Bi-directional Prediction of Wood Fiber Production Using the Combination of Improved Particle Swarm Optimization and Support Vector Machine

Yunbo Gao,[a] Jun Hua,[a,]* Guangwei Chen,[a] Liping Cai,[b,c] Na Jia,[a] and Liangkuan Zhu [a]

In order to investigate the relationship between production parameters and evaluation indexes for wood fiber production, a bi-directional prediction model was established to predict the fiber quality, energy consumption, and production parameters based on the improved particle swarm optimization and support vector machine (IPSO-SVM). SVM was applied to build the bi-directional prediction model, and IPSO was used to optimize the SVM parameters that affect the performance of prediction greatly. In the case of the forward prediction, the model can predict the fiber quality and energy consumption using the production parameters as input information; in the case of the backward prediction, the model can estimate production parameters using the fiber quality and energy consumption as evaluation indexes for input information. The results showed that the IPSO-SVM model had high accuracy and good generalization ability in the prediction for the wood fiber production. Additionally, based on the effectiveness of the proposed model and preset evaluation indexes, the corresponding production parameters were determined, which was able to save the wooden resources as well as reduce energy consumption in the fiberboard production.

Keywords: Wood fiber production; Fiber quality; Energy consumption; Bi-directional prediction; IPSO-SVM

Contact information: a: College of Electromechanical Engineering, Northeast Forestry University, Harbin, 150040, China; b: Mechanical and Energy Engineering Department, University of North Texas, Denton, TX 76201, USA; c: Nanjing Forestry University, Nanjing, 210037, China;
** Corresponding author: huajun81@163.com*

INTRODUCTION

Medium density fiberboard (MDF) is a wood-based panel that is composed of wood fibers bonded together with resin under heat and pressure (Kartal and Green 2003). It is widely used in many product areas such as furniture, kitchen cabinets, and interior decoration (Wang *et al.* 2001; Hua *et al.* 2012; Li *et al.* 2013). Production parameters during refining have a great effect on the fiber quality and energy consumption, which further influence the product quality and cost. Currently, the prediction of the fiber quality and energy consumption and the adjustment of production parameters mainly relies on the experience of operators, resulting in many problems such as the inaccurate prediction caused by subjective factors and a lack of real-time analysis. Therefore, it is important to develop a bi-direction prediction model for fiber refining to confirm the relationships between the production parameters and evaluation indexes.

The effects of the single or multiple refining parameters on the quality of the fiber or fiberboard and energy consumption have been investigated through experimental analysis and simple regression. These studies mainly focused on the relationship between evaluation indexes and production parameters such as refining temperature (Roffael *et al.* 2001), steam pressure (Krug and Kehr 2001), preheating retention time (Xing *et al.* 2006), wood mixture (Jia *et al.* 2015), *etc*. The influences of refining conditions on the fiber geometry were investigated with the analysis of variance and the least significant difference method by Aisyah *et al*. (2012), which indicated that the pressure and time significantly affected the fiber length and aspect ratio. Through the measurements of screening value under different straw-wood ratios and steaming conditions, Wei *et al*. (2013) achieved the optimal thermal grinding condition, which was helpful for improving the straw-wood fiber yield. Hua *et al*. (2010) separately mixed Chinese poplar chips of two different quantities into wood chips during fiber refining. The results indicated that the incorporation of poplar played a favorable role in terms of the fiber size and energy consumption. To predict the energy demand in an MDF plant, Li *et al*. (2006) developed a model based on the commercial production process with the methods of the empirical correlation and the theoretical calculation. Li *et al*. (2007) also built a model to predict thermal energy with discrepancy of -17 % to +6 %, which was evaluated with the inputs of annual production, operation hours, and product grade. However, because fiber production is a highly nonlinear system composed of production parameters and evaluation indexes, the previously described studies covered the relationships between the production parameters and evaluation indexes using the methods of experimental analysis and simple regression, resulting in low accuracy prediction.

With the springing up of intelligent algorithms, the theory of intelligent algorithm has provided a powerful tool for disclosing the relationships between the production parameters and evaluation indexes in the fiberboard production field. A Takagi-Sugeno fuzzy model for the wood chip refiner process in fiberboard production was established by Runkler *et al*. (2003) to provide on-line predictions for flexural strength and water uptake of fiberboards. However, the fuzzy rules depend on the experts' knowledge and experience to a large extent, which limit the application of the fuzzy algorithm. Even though many studies have demonstrated that adaptive neuro-fuzzy inference system (ANFIS) is promising in the area of estimating (Gao *et al*. 2018), it may suffer from the problems of network architecture design, fuzzy rule selection, and the amount of training samples, which will affect the model performance (Yu *et al*. 2018b). The neural network is able to express complex nonlinear systems without using deduction rules (Huang and Lu 2016), which was used as a predictive method to determine internal bond strength and thickness swelling of fiberboard after an aging cycle in humid conditions (Esteban *et al*. 2010). Taking the production parameters as the optimization goals during the hot-press process, Tian *et al*. (2010) established a predictive model for the MDF property estimation after the hot-pressing using the methods of stepwise regression and neural network. The training of a neural network is time consuming and is likely to fall into local minima when the numbers of samples are limited (Hong *et al*. 2013).

Support vector machine (SVM) is a relatively new machine learning method based on the structural risk minimization principle rather than the empirical risk minimization principle that is implemented by most traditional neural network models. Based on the structural risk minimization principle, SVM achieves an optimum network structure and improves the generalization ability and nonlinear modeling properties (Xiao *et al*. 2014; Zhou *et al*. 2016), which is more prominent in small-sample learning (Niu *et al*. 2010; Yu *et al*. 2018a). SVM can be used for pattern recognition, anomaly detection, the classification of data and text, and system modeling and prediction (Jiao *et al*. 2016). The most important problem encountered in establishing an SVM model lies in optimizing of the parameters to improve the performances of prediction. Recently, the intelligence optimization algorithms were applied to select the SVM parameters, such as genetic algorithm (GA) and particle swarm optimization (PSO) (Yu *et al*. 2016). However, some drawbacks of GA have been identified regarding the convergence rate because of random crossover and mutation operation in previous studies (Ab Wahab *et al*. 2015). PSO is a promising algorithm that can be applied to optimize the parameters of SVM. However, its drawback is that it is easy to fall into local optimum in the case of limited training samples. Thus, the PSO algorithm needs to be improved to optimize the parameters of SVM better. The hybrid IPSO-SVM combination has attracted attention and gained extensive application, *e.g*., sales growth rate forecasting (Wang *et al*. 2014), photosynthesis prediction (Li *et al*. 2017), and magnetorheological elastomer- (MRE) based isolator forecasting (Yu *et al*. 2015). Although IPSO-SVM has been employed in many fields because of the advantages of its prediction performance, especially in small-sample learning, it is unique to use IPSO-SVM for modeling the fiber refining process in fiberboard production. However, the previous models only predicted the evaluation indexes based on the inputs, *i.e*., production parameters in one direction, which could not predict the production parameters from evaluation indexes on the opposite direction.

Due to the drawbacks of previously described reports, the proposed IPSO-SVM hybrid model that is able to bi-directionally forecast a productive process for fiber refining process was proposed based on the data collected from a real fiberboard production line. The overall chart of bi-directional prediction model of wood fiber production is shown in Fig. 1. This model consists of forward prediction and backward prediction. The forward prediction is the process of the prediction for evaluation indexes from production parameters. It means that the corresponding fiber quality and energy consumption fluctuates with the variations of production parameters. Conversely, the backward prediction is the process of the prediction for production parameters from evaluation indexes, which can be considered as the production scheme design for new types of wood fibers. Thus, it could forecast the production parameters and the evaluation indexes with the proposed model in two directions.

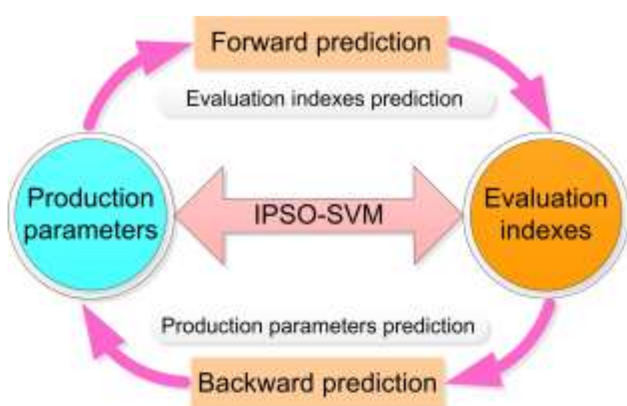

Fig. 1. Bidirectional prediction model of wood fiber production

The outline of this paper is described as follows: The first section describes the research background and motivation of this paper; the second section introduces the materials and methods of experiments and the process of establishing the bi-directional prediction model of wood fiber production; the third section verifies the performance of the proposed model with the experimental data and compares the results with other homogeneous methods. Then, applications of the bi-direction model were investigated. Finally, the research conclusions are presented.

EXPERIMENTAL

Materials

Fiberboard production (Fig. 2) consists of the following sequence of steps: material preparation, chip refining, fiber drying and sizing, mat forming and prepressing, hot pressing, and fiberboard finishing (Li *et al*. 2007). Among these steps, the chip refining process is especially important. Figure 2 shows the main technological process of refining. The experiment was conducted at a local MDF plant with a 50-ICP refiner manufactured by Andritz Group (Graz, Austria) with two 50SC020 disks. The raw material from the hopper was fed by feeding screw to the pre-heater, where hot steam was used to heat the chips and thus soften the lignin. In this way, the energy consumption during defiberation was reduced sharply. The steaming time was determined by accumulated chip height in the pre-heater. The material from the pre-heater was transferred by conveyer screw to the center of the stationary refiner disc after the steam-softening, and hence into the refining zone. Under the combined action of the tensile force, compression force, shear force, torsion force, friction force and impact force from refining disks applied to the wood material, it was eventually separated into fibers. The fibers were unloaded through the discharge pipe at the bottom of the refiner under the steam pressure. By adjusting the opening ratio of the valve installed on the discharging pipe, it was possible to control the amount of unloaded fibers.

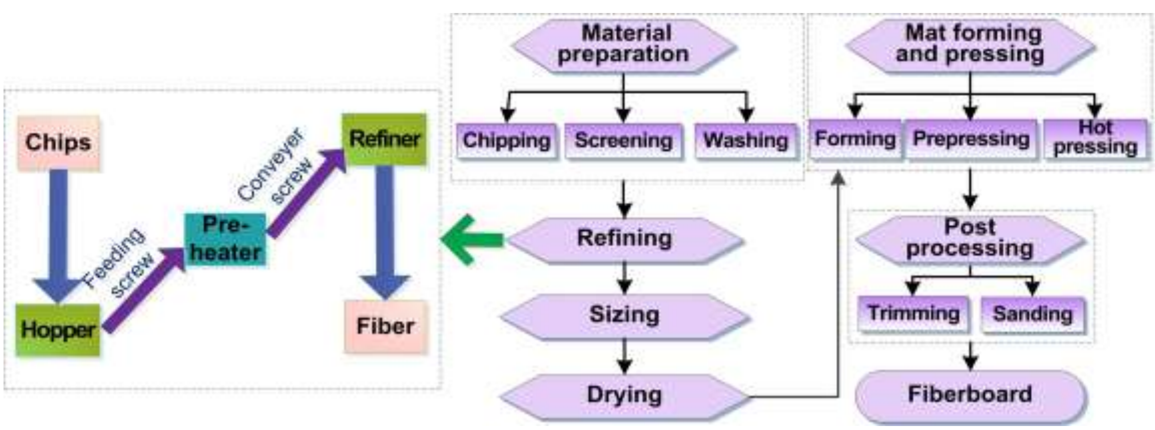

Fig. 2. Principal steps in fiberboard production

In this trial, the raw material for fiberboard production was wood chips with the sizes of 2 to 10 mm in thickness and 20 to 100 mm in length and width. These wood chips were a mixture of Chinese poplar (*P. lasiocarpa* Oliv.) and Chinese larch (*Larix potaninii*). The moisture content of the wood chips was increased with the washing and steaming and was reduced with being squeezed by screws, and the final moisture content of the chips became constant at 50% before refining. The steam pressure of wood chips at the refiner's entrance remained nearly constant, but the pressure changed slightly with the adjustment of the opening ratio of the discharge valve. The variation range of the steam pressure changed from 0.847 MPa to 0.877 MPa. The average pressure was 0.865 MPa, and the corresponding saturated steam temperature was 173.709 °C. The gap between the two refining disks was pre-set to 0.1 mm.

Fiber quality is normally assessed by screening values in practical production (Wei *et al*. 2013), as the length of the fiber is very important to the mechanical strength of the wood products (Garcia-Gonzalo *et al*. 2016). Fibers with moderate ratios of length/width in shape are vital for the quality of MDF. Based on mill practices, fibers of sizes from 20 to 120-screen mesh were considered as qualified fibers. Fibers smaller than 120 mesh were too small, and they consumed excessive energy.

The energy consumption was denoted with specific energy consumption (SEC, power consumption for per ton dry fibers); the fiber quality was denoted with percentage of qualified fibers (PQF) in total amount of fibers, calculated as follows:

$$\text{PQF (\%)} = \text{mass of qualified fiber (g)} / 10\ \text{g} \times 100 \quad (1)$$

For each measurement, 10 g fibers were collected off the production line every 2 h and screened into qualified fibers with a fiber classifier. Data including content of Chinese poplar (CP), accumulated chip height (CH), conveyer screw revolution speed (SR), opening ratio of the discharge valve (OV), and the changes in SEC were monitored and recorded every 2 h by sensors installed on the production line.

A bi-directional prediction model was established with the experimental data. For the model, the inputs were CP, CH, SR, and OV, and the outputs were PQF and SEC in the forward prediction. These sets of parameters were switched for the backward prediction.

Methods

The SVM model

Proposed by Vapnik (1999), SVM is a promising new classification and regression algorithm. Due to both powerful intelligent leaning capability and solid statistical theoretical foundation (Cao *et al*. 2017; Tang *et al*. 2017), the SVM possesses excellent prediction performance for the indeterminate and nonlinear relationship between the refining parameters and evaluation indexes. Based on the structural risk minimization principle, SVM achieves an optimum network structure. The structure of SVM is shown in Fig. 3.

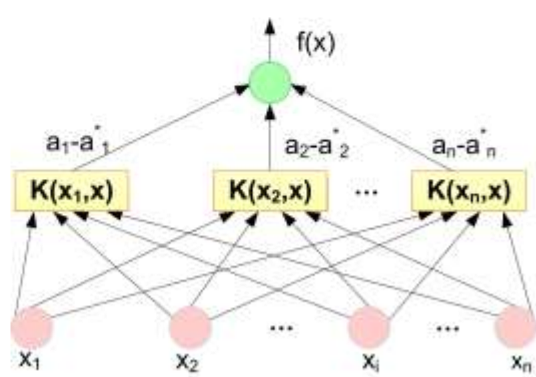

Fig. 3. The structure of support vector machine

The SVM is exhibited as a three-layered network structure (Chu *et al*. 2017), where x_i is the input data, $f(x_i)$ is the output data, and $K(x_i, x_j)$ is kernel function. The radial basis function (RBF) was chosen as the kernel function due to its good properties of nonlinear forecast limited number of parameters (Keerthi and Lin 2003). The performance of SVM depends on two important parameters, *i.e.*, the penalty factor "*C*" and the width of the RBF kernel "σ". In this study, IPSO was used to optimize both parameters of the SVM model.

Overview of particle swarm optimization and its improvement methods

The PSO algorithm is an evolutionary computation algorithm that is inspired by the behavior of birds flocking (Kennedy and Eberhart 1995). PSO obtains the optimal solution of space through iterative optimization in the D-dimension search space. The particles' speed (V) and location (X) are calculated and updated by tracking two target values (individual extremum and global optimal solution) according to Eq. 2 and Eq. 3,

$$V_{id}^{k+1} = \omega \times V_{id}^{k} + c_1 \times r_1 \times (P_{id}^{k} - X_{id}^{k}) + c_2 \times r_2 \times (P_{gd}^{k} - X_{gd}^{k}) \tag{2}$$

$$X_{id}^{k+1} = X_{id}^{k} + V_{id}^{k+1} \tag{3}$$

where ω denotes the inertia weight that determines the impact of previous velocity, k denotes the current generation, V_{id}^{k} and X_{id}^{k} denote the velocity and position of the i-th particle on dimension d (d = 1, 2, …, D), respectively, P_{id}^{k} and P_{gd}^{k} denote its best individual position and global position on dimension d, c_1 and c_2 are personal and social learning factors, and r_1 and r_2 are two random numbers distributed uniformly in the range [0,1].

Although PSO has been applied to many practical problems, it still suffers from premature convergence and poor quality of solution in the case of small amount of training samples. To overcome the shortcomings, the algorithm can adaptively modify the parameters of ω, c_1, and c_2 that have important influence on the optimization effects of PSO algorithm according to the number of iterations as follows,

$$\begin{cases} \omega = \omega_{\max} - (\omega_{\max} - \omega_{\min}) (\frac{k}{T_{\max}})^2 \\ c_1 = c_{1\max} - (c_{1\max} - c_{1\min}) (k / T_{\max}) \\ c_2 = c_{2\min} + (c_{1\max} - c_{1\min}) (k / T_{\max}) \end{cases} \tag{4}$$

where $T_{\max}$ is the maximum generation, $\omega_{\min}$ and $\omega_{\max}$ respectively represent the minimum and maximum inertia weights, and $c_{1\min}$, $c_{2\min}$, $c_{1\max}$, and $c_{2\max}$ represent the minimum and maximum learning factors, *i.e.*, $\omega \in [\omega_{\min}, \omega_{\max}]$, $c_1 \in [c_{1\min}, c_{1\max}]$, and $c_2 \in [c_{2\min}, c_{2\max}]$.

SVM based on the IPSO

The IPSO can automatically determine the parameters of SVM and control the predictive accuracy and generalization ability simultaneously. The overall framework of the proposed IPSO-SVM forecasting model is shown in Fig. 4 and the details of optimizing the parameters of the SVM model based on IPSO are described as follows:

Step 1: Initializing parameters

Initialized IPSO parameters including the particle population, the maximum generation, the rage of ω, c_1, and c_2 and the space of the particles [$X_i(1)$, $X_i(2)$], which represents the parameters [C, σ] of the SVM model. Besides, to alleviate the adverse effect of over-fitting phenomenon, the parameter k for k-fold cross-validation technique needs to be determined in IPSO algorithm.

Step 2: Initializing the particle swarm.

Set gen = 0, randomly initialize the location X and flight velocity V of particle swarm for each individual particle i, and calculate the initial fitness with the beginning location and velocity. Copy the fitness and position vector of each particle to itself memory fitness and memory position vector, respectively.

Step 3: The iterative optimization

The velocity and location of each individual particle were updated according to Eq. 2 to 4. The individual optimal value and the global optimal value were updated based on the fitness of new particle and store the X_{id} and X_{gd} at the current iteration. Set gen = gen + 1.

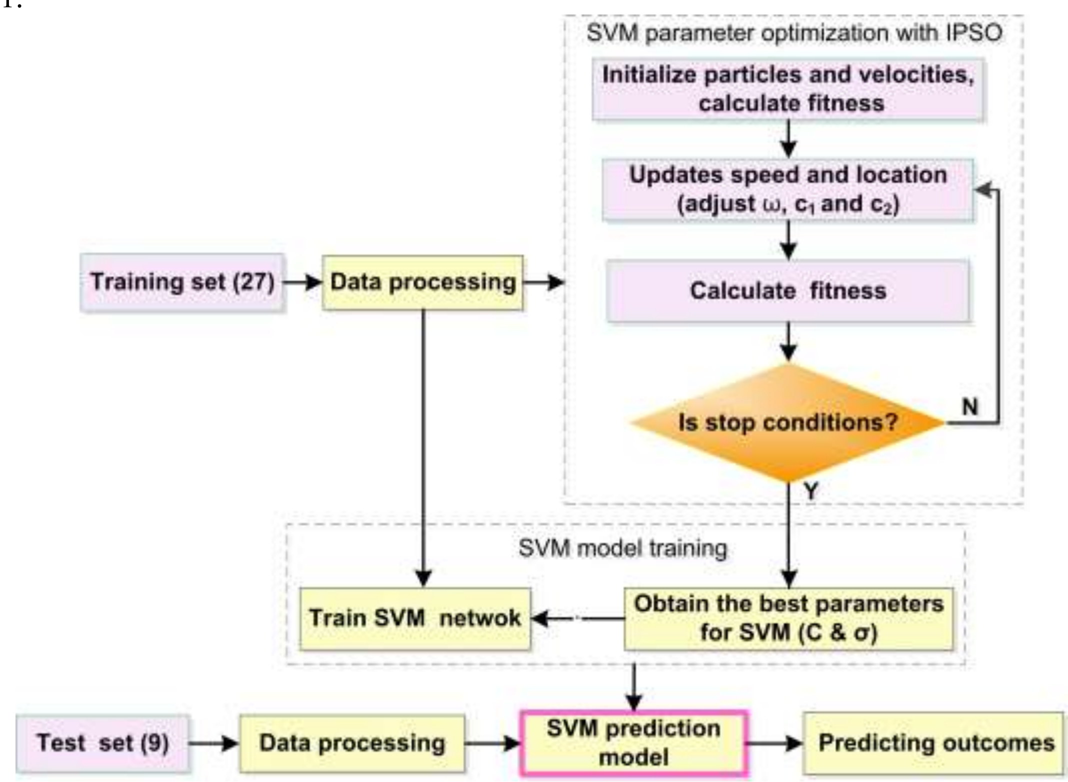

Fig. 4. Diagram of the proposed IPSO-SVM forecasting model

Step 4: Circulation stops

If the stop condition, *i.e.*, the maximum number of iterations or preset accuracy is reached, is met, then the location of the global optimal particle (the best C and the best σ) is obtained and inputted into the SVM model for training; otherwise, go back to Step 3.

The preprocessing of sample data

After eliminating singular data to reduce the possibility of overfitting, 36 groups of data were used as sample, in which 27 groups of data were selected as training set to establish the models, while the remaining 9 groups of data were chosen as test set to assess the prediction capability and robustness of the model. In order to ensure the training stability of the models and avoid the negative influence caused by discrepancy of quantitative dimension, the preprocessing of sample data should be implemented firstly. The data is normalized according to the following formulas.

$$X = \{x_M\} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}, \quad i = 1, 2, 3, \cdots, n \tag{5}$$

In Eq. 5, x_M is the normalized data; x_i is the original data from the experiment; n is the number of each variable; x_{max} and x_{min} denote the maximum and the minimum raw input and output values, respectively. The original data are normalized to the range of 0 to 1.

In order to examine the performance of the new prediction models, the proposed IPSO-SVM model was compared to the back propagation neural networks (BPNN), radial basis function neural networks (RBFNN), SVM and PSO-SVM, respectively, with the test set. After several independent trials, two neuron numbers in the hidden layer of BPNN were set as 10 and 12, and the expansion speed of RBF in RBFNN was set as 35. The necessary initialization parameters of the other methods are presented in Table 1.

Table 1. Values of the Parameters Involved in the Algorithms

Parameters	IPSO-SVM	PSO-SVM	SVM
Searching rage of C	(0.1,100)	(0.1,100)	(-8,8)
Searching rage of σ	(0.01,1000)	(0.01,1000)	(-8,8)
Maximum generation	200	200	——
Particle population	20	20	——
Learning factor c_1 and c_2	——	1.5, 1.7	——
c_{1max} and c_{1min}	2.5, 0.5	——	——
c_{2max} and c_{2min}	2.5, 0.5	——	——
Internal weight ω	——	1	——
ω_{max} and ω_{min}	1.2, 0.8	——	——
k	5	5	5

Additionally, assessment indicators were the mean absolute error (MAE), root mean square error (RMSE), mean relative error (MRE), and Theil's inequality coefficient (TIC). They are defined according to the following formulas,

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{6}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{7}$$

$$\text{MRE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{8}$$

$$\text{TIC} = \frac{\sqrt{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}}{\sqrt{\sum_{i=1}^{n}(y_i)^2} + \sqrt{\sum_{i=1}^{n}(\hat{y}_i)^2}} \tag{9}$$

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

RESULTS AND DISCUSSION

Forward Prediction

In forward prediction, the parameters of fiber production were set as inputs, while corresponding evaluation indexes as outputs. The best parameters for SVM were gained through optimizing them based on the IPSO algorithm, and then the forward prediction model was established based on SVM with 18 support vectors. Figure 5 shows the comparison curves between actual and predicted values of training sample set. The predicted values had a high level of agreement with the actual data. The relative error of the IPSO-SVM model based on training set for forward prediction is shown in Fig. 6. For PQF and SEC, the maximum relative errors were 5.86% and 3.36%, and the MRE were 1.37% and 1.04%, respectively. Thus, the proposed IPSO-SVM model has high accuracy and good performance.

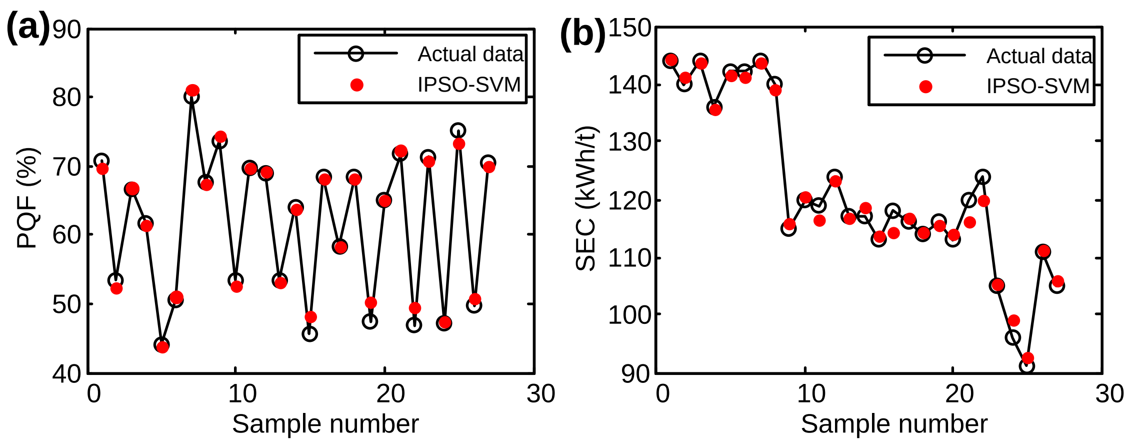

Fig. 5. Training results of the IPSO-SVM model for forward prediction: (a) PQF, and (b) SEC

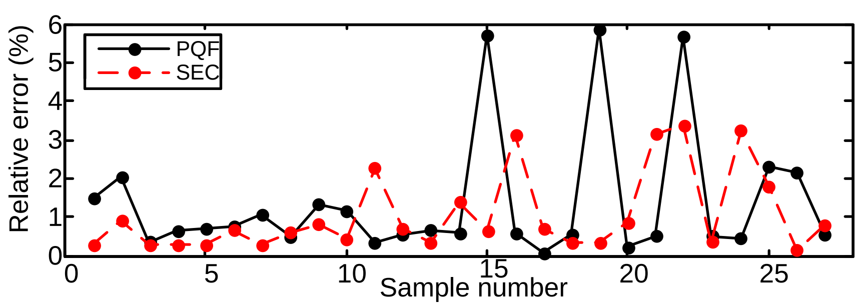

Fig. 6. The relative error of the IPSO-SVM model based on training set for forward prediction

To further elaborate the superiority of the proposed model in terms of the forward prediction, based on the test set, the performances of several methods, including IPSO-SVM model, SVM, PSO-SVM, and other commonly used soft computing techniques, such as BPNN, RBFNN, were compared.

Figure 7 gives the test errors of these methods. For PQF, the maximum errors of BPNN, RBFNN, SVM, PSO-SVM, and IPSO-SVM were 10.43%, -7.80%, 6.40%, 2.68%, and -2.21%, respectively; while for SEC of those were 15.49 kWh/t, 18.20 kWh/t, 9.91 kWh/t, 6.46 kWh/t, and 5.53 kWh/t, respectively. Obviously, the proposed IPSO-SVM had the minimum absolute errors.

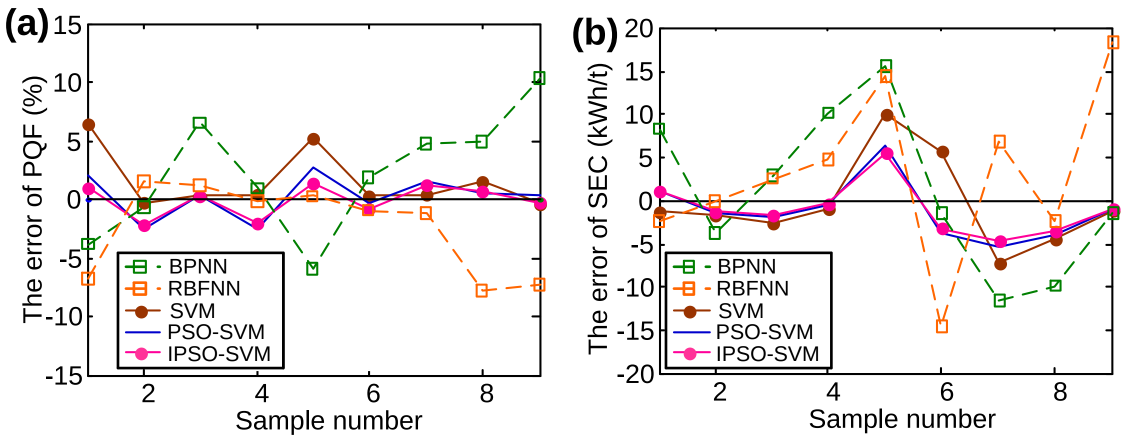

Fig. 7. Test errors of the models based on BPNN, RBFNN, SVM, PSO-SVM and IPSO-SVM: (a) PQF, and (b) SEC

The detailed errors are listed in Table 2. Compared with the BPNN, RBFNN, SVM and PSO-SVM methods, MAE of IPSO-SVM decreased by 68.97%, 65.14%, 35.51%, and 16.31%, respectively. Similarly, RMSE decreased by 68.94%, 68.97%, 44.14%, and 17.71%, MRE decreased by 71.98%, 65.84%, 36.66%, and 17.95%, and TIC decreased by 70.64%, 69.25%, 46.52% and 19.61%, respectively. IPSO-SVM had better predictive performance than the other methods for the forward prediction of fiber production.

Table 2. Comparison of Errors among the Models based on BPNN, RBFNN, SVM, PSO-SVM and IPSO-SVM Methods

Algorithms	Evaluation Indexes	MAE	RMSE	MRE(%)	TIC
BPNN	QF	4.4382	5.3153	8.7326	0.0487
	SEC	7.2461	8.6219	6.2155	0.0350
	Mean	5.8421	6.9686	7.4740	0.0419
RBFNN	QF	3.0387	4.3033	5.8150	0.0411
	SEC	7.3619	9.6444	6.4443	0.0388
	Mean	5.2003	6.9739	6.1297	0.0400
SVM	QF	1.6777	2.8006	3.2002	0.0258
	SEC	3.9442	4.9479	3.4117	0.0202
	Mean	2.8110	3.8742	3.3060	0.0230
PSO-SVM	QF	1.4236	1.7270	2.6072	0.0161
	SEC	2.9084	3.5330	2.4975	0.0145
	Mean	2.1660	2.6300	2.5523	0.0153
IPSO-SVM	QF	1.1196	1.2925	2.0366	0.0121
	SEC	2.5060	3.0362	2.1516	0.0124
	Mean	1.8128	2.1643	2.0941	0.0123

Backward Prediction

The backward prediction is the reverse process of the forward prediction. Thus, evaluation indexes were set as inputs and production parameters as outputs for the backward prediction. The best parameters for SVM were obtained by optimizing them based on the IPSO algorithm, and then the backward prediction model was established based on SVM with 22 support vectors. Figure 8 shows the comparison curves between actual and predicted values of training set. The predicted values of the training set matched the experimental data well in general. Figure 9 shows the relative errors of the IPSO-SVM model based on the training set for the backward prediction. For CP, CH, SR, and OV, the maximum relative errors were 1.79%, 3.70%, 10.12%, and 7.25%, and the MRE were 0.91%, 0.61%, 1.43%, and 2.13%, respectively. The new model established by the IPSO-SVM algorithm clearly had promising prediction ability.

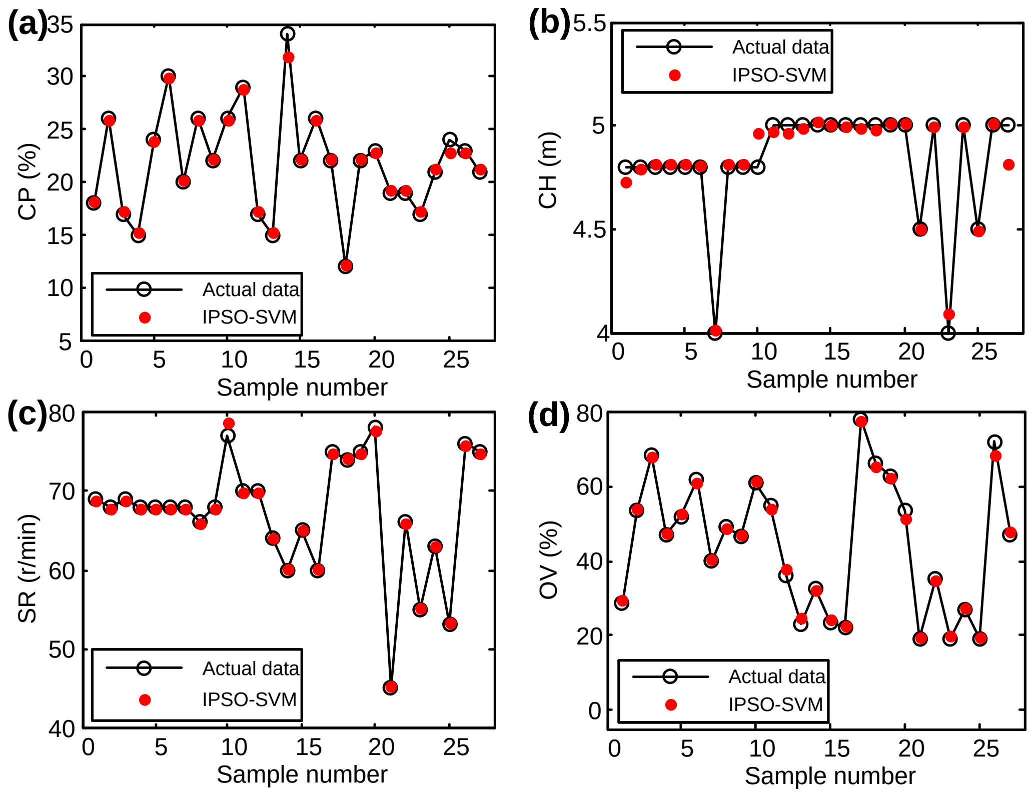

Fig. 8. Training results of the IPSO-SVM model for backward prediction: (a) CP, (b) CH, (c) SR, and (d) OV

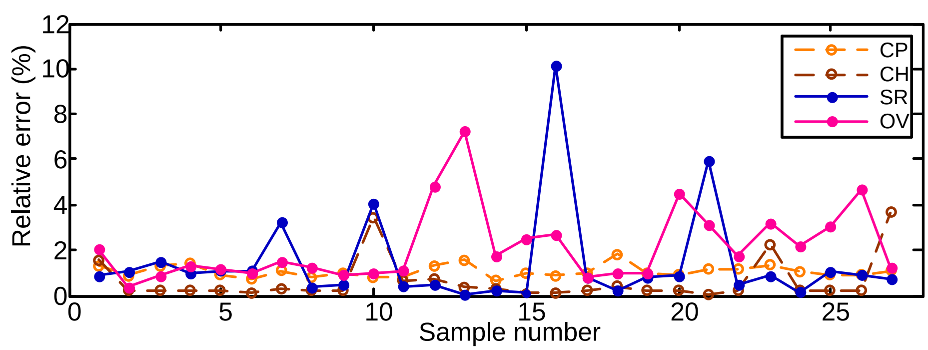

Fig. 9. The relative errors of the IPSO-SVM model based on training set for backward prediction

Errors for the IPSO-SVM were also compared to those of BPNN, RBFNN, SVM and PSO-SVM based on the test set, which is shown in Fig. 10. For CP, the maximum errors of BPNN, RBFNN, SVM, PSO-SVM and IPSO-SVM were 5.43%, -4.20%, -1.58%, 0.23%, and 0.23%; for CH, they were -0.35 m, -0.43 m, -0.20 m, -0.14 m, and -0.11 m; for SR, they were 22.83 r/min, 12.91 r/min, 6.57 r/min, 4.15 r/min, and 3.87 r/min; and for OV, they were -12.88%, -17.25% -12.97%, 5.83%, and 4.03 %, respectively.

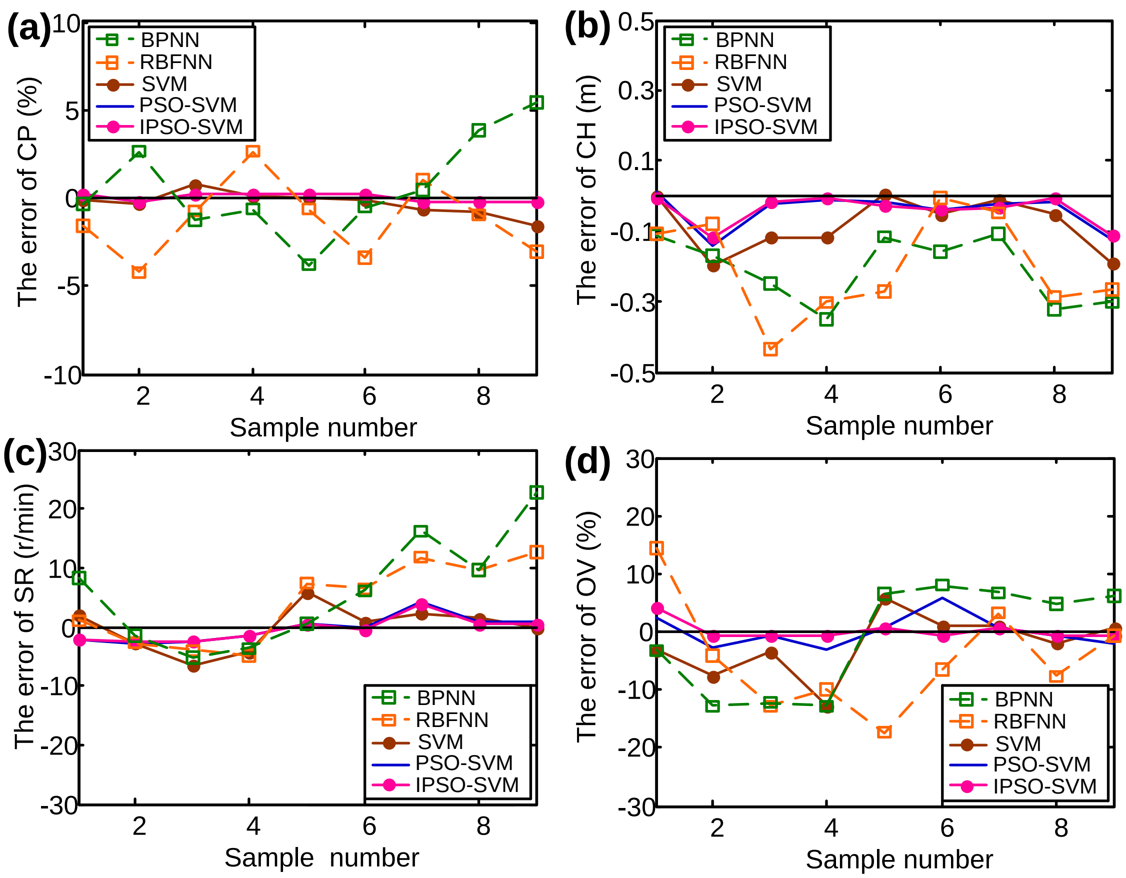

Fig. 10. Test errors of the models based on BPNN, RBFNN, SVM, PSO-SVM, and IPSO-SVM for backward prediction: (a) CP, (b) CH, (c) SR, and (d) OV

The detailed errors are listed in Table 3. Respectively compared with BPNN, RBFNN, SVM, and PSO-SVM methods, the values of MAE, RMSE, MRE, TIC of IPSO-SVM evidently decreased, with the descent rates of 84.98%, 84.06%, 63.61%, and 29.87% for MAE, 83.56%, 81.91%, 63.24% and 25.89% for RMSE, 85.53%, 85.29%, 60.10%, and 31.87% for MRE, and 83.06%, 82.26%, 62.77%, and 23.91% for TIC, respectively. The IPSO-SVM had better predictive performance than the other methods for the backward prediction of the fiber production.

Table 3. Comparison of Errors among the Models based on BPNN, RBFNN, SVM, PSO-SVM and IPSO-SVM

Algorithms	Production Parameters	MAE	RMSE	MRE	TIC
BPNN	CP	2.0870	2.7432	8.5811	0.0536
	CH	0.2090	0.2283	4.0751	0.0229
	SR	8.2028	10.6690	12.9148	0.0765
	OV	8.1003	8.8016	22.2896	0.0950
	Mean	4.6498	5.6105	11.9652	0.0620
RBFNN	CP	2.0471	2.3885	8.3013	0.0492
	CH	0.1998	0.2412	3.8863	0.0242
	SR	6.7466	7.7471	10.6173	0.0563
	OV	8.5364	10.0124	24.2771	0.1071
	Mean	4.3825	5.0973	11.7705	0.0592
SVM	CP	0.5133	0.7081	1.8835	0.0143
	CH	0.0831	0.1102	1.6205	0.0109
	SR	2.8597	3.5309	4.1892	0.0265
	OV	4.2223	5.6875	9.6597	0.0611
	Mean	1.9196	2.5091	4.3383	0.0282
PSO-SVM	CP	0.2197	0.2198	0.9498	0.0044
	CH	0.0519	0.0822	1.0176	0.0081
	SR	1.6387	2.0266	2.4662	0.0152
	OV	2.0743	2.6488	5.7295	0.0274
	Mean	0.9962	1.2443	2.5408	0.0138
IPSO-SVM	CP	0.2183	0.2184	0.9454	0.0044
	CH	0.0509	0.0819	0.9976	0.0081
	SR	1.5454	1.9303	2.3176	0.0145
	OV	0.9798	1.4583	2.6633	0.0150
	Mean	0.6986	0.9222	1.7310	0.0105

Application of the Bi-direction Prediction Model

As shown in Fig. 11, the flow diagram of the application of the bi-direction prediction model includes two parts, i.e., the backward prediction and forward prediction. The part of backward prediction consisted of several steps. Based on the backward prediction model, the production parameters were predicted with the inputs of the expected evaluation indexes, which were preset according to the requirement by the mill. The production parameters were applied into the practice to obtain the measured evaluation indexes, which were compared to the expected ones. For the part of forward prediction, based on the forward prediction model, the evaluation indexes were predicted with the inputs of the production parameters and were compared to the measured evaluation indexes.

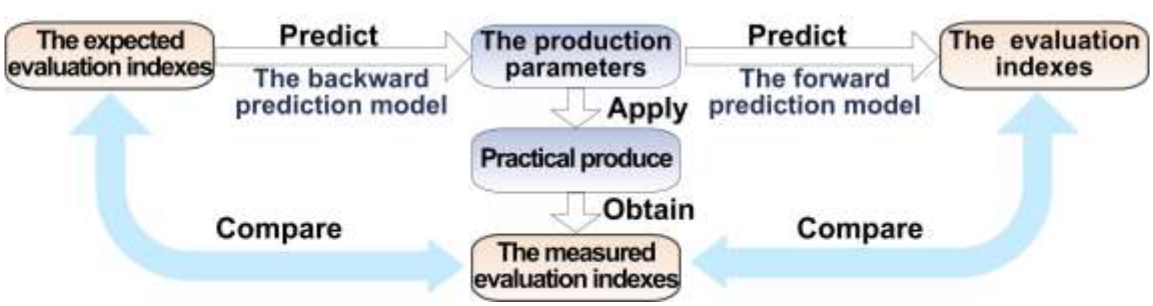

Fig. 11. The application of the bi-direction prediction model

The expected evaluation indexes and predicted production parameters based on the backward prediction model are shown in Table 4. The measured evaluation indexes including PQF and SEC were measured 10 times on the production line, and their averages were 76.63% and 112.92 kWh/t with standard deviations of 0.36% and 0.64 kWh/t, respectively. The expected evaluation indexes and measured ones were compared. The mean relative errors were 2.13% and 1.70%, and maximum errors 3.08% and 2 kWh/t, which indicated the backward prediction model could be considered as a design tool for the expected evaluation indexes.

Table 4. Evaluation Indexes Expected and Predicted Production Parameters Based on the Backward Prediction Model

The evaluation indexes expected		The predicted production parameters			
PQF (%)	SEC (kWh/t)	CP (%)	CH (m)	SR (r/min)	OV (%)
75	111	25.93	5.02	62.19	21.60

The production parameters and predicted evaluation indexes based on the forward model are shown in Table 5. The evaluation indexes based on forward prediction model were compared to the measured values. As a result, the mean relative errors were 2.73% and 1.05%, and the maximum errors were 3.54% and 1.27 kWh/t, respectively, which showed that the forward prediction model could predict the evaluation indexes accurately.

Table 5. Production Parameters and Predicted Evaluation Indexes Based on the Forward Prediction Model

The production parameters				The predicted evaluation indexes	
CP (%)	CH (m)	SR (r/min)	OV (%)	PQF (%)	SEC (kWh/t)
25.93	5.02	62.19	21.60	74.54	111.73

Based on the bi-direction model, when the PQF and SEC were preset as 75% and 111 kWh/t, the production parameters CP was 25.9%, CH was 5 m, SR was 62 r/min and OV was 21.6%, which can provide technical support for improving fiber quality, reducing energy consumption and optimizing MDF production parameters.

In this research, SVM optimized by proposed IPSO was applied to develop a bi-directional prediction model for the fiber production. There are several other swarm-based algorithms that can be used to optimize the SVM, such as fruit fly algorithm and cat swarm algorithm, which can perform well in parameter identification as well as convergence rate and will be investigated in our future work.

CONCLUSIONS

1. Due to the highly non-linear relationship between evaluation indexes (the percentage of qualified fibers, PQF, and the specific energy consumption, SEC) and the production parameters, *i.e.*, the content of Chinese poplar (CP), accumulated chip height (CH), conveyer screw revolution speed (SR), and opening ratio of the discharge valve (OV), the bi-directional predictions are very complicated. The improved particle swarm optimization and support vector machine (IPSO-SVM) were

applied to develop a bi-directional prediction model, which included forward prediction and backward prediction. The forward prediction can be used as a model for predicting evaluation indexes, where parameters of fiber production were utilized as inputs and corresponding evaluation indexes as outputs. The backward prediction can be used as a model for estimating production parameters, where evaluation indexes of fiber production were employed as inputs and the corresponding production parameters as outputs.

2. The training results of the IPSO-SVM model were validated by experimental data. In the forward prediction, the mean relative errors for PQF and SEC were 1.37% and 1.04%, respectively; in the backward prediction, the mean relative errors for CP, CH, SR, and OV were 0.91%, 0.61%, 1.43%, and 2.13%, respectively. The results demonstrated that the proposed IPSO-SVM model had high accuracy and excellent modeling performance. Additionally, the performance of the proposed IPSO-SVM model was compared with BPNN, RBFNN, SVM and PSO-SVM methods. The test results showed that the proposed IPSO-SVM method was superior to other four models in prediction accuracy and generalization ability.
3. Based on the effectiveness of the IPSO-SVM bi-direction prediction model and the preset evaluation indexes of 75% PQF and 111 kWh/t SEC, production parameters were designed as CP of 25.9%, CH of 5 m, SR of 62 r/min, and OV of 21.6%, which improved fiber quality, reduced energy consumption, and optimized production parameters.

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).

REFERENCES CITED

Ab Wahab, M. N., Nefti-Meziani, S., and Atyabi, A. (2015). "A comprehensive review of swarm optimization algorithms," *PLoS One* 10(5), e0122827. DOI: 10.1371/journal.pone.0122827

Aisyah, H. A., Paridah, M. T., Sahri, M. H., Astimar, A. A., and Anwar, U. M. K. (2012). "Influence of thermo mechanical pulping production parameters on properties of medium density fibreboard made from kenaf bast," *Applied Sciences* 12(6), 575-580. DOI: 10.3923/jas.2012.575.580

Cao, J., Liang, H., Lin, X., Tu, W. J., and Zhang, Y. Z. (2017). "Potential of near-infrared spectroscopy to detect defects on the surface of solid wood boards," *BioResources* 12(1), 19-28. DOI: 10.15376/biores.12.1.19-28

Chu, F., Dai, B. W., Dai, W., Jia, R. D., Ma, X. P., and Wang, F. L. (2017). "Rapid modeling method for performance prediction of centrifugal compressor based on model migration and SVM," *IEEE Access* 5, 21488-21496. DOI: 10.1109/Access.2017.2753378

Esteban, L. G., Fernandez, F. G., Palacios, P. D., and Rodrigo, B. G. (2010). "Use of artificial neural networks as a predictive method to determine moisture resistance of particle and fiber boards under cyclic testing conditions (Une-En 321)," *Wood and Fiber Science* 42(3), 335-345

Gao, Y. B., Hua, J., Cai, L. P., Chen, G. W., Jia, N., Zhu, L. K., and Wang, H. (2018). "Modeling and optimization of fiber quality and energy consumption during refining based on adaptive neuro-fuzzy inference system and subtractive clustering," *Bioresources* 13(1), 789-803. DOI: 10.15376/biores.13.1.789-803

Garcia-Gonzalo, E., Santos, A. J. A., Martinez-Torres, J., Pereira, H., Simoes, R., Garcia-Nieto, P. J., and Anjos, O. (2016). "Prediction of five softwood paper properties from its density using support vector machine regression techniques," *BioResources* 11(1), 1892-1904. DOI: 10.15376/biores.11.1.1892-1904

Hong, W. C., Dong, Y., Zhang, W. Y., Chen, L. Y., and Panigrahi, B. K. (2013). "Cyclic electric load forecasting by seasonal SVR with chaotic genetic algorithm," *International Journal of Electrical Power & Energy Systems* 44(1), 604-614. DOI: 10.1016/j.ijepes.2012.08.010

Hua, J., Chen, G. W., and Shi, S. Q. (2010). "Effect of incorporating Chinese poplar in wood chips on fiber refining," *Forest Products Journal* 60(4), 362-365. DOI: 10.13073/0015-7473-60.4.362

Hua, J., Chen, G. W., Xu, D. P, and Shi, S. Q. (2012). "Impact of thermomechanical refining conditions on fiber quality and energy consumption by mill trial," *Bioresources* 7(2), 1919-1930. DOI: 10.15376/biores.7.2.1919-1930. DOI: 10.15376/biores.7.2.1919-1930

Huang, H. X., and Lu, S. (2016). "Neural modeling of parison extrusion in extrusion blow molding," *Journal of Reinforced Plastics and Composites* 24(10), 1025-1034. DOI: 10.1177/0731684405048201

Jia, N., Liu, B., Hua, J., and Lin, X. L. (2015). "Effects of bark proportion on defibrator energy consumption and fiber quality," *Wood industry* 29(3), 35-38.

Jiao, G., Guo, T., and Ding, Y. (2016). "A new hybrid forecasting approach applied to hydrological data: A Case Study on Precipitation in Northwestern China," *Water* 8(12), 367. DOI: 10.3390/w8090367

Kartal, S. N., and Green, F. (2003). "Decay and termite resistance of medium density fiberboard (MDF) made from different wood species," *International Biodeterioration & Biodegradation* 51(1), 29-35. DOI: 10.1016/S0964-8305(02)00072-0.

Keerthi, S. S., and Lin, C. J. (2003). "Asymptotic behaviors of support vector machines with Gaussian kernel," *Neural Comput* 15(7), 1667-1689. DOI: 10.1162/089976603321891855

Kennedy, J., and Eberhart, R. (1995). "Particle swarm optimization," *Proc. of 1995 IEEE Int. Conf. Neural Networks* 4, 1942-1948.

Krug, D., and Kehr, E. (2001). "Influence of high pulping pressures on permanent swelling-tempered medium density fiberboard," *Holz Roh-Werkst* 59, 342–343. DOI: 10.1007/s001070100221

Li, J., and Pang, S. (2006). "Modelling of energy demand in an MDF plant," *Chemeca Knowledge & Innovation*, 1-6

Li, J. G., Pang, S. S., and Scharpf, E. W. (2007). "Modeling of thermal energy demand in MDF production," *Forest Products Journal* 57(9), 97-104

Li, K. Y., Fleischmann, C. M., and Spearpoint, M. J. (2013). "Determining thermal physical properties of pyrolyzing New Zealand medium density fibreboard (MDF),"

Chemical Engineering Science 95, 211-220. DOI: 10.1016/j.ces.2013.03.019.
Li, T., Ji, Y. H., Zhang, M., Sha, S., and Li, M. Z. (2017). "Universality of an improved photosynthesis prediction model based on PSO-SVM at all growth stages of tomato," *International Journal of Agricultural and Biological Engineering* 10(2), 63-73. DOI: 10.3965/j.ijabe.20171002.2580
Niu, D., Wang, Y., and Wu, D. D. (2010). "Power load forecasting using support vector machine and ant colony optimization," *Expert Systems with Applications* 37(3), 2531-2539. DOI: 10.1016/j.eswa.2009.08.019
Roffael, E., Dix, B., and Schneider, T. (2001). "Thermomechanical (TMP) and chemo-thermomechanical pulps (CTMP) for medium density fibreboards (MDF)," *Holzforschung* 55(2), 214-218. DOI: 10.1515/HF.2001.035
Runkler, T. A., Gerstorfer, E., Schlang, M., Junnemann, E., and Hollatz, J. (2003). "Modelling and optimisation of a refining process for fibre board production," *Control Engineering Practice* 11(11), 1229-1241. DOI: 10.1016/S0967-0661(02)00233-2
Tang, L., Wang, A. Y., Xu, Z. J., and Li, J. (2017). "Online-purchasing behavior forecasting with a firefly algorithm-based SVM model considering shopping cart use," *Eurasia Journal of Mathematics Science and Technology Education* 13(12), 7967-7983. DOI: 10.12973/ejmste/77906
Tian, Y. Q., Xu, K. H., and Liu, X. L. (2010). "Simulation modeling for hot pressing process of medium density fiberboard," *Journal of Northeast Forestry University* 38(12), 121-123.
Vapnik, V. N. (1999). "An overview of statistical learning theory," *IEEE Trans Neural Netw* 10(5), 988-999. DOI: 10.1109/72.788640
Wang, S., Winistorfer, P. M., Young, T. M., and Helton, C. (2001). "Step-closing pressing of medium density fiberboard, Part 1. Influences on the vertical density profile," *Holz als Roh- und Werkstoff* 59, 19-26. DOI: 10.1007/s001070050466
Wang, X., Wen, J., Alam, S., Gao, X., Jiang, Z., and Zeng, J. (2014). "Sales growth rate forecasting using improved PSO and SVM," *Mathematical Problems in Engineering* 2014, 1-13. DOI: 10.1155/2014/437898
Wei, P. X., Zhang, Y., Xu, D. W., Li, H. Y., and Zhou, D. G. (2013). "Effect of thermal grinding conditions on fiber quality of straw-wood terial," *Forestry Machinery & Woodworking Equipment* 41(2), 29-31
Xiao, C. C., Hao, K. R., and Ding, Y. S. (2014). "The bi-directional prediction of carbon fiber production using a combination of improved particle swarm optimization and support vector machine," *Materials (Basel)* 8(1), 117-136. DOI: 10.3390/ma8010117
Xing, C., Deng, J., and Zhang, S. Y. (2006). "Effect of thermo-mechanical refining on properties of MDF made from black spruce bark," *Wood Science and Technology* 41(4), 329-338. DOI: 10.1007/s00226-006-0108-3
Yu, Y., Li, W. G., Li, J. C., and Nguyen, T. N. (2018a). "A novel optimised self-learning method for compressive strength prediction of high performance concrete," *Construction and Building Materials* 184, 229-247. DOI: 10.1016/j.conbuildmat.2018.06.219
Yu, Y., Li, Y. C., and Li, J. C. (2015). "Forecasting hysteresis behaviours of magnetorheological elastomer base isolator utilizing a hybrid model based on support vector regression and improved particle swarm optimization," *Smart Materials and Structures* 24(3), 035025. DOI: 10.1088/0964-1726/24/3/035025

Yu, Y., Li, Y. C., Li, J. C., and Gu, X. Y. (2016). "Self-adaptive step fruit fly algorithm optimized support vector regression model for dynamic response prediction of magnetorheological elastomer base isolator," *Neurocomputing* 211, 41-52. DOI: 10.1016/j.neucom.2016.02.074

Yu, Y., Zhang, C. W., Gu, X. Y., and Cui, Y. F. (2018b). "Expansion prediction of alkali aggregate reactivity-affected concrete structures using a hybrid soft computing method," *Neural Computing and Applications*. DOI: 10.1007/s00521-018-3679-7

Zhou, Z., Yin, J. X., Zhou, S. Y., Zhou, H. K., and Zhang, Y. (2016). "Detection of knot defects on coniferous wood surface using near infrared spectroscopy and chemometrics," *BioResources* 11(4), 9533-9546. DOI: 10.15376/biores.11.4.9533-9546

Article submitted: May 10, 2019; Peer review completed: June 29, 2019; Revised version received: July 19, 2019; Accepted: July 22, 2019; Published: July 29, 2019.
DOI: 10.15376/biores.14.3.7229-7246