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Multi-objective optimization of particle gluing operating parameters in particleboard production based on improved machine learning algorithms

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Abstract

Particle gluing operating parameters in particleboard (PB) production have an important influence on the mechanical properties of PBs. This study developed a multi-objective optimization model based on support vector regression (SVR) optimized by the non-dominated sorted genetic algorithm-II (NSGA2) to realize the multi-objective accurate prediction of PB mechanical properties (modulus of elasticity (MOE), modulus of rupture (MOR), and internal bonding (IB) strength) by adjusting particle gluing operating parameters. The NSGA2-SVR multi-objective prediction model was trained by 496 groups of experimental data of particle gluing operating parameters and PB mechanical properties. The prediction results of the NSGA2-SVR multi-objective prediction model were evaluated by 124 groups of experimental data and compared with the prediction results of the back propagation neural network (BPNN) model, general regression neural network (GRNN) model, and SVR model. The mean absolute percentage errors (MAPEs) of the NSGA2-SVR model were 49.11%, 33.64%, and 24.20% lower than that of the BPNN model, GRNN model, and SVR model, respectively. The Theil's inequality coefficients (TICs) of the NSGA2-SVR model were 40.93%, 27.39%, and 18.58% lower than that of the BPNN model, GRNN model, and SVR model, respectively. The results showed that the multi-objective prediction model based on NSGA2-SVR has a superior fitting and higher prediction accuracy for the prediction performance of particle gluing operating parameters, and the NSGA2-SVR model can be applied to the multi-objective synchronous prediction of particle gluing operating parameters in the PB production line.

Keywords: Particle gluing, Mechanical properties, Multi-objective predictions, NSGA2, SVR

Introduction

Particleboards (PB) have advantages of low cost, good processing performance, renewable raw materials, and reasonable mechanical properties, which have become one of the commonly used panels for furniture and indoor decoration [1]. In the PB production process, the particle gluing process operation has a great influence on the mechanical properties of PB [2], so operators often adjust the operating parameters of particle gluing according to the mechanical properties test results of PB [3]. However, depending only on the actual production experience of operators, it is difficult to accurately control the particle gluing operating parameters.

The operating parameters of particle gluing can be accurately predicted and adjusted according to the developed mathematical model. Haftkhani et al. [4] used the pi-theorem theory to develop a linear regression prediction model between the parameters such as gluing ratio and the mechanical properties of PB. But, the prediction accuracy of particle gluing operating parameters with nonlinear data characteristics in the linear prediction model was poor [5]. de Melo et al. [6] constructed

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an artificial neural network model to predict the modulus of elasticity (MOE) and modulus of rupture (MOR) of PB through parameters such as adhesive types. Nevertheless, the ANN model may lead to the prediction results falling into locally optimal solutions [7]. Yang et al. [8] used Random Forest algorithm to develop a prediction model for 23 operating parameters such as particle gluing to predict the mechanical properties of PB. Yet too many dimensions would reduce the prediction accuracy of the Random Forest model [9].

Support Vector Regression (SVR) is a nonlinear regression prediction method derived from Support Vector Machine [10]. SVR has the advantages of high robustness and strong generalization ability and has a good prediction effect for small nonlinear samples [11]. In our previous studies [12], the SVR model was used to predict the operating parameters of particle gluing. The results show that the SVR nonlinear regression prediction model has good prediction performance for the internal bonding (IB) strength of PB. But the disadvantage of the SVR model is that it cannot predict multiple targets synchronously [13].

Non-dominated sorting genetic algorithm-II (NSGA2) is a multi-objective optimization algorithm with low computational complexity and good convergence [14]. The multi-objective optimization of SVR model parameters by NSGA2 can transform the model solving process from single-objective multiple predictions to multi-objective synchronous predictions. The multi-objective prediction model of particle gluing operating parameters was developed based on NSGA2-SVR, which can realize the simultaneous predictions of multiple mechanical properties of PB by coupling and nonlinear particle gluing operating parameters.

This study developed a multi-objective prediction model of particle gluing operating parameters and PB mechanical properties (including MOE, MOR, and IB) based on NSGA2-SVR. Firstly, the fitting and prediction accuracy of the NSGA2-SVR model were analyzed by comparing the predicted and experimental values. Secondly, the prediction performance of the NSGA2-SVR multi-objective prediction model was evaluated and compared with that of the SVR single-objective multiple prediction models. Finally, according to the actual production situation of the factory, the adjustment of particle gluing operating parameters based on the NSGA2-SVR multi-objective prediction model was applied. Particle gluing operating parameters and PB mechanical properties are coupled and inseparable. Multiple single-objective predictions cannot synchronize the mechanical properties to the expected value. Therefore, according to the literature review, the multi-objective synchronization and accurate prediction of particle gluing operating parameters and mechanical properties of PB based on NSGA2-SVR are unique, meaningful, and valuable.

Experimental

Materials

In this experiment, the data acquisition site was a real PB production line with an annual output of 250,000 m^3 in Tangshan, China. The core particles, surface particles, and adhesive used as raw materials were experimented with in the particle gluing equipment. Among them, the blender of IPLCTS/ASS produced by IMAL-PAL (Italy) was the key equipment in particle gluing experiment. The core particles and surface particles used in the experiment were made from mixed wood species (a ratio of pine:fruit wood:other wood species = 2:2:1). Surface particle sizes (length × width × thickness) were from $3 \times 0.5 \times 0.3$ mm to $15 \times 1.5 \times 0.4$ mm. The core particle sizes (length × width × thickness) were from $15 \times 3 \times 0.4$ mm to $45 \times 10 \times 0.6$ mm. The main component of the adhesive used in the experiment was urea–formaldehyde resin, and the resin content was 64.5%. Before gluing, the adhesive temperature was maintained at 25 °C, and the potential of hydrogen (PH) value was maintained between 8.5 and 9.

In the process of particle gluing, firstly, the particles were transported to the blender by the built-in conveyor belt of the metering bins. At the same time, the discharge speed of particles was weighed by the belt scale in the metering bins during the transportation. Among them, the core particle discharge speed was recorded as f_{core}, and the surface particle discharge speed was recorded as f_{surface}. Secondly, the adhesive was sprayed onto the particle surface at a certain pressure and flow rate by controlling the atomization spray head in the blender. Among them, the pressure and flow rate of the adhesive were controlled by multi-pump dosing system and air pressure pump connected with the atomization spray head. The flow rate of core particle glue from the multi-pump dosing system was recorded as v_{core}, the flow rate of surface particle glue from the multi-pump dosing system was recorded as v_{surface}, the pressure on surface particle gluing from the air pressure pump was recorded as p_{core}, and the pressure on surface particle gluing from the air pressure pump is recorded as p_{surface}. Finally, the glued particles were stirred evenly in the blender and discharged. The discharged particles were used to make PBs with a density of 650–700 kg/m^3 and a thickness of 18 mm through mat-forming and hot-pressing processes, and then the mechanical properties of PBs were examined. During the hot-pressing process, the temperature ranges of the four zones are 224–230 °C, 224–230 °C, 220–226 °C, and 194–196 °C, respectively. The particle gluing process is shown in Fig. 1.

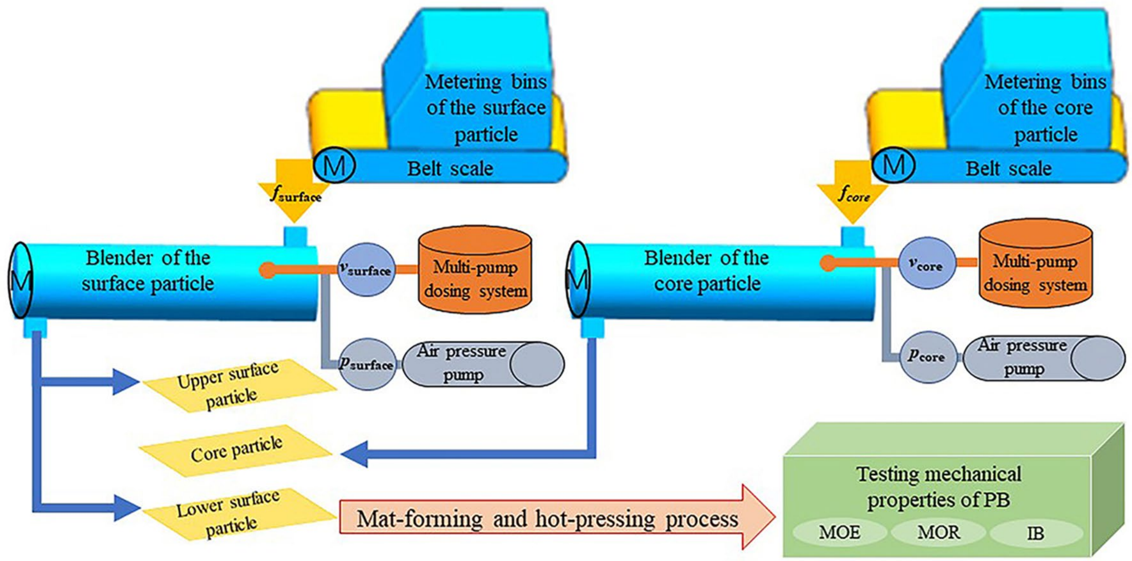

Fig. 1 Flowchart of particle gluing

In this experiment, the mechanical properties (MOE, MOR, and IB) of PB without sanding treatment were tested by the Mod. IB700 testing machine, produced by IMAL–PAL in Italy. The test process followed the standard "GB/T 17657-2013 Test methods of evaluating the properties of wood-based panels and surface decorated wood-based panels" [15]. The test results of MOE, MOR, and IB were reported by averaging six PB specimens.

To eliminate the influence of other factors on the modeling, the key operating parameters of the process after particle gluing should be constant or stable within a certain range. On the above premise, the 620 groups sample data of operating parameters (f_{core}, f_{surface}, v_{core}, v_{surface}, p_{core}, and p_{surface}) of particle gluing and mechanical properties (MOE, MOR, and IB) of PB were collected for modeling.

Methods

The multi-objective prediction model of particle gluing operating parameters was developed based on the NSGA2-SVR. SVR nonlinear regression prediction model that was used to train the sample data of particle gluing operating parameters and PB mechanical properties. Taking the minimization of the prediction generalization errors of MOE, MOR, and IB as the objective function, the NSGA2 algorithm was used to conduct the multi-objective optimization of the parameters of the SVR model. The multi-objective prediction model of particle gluing operating parameters based on NSGA2-SVR was developed with the optimal model parameters.

Support vector regression

SVR regression prediction model is suitable for training nonlinear, small sample, and high-dimensional data sets [16]. It has the characteristics of small structural risk and strong generalization ability and can avoid dimension disaster and over-fitting problems caused by prediction results [17]. Therefore, the particle gluing parameters with limited samples and nonlinear characteristics can be modeled and predicted by SVR.

Given the sample data set $D = \{\boldsymbol{x}_i, y_i\}_{i=1}^{n}$, where n is the number of training set data sets, $\boldsymbol{x}_i \in R$ and $y_i \in R$ are input samples and output samples, respectively. The regression function can be expressed as:

$$f(x) = \boldsymbol{\omega}^T \varphi(x) + b, \tag{1}$$

where $\boldsymbol{\omega} \in \mathrm{R}$ is the weight vector, and b is the threshold. To include more model samples within the boundary conditions, the tolerance deviation ε and slack variables $\xi_i \geq 0, \xi_i^* \geq 0$ are introduced [18]:

$$\begin{cases} y_i - \boldsymbol{\omega}^T \varphi(x_i) - b \leq \varepsilon + \xi_i \\ \boldsymbol{\omega}^T \varphi(x_i) + b - y_i \leq \varepsilon + \xi_i^* \end{cases}. \tag{2}$$

Based on this structural risk minimization principle, the optimal solution of the regression function can be obtained:

$$\min_{\omega,b,\xi,\xi^*} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi + \xi^*), \tag{3}$$

where C is the penalty factor. The regression function can be obtained using Lagrange multiplier [19]:

$$f(x) = \sum_{i=1}^{n} (a_i - a_i^*) \left[\varphi(x_i)^T \varphi(x_j)\right] + b, \tag{4}$$

where a_i and a_i^* are the Lagrange multipliers. The regression function of SVR can be obtained by replacing $\varphi(x_i)^T\varphi(x_j)$ with Radial basis function (RBF) [20]:

$$f(x) = \sum_{i=1}^{n} (a_i - a_i^*) \left[\exp\left(\frac{-\|x_i - x_j\|^2}{2\sigma^2}\right)\right] + b, \tag{5}$$

where σ is the width of RBF. C and σ plays a decisive role in the prediction effect of the SVR model, and they are often optimized by grid search [21]. Prediction of multiple targets by the SVR model needs to be modeled separately for each target. However, the relationship between particle gluing operating parameters and the mechanical properties of each PB was mutually coupled. Multiple single-objective modeling would make the model lose the feedback prediction mechanism. In this study, the multi-objective algorithm was used to optimize the model parameters C and σ of SVR, which can realize the multi-objective synchronous prediction of PB mechanical properties based on the SVR model.

Non-dominated sorting genetic algorithm-II

NSGA2 is a multi-objective optimization algorithm, which can solve the Pareto optimal solution set of several highly nonlinear objective functions under different constraints [22]. Given that there are any two different and random individuals a and b in the population P with initialized size N when a dominates b, the following relationship is satisfied:

$$\begin{cases} \forall k \in \{1, 2, \cdots, s\}, g_k(a) \le g_k(b) \\ \exists l \in \{1, 2, \cdots, s\}, g_l(a) < g_l(b) \end{cases}, \tag{6}$$

where $g_i(x)$ is the objective function, and s is the number of objective functions. Any individual i in the population P is subjected to fast non-dominated sorting according to Formula (7) to obtain its non-dominated rank number i_{rank}. The aggregation density D_i of any individual i is calculated by crowding degree [23]:

$$D_i = \sum_{k=1}^{s} \left(\left| g_k^{i+1}(x) - g_k^{i-1}(x) \right| \right). \tag{7}$$

After non-dominated sorting and crowding calculation, any individual i in population P is given i_{rank} and D_i. For any two different and random individuals a and b, the better individual a is selected for crossover and mutation if and only if satisfied:

$$a_{\text{rank}} \le b_{\text{rank}} \cap D_a > D_b. \tag{8}$$

NSGA2 algorithm increases the probability of retaining excellent individuals through the elitism strategy [24]. In the elitism strategy, the parent population P produces the offspring population Q after selection, crossover, and mutation. Then the population P is merged with the population Q to form a new population R with a population size of 2 N. After a new round of iterative selection, population R generates a new population $P2$ with a population size of N. Finally, the population Pt was obtained after t iterations of population P. The dominant individual set S_{dom} in population Pt is the Pareto optimal solution set obtained by the NSGA2 algorithm. The flowchart of NSGA2 algorithm is shown in Fig. 2.

NSGA2-SVR multi-objective prediction model

Normalization of sample data Different operating parameters of particle gluing and dimension of PB mechanical properties would affect the training results of the NSGA2-SVR model. Normalization is to reduce the data sample to the range of [0, 1] in proportion. Then the samples with dimension are transformed into dimensionless values to eliminate the influence of model training:

$$X_{\text{N}} = \frac{x - \text{MIN}(x)}{\text{MAX}(x) - \text{MIN}(x)}, \tag{9}$$

where x is the sample data, X_{N} is the normalized data.

Sample data splitting The sample data set is split into training set and test set after normalization. The training

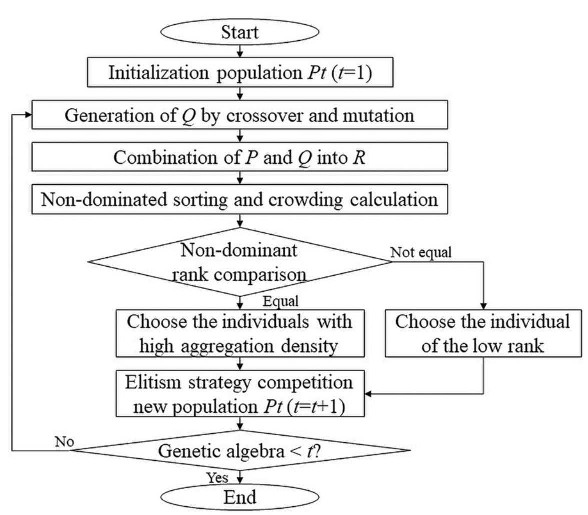

Fig. 2 Flowchart of NSGA2 algorithm

set is split into K parts in K-fold cross-validation (K-CV). Each cross-validation takes (K-1) parts of data to train the model and takes a part of the remaining data as the validation set to calculate the mean square error (MSE) between the predicted value and the actual value of the model in this round of training, as shown in Formula [10]. Test set is mainly used for model prediction performance evaluation after the model establishment:

$$\mathrm{MSE} = \frac{1}{r}\sum_{i=1}^{r}[y_i - \widehat{y}_i]^2, \tag{10}$$

where r is the number of the validation set samples, y_i is the actual value of the validation set output samples, and $\widehat{y}_i$ is the predictive value of the validation set input samples.

Constructing the objective function of NSGA2 algorithm The training set data is repeatedly trained K times by the K-CV method. The K-CV generalization error $CV^{(K)}$ of the model can be obtained when the penalty factor is C and the width of RBF is σ by calculating the mean of MSE of K training:

$$CV^{(K)}(C,\sigma) = \frac{1}{K}\sum_{j=1}^{K}\mathrm{MSE}_j^{C,\sigma}. \tag{11}$$

When the $CV^{(K)}$ of the SVR model is lower, the fitting effect of the model is better. The objective function of the NGSA-II algorithm is established with C and σ as decision variables and $CV^{(K)}$ minimization of MOE, MOR and IB as optimization:

$$f(C,\sigma) = \mathrm{MIN}\left\{\begin{array}{c} CV_{\mathrm{MOE}}^{(K)}(C,\delta) \\ CV_{\mathrm{MOR}}^{(K)}(C,\delta) \\ CV_{\mathrm{IB}}^{(K)}(C,\delta) \end{array}\right\}, \tag{12}$$

$$S.t.\{C_{\min} \le C \le C_{\max}, \delta_{\min} \le \delta \le \delta_{\max}\}. \tag{13}$$

Initializing parameters of NSGA2 algorithm Before the multi-objective optimization of SVR model parameters by the NSGA2 algorithm, the relevant parameters need to be initialized. The NSGA2-SVM parameters include the range of decision variable C: ($C_{\min}$, $C_{\max}$), the range of decision variable σ: ($\sigma_{\min}$, $\sigma_{\max}$), the K-CV coefficient K, population number N, maximum iteration number k, crossover operator CO and mutation operator MO, and the parameters are set as shown in Table 1.

Multi-objective optimization of SVR model parameters by NSGA2 algorithm The NSGA2 algorithm takes $f(C, \sigma)$ as the objective function to conduct multi-objective optimization for variables C and σ, and finally obtains their Pareto solution. Then the maximum generalization errors in the Pareto solution were minimized, so that the model parameters C and σ satisfy:

$$\mathrm{MIN}\{\,\mathrm{MAX}\ [CV_{\mathrm{MOE}}^{5}(\delta,g),\ CV_{\mathrm{MOE}}^{5}(\delta,g),\ CV_{\mathrm{IB}}^{5}(\delta,g)\,]\,\}. \tag{14}$$

Finally, NSGA2-SVR multi-objective prediction model is constructed with the optimal solution of C and σ. The flowchart of the model is shown in Fig. 3.

Table 1 The initialization setting of NSGA2-SVM parameters

Parameters	Values
($C_{\min}$, $C_{\max}$)	(− 20, 20)
($\sigma_{\min}$, $\sigma_{\max}$)	(− 20, 20)
K	5
N	200
k	120
CO	0.8
MO	0.05

Evaluation of the NSGA2-SVR model The test set samples are brought into the NSGA2-SVR multi-objective prediction model. The evaluation indexes of mean absolute percentage error (MAPE) and Theil's inequality coefficient (TIC) without dimensional constraints are used to analyze the convergence of the predicted values of the model relative to the experimental values. In this way, the prediction performance of the NSGA2-SVR model is evaluated:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_i^*}{y_i}\right| \times 100\%, \tag{15}$$

$$\mathrm{TIC} = \frac{\sqrt{\sum_{i-1}^{n}(y_i - y_i^*)^2}}{\sqrt{\sum_{i-1}^{n}(y_i)^2} + \sqrt{\sum_{i-1}^{n}(y_i^*)^2}}, \tag{16}$$

where y_i^* is the actual value of the output parameters of the test set, and y_i is the predicted value of the input parameters of the test set.

Results and discussion

Optimization results of NSGA2-SVR model parameters

The 620 groups of experimental data collected on the PB production line were used as samples, four-fifths of the data (496 groups) were randomly selected as the training

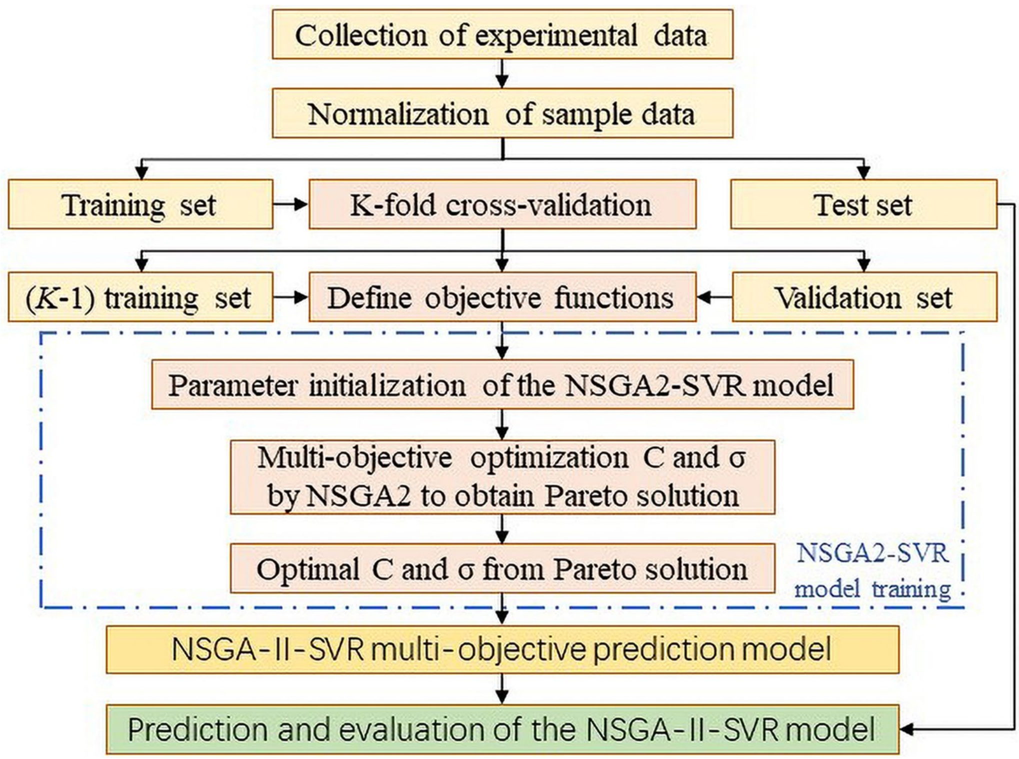

Fig. 3 Modeling flowchart of NSGA2-SVR multi-objective prediction model

Table 2 The statistical results of mean, Max, Min, and SD of the training set and test set

Parameters		Operating parameters of particle gluing						Mechanical properties of PB		
		f_{core} (kg/min)	$f_{surface}$ (kg/min)	v_{core} (L/min)	$v_{surface}$ (L/min)	p_{core} (bar)	$p_{surface}$ (bar)	MOE (MPa)	MOR (MPa)	IB (MPa)
Min	Train	174	98	24.9	15.8	1.20	1.30	1895	11.37	0.33
	Test	172	106	25.8	18.6	1.40	1.40	1963	12.04	0.41
	Total	172	98	24.9	15.8	1.20	1.30	1895	11.37	0.33
Max	Train	357	215	42.2	37.6	2.31	3.10	2603	15.95	0.59
	Test	354	211	43.5	35.7	2.31	2.52	2467	16.18	0.56
	Total	357	215	43.5	37.6	2.31	3.10	2603	15.95	0.59
Mean	Train	294	146	34.6	26	1.78	1.77	2188	13.34	0.47
	Test	296	148	35.2	26.3	1.80	1.79	2211	13.42	0.48
	Total	294	147	34.8	26.1	1.79	1.78	2192	13.35	0.47
SD	Train	30	19	3.4	3.4	0.21	0.21	110	0.72	0.03
	Test	35	22	3.2	3.7	0.21	0.23	98	0.78	0.03
	Total	31	20	3.4	3.5	0.21	0.21	108	0.73	0.03

set to construct the model, and the remaining one-fifth of the data (124 groups) was used as the test set to verify the model. The statistical results (Mean, Max, Min, Standard deviation (SD)) for the operating parameters and mechanical properties of the train set and test set are shown in Table 2.

The NSGA2-SVR multi-objective prediction model took the operating parameters (f_{core}, $f_{surface}$, v_{core}, $v_{surface}$, p_{core}, and $p_{surface}$) of particle gluing as the input variables and the mechanical properties (MOE, MOR, and IB) of PB as the output variables. The 5-CV method was used to train 496 groups of experimental data. After 120

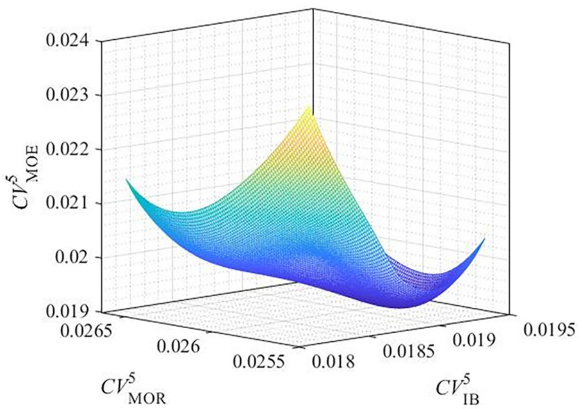

Fig. 4 Pareto fronts of CV^5_{MOE}, CV^5_{MOR}, and CV^5_{IB}

iterations of the NSGA2 algorithm, population P finally converges to the Pareto front as shown in Fig. 4. It can be seen from the figure that the target spatial distribution is continuous and uniform, belonging to the regular Pareto front. Therefore, the solutions in the Pareto front are non-inferior solutions.

In order to balance the prediction effect of the NSGA2-SVR model on MOE, MOR, and IB, the Pareto solutions were screened according to Formula (14). Finally, the optimal parameters of the SVR model were $C = -0.5$ and $\sigma = 2.5$, and the NSGA2-SVR multi-objective prediction model was established using these model parameters.

Prediction performance evaluation of the NSGA2-SVR model

The relative deviation of the test set prediction value can reflect the prediction accuracy of the NSGA2-SVR multi-objective prediction model. The 124 groups of test sets were brought into the NSGA2-SVR multi-objective prediction model to predict the target values. By calculating the relative deviation between the predicted values and the experimental values, the average relative deviations of 124 groups of predicted values of MOE, MOR, and IB were 1.08%, 1.40%, and 1.85%. It was indicated that the prediction accuracies of the NSGA2-SVR multi-objective prediction model for MOE, MOR, and IB were relatively balanced.

In addition, the proportions of the test set samples with relative deviations of the predicted value and the experimental value in the range of 0–5% were counted. Among them, the proportions of samples with relative deviations of MOE, MOR, and IB in the range of 0–5% were 95.16%, 92.74%, and 95.16%, respectively. It was shown that the prediction accuracy of the NSGA2-SVR multi-objective prediction model for particle gluing operating parameters and PB mechanical properties was high.

Table 3 Evaluation results of the BP model, GRNN model, SVR model, and NSGA2-SVR model

Model types	Evaluation index	MOE	MOR	IB	Mean
BPNN	MAPE	0.0196	0.0278	0.0376	0.0283
	TIC	0.0129	0.0197	0.0254	0.0193
GRNN	MAPE	0.0189	0.0209	0.0254	0.0217
	TIC	0.0146	0.0163	0.0163	0.0157
SVR	MAPE	0.0170	0.0210	0.0189	0.0190
	TIC	0.0123	0.0163	0.0133	0.0140
NSGA2-SVR	MAPE	0.0107	0.0143	0.0183	0.0144
	TIC	0.0089	0.0133	0.0121	0.0114

The dimensionless evaluation indexes MAPE and TIC can better evaluate the multi-objective prediction performance of particle gluing operating parameters in the NSGA2-SVR model. The prediction results of the test set of the NSGA2-SVR model are brought into Formula [15] and Formula [16]. It can be concluded that the MAPE of MOE, MOR, and IB of PB mechanical properties were 0.0107, 0.0143, and 0.0183, respectively. And the MAPE of MOE, MOR, and IB were 0.0089, 0.0133, and 0.0121, respectively. It can be seen that the evaluation indexes MAPE and TIC of the NSGA2-SVR model were low. The results showed that the multi-objective prediction model of particle gluing operating parameters based on NSGA2-SVR had better prediction performance.

The particle gluing operating parameters were established and predicted by the back propagation neural network (BPNN) model, general regression neural network (GRNN) model, and SVR model, respectively, and then the prediction results were evaluated by MAPE and TIC. The results are shown in Table 3. The average MAPEs of the NSGA2-SVR model were 49.11%, 33.64%, and 24.20% lower than that of the BPNN model, GRNN model, and SVR model, respectively. The average TICs of the NSGA2-SVR model were 40.93%, 27.39%, and 18.58% lower than that of the BPNN model, GRNN model, and SVR model, respectively. Compared with the BP model, GRNN model, and SVR model, the NSGA2-SVR model had a better prediction accuracy on the prediction of particle gluing operating parameters.

The significance tests were carried out to verify the reduction of prediction deviations of the NSGA2-SVR model compared with the BPNN model, GRNN model, and SVR model using the analysis of variance (ANOVA) test. The test results showed that, excepted for the IB of SVR, the predictive accuracies of all mechanical properties of the NSGA2-SVR model were significantly improved compared to the BPNN, GRNN, and SVR models as presented in Table 4 (smaller than $\alpha = 0.05$).

Table 4 Significances (*P*-values) of ANOVA test results for prediction bias

	MOE	MOR	IB
BPNN	2.22×10^{-7}	5.13×10^{-6}	2.33×10^{-11}
GRNN	5.97×10^{-4}	2.81×10^{-2}	3.52×10^{-3}
SVR	1.85×10^{-3}	3.25×10^{-2}	7.66×10^{-1}

According to ANOVA test results, compared to that of SVR, the IB of the deviation reduction of NSGA2-SVR model was slightly reduced from 0.0091 to 0.0087, but the ANOVA test indicated that the reduction was not significantly because the P-value was larger than $\alpha = 0.05$ (Table 4).

Application of NSGA2-SVR multi-objective prediction model for particle gluing

In the production process of PB, manufacturers would change the gluing amount for particles according to the production demand and cost consideration of actual orders [25]. The operating parameters of particle gluing can be adjusted based on the NSGA2-SVR multi-objective prediction model according to the actual gluing requirements, to improve the MOE, MOR, and IB of the produced PB.

It was assumed that f_{core} ran at 300 kg/min in a certain period. In order to maximize the PB mechanical properties with less particle gluing cost, the arithmetic progression of 100 particle gluing operating parameters within the parameter range were input into the NSGA2-SVR multi-objective prediction model for prediction. Then NSGA2 was used to find non-inferior solutions for MOE, MOR and IB predicted by the model, and the results are shown in Table 5. It can be seen that Result3 had the smallest sum of v_{core} and v_{surface} among the five non-inferior solutions. At this time particle gluing operating parameters were: $f_{\text{surface}} = 113.80$ kg/min, $v_{\text{core}} = 31.30$ L/min, $v_{\text{surface}} = 21.04$ L/min, $p_{\text{core}} = 1.50$ bar, $p_{\text{surface}} = 1.62$ bar. The optimal values of MOE, MOR, and IB of PB properties were 2341 MPa, 14.60 MPa, and 0.53 MPa, respectively.

On the other hand, manufacturers can adjust the supply of raw materials according to the demand for PB production in actual orders [26]. The raw material adjustment would change the particle gluing operating parameters f_{core} and f_{surface}. The multi-objective model of NSGA2-SVR particle gluing operating parameters can make the mechanical properties of PB to reach the optimal values or meet the minimum requirements of enterprise standards under these parameters. Therefore, the utilization of NSGA2-SVR to model the operating parameters of particle gluing is conducive to reducing the cost of gluing and improving the production quality of PBs.

Conclusions

(1) In this study, a multi-objective optimization model was developed based on NSGA2-SVR, and the mechanical properties (MOE, MOR, and IB) of PBs were predicted and optimized by adjusting the operating parameters (f_{core}, f_{surface}, v_{core}, v_{surface}, p_{core}, and p_{surface}) of particle gluing. This model can quantitatively evaluate the influence of particle gluing operating parameters on the mechanical properties of PBs. On the one hand, through the combination of the NSGA2 algorithm and SVR model, the randomness and experience of the SVR model in parameter selection were overcome. On the other hand, through the multi-objective optimization of SVR model parameters by NSGA2, the multi-objective simultaneous prediction of particle gluing operating parameters by the NSGA2-SVR model was realized, which provides a new theoretical method for the particle gluing process.

Table 5 Multi-objective optimization sets of MOE, MOR and IB

Parameters	Operating parameters of particle gluing						Mechanical properties of PB		
	f_{core} (kg/min)	f_{surface} (kg/min)	v_{core} (L/min)	v_{surface} (L/min)	p_{core} (bar)	p_{surface} (bar)	MOE (MPa)	MOR (MPa)	IB (MPa)
Upper limit	175	100	25	16	1.2	1.3	–	–	–
Lower limit	385	215	43	37	2.3	3.1	–	–	–
Results1	300	148.30	37.60	24.19	1.70	1.64	2181	13.28	0.54
Results2	300	112.65	31.66	22.09	1.55	1.61	2467	14.39	0.51
Results3	300	113.80	31.30	21.04	1.50	1.62	2341	14.60	0.53
Results4	300	135.65	35.80	25.66	1.81	1.64	2328	15.11	0.50
Results5	300	118.40	31.84	22.30	1.60	1.73	2431	14.40	0.46

(2) The predicted values of the NSGA2-SVR multi-objective prediction model were compared with the actual experimental values. The results were that the predicted values of the model were highly consistent with the actual values. The results showed that the multi-objective prediction model of particle gluing operating parameters and PB mechanical properties based on the NSGA2-SVR had a good fitting. By calculating the predicted relative deviations of PB mechanical properties in the NSGA2-SVR model, it was concluded that the predicted relative deviations of MOE, MOR, and IB were 95.16%, 92.74%, and 95.16%, respectively, in the range of 0–5%. The results showed that the particle gluing model based on NSGA2-SVR has good prediction accuracy.
(3) The multi-objective prediction model of NSGA2-SVR was evaluated by MAPE and TIC indicators. The results showed that, for MOE: MAPE = 0.0107, TIC = 0.0089; for MOR: MAPE = 0.0143, TIC = 0.0133; for IB: MAPE = 0.0183, TIC = 0.0121. The MAPE and TIC of the NSGA2-SVR model, SVR model, BPNN model, and GRNN model were compared. The average MAPE of the NSGA2-SVR model was 49.11%, 33.64%, or 24.20% lower than that of the BPNN model, GRNN model, and SVR model, respectively. The average TIC of the NSGA2-SVR model was 40.93%, 27.39%, or 18.58% lower than that of the BPNN model, GRNN model, and SVR model, respectively. The evaluation results showed that the NSGA2-SVR multi-objective prediction model had better prediction performance.
(4) The NSGA2-SVR multi-objective prediction model can predict the mechanical properties of PBs in real-time according to the operating parameters of particle gluing. In the actual production process, by adjusting the operating parameters of particle gluing, the mechanical properties of PBs can reach the optimal or meet the minimum standard requirements of enterprises under the desires of improving production capacity and/or reducing resin consumption. The development of the NSGA2-SVR multi-objective prediction model for particle gluing operating parameters helps to produce PB with low cost or high efficiency, which has guiding significance and application value for the actual production of PBs.

Abbreviations
NSGA2: Non-dominated sorted genetic algorithm-II; SVR: Support vector regression; PB: Particleboards; MOE: Modulus of elasticity; MOR: Modulus of rupture; IB: Internal bonding; f_{core}: Core particle discharge speed in belt scale; $f_{surface}$: Surface particle discharge speed in belt scale; v_{core}: Flow rate of core particle glue from multi-pump dosing system; $v_{surface}$: Flow rate of surface particle glue from multi-pump dosing system; p_{core}: Pressure on core particle gluing from atomization spray head; $p_{surface}$: Pressure on surface particle gluing from atomization spray head; I_{core}: Current for core particle gluing in blender; $I_{surface}$: Current for surface particle gluing in blender; PH: Potential of hydrogen; MSE: Mean square error; MAPE: Mean absolute percentage error; TIC: Theil's inequality coefficient; CV: Cross-validation; SD: Standard deviation; BPNN: Back propagation neural network; GRNN: General regression neural network; ANOVA: Analysis of variance.

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Author contributions
BZ analyzed the experimental data and drafted the manuscript. JH is the project leader and responsible for the experimental design and manuscript review. LC responsible for manuscript review and language editing. YG checked algorithm prediction results. YL assisted the experiments. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

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