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Optimization of production parameters of particle gluing on internal bonding strength of particleboards using machine learning technology

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Abstract

The particleboard (PB) production is an extremely complex process, many operating parameters affecting panel quality. It is a big challenge to optimize the PB production parameters. The production parameters of particle gluing have an important influence on the internal bond (IB) strength of PB. In this study, using grey relation analysis (GRA) and support vector regression (SVR) algorithm, a prediction model was developed to accurately predict IB of PB through particle gluing processing parameters in a PB production line. GRA was used to analyze the grey relational grade between the particle gluing processing parameters and IB of PB, and the variables were screened. The SVR algorithm was used to train 724 groups of particle gluing sample data between six particle gluing processing parameters and IB. The SVR model was tested with 181 sets of experimental data. The SVR model was verified by 181 sets of experimental data, and the values of mean absolute error (MAE), mean relative error (MRE), root mean square error (RMSE), and Theil's inequality coefficient (TIC) of the model were 0.008, 0.017, 0.013, and 0.014, respectively. The results showed that the prediction performance of the nonlinear regression prediction model based on GRA–SVR is superior, and the GRA–SVR prediction model can be used to real-time predict the IB in the PB production line.

Keywords: Particle gluing, Internal bond strength, GRA, SVR, Prediction model

Introduction

Particleboards (PB) have the characteristics of wide adaptability of raw materials and good mechanical properties, which has become one of the common boards in furniture manufacturing [1]. Three-layer particleboard is the most common PB, in which three-layer particles with different sizes are mixed with adhesive and hot-pressed at a certain temperature [2]. In the production process, the mechanical properties of PB are the key evaluation indexes of its quality [3], and the internal bond (IB) strength is one of the most important mechanical characteristics [4].

By combining image analysis technology with the mathematical model, Dai et al. [5–7] found that the resin content and particle thickness and other parameters would change the particle surface glue cover rate, and the glue cover rate would affect the cohesive force between particles, resulting in the reduction in IB. In subsequent studies, the team established a mechanistic model for estimating IB of PB, and the prediction results showed that there was a nonlinear relationship between IB and resin content, particle dimensions, product density and other parameters [8]. Lin et al. [9] used single image multi-processing analysis technology to obtain the edge photos of PB and found that there was a significant correlation between adhesive and IB, which could reflect the important influence of particle gluing production parameters on IB of PB. Based on the above studies, it can be

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seen that the production parameters of particle gluing have an important impact on IB of PB. However, due to the lack of theoretical guidance related to the production parameters of particle gluing, tuning its parameters can only be completed based on the actual experiences of workers, which is difficult to meet the accuracy of parameter regulation in the gluing process [10]. Using particle gluing parameters and IB to develop a nonlinear prediction model can improve the accuracy of parameter adjustment in particle gluing process, which is conducive to improving the quality of PB, stabilizing PB production, and provide theoretical guidance for the actual production of PB. Therefore, it is necessary to develop the prediction model of particle gluing parameters for IB of PB.

Young et al. [11] developed the prediction model of IB of the fiberboard based on quantile regression (QR), and the prediction results are better than those of the model developed by multiple linear regression (MLR). The results from the study could save the production cost of fiberboard. Therefore, it is particularly important to find a suitable method for particleboard modeling and prediction. In the past few decades, technological progress has been made in the international research on the influence of particle gluing production parameters on IB of PB. Haftkhani et al. [12] constructed a linear regression model based on pi-theorem theory to predict IB of PB according to particle size, adhesive ratio, and other parameters, but the linear model could not effectively evaluate the nonlinear relationship between particle gluing production parameters and IB. Tiryaki et al. [13] established an artificial neural network (ANN) model to predict the effects of adhesive and compression time on IB of Oriental beech using polyvinyl acetate adhesives. The results showed that mean absolute percentage error between the predicted results of the ANN model and the experimental values was 2.5%. However, the ANN model training is time-consuming and easy to fall into locally optimal solution [14]. Yang et al. [15] established a mathematical model between the mechanical properties of PB and 23 production process parameters of PB such as moisture content and glue amount based on principal component regression analysis and random forest (RF), and determined the relationship between the production process parameters of PB and the mechanical properties, such as IB and bending strength. However, under the coupling effect of various factors, excessive multidimensionality would lead to excessive fitting of the model, and it could limit the upper limit of prediction accuracy [16].

Support vector regression (SVR) is an application of support vector machine (SVM) to regression problems [17]. SVM is to solve the sample distance hyperplane maximization problem, and SVR principle transforms it into a structured risk minimization problem [18]. SVR can be applied to nonlinear model modeling, which has the advantages of simple structure and strong generalization ability [19–21], and it has successfully addressed the issues of regression forecasting in many areas. In terms of wood-based panels, Gao et al. [22] used SVR algorithm to establish a model to predict the fiber quality of medium density fiberboard with the parameters of conveyer screw revolution speed, accumulated chip height, and compared with the linear prediction model. The prediction results showed that the mean absolute error (MAE), mean relative error (MRE), root mean square error (RMSE) and Theil's inequality coefficient (TIC) of the SVR model were reduced by 92.19%, 92.36%, 87.29% and 87.21% compared with the mixed logistic regression (MLR) linear prediction model. The excellent model prediction results show that SVR algorithm can be applied to the prediction of panel production parameters.

Grey relation analysis (GRA) mainly describes the relationship between the attributes of each variable by searching the Grey relational grade (GRG), and then determines the correlation degree of the influence of each variable on the target [23]. By utilizing GRA, the correlation between the production parameters of particle gluing and IB of PB was compared, and the production parameters with less correlation with IB of PB were screened out, so as to improve the upper limit of model prediction.

This study intended to establish the relationship between eight particle gluing production parameters including core particle discharge speed (f_{core}) in belt scale, surface particle discharge speed (f_{surface}) in belt scale, flow rate of core particle glue (v_{core}) from multi-pump dosing system, flow rate of surface particle glue (v_{surface}) from multi-pump dosing system, pressure on core particle gluing (p_{core}) from atomization spray head, pressure on surface particle gluing (p_{surface}) from atomization spray head, current for core particle gluing (I_{core}) in blender, and current for surface particle gluing (I_{surface}) in blender and IB of PB. First, by GRA, the production parameters with low correlation with IB were screened to improve the upper limit of model prediction. Second, the nonlinear regression prediction model of particle gluing production parameters and IB was established using SVR. Third, the prediction accuracy of the model was tested by comparing the predicted values with the experimental values. Finally, the influence of particle gluing production parameters on IB of PB was evaluated according to the model prediction results. Since the real PB production is an extremely complex process, it is a big challenge to optimize the PB production parameters. According to the literature review, this work is unique, because the relationships between particle gluing parameters and IB of PB were initially analyzed and controlled using GRA and SVR algorithms with a big data.

Experimental

Materials

In this study, the test data were collected in a real PB production line with an annual yield of 250,000 m^3. In this experiment, pine, fruit and miscellaneous wood were used as main raw materials to produce PB with a size of 2440 mm × 1550 mm × 18 mm. The produced PB without sanding and cooling process were examined and analyzed in this study.

In the production process, pine, fruit, and miscellaneous wood particles were mixed at a weight ratio of 2:2:1 for processing core and surface particles. The mixed raw wood materials were converted into core particles and surface particles through chipping, flaking, drying, screening and sifting processes, and then mixed with adhesives and other additives to conduct particle gluing. Among them, the urea–formaldehyde resins were used in the particleboard production. The temperature of the adhesive was maintained at about 25 °C before sizing, the potential of hydrogen value of the adhesive was maintained between 8.5 and 9.0, and the viscosity of adhesive measured to be 30–40 s at 25 ℃ using the T-4 Viscosity Cup Method. The NDJ-5 viscometer, produced by Lichen in China, was used in the T-4 Viscosity Cup Method. The production parameters before particle gluing are shown in Table 1.

Experimental equipment, parameters, and testing

Main working process of gluing equipment

The main accessories and working principle of gluing equipment for core and surface particles are the same. The main components are shown in Fig. 1. The multi-pump dosing system (1) sends the adhesive to the atomization spray head (3) at a certain flow rate. By controlling the atomization spray head (3) using the air pressure pump (2), the adhesive is sprayed into the interior of the blender (4) in the form of "fog umbrella". At the same time, the particles are continuously transported to the belt scale (5) then to the blender (4) for full gluing. Finally, the particles are discharged uniformly by the micro-computer controller (6).

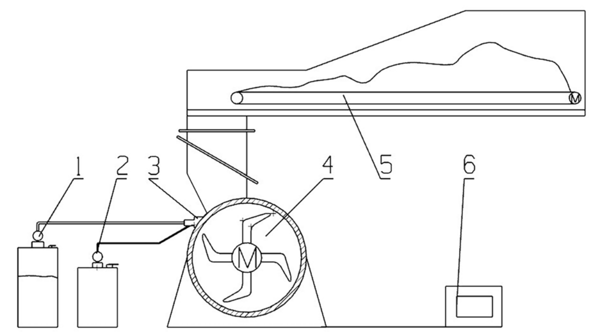


Fig. 1 Major components of PB gluing: 1. multi-pump dosing system; 2. air pressure pump; 3. atomization spray head; 4. blender; 5. belt scale; 6. micro-computer controller

In Fig. 1, the adhesive flow rate recorded by the multi-pump dosing system (1); the pressure value of atomization spray head (3) is shown by the pressure gauge on the air pressure pump (2); weighing and calculating particle feeding speed by the belt scale (5); the micro-computer controller (6) real-time displays the current in the blender (4).

Table 1 Production parameter information before sizing

Name	value	Unit
Core particle size	15 × 3 × 0.4 – 45 × 10 × 0.6	mm
Surface particle size	3 × 0.5 × 0.3 – 15 × 1.5 × 0.4	mm
Dry moisture content	1.5–2.5	%
Surface emulsion	0.75 ± 0.02	%
Core paraffin emulsion	0.57 ± 0.02	%
Surface curing agent	2 ± 0.02	%
Core curing agent	3 ± 0.04	%
Surface water	10 ± 0.05	%

Equipment parameters of blender

The blender used in the experiment was produced by IMAL–PAL, Italy. The internal picture of the blender is shown in Fig. 2, and blender parameters are listed in Table 2.

Fig. 2 Internal structure of the blender in particle gluing section

Test method

The IB of PB was tested by taking samples from plain PB after 48 h conditioning. The test method of IB in this study followed the standard of GB/T 17,657–2013 Test methods of evaluating the properties of wood-based panels and surface decorated wood-based panels [24]. The Mod.IB700 testing machine, produced by IMAL–PAL in Italy, was used in this study. The specimen with a size of 50 mm × 50 mm × 18 mm was placed in a conditioning chamber with a temperature of 20 ± 2 °C and a relative humidity of 65 ± 5% for equilibrating samples to a constant moisture content before the testing. The fracture specimen after IB tests is shown in Fig. 3.

To ensure that the relationship between the particle gluing production parameters and the IB of PB is not affected by the production parameters of other processes, the key production parameters of other processes after gluing are required to be constant or stable in a certain range. the 905 groups of sample data that meet the above requirements are used for modeling.

Methods

Grey relation analysis

GRA analysis process is to unify the data to an approximate range and calculate the grey relational grade between parameters through the data change trend of each parameter [25]. To reduce the absolute numerical difference of data caused by different dimensions of parameters, normalization is needed before the GRA analysis. Normalization usually uses min–max normalization or mean normalization in GRA [26]. This study selected the process of averaging data, as shown in the following equation:

$$f(x(k)) = \frac{x(k)}{\overline{x}} = y(k), \quad \overline{x} = \frac{1}{n}\sum_{k=1}^{n} x(k) \tag{1}$$

where $x(k)$ is a vector of normalized parameters, k is the k^{th} data in normalized parameters vector, $\overline{x}$ is the mean value of data in normalized parameter vector. Grey relation analysis is shown in the following equation:

$$\zeta_i(k) = \frac{\min_i \min_k \left|x_0(k) - x_i(k)\right| + \rho \cdot \max_i \max_k \left|x_0(k) - x_i(k)\right|}{\left|x_0(k) - x_i(k)\right| + \rho \cdot \max_i \max_k \left|x_0(k) - x_i(k)\right|} \tag{2}$$

where $x_0(k)$ is a vector of target parameters, $x_i(k)$ is the i^{th} parameter vector, and ρ is discrimination coefficient, usually the smaller the resolution coefficient, the better the resolution, typically 0.5 [27].

Support vector regression algorithm

SVR has advantages in small sample, non-linear and high-dimensional pattern recognition [28]; therefore, SVR has excellent prediction effect between particle gluing production parameters and IB of PB.

Given a training sample set on $T = \{(\boldsymbol{x}_1, y_1), (\boldsymbol{x}_2, y_2), \cdots, (\boldsymbol{x}_n, y_n)\}$ a feature space, where $\boldsymbol{x}_i \in R^n$ is the input sample vector, $y_i \in R^n$ is the corresponding output sample, and n is the number of training data. Regression function as shown in the following equation:

$$f(x) = \omega^T \varphi(x) + b \tag{3}$$

where $\omega \in R^n$ represents the weight vector, $\varphi(x)$ represents the nonlinear mapping function, and b represents the deviation, so as to obtain the minimum structural risk of the regression function. The optimal solution of SVR regression problem can be obtained by introducing relaxation variable $\xi_i \geq 0, \xi_i^* \geq 0$ [29], as shown in Eqs. 4–5:

Table 2 Blender parameters

Parameter name	Blender for core particles	Blender for surface particles	Unit
Power	90	110	kW
Nominal current	159	201	A
Max throughput	12,000	22,000	kg/h
Chamber length	3500	4500	mm
Chamber inner Diameter	700	850	mm
Chamber volume	1350	2552	L
Shaft rotation	520	416	r/min
Mixing tool rim speed	19	18.5	m/s

Fig. 3 Fracture position diagram of specimens after IB tests

$$\min_{(\omega,b,\xi)} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{4}$$

$$s.t.\begin{cases} y_i - \omega^T\varphi(x) - b \le \varepsilon + \xi_i \\ \omega^T\varphi(x) + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0, i = 1, 2, \cdots, n \end{cases} \tag{5}$$

where C is the penalty factor, indicating the correlation between the empirical error of the model and the smoothness. ε is a prescribed parameter, and the Lagrange multiplier is used to solve the bi-objective optimization problem. By introducing the Lagrange multiplier (a_i and a_i^*) [30], the regression function is obtained by dual solution as shown by Eq. 6,

$$f(x) = \omega^T\varphi(x) + b = \sum_{i=1}^{n}(a_i - a_i^*)[\varphi(x_i)^T \cdot \varphi(x_j)] + b \tag{6}$$

Introducing $\varphi(x)^T\varphi(x)$ in the kernel function $K(x_i, x_j)$ substitution, as shown by Eq. 7,

$$f(x) = \sum_{i=1}^{n}(a_i - a_i^*)K(x_i, x_j) + b \tag{7}$$

Since the Gaussian Radial Basis Function (RBF) has good generalization, nonlinear prediction performance and less adjustment parameters [31], this paper selects RBF as the kernel function. RBF function as shown by Eq. 8,

$$K(x_i, x_j) = \exp\left(\frac{-\|x_i - x_j\|}{2\sigma^2}\right) \tag{8}$$

To improve the prediction accuracy of the model, it is necessary to optimize the penalty coefficient "C" and the width of Gaussian RBF kernel "σ" [32]. In this paper, the 5-folder cross-validation was used to conduct grid search the training set samples.

The GRA–SVR prediction model for IB

Step 1: GRA correlation analysis

Through the GRA analysis of f_{core}, f_{surface}, v_{core}, v_{surface}, p_{core}, p_{surface}, I_{core} and I_{surface} on the grey relational grade of IB, the variables with low grey relational grade were screened out.

Step 2: Normalization of sample data

The normalization of sample data was to scale the data in the interval [0, 1], remove the unit limitation of sample data, and transform it into dimensionless pure values, so that different units can be maintained stable in the training process of the SVR model.

$$X_{changed} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

Step 3: Optimization of grid search parameters by K-fold cross validation

The grid search trains all the candidate parameters by the exhaustive method. Combined with the K-fold cross validation, the sample data set of the validation set was divided into k subsets and each subset performed the validation set once. The subset was used as the training set, and the validation K times were trained repeatedly until the penalty coefficient "C" of the minimum mean square error and the width "σ" of the Gaussian RBF kernel were selected as the optimal parameters.

Step 4: Constructing SVR nonlinear prediction model

The SVR prediction model for IB was established through the determined optimal parameters, and the model can predict each input. The SVR prediction models imported from the training set and the testing set were, respectively, used for prediction. The predicted values of the model output were compared with the experimental values, and the deviation of the model prediction was analyzed. The GRA–SVR prediction model diagram, as shown in Fig. 4.

Step 5: Evaluation of GRA–SVR model

MAE, MRE, RMSE and TIC were used to analyze the convergence of predicted values of GRA–SVR model to experimental values, and then the prediction performance of the model was accurately evaluated.

$$\text{MAE} = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n} \tag{10}$$

$$\text{MRE} = \frac{\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|}{n} \tag{11}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{12}$$

$$\text{TIC} = \frac{\sqrt{\sum_{i-1}^{n}(y_i - \hat{y}_i)^2}}{\sqrt{\sum_{i-1}^{n}(y_i)^2} + \sqrt{\sum_{i-1}^{n}(\hat{y}_i)^2}} \tag{13}$$

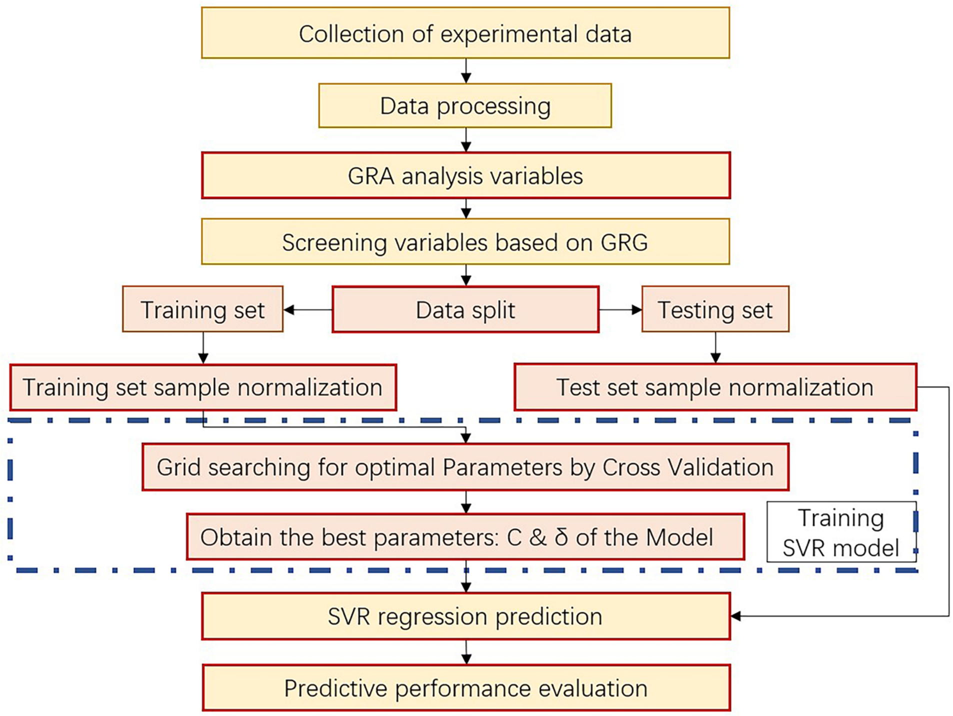


Fig. 4 Flow chart of the GRA–SVR regression prediction model

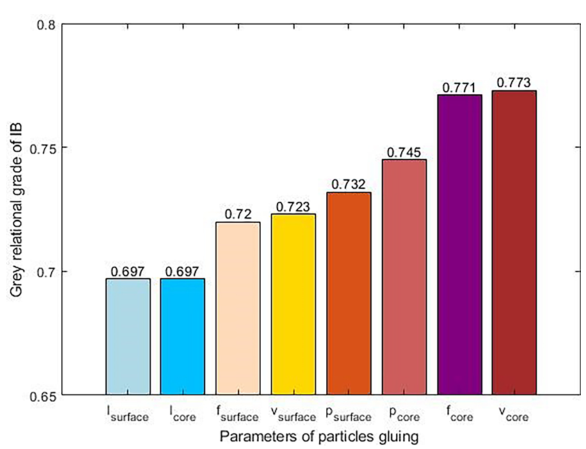


Fig. 5 GRA histogram of particle gluing processing parameters and IB of PB

Results and discussion

Grey relation analysis production parameters of particle gluing

The grey relational grade results of particle gluing production parameters of f_{core}, $f_{surface}$, v_{core}, $v_{surface}$, p_{core}, $p_{surface}$, I_{core} and $I_{surface}$ on IB calculated by GRA are shown in Fig. 5. The order of correlation between the production parameters of particle gluing and the IB of PB can be obtained intuitively: $v_{core} > f_{core} > p_{core} > p_{surface} > v_{surface} > f_{surface} > I_{core} > I_{surface}$.

On the one hand, the grey relational grades of v_{core}, f_{core} and p_{core} on IB were 0.773, 0.771 and 0.745, respectively, which are higher than that of $p_{surface}$, $v_{surface}$ and $f_{surface}$ on IB. It can be proved that the production parameters of core particle gluing have higher influence on the IB of PB than that of surface particle gluing. On the other hand, because the grey relational grades of I_{core} and $I_{surface}$ to IB were 0.697 and 0.697, respectively, which were far lower than other production parameters, it was proved that I_{core} and $I_{surface}$ had little effect on IB. The input of these two parameters into SVR regression prediction model for training would lead to lower prediction accuracy of the model. Therefore, only parameters of f_{core}, $f_{surface}$, v_{core}, $v_{surface}$, p_{core} and $p_{surface}$ were taken into account for the training of the SVR model.

Regression prediction of GRA–SVR algorithm

The prediction model of particle gluing process parameters and IB using GRA–SVR was trained. The input variables were f_{core}, $f_{surface}$, v_{core}, $v_{surface}$, p_{core}, $p_{surface}$, and the output variable was IB. The total experimental data obtained by the experiment was 905 groups, of which 724 groups of data were used as a training set to build the model and 181 groups of data as a validation set to verify

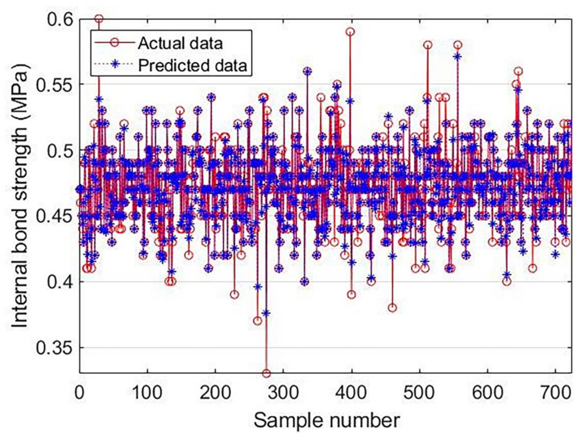


Fig. 6 Comparison between the experimental and predicted values of the training set based on the GRA–SVR model

the model. SVR parameters were optimized by 5-CV. The penalty coefficient "C" was 0.71, and the width "σ" of Gaussian RBF kernel was 8. Figure 6 shows that the prediction IB values obtained by the training set into the nonlinear regression prediction model were compared with the experimental values. The predicted values of the model in the image were highly consistent with the experimental values, which proved that the model had appealing fitting.

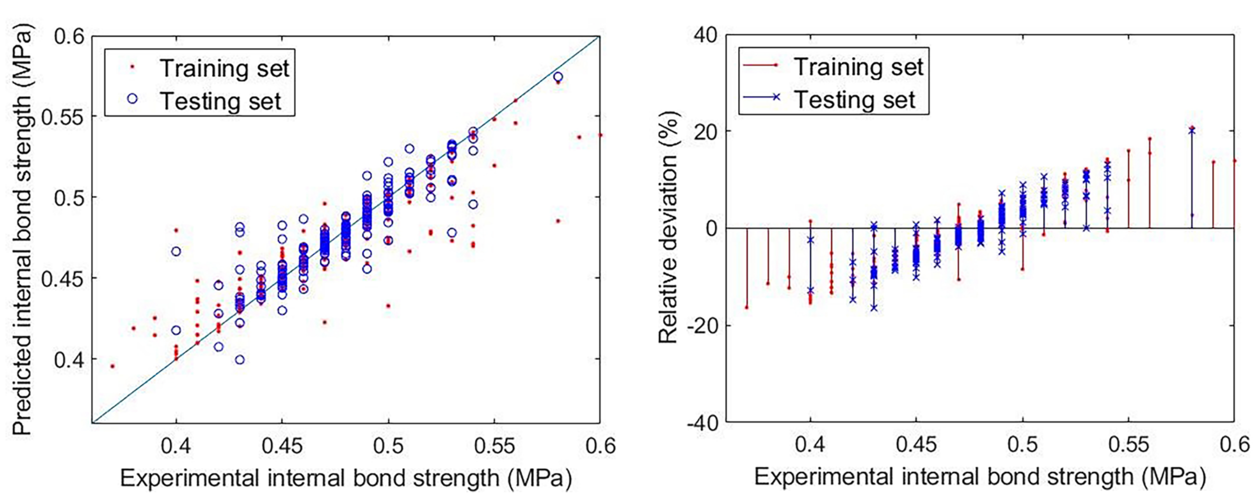
To accurately evaluate the prediction accuracy of the nonlinear prediction model of particle gluing production parameters and IB, the scatter distribution of the predicted and experimental values of the training set and the testing set was plotted using the image analysis model as shown in Fig. 7. If the predicted values of the model match the experimental values completely, all data points would be on the main diagonal. Figure 7a shows that the sample points of the training set and the testing set are very close to the main diagonal. Figure 7b shows that the relative deviation between the predicted values and the experimental values are small. It is indicated that the IB of PB model using GRA–SVR has good prediction accuracy.

As shown in Fig. 8, 91.16% testing data were within the 0–10% relative deviation between the predicted values and the experimental values, 28.28% testing data were ranged from 10 to 20% relative deviation, and 0.55% testing data were in 20–30% relative deviation. It was shown that the GRA–SVR prediction model of IB of PB had excellent accuracy.

Prediction performance evaluation of GRA–SVR algorithm

As shown in Fig. 8, although the GRA–SVR model had high accuracy, there was still 8.83% of the relative deviation of the predicted value between 10 to 30%. In addition to the nonlinear model itself, the error of data collection would also affect the accuracy of the model. Dai et al. [33] believed that vertical density profile (VPD) had a great influence on the IB of PB. Jin et al. [34] explored the regression relationship between IB and density of PB through the laminated beam theory, and the results showed that there was a positive correlation between IB and density of PB.

To explore the influence of VPD of PB on the prediction accuracy of GRA–SVR model, this study conducted



(a) Comparison between predicted and experimental values. (b) Relative deviation

Fig. 7 Comparison and relative deviation between predicted and experimental values. **a** Comparison between predicted and experimental values. **b** Relative deviation

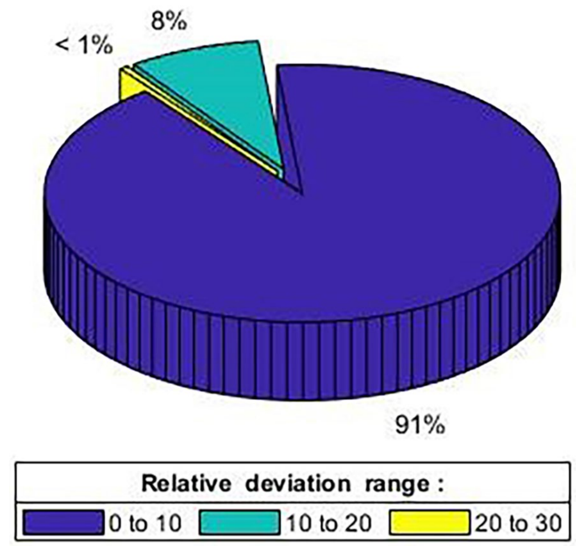


Fig. 8 Proportion of predicted values of the GRA–SVR model within relative deviations

six VPD tests on a randomly selected specimen, and the results are shown in Fig. 9. It could be seen from the figure that with the increase of PB thickness, the variation trend of density in the vertical direction was a profile of 'M'. The density variation trend of the middle layer of PB

Table 3 Prediction error results of GRA–SVR

Sample data	MAE	MRE	RMSE	TIC
Training	0.004	0.008	0.011	0.011
Testing	0.008	0.017	0.013	0.014

was relatively flat, but there was still ± 30 kg/m^3 density fluctuation. Because the density of particleboard was positively correlated with IB, if the fracture position of the specimen changes during IB tests, it would lead to the deviation of IB test results. This indicates that the more uniform density of PB intermediate layer, the higher the accuracy of GRA–SVR model can be achieved.

The training set sample data and the testing set sample data were inputted into the model for prediction, and MAE, MRE, RMSE, and TIC were used to evaluate the prediction performance of the model. As shown in Table 3, the results showed that the model errors were small, indicating the model had good prediction performance.

Application of the GRA–SVR model

Manufacturers would change PB production according to different order requirements. The particle discharge speed in the belt scale in the particle gluing process would change with the change of PB yield. The

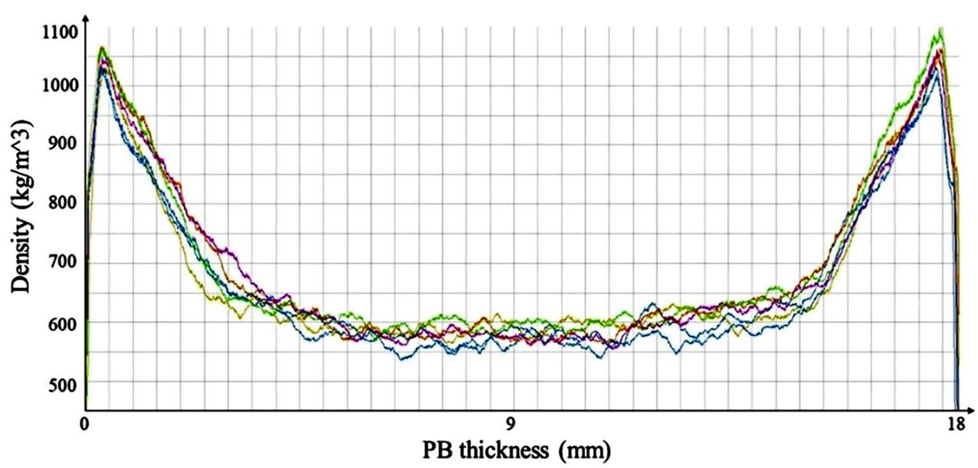


Fig.9 Results of VPD tests for IB test specimens by VPD analyzer

Table 4 Search range and optimization results of parameters

Parameters	f_{core} (kg/min)	$f_{surface}$ (kg/min)	v_{core} (L/min)	$v_{surface}$ (L/min)	p_{core} (bar)	$p_{surface}$ (bar)
Range	325	100 to 215	24 to 54	16 to 38	1.2 to 2.4	1.0 to 3.3
Results	325	154.1	37.5	27	1.9	1.8

GRA–SVR model in this study could change the production parameters of particle gluing according to the actual production demand, so as to improve the IB of PB.

Assuming that f_{core} was adjusted to 325 kg/min to meet the production demand of PB, the production parameters of particle gluing are predicted. The range of particle gluing production parameters is shown in Table 4. The prediction process took $f_{\text{core}} = 325$ kg/min as a constant, and the other five production parameters used 100 as the step length to bring into the GRA–SVR model for the grid search optimization. When the value of particle gluing production parameters was $f_{\text{surface}} = 154.1$ kg/min, $v_{\text{core}} = 37.5$ L/min, $v_{\text{surface}} = 27$ L/min, $p_{\text{core}} = 1.9$ bar, $p_{\text{surface}} = 1.8$ bar, the optimal value of IB of PB was 0.55 MPa.

On the other hand, PB manufacturers would reduce production costs by reducing adhesive consumption according to the actual situation of orders. Reducing the adhesive consumption of PB would lead to the decrease of IB [35]. The GRA–SVR model was used to predict the production parameters of particle gluing after reducing the flow rate of the particle glue from multi-pump dosing system, which could ensure the production of PB under the minimum IB for meeting the enterprise standards. Therefore, the modeling and optimization of particle gluing processing parameters and IB of PB are conducive to reducing the production cost of PB and improving the quality of products.

Conclusions

In this study, a nonlinear regression prediction model between particle gluing processing parameters and IB of PB was developed using GRA–SVR. The six input parameters of f_{core}, f_{surface}, v_{core}, v_{surface}, p_{core} and p_{surface} were used to predict IB, which can quantitatively evaluate the influence of particle gluing production parameters on IB of PB and provide a new method for particle gluing process.

(1) GRA was used to analyze the grey relational grade between the particle gluing parameters of f_{core}, f_{surface}, v_{core}, v_{surface}, p_{core}, p_{surface}, I_{core} and I_{surface} and IB of PB. The results showed that the core particle gluing parameters had a higher proportion of the influence on the IB strength compared with the surface particle gluing parameters. I_{core} and I_{surface} had smaller influence on IB compared with other parameters.

(2) The predicted IB values obtained using the nonlinear regression prediction model were compared with experimental values. The results showed that the predicted values were in good agreement with the experimental values, and the relative deviations of 91.16% data points were in the range of 0–10%, indicating that the particle gluing model using GRA–SVR had satisfactory regression prediction accuracy.

(3) The sample data of training set were used by the GRA–SVR nonlinear regression prediction model to predict particleboard IB and the production parameters of particle gluing. The evaluation results showed that MAE was 0.004, MRE was 0.008, RMSE was 0.011, and TIC was 0.011, proving that the GRA–SVR model had good fitting. The GRA–SVR regression prediction model was used to predict the testing set sample data. The evaluation results showed that MAE was 0.008, MRE was 0.017, RMSE was 0.013, and TIC was 0.014, proving that the application of GRA–SVR model has excellent accuracy.

Using the GRA–SVR regression prediction model, IB of PB can be predicted in real time according to the production parameters of particle gluing. The manufacturers would adjust particle discharge speed in the belt scale and flow rate of particle glue from multi-pump dosing system in the process of particle gluing according to the actual production demands, so as to improve the yield of PB or reduce the adhesive consumption. The GRA–SVR model was used to predict the production parameters of particle gluing after the adjustment, so that the IB of PB meets the requirements of enterprise standards. The GRA–SVR modeling and prediction are helpful to guide the production practice of particleboards and has promising application future for efficient and stable production in the particleboard manufacturing industry.

Abbreviations

IB: Internal bond strength; PB: Particleboards; GRA: Grey relation analysis; SVR: Support vector regression; MAE: Mean absolute error; MRE: Mean relative error; RMSE: Root mean square error; TIC: Theil's inequality coefficient; MLR: Mixed logistic regression; ANN: Artificial neural network; 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; VPD: Vertical density profile.

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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.

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Availability of data and materials

The data sets 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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