

Prediction of Fiber Quality Using Refining Parameters in Medium-density Fiberboard Production *via* the Support Vector Machine Algorithm

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Fiber quality greatly influences the performance of medium-density fiberboard (MDF). To evaluate the fiber quality more accurately during refining, a novel quantitative parameter-property relationship model was developed based on the support vector machine (SVM) algorithm. Based on the mill production conditions, a total data set of 1173 experimental fiber quality data points under a wide range of five refining parameters was employed to train and verify the model. By comparing the effectiveness between the model using nonlinear SVM and the model based on multiple linear regression (MLR), the values of mean absolute error (MAE), mean relative error (MRE), root mean square error (RMSE), and Theil's inequality coefficient (TIC) were reduced 92.19%, 92.36%, 87.29%, and 87.21%, respectively. The results showed that the performance of the predictive model developed using SVM was superior to the MLR model. Furthermore, the variations of the percentage of qualified fibers with each production parameter were predicted using the established model. The prediction model that resulted can be applied to predict the fiber quality during the refining process in an MDF production mill.

Keywords: Fiber quality; MDF; Refining; Predictive model; SVM

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INTRODUCTION

Medium-density fiberboard (MDF) has been widely applied in the furniture and interior decoration markets due to its dimensional stability, workability, flatness, smooth appearance, good bond strength, and screw-holding ability (Hua *et al.* 2012). A crucial step in the fiberboard production is the refining process (Runkler *et al.* 2003). It is impractical and costly to evaluate which fiber qualities are affected by certain production parameters through experimental determination techniques during the refining process. Production parameters are mainly adjusted based on the experience of workers, which suffers from poor accuracy due to the lack of theoretical guidance on the model of fiber quality relating to production parameters. Therefore, it is essential to develop new models to predict fiber quality according to production parameters.

To investigate the influence of production parameters during refining on the fiber or the fiberboard quality, some studies have been carried out over the past decade. Chen and Hua (2009) developed a constraint relationship between the fiber productivity and fiber quality using third-order polynomial and linear regressions, and an optimization method was developed to adjust the fiber quality by modifying fiber productivity that depends on the feeding screw revolution speed and the opening percentage of the discharge valve. The

relationship between the content of bark and the fiber quality was investigated by Jia *et al.* (2015). It was demonstrated that the fiber screening value first presented an increasing trend and then descended with an increase in bark content. Xing *et al.* (2006) investigated the influence of thermo-mechanical refining on the properties of MDF panels made from black spruce bark, and the results showed that the preheating retention time was an important factor for both the modulus of rupture and the modulus of elasticity. The steam pressure was an important factor for internal bond strength, modulus of rupture (MOR), and modulus of elasticity (MOE). The previously described studies revealed the relationship between the production parameters during refining and the quality of fiber or fiberboard based on linear or polynomial regression, which was shown to be disadvantaged by low accuracy and the inability to predict the quality online.

To address these drawbacks, some researchers developed models between the production parameters during refining and the quality of fiber or fiberboard with intelligent algorithms. To determine the process set points leading to minimum production cost for the target quality, Gerstorfer *et al.* (2001) established a Takagi-Sugeno-Fuzzy model for the refining process based on the experts' knowledge as well as the data collected. The neuro-fuzzy modeling methods were used by Runkler *et al.* (2003) to model the wood chip refiner process for fiberboard production to provide online predictions of the two important quality indices (flexural strength and water uptake). The results showed that the model accuracies achieved were approximately ± 5 N/mm² for flexural strength and approximately $\pm 10\%/24$ h for water uptake. However, the fuzzy rules were determined on the dependence of experts' technological experience, which only leads to a certain extent of improvement on the prediction accuracy. Because the artificial neural network (ANN) can model highly nonlinear systems without using complex deduction rules or large data (Huang and Lu 2016), it was used as a predictive method to determine the moisture resistance of particle- and fiberboards under cyclic testing conditions by Esteban *et al.* (2010). However, the training procedure for ANN models is not only time consuming but it is also possible to get trapped in local minima (Hong *et al.* 2013).

With the advantages of a simple structure, good generalization ability, nonlinear modeling properties (Wang *et al.* 2009; Zhou *et al.* 2016; Sun *et al.* 2016), and avoidance of the problems of over-fitting, local extremum, and dimension disaster (Shi *et al.* 2010; Zhao *et al.* 2014; Sun *et al.* 2016), the support vector machine (SVM) has become a promising classification and regression algorithm. The SVM can be used for classification of data and text, system modeling and prediction, pattern recognition, anomaly detection, and time series prediction (Jiao *et al.* 2016) in many fields (Mokhtarzad *et al.* 2017; Roushangar and Ghasempour 2017; Huang *et al.* 2018). Among these fields, Zhang *et al.* (2016) employed the SVM method to establish parameters-properties models in the papermaking field. Although SVM has been employed in many fields because of its advantages of nonlinear relationship expression, it has not been used for the modeling of fiber quality during the refining process in MDF production.

This study is aimed at increasing the percentage of qualified fibers (QF) by adjusting five parameters, *i.e.*, the conveyer screw revolution speed (SR), accumulated chip height (CH), opening ratio of the discharge valve (OV), content of log bark (CB), and content of Chinese poplar (CP) during refining. The QF were evaluated by fiber size, *i.e.*, the screen mesh grades of the fibers. Firstly, a large amount of fiber quality data was collected from the MDF production mill under a wide range of SR, CH, OV, CB, and CP to uncover the relationship between the refining parameters and fiber quality. Secondly, SVM was utilized to construct the nonlinear predictive model of fiber quality during the

refining. The experimental values and predicted outputs of the model were compared, and the accuracy of the model was established. Thirdly, the results from the SVM-based model and the multiple linear regression (MLR)-based model were compared, showing that the SVM model predicted fiber quality more effectively and accurately than that from the MLR.

EXPERIMENTAL

Materials

Data collection

The data were collected in a production line at a MDF mill in Northern China and two major species, namely Chinese poplar (*Populus lasiocarpa* Oliv.) and Chinese larch (*Larix potaninii* Batalin), were used in the production. In the production line, the 4000 kW refiner (model: 50-ICP; Andritz Group, Graz, Austria) utilized had double 1372-mm diameter disks running at a rotational velocity of 1,500 r/min.

Figure 1 shows the major components of the refiner. A feeding screw (2) transfers the wood chips in the hopper (1) to the pre-heater (3). The preheating retention time was determined by CH. Chips were discharged to the refiner (6) using a conveyer screw (4) after the steam-softening. Through the discharge pipe (5), the refined fibers were unloaded under the steam pressure in the refiner. The opening ratio of the valve installed on the discharge pipe (5) was used to adjust the amount of unloaded fibers.

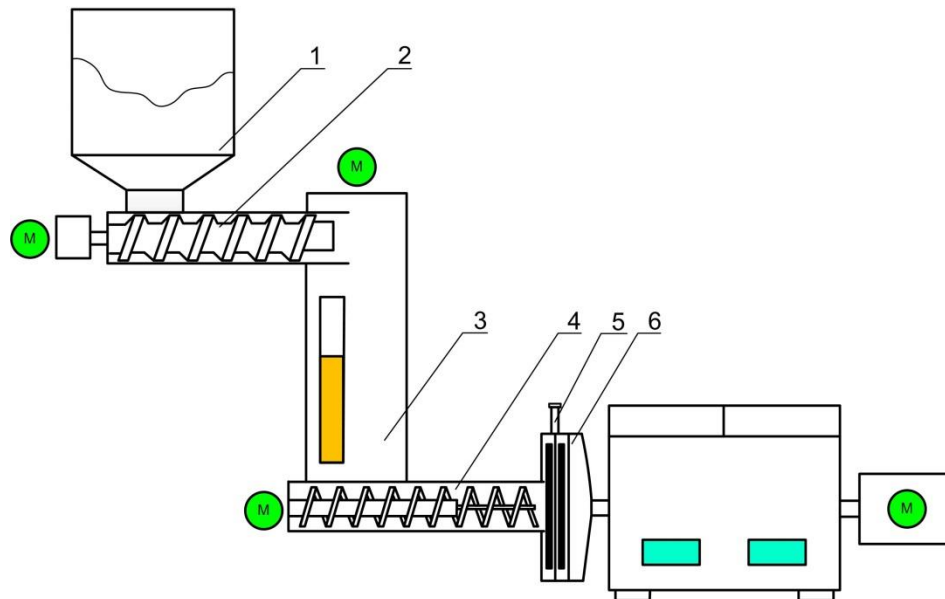


Fig. 1. The major components of the refiner: 1) Hopper, 2) Feeding screw, 3) Pre-heater, 4) Conveyer screw, 5) Discharge pipe, and 6) Refiner

In the chip washing and steaming processes, the moisture content of the wood chips increased. However, during the chip transportation, the feeding screw squeezed the moisture from the chips in the feeding pipe and brought the final moisture content of the chips to 50%.

In the pre-heating process, the steaming pressures usually slightly fluctuate from 0.766 MPa to 0.990 MPa (corresponding to a steaming temperature that ranged from 168.6

°C to 179.5 °C). The gap between the two refining disks was pre-set to 0.1 mm. The sensors installed on the production line measured five refining parameters, including SR, CH, OV, CB, and CP, hourly under usual production conditions.

Generally, large fiber size would produce panels with poor board appearance, while smaller-sized fibers could cause the reduction in panel strength (Shi *et al.* 2006). Technically, the good fiber shape for MDF requires a moderate ratio of length/width of the fiber (Chen 2012). Based on the mill's practices, the fibers with a size between 20 to 120 screen mesh were considered to be qualified in this study.

In the fiber processing, 10 g of fiber were collected and weighed with a balance off the production line to determine the fiber sizes for each measurement. The percentage of the QF in the total amount = (The weight of qualified fiber (g) / 10 g) × 100%.

It was hypothesized that the response variable (QF) during the refining could be estimated by correlating the predictor variables (SR, CH, OV, CB, and CP). A large sample size, 1,173 measurements for each variable, was analyzed in this study. Two models, namely, MLR and SVM, were developed for predicting the fiber quality. The accuracies of the two models were validated and compared using the data collected in the MDF production line.

Methods

Support vector machine algorithm

The SVM, proposed by Vapnik (1999), is a relatively new and promising classification and regression algorithm based on the statistical learning theory and structural risk minimization principle. Based on this principle, SVM possesses an optimum network structure that is beneficial to reduce the global error of the model (Xiao *et al.* 2014).

The basic principle is as follows (Chu *et al.* 2017). Training data are presented in the form $\{x_i, y_i\}_{i=1}^n$, where x_i values are the input data, y_i values are the corresponding output data, and n is the number of training data points. The SVM is used to search an optimal regression function, which can estimate all of the training data (Drucker *et al.* 1997). The regression function can be expressed as,

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

where $w \in R^n$ denotes the weight vector, $\varphi(x)$ denotes the nonlinear mapping function, and b denotes the bias. As mentioned previously, SVM is based on risk minimization, while w and b are estimated by minimizing the regularized risk function as below,

$$R(C) = \frac{1}{2} \|\omega\|^2 + \frac{C}{n} \sum_{i=1}^n L_\varepsilon(y_i, f(x_i)) \quad (2)$$

where $1/2\|\omega\|^2$ is the flatness of the function, C is the penalty factor, which is the correlation between empirical error and flatness of the model (Yan and Shi 2010), ε is a prescribed parameter, and $L_\varepsilon(y_i, f(x_i))$ is the ε -insensitive loss function that can be defined as:

$$L_\varepsilon(y, f(x)) = \begin{cases} |f(x) - y| - \varepsilon, & |f(x) - y| \geq \varepsilon \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

By introducing the slack variables ζ and ζ^* , Eq. 2 can be written as:

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

$$s.t. \begin{cases} y_i - f(x_i) \leq \varepsilon + \xi_i \\ f(x_i) - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0, \quad i = 1, 2 \dots n \end{cases} \quad (5)$$

The dual objective optimization problem can be solved using the Lagrange multipliers (Ma *et al.* 2003). Finally, the regression function is obtained as the following equation,

$$f(x, a_i, a_i^*) = \sum_{i=1}^{nsv} (a_i - a_i^*) K(x_i, x_j) + b \quad (6)$$

where a_i and a_i^* are the Lagrangian operators, nsv is the number of support vectors, and $K(x_i, y_i)$ is the kernel function. It is important to select the kernel function and its parameters because the generalization performance of SVM depends on the type of kernel function, its parameters, and several internal parameters of SVM (Zhao *et al.* 2016).

The Gaussian Radial Basis Function (RBF) is mostly used for the kernel function due to its properties of good generalization and nonlinear forecast as well as its characteristic of few parameters that need to be adjusted (Bishop 1995; Keerthi and Lin 2003). Therefore, in this study, the Gaussian RBF was selected as the kernel function using the following formula,

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

where σ is the width of RBF.

Therefore, there are two variables that need to be selected in the SVM model, which are the constant “ C ” and the width of the Gaussian RBF kernel “ σ ”. In this study, the optimization of these parameters was performed by a systematic grid search of the parameters using the cross-validation on the training set.

The SVM predictive model for fiber quality

In this paper, the software used for analysis was Matlab (MathWorks, R2010a, Natick, MA, USA). The diagram of the SVM predictive model is illustrated in Fig. 2. The details of the operation process for the SVM model are discussed below.

Step 1: Data preprocessing

To ensure the training stability of the SVM and avoid the bad influence caused by discrepancy of quantitative dimension, the data from experiments were normalized with the following mapping function,

$$x_M = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (8)$$

where x_M is the normalized data, x is the original data, and x_{\max} and x_{\min} denote the maximum and minimum raw input values, respectively. The original data were normalized to the range of 0 to 1.

Step 2: Cross validation (CV) to select the best parameters of regression, C , and σ

First, the fitness function (mean square error) was determined based on 3-CV, ε was pre-set as 10^{-4} , and the range of C and σ were defined and meshed. Second, the fitness function was recalculated through updating C and σ within the grid. Finally, the C and σ that generate the minimum average mean square error (MSE) of the three models were selected as the best parameters.

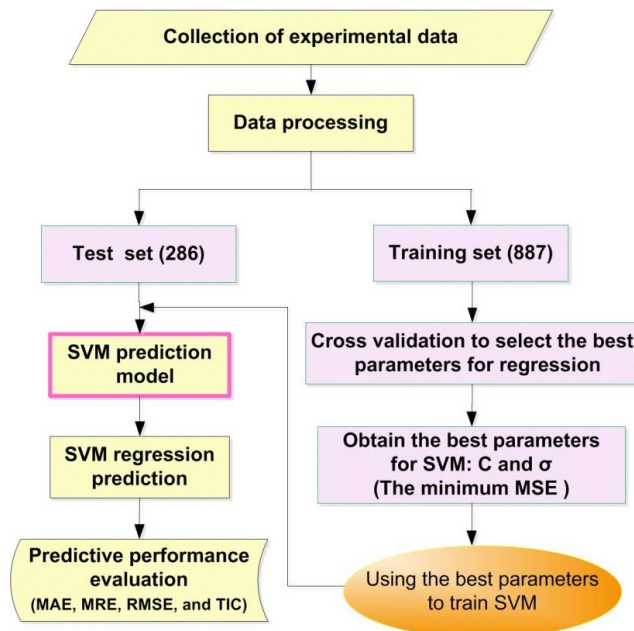


Fig. 2. Diagram of the support vector machine predictive model

Step 3: Building the SVM model for fiber quality

The SVM model for fiber quality was trained and established based on the best parameters obtained in step 2, which can be used to investigate the relationships between the parameters and the property.

Step 4: SVM regression prediction

The built SVM model was used to predict the training set and test set, and then the fiber quality under prediction was compared with the experimental data.

Step 5: Evaluation of predictive performance

The predicted performance was evaluated in terms of mean absolute error (MAE), mean relative error (MRE), root mean square error (RMSE), and Theil's inequality coefficient (TIC). They are defined according to the following formulas, respectively,

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (9)$$

$$MRE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (10)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (11)$$

$$TIC = \frac{\sqrt{\sum_{i=1}^n (y_i - \hat{y}_i)^2}}{\sqrt{\sum_{i=1}^n (y_i)^2} + \sqrt{\sum_{i=1}^n (\hat{y}_i)^2}} \quad (12)$$

where y_i are the actual outputs (experimental qualified fibers), \hat{y}_i the outputs of models (predicted qualified fibers), and n is the number of compounds in the analyzed data set.

RESULTS AND DISCUSSION

Results of the SVM Algorithm

The inputs for the fiber quality model using the SVM algorithm were SR, CH, OV, CB, and CP, and the output was QF. Out of a total set consisting of 1173 groups of data from the experiment, 887 groups of data were used to build the model as a training set, while 286 groups of data were used to validate the model established as a test set. In selecting the SVM parameters, K-CV can effectively avoid the occurrence of overlearning and under-learning. In this paper, the optimization of the SVM parameters was carried out by 3-CV. Figure 3 illustrates the SVM parameter selection process and results (contour map and 3D view). As shown in Fig. 3a, contour lines represent the C and σ corresponded MSE based on the K-CV method. The most optimum condition where the MSE of the 3-CV method equaled 0.00025373 was selected. The final optimization results were $C = 1$ and $\sigma = 5.6569$.

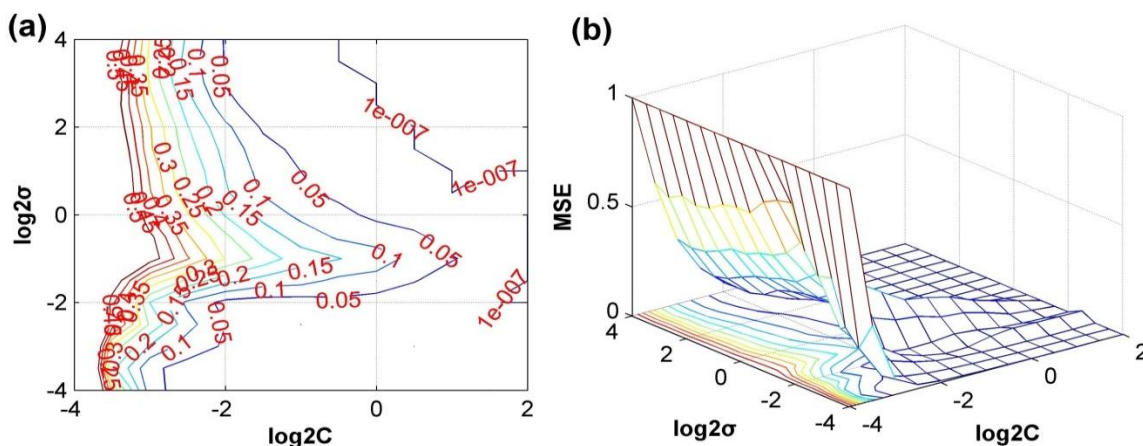


Fig. 3. SVM parameter selection process and results: (a) contour map, and (b) 3D view

To estimate the accuracy of the fiber quality model, the experimental data were compared with the predicted outputs as shown in Fig. 4. In Fig. 4a, the scatter plots of the predictive *versus* the experimental outputs for the qualified fibers were observed. If the model exactly matched the actual values, all data points would be on the main diagonal. It

was revealed that the data points were indeed close to the main diagonal, indicating good model accuracy. As described in Fig. 4b, the relative deviations of the predicted qualified fibers values in comparison with experimental values indicated that the new model established by the SVM algorithm clearly possessed promising prediction properties.

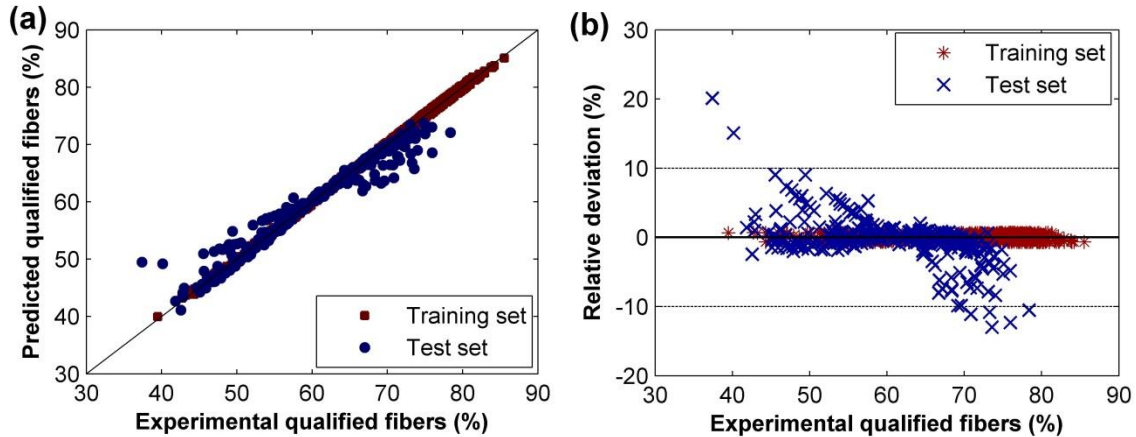


Fig. 4. Predicted *versus* experimental qualified fibers using the SVM algorithm: (a) predicted qualified fibers, and (b) relative deviation

As described in Fig. 5, the percent of value shows 97.02% in the range of 0% to 5%, 2.39% in 5% to 10%, 0.43% in 10% to 15%, and 0.17% in 15% to 20%. The associated estimation error for the majority of data points (99.41%) lies in the range of 0% to 10%, which demonstrates a good predictive accuracy for the fiber quality.

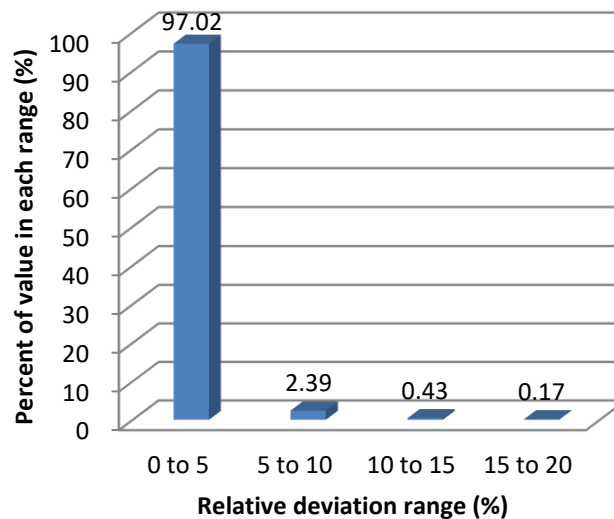


Fig. 5. Percent of value for relative deviation range under the SVM model

The Comparison of Results for SVM and MLR

The performance of SVM was compared with that of MLR based on the training set and test set. Figure 6 shows the predicted qualified fibers *versus* the experimental ones using the MLR algorithm. In Fig. 6a, the predicted qualified fibers were not in good agreement with the corresponding experimental fiber quality, and fewer data points of

qualified fibers were close to the diagonal. As shown in Fig. 6b, approximately 11.2% of the relative deviation of predicted qualified fibers was above 20%, and the maximum value even reached up to 51.2%. This demonstrated that the fiber quality prediction was not a simple linear problem, and the fiber quality model established by the MLR linear algorithm had certain limitations.

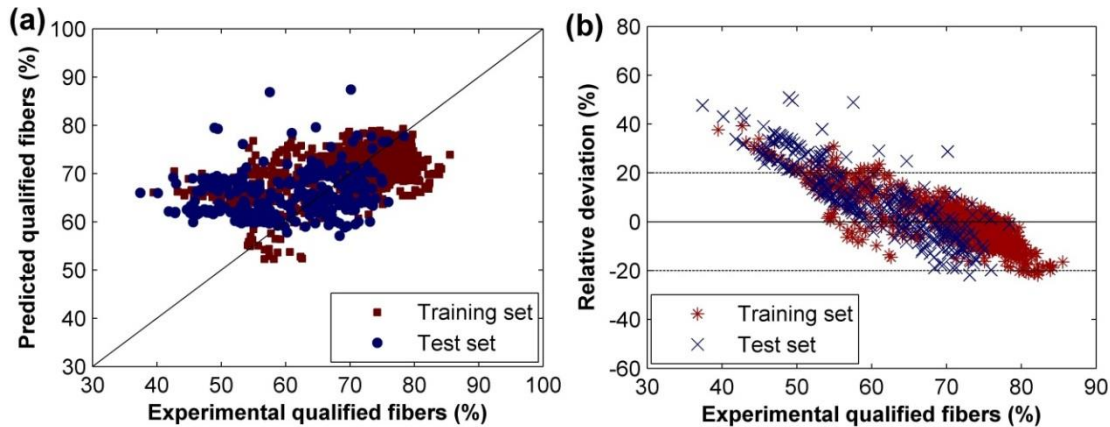


Fig. 6. Predicted *versus* experimental qualified fibers using the MLR algorithm: (a) predicted qualified fibers, and (b) relative deviation

The errors of the MLR algorithm were compared with that of the SVM algorithm, and the detailed results are listed in Table 1. As can be seen in Table 1, on the basis of MAE, the SVM achieved a decrease of 92.19% compared to the MLR. Similar results were obtained from the other error analyses, such as a MRE with a decrease of 92.36%, RMSE with a decrease of 87.29%, and TIC with a decrease of 87.21%. It was demonstrated that the SVM algorithm performed better than the MLR in predicting fiber quality.

Table 1. Comparison of Errors by the MLR and SVM Algorithms

Algorithms	Sets	No.	MAE	MRE (%)	RMSE	TIC
MLR	Training	887	5.425	8.326	7.110	0.050
	Test	286	8.538	15.917	10.934	0.086
	Total	1173	6.184	10.177	8.210	0.059
SVM	Training	887	0.248	0.360	0.286	0.002
	Test	286	1.212	2.075	2.052	0.017
	Total	1173	0.483	0.778	1.043	0.008

Application of the Predictive Model of Fiber Quality

According to actual producing conditions, the ranges of production parameters selected in the prediction model are shown in Table 2. Because the established predictive model of fiber quality was effective and accurate, the effect of variation of single parameters on fiber quality was analyzed.

Table 2. The Range of Production Refining Parameters

Parameter	SR (r/min)	CH (m)	OV (%)	CB (%)	CP (%)
Range	40 to 72	4 to 5.9	13.4 to 68	5.8 to 23.4	11.2 to 41.5

One parameter was selected as a variable and the other four parameters remained unchanged in each prediction. A parameter was selected as a variable with its range provided in Table 2. However, the values of parameters selected as constants were SR = 50 r/min, CH = 5 m, OV = 45%, CB = 12.55%, and CP = 24%. By inputting those values into the developed fiber quality model, the variations of each production parameter with the fiber quality were obtained as shown in Fig. 7.

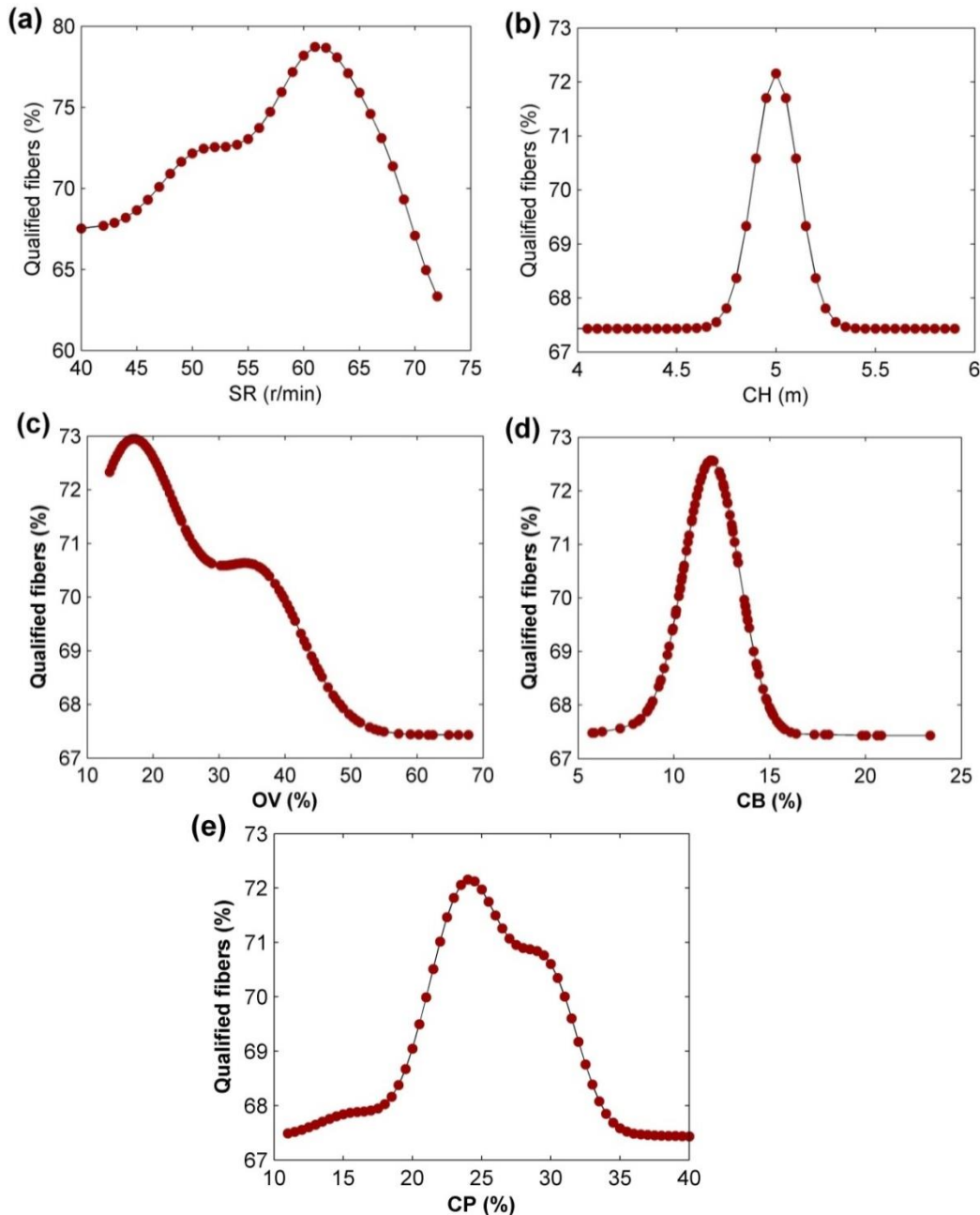


Fig. 7. Variations of the percentage of qualified fibers with each production parameter: (a) SR, (b) CH, (c) OV, (d) CB, and (e) CP

As shown in Fig. 7a, when the SR was less than 62 r/min, the percentage of qualified fibers increased with the increase of SR. However, when it was more than 62

r/min, the percentage of qualified fibers decreased with the increase of SR. The increase in SR led to the increase in the amount of chips and resulted in enhanced friction among fibers between refining disks. The increased friction greatly reduced the excess crushing and cutting of fibers due to its direct contact with the disks and improved the fiber quality. However, too much feed caused by the excessive conveyer screw revolution speed led to the increase of the gap between disks. This reduced the force between the wood chips, resulting in insufficient defibrination. Consequently, more coarse fibers were produced, resulting in a reduction in the amount of qualified fibers.

As shown in Fig. 7b, when the CH was less than 5 m, the percentage of qualified fibers increased with the increase of CH; however, when it was more than 5 m, the percentage of qualified fibers decreased with the increase of CH. The CH had a positive correlation with steaming time, which is a vital parameter deciding the degree of softening of wood chips. The increase in CH extended the steaming time of the chips and weakened the inter-fiber connection. As a result, the percentage of qualified fibers increased due to better fiber shape and less mechanical damage of fibers during refining. Nevertheless, excess steaming time destroyed the fiber itself due to the increase of the proportion of rupture of long molecular chains of the cellulose and hemicellulose in fiber cells, and the intensification of the loss of intercellular layer material, which was likely to generate more tiny fibers and resulted in a decreased percentage of qualified fibers.

As shown in Fig. 7c, the percentage of qualified fibers generally decreased with the increase of OV. The increase in OV caused a gradual increase of the pressure difference between the inside and outside of grinding chamber, where the chips defibered, and the aggravating of fluidity outward of fibers. This led to the decrease of the percentage of qualified fibers due to the increase in coarse fibers caused by the insufficient grinding, which resulted from less refining time. However, there existed an optimum point at 18.2%, where the fluidity outward and degree of grind of fibers achieved a balance, leading to the optimum fiber size.

As shown in Fig. 7d, when the CB was less than approximately 12%, the percentage of qualified fibers increased with the increase of CB. However, when the CB was more than approximately 12%, it decreased with the increase of CB. The fiber quality was improved by the longer bast fibers in the bark. However, if the bark content was too high, excess skinny fiber in the bark resulted in the reduction of the percentage of qualified fibers.

As shown in Fig. 7e, when the CP was less than approximately 24%, the percentage of qualified fibers increased with the increase of CP. However, when the CP was more than approximately 24%, it decreased with the increase of CP. Chinese poplar is a broad-leaved wood whose fibers are shorter. Therefore, the proportion of coarse fibers decreased and the proportion of finer fibers slightly increased when the CP increased, improving the ratio of qualified fibers. Nevertheless, too much CP resulted in the exceeding proportion of finer fibers, which reduced the percentage of qualified fibers.

CONCLUSIONS

1. Using 1173 groups of mill production data, an effective and powerful model based on the SVM algorithm was developed to predict the fiber quality during the refining process in the MDF production. The model was constructed with five predictor variables including the conveyer screw revolution speed (SR), accumulated chip height (CH), opening ratio of the discharge valve (OV), content of log bark (CB), and content

of Chinese poplar (CP), which enable the evaluation of fiber quality more comprehensive and more suitable to be used in the mill conditions.

2. The predicted outputs of the SVM model were compared with the experimental data. The results showed that the predicted values agreed with the experimental ones well, and the estimation relative deviation for the majority of data points (99.41%) were in the range of 0% to 10%, indicating that the new model established by the SVM algorithm had a good predictive accuracy.
3. The performance of the SVM was compared with that of MLR based on the training set and test set. The results demonstrated that the MAE, MRE, RMSE, and TIC values of the total data set of the SVM were decreased by 92.19%, 92.36%, 87.29%, and 87.21%, respectively. Compared to the model established by MLR, the model established by SVM possessed better properties in accuracy and validity.
4. Additionally, the variations of the percentage of qualified fiber with each parameter were presented using the developed predictive model, and the reasons of variations were described. It was demonstrated that the model established by the SVM algorithm can be used as a promising guideline for a fiberboard mill manager to predict fiber quality.

ACKNOWLEDGMENTS

This research was funded by the Graduate Student Independent Innovation Fund Project of Central Universities (Grand No. 2572017AB17) and the Specialized Research Fund for the Doctoral Program of Higher Education of China (Grant No. 20130062110005).

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Article submitted: July 1, 2018; Peer review completed: August 28, 2018; Revised version received and accepted: September 8, 2018; Published: September 13, 2018.
DOI: 10.15376/biores.13.4.8184-8197