogay and Adeli 2023). Therefore, this paper will continue to optimize the process of finding the parameters of the support vector regression model.

GA and Particle Swarm Optimization Algorithm

The SVR model has been optimized using the grid search approach to identify appropriate parameter values. Nevertheless, as a result of the limitations imposed by the baseline parameters in the regression model, the values obtained by the grid search approach are more likely to represent local optima rather than global optima. Hence, to ascertain the global optimal value of the model and perform an analysis, this work employed GA and PSO to optimize the parameter search procedure (Rahimi *et al.* 2023).

Table 6. GA Parameter Setting

	Population Size	Generations	Chromosome Number	Gene Number
Group1	20	5	0 to 20	0 to 100
Group2	20	10	0 to 20	0 to 100
Group3	20	15	0 to 20	0 to 100

Table 7. PSO Parameter Setting

	Particles	Iterations	Weight	Individual Cognitive Factor	Social Factor
Group1	20	15	0.3	1	1
Group2	20	20	0.3	1	1
Group3	20	25	0.3	1	1

Table 8. Partial Training Result Metrics

	MSE (Fitness)	RMSE	MAE	MAPE
Group1	0.0037	0.0607	0.06	9.5%
Group2	0.005	0.0707	0.09	14.32%
Group3	0.01	0.1	0.10	6.88%

Table 9. Partial Training Result Metrics

	Model Training Time	R ²	c	g
Group1	8.583 s	78.7%	19.24	1.16
Group2	12.25 s	56.7%	18.13	0.24
Group3	14.491 s	64.8%	1.02	38.06

This study established the initial values for the GA, encompassing population size, chromosome count, gene length of chromosomes, and the maximum number of evolutions, based on the features of wood drying and kernel functions. The PSO requires the specification of certain starting variables, which include the swarm size, maximum iteration count, inertia weight, individual cognitive factor, and social component. The parameter settings for the GA are shown in Table 9, while the parameter settings for the PSO can be found in Table 10 (Costa *et al.* 2019).

After comparing the results of optimization using three different sets of initial parameters for GA, it was found in Tables 11 and 12 that the first set of initial parameters resulted in the best model performance. In this case, the training time was 8.583 s, MSE was 0.0037, RMSE was 0.0607, MAE was 0.06, MAPE was 9.5%, and R² was 78.7%.

In the optimization iteration of the GA, the MSE of the training reached 0.0037 for the minimum MSE error in the 15th generation of the GA. The true and predicted values of wood drying are shown in Fig. 11, where the error between the true and predicted values was quite large, and about 30% of the data in the validation set reached an error of 0.3.

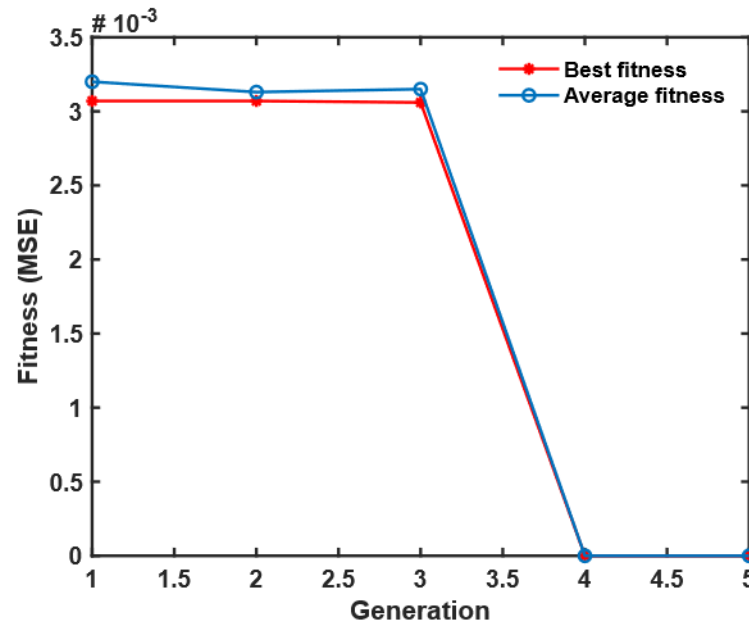


Fig. 11. The variation process of MSE with the genetic generations under the first set of initial GA parameter setting

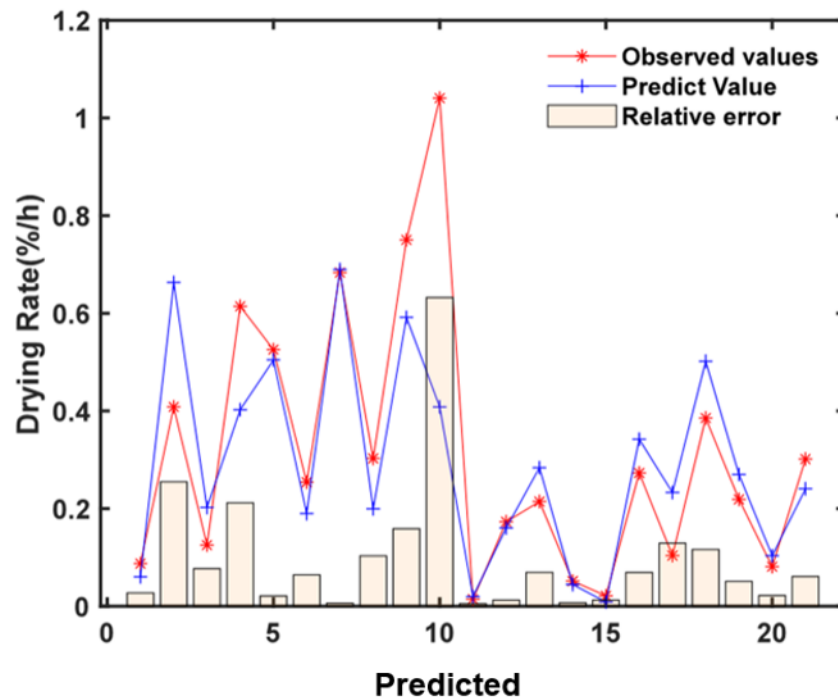


Fig. 12. True and predicted values and relative errors under the first set of parameters

Table 10. PSO Partial Training Result Metrics

	MSE (Fitness)	RMSE	MAE	MAPE
Group1	0.0152	0.123	0.097	8.2%
Group2	0.0028	0.053	0.059	6.5%
Group3	0.00105	0.246	0.0039	6.04%

Table 11. PSO Partial Training Result Metrics

	Model Training Time	R ²	c	g
Group1	0.766s	59.0%	9.5994	45.089
Group2	0.303s	86.7%	2.6679	34.0428
Group3	0.275s	91.7%	5.34	67.48

Through comparing the outcomes of three distinct groups of PSO, as presented in Tables 13 and 14, it is evident that the model achieved the most optimal performance through the optimization of the third group's initial parameters.

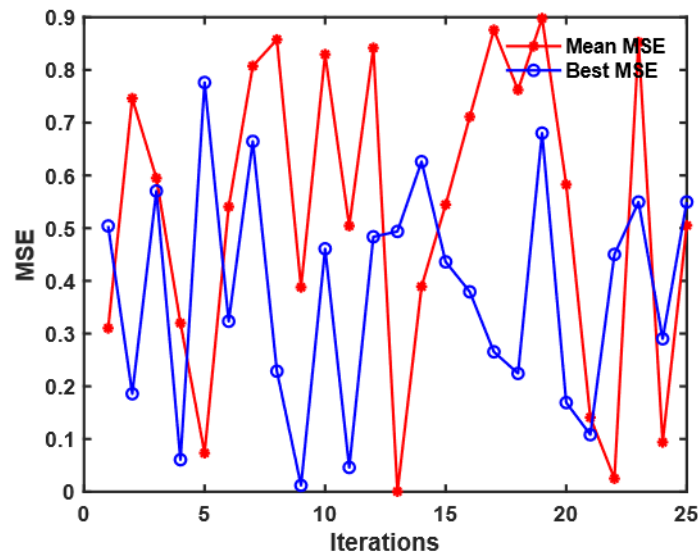


Fig. 13. MSE and the ideal MSE were computed for the third set of parameters while varying the length of iteration in the PSO algorithm

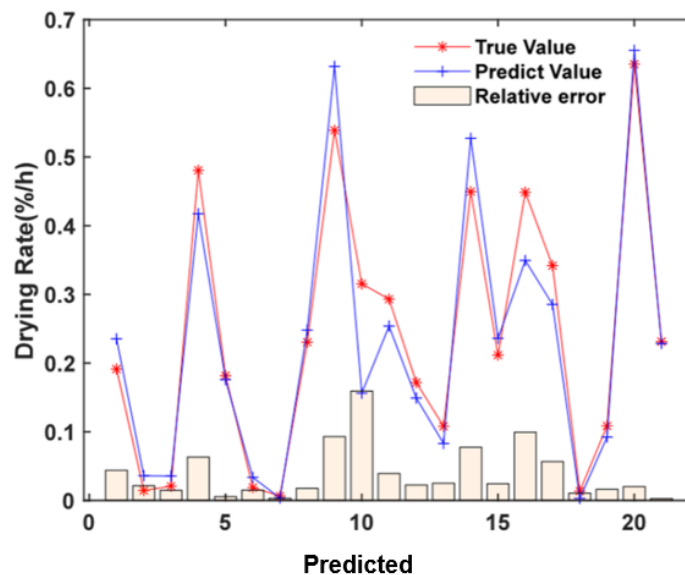


Fig. 14. The average MSE and ideal MSE are examined under the third set of parameters while varying the length of iteration in the PSO algorithm

This optimization yielded a MSE of 0.00105, a RMSE of 0.246, a MAE of 0.0039, a MAPE of 6.04%, a R^2 value of 91.7%, and a training time of 0.275 s.

The PSO-SVM was utilized to observe the variation in the average MSE and the best MSE. It was found that in the 9th generation, the average MSE reached its minimum value of 0.00105. Based on the depicted Fig. 14, it is evident that the discrepancy between the actual value and the projected value was predominantly negligible, with individual anomalies of the discrepancy hovering around 0.15. Consequently, the discrepancy may be characterized as minuscule in magnitude.

The outcomes of the extensive evaluation of the Branch Vector Machine Regression, GA Optimization Model, and PSO Optimization Model are presented in Tables 15 and 16. These tables display the performance of each parameter.

Table 12. Grid Search Method GA PSO Results Comparison (1)

	MSE (Fitness)	RMSE	MAE	MAPE
GSM-SVR	0.0018	0.042	0.0348	6.7 %
GA-SVR	0.0037	0.0607	0.06	9.5 %
PSO-SVR	0.00105	0.246	0.039	6.04 %

Table 13. Grid Search Method GA PSO Optimization Results Comparison (2)

	Model Training Time	R^2	c	g
GSM-SVR	3.430 s	88.6 %	274.3	1.0718
GA-SVR	8.583 s	78.7 %	19.24	1.16
PSO-SVR	0.275 s	91.7 %	5.34	67.48

Based on the presented tables and pictures, it is evident that the optimized SVR using the PSO outperformed both the grid search method and the GA in terms of prediction accuracy and model construction time. In the context of MSE dimension, the PSO demonstrates a substantial enhancement in accuracy, with an approximate improvement of 80% when compared to the Grid Search approach, and a notable increase of 200% when compared to the GA during the prediction phase, the PSO demonstrates superior efficiency in optimizing the SVR compared to both the grid search method and the GA. Specifically, the PSO achieved optimization of the SVR within an obviously reduced timeframe, approximately 1/12 of the time required by the grid search method and approximately 1/30 of the time required by the GA.

CONCLUSIONS

This study developed a wood drying rate prediction model using temperature, humidity, and moisture content as input variables, and compared the performance of Support Vector Machines (SVM) and neural networks. The results indicated that SVM clearly outperformed neural networks, with its optimal model achieving MSE = 0.0018 and R^2 = 88.6%, compared with MSE = 0.0073 and R^2 = 54.3% for the neural network—approximately one third of its prediction error. Further comparison of hyperparameter optimization methods showed that the PSO-SVM model performed best (MSE = 0.00105, R^2 = 91.7%, MAPE = 6.04%) and requires only 0.275 s for training, which was about

1/12 and 1/30 of the training time of grid search and genetic algorithms, respectively, making it more suitable for real-time monitoring and control.

To contextualize the findings, the proposed model was critically compared with physics-based drying models and recent data-driven approaches. Classical heat and mass transfer models provide physical interpretability but require numerous difficult-to-measure parameters, making their accuracy sensitive to variations in species, initial moisture content, and airflow conditions in industrial kilns. In contrast, the proposed model relies solely on measurable variables, offering greater practicality for industrial deployment. Compared with recent machine-learning approaches—such as random forests, XGBoost, neural networks, and LSTM models, which typically achieve R^2 values of 70% to 88% and MSE values of 0.003 to 0.02—the PSO-SVM model demonstrated superior accuracy and computational efficiency, indicating its potential for rapid adjustment and online optimization in industrial drying processes.

From an engineering perspective, the model's prediction error meets industrial accuracy requirements (MSE equivalent to approximately -0.3 on a 10-point scale). Its R^2 exceeding 90% indicates that it effectively captures the dominant mechanisms governing drying rate variation. Nevertheless, its performance remains dependent on data coverage, and its generalization ability across different wood species and kiln types warrants further investigation. Moreover, purely data-driven models lack the capability to reveal internal moisture migration mechanisms. Future work could focus on embedding this model into a control assistance program and validating its performance in practice, thereby demonstrating its effectiveness in real-world industrial applications.

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