Modeling and Optimization of Fiber Quality and Energy Consumption during Refining Based on Adaptive Neuro-fuzzy Inference System and Subtractive Clustering

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Refining is a critical step in the manufacturing of medium-density fiberboard (MDF). To ensure fiber quality and control of the energy consumption during refining, proper production parameters, such as feeding screw revolution speed (SR), accumulated chip height (CH), opening ratio of the discharge valve (OV), and content of Chinese poplar (CP), are vital. These parameters were monitored and recorded in an MDF mill to investigate the relationships between the parameters and the fiber quality and energy consumption. In this study, fuzzy models of the fiber quality and the energy consumption during refining were established based on subtractive clustering and an adaptive neuro-fuzzy inference system (ANFIS). The fiber quality and energy consumption models demonstrated high prediction accuracy because their predictive mean relative errors were as low as 4.14% and 6.72%, respectively. The errors of fiber quality were optimized using the simulated annealing method, and the input parameters were obtained. Based on the energy consumption model, the minimum energy consumption was 41.51 kWh/t, on the premise of the minimum requirement of fiber quality. This study can be a guideline for MDF production management to improve fiberboard quality and reduce energy consumption.

Keywords: Fiber quality; Energy consumption; Refining; Fuzzy model; ANFIS; Subtractive clustering

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INTRODUCTION

With its dimensional stability, workability, flatness, smooth appearance, good bond strength, and screw-holding ability, medium-density fiberboard (MDF) has been widely accepted in the furniture and interior decoration markets (Hua *et al.* 2012). The crucial step of fiberboard production is refining, because it determines the major properties of fiberboards. An improper refining process results in poor fiber quality, which cannot be compensated for in the subsequent processing steps (Runkler *et al.* 2003). Additionally, the energy consumption of the fiber refining process makes up a high proportion of the total energy consumption during fiberboard production. Therefore, the fiber thermomechanical refining process is high on the priority list in terms of product quality and energy consumption in MDF production.

The fiber refining process is a nonlinear system that includes wood chip feeding, preheating, steaming, grinding, and discharging. Each subsystem has its own control parameters. These parameters directly affect the performance of the whole system. Fiber quality and energy consumption are affected by interrelation and coupling among the subsystems. Therefore, it is difficult to establish a precise mathematical model to linearly represent the relation between property indices and production parameters. The structure of the adaptive neuro-fuzzy inference system (ANFIS) is decided by subtractive clustering that can avoid regular expansion (Yue *et al.* 2006; Wu and Zhou 2007). With the advantages of relatively fast convergence, small error, fewer samples, and the ability to approximate nonlinear functions with arbitrary precision (Jang 1993), ANFIS and the subtractive clustering method (SCM) provide an effective way to solve the control problem of this type of complex nonlinear process. Additionally, ANFIS-SCM avoids the problems of low precision of the expert system control and the "bottleneck" of the acquisition of the knowledge. Model parameters are acquired by neural network learning at the same time, which solves the problem of traditional fuzzy control model parameters that are difficult to be determined (Fan *et al.* 2015).

Modeling and optimizing for fiber quality and energy consumption in the refining process have been investigated in prior research. Karlström and Eriksson (2014) established a micromodel describing the fluid mechanics of refining cellulose, as well as an extended thermodynamic model that described the balance between the raw material and energy in the whole refining process, to realize a more realistic dynamic viscosity of the actual estimated fibers. The results showed that the dynamic viscosity of fiber was related to the refining energy consumption at the macro and micro levels. Berg *et al.* (2008) established an analytical model used to estimate the strain energy density in the process of the wood chips being stretched or cut into fibers. The results showed that the energy consumption was determined by the microfibril angle of the wood secondary wall, loading direction, cell wall thickness, fiber separation mode, moisture content, and temperature, and that the energy consumption needed for earlywood fiber separation was lower than that of latewood fibers. Li *et al.* (2007) developed an energy model for MDF production. The thermal energy demand was estimated with the input of annual production, operation hours, product grade, and fiber drying method. The effects of thermo-mechanical refining conditions on the properties of MDF made from black spruce (*Picea mariana*) bark were evaluated by Xing *et al.* (2006), and the results indicated that the preheating retention time significantly affected both the modulus of rupture (MOR) and the modulus of elasticity (MOE). The steam pressure significantly influenced the internal bond strength (IB), MOR, and MOE. However, the previously described studies investigated the effect of production parameters solely on either fiber quality or energy consumption, and no study has been completed to optimize the fiber size/quality and the minimize energy consumption simultaneously.

The data-based modeling and model-based optimization are important topics in the control of industrial production today. The ANFIS and subtractive clustering method have been successfully applied in these fields, as they seem especially suited to model the complex nonlinear processes of real-world industries. The fuzzy clustering method was applied to data modeling, data compression, and process optimization by Runkler *et al.* (2001), and they were able to minimize cost function under the premise of meeting the qualified recycled paper production. The ANFIS and subtractive clustering method was developed to estimate normalized electromyography (NEMG) responses by Çakıt and Karwowski (2017). As demonstrated by the experimental results, ANFIS and the subtracted clustering method had better predictive accuracy than multiple linear regression. The models for rock porosity and rock water saturation were developed by Fattahi and Karimpouli (2016) with the support vector regression-particle swarm optimization (SVR-PSO) method and ANFIS-SCM, respectively, and the results indicated that the ANFIS-

SCM model had strong potential for indirect estimation of porosity and water saturation with a high degree of accuracy and robustness. Although ANFIS-SCM has been employed in many fields because of its advantages of nonlinear relationship expression, it is unique to use ANFIS-SCM for the modeling of the fiber quality and the energy consumption during the refining in fiberboard production.

In this study, high fiber quality and low energy consumption were chosen as the objectives. Fiber quality and energy consumption are usually represented by the amount of qualified fibers (QF) and the SEC (the energy consumption divided by total amount of dry fibers), respectively. The data from the actual production processes were used to establish the models for fiber quality and energy consumption based on ANFIS-SCM. With these models, fiber quality and energy consumption can be predicted online. The minimum requirement of fiber quality was selected as target quality. With the use of the simulated annealing method, which is an optimization algorithm method, the input parameters that meet the minimum requirement of fiber quality were optimized based on the fiber quality model. The minimum energy consumption was obtained based on the energy consumption model, on the premise of the minimum requirement of fiber quality, which could be of great importance to reduce energy consumption in the fiber refining process.

EXPERIMENTAL

Materials

The experiments were performed at a local MDF mill with an annual production of 150,000 m³ in Beijing, China. The experimental material was a wood species mixture of Chinese poplar (*Populus lasiocarpa* Oliv.) and Chinese larch (*Larix potaninii* Batalin). Chips of Chinese poplar were stored separately and then mixed with chips of other wood species, making it easy to ensure the content of Chinese poplar chips. The chips were defibrated in the 50-ICP Refiner manufactured by Andritz Group (Graz, Austria) with a rated power of 4000 kW, 54SB020 disks with a diameter of 1372 mm, and a revolution rate of 1500 r/min.

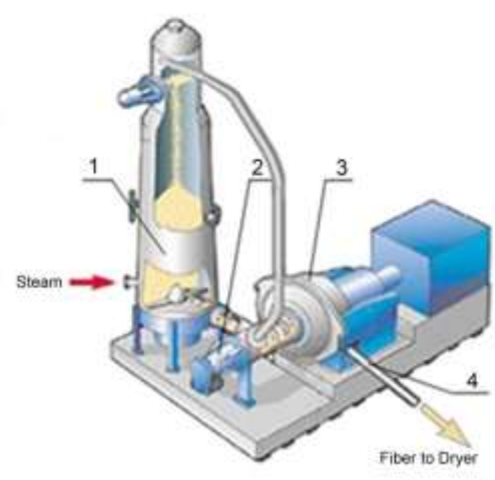

Fig. 1. Technological refining process: 1- Pre-heater; 2- Feeding screw; 3- Refiner; 4- Discharging pipe fiber to dryer

The refining process is shown in Fig. 1. The wood chips were preheated using steam in the pre-heater (1). Retention time was controlled by the height of the accumulated chips in the pre-heater. After steam-softening, they were discharged to the refiner (3) through a feeding screw (2). The refined fibers were discharged through the discharge pipe (4). The amount of unloaded fibers was adjusted by opening the valve installed on the discharging pipe.

The gap between the two disks in the refiner was pre-set to 0.1 mm. The steam pressure at the entrance of the refiner remained constant during the trial, but it may have varied slightly with the opening of valve (OV). The actual steaming pressures varied normally with a mean value of 0.869 MPa and a standard deviation of 0.003 MPa (with an average temperature of 173 °C and standard deviation of 24 °C) during the pre-heating process. The moisture content of the wood chips increased during the chip washing and steaming. However, without adding any dilution water, the final moisture content was 50%, as a result of the feeding screw squeezing the moisture from the chips in the feeding pipe. The moisture content was measured when replacing the disks (Hua *et al.* 2012).

Experimental data were acquired in the production spot for 21 days, mainly containing monitoring data of the total controlling refiner, and then were counted and analyzed. The production parameters, including screw revolution speed (SR), chip height (CH) in the steaming pot, opening ratio of the discharge valve (OV), content of Chinese poplar (CP), and the variation in specific energy consumption (SEC) in the refining process were monitored and recorded. All the data were recorded hourly and the reported values were the averages of 8 values (every 8-hour). Among the predictor variables, the average of CH ranged from 4 m to 5.7 m (with a standard deviation ranged from 0.08 m to 0.35m), the average of SR varied from 33 rpm to 76 rpm (with a standard deviation in the range of 0.65 rpm to 3.46 rpm), the average of OV fluctuated from 13.4% to 100% (with a standard deviation within the limits of 1.39% to 3.46%), and the average of CP changed from 12% to 63% (with a standard deviation ranged from 0.11% to 2.25%).

The fiber quality was evaluated by its size, which was graded by a vibrating type fiber classifier. Large fibers can result in poor board appearance, while smaller fibers can reduce the strength of the boards (Shi *et al.* 2006). Technically, separated fiber was required for structural integrity, *i.e.*, less broken material, a moderate ratio of length/width in shape, and a size between 20-mesh and 120-mesh (Chen 2012). Based on the mill's good manufacturing practices, it was recommended that the fiber with a size between a screen mesh of 20-mesh and 120-mesh be appropriated for MDF was considered to be qualified. Fibers larger than 20-mesh needed to be further defibrated, while those smaller than 120-mesh were screened out, because they would result in a strength reduction for MDF boards.

The percentage of qualified fiber can be determined in the following way:

1. Sampling: sampling the fiber in the slab-forming part of the fiberboard production line hourly.
2. Weighing and screening: weighing 10 g of fiber with a physical balance, screening the fiber into qualified fiber with a vibrating fiber screen mesh (20-mesh to 120-mesh), and then weighing the screened qualified fiber.
3. Calculating: The percentage of qualified fiber in total fiber = (The weight of qualified fiber (g)/10 g total fiber) × 100%.

The fiber quality and energy consumption were applied to assess the performance of the refiner. The inputs were SR, CH, OV, and CP, while the outputs were QF and SEC, respectively. Fuzzy models of the fiber quality and energy consumption were established.

Methods

The study included modeling and optimization. The modeling consisted of three main phases. In the first phase, experimental data were collected in a MDF mill, and then they were divided into training data and checking data. In the second phase, to reduce complexity and improve convergence rate, subtractive clustering was used to sort the input on the premise of meet the precision. In the third phase, two ANFIS models were developed to investigate the relationships between the parameters and the fiber quality and energy consumption. The main steps of modeling are illustrated in Fig. 2.

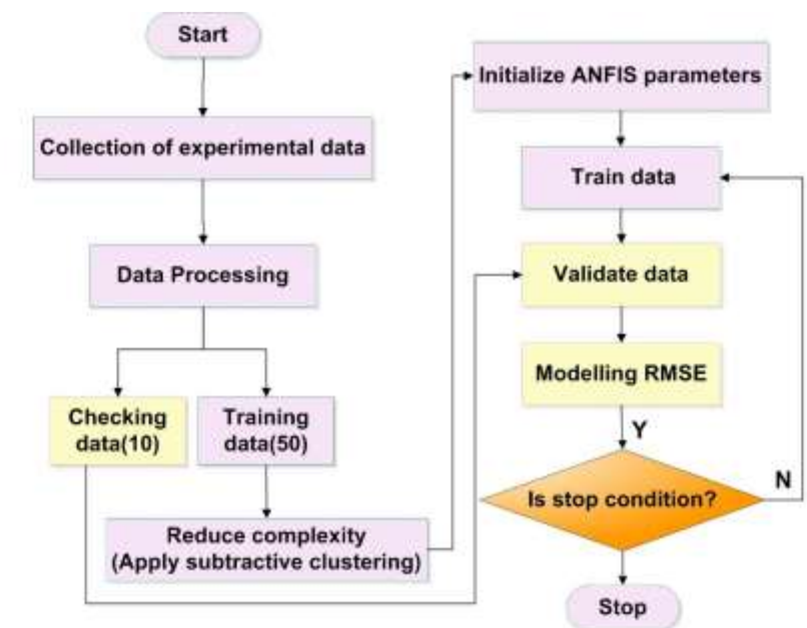

Fig. 2. The main steps of modeling

With respect to optimization, the target function was calculated based on the fiber quality model; the simulated annealing was used to optimize the procedure, and the input parameters were obtained. Based on the energy consumption model, the minimum energy consumption was found on the premise of the minimum fiber quality. The processes of optimization are shown in Fig. 3.

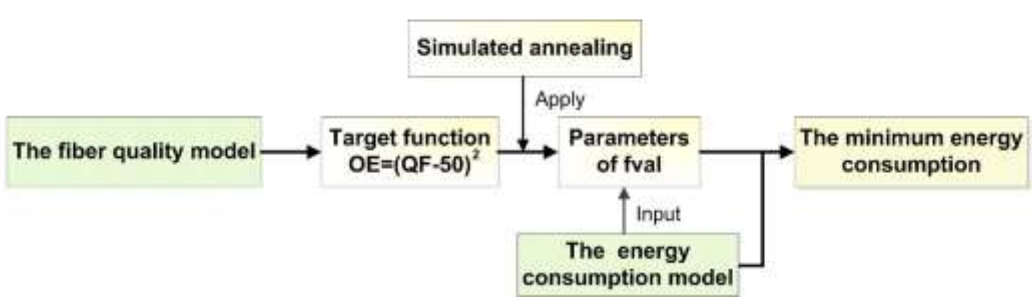

Fig. 3. The processes of optimization

Subtraction clustering

Chiu (1994) introduced the SCM, in which data points are considered as the candidates for a center of clusters. The algorithms are as follows:

At first, a collection of *n* data points $\{X_1, X_2, X_3, ..., X_n\}$ in an M-dimensional space is considered. Because each data point is a candidate for a cluster center, a density measure at data point X_i is defined as,

$$D_i = \sum_{j=1}^{n} \exp\left(-\frac{\left\| x_i - x_j \right\|^2}{(r_a/2)^2}\right) \tag{1}$$

where r_a is a positive constant. Therefore, a data point will have a high-density value if it has many neighboring data points. The radius r_a defines a neighborhood; data points outside this radius contribute only slightly to the density measure. After the density measure of each data point has been calculated, the data point with the highest density measure is selected as the first cluster center.

Let X_{c1} be the point selected and D_{c1} its density measure. Next, the density measure for each data point x_i is revised as follows,

$$Di = D_i - D_{c1} \exp\left(-\frac{\left\| x_i - x_{c1} \right\|^2}{(r_b/2)^2}\right) \tag{2}$$

where r_b is a positive constant. After the density calculation for each data point is revised, the next cluster center X_{c2} is selected, and all of the density calculations for data points are revised again. This process is repeated until a sufficient number of cluster centers are generated.

Adaptive neuro-fuzzy inference system

Jang (1993) introduced the ANFIS, which is a fuzzy inference system implemented in the framework of an adaptive neural network (Soualhi *et al.* 2013). Recently, ANFIS has been employed successfully in prediction problems, where the prediction is carried out *via* a fuzzy system while its parameters are optimized through an artificial neural network.

An ANFIS is a multilayer feed-forward network that uses neural network learning algorithms and fuzzy reasoning to map inputs into an output (Wang and Elhag 2008). Suppose that there is an ANFIS with two inputs, x_1 and x_2, and two outputs, y_1 and y_2, represented. Based on the first-order Sugeno fuzzy model, two typical rules set with two fuzzy rules can be expressed as follows:

Rule 1: if x_1 is A_1 and x_2 is B_1 then $y_1 = a_1x_1 + b_1x_2 + c_1$

Rule 2: if x_1 is A_2 and x_2 is B_2 then $y_2 = a_2x_1 + b_2x_2 + c_2$

Figure 4 shows the ANFIS structure in five layers (Jang 1993; Jang *et al*. 1996). Layer 1 is a fuzzification layer that outputs the membership function of the corresponding input fuzzy set. Layer 2 is a rule layer, and every node in this layer is a fuzzy rule, with the output node indicating the fitness value of each rule. Layer 3 is a normalization layer, and the normalization of the last layer output is performed. Layer 4 is a defuzzification layer, which determines the output of each fuzzy rule. Layer 5 is the output layer, calculating the output of all of the rules.

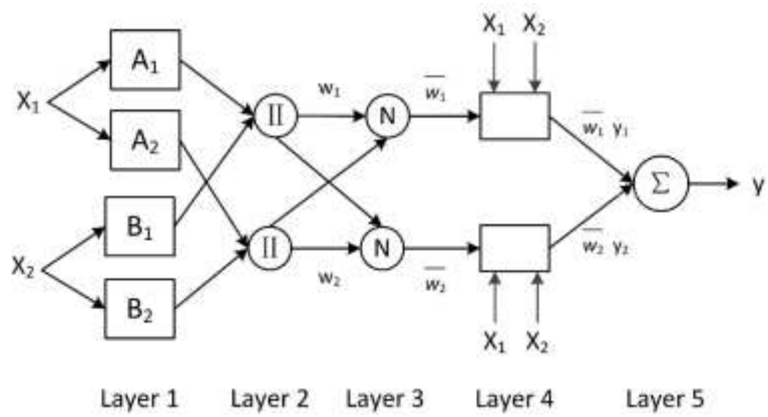

Fig. 4. The ANFIS structure of the model

Fuzzy models for the fiber quality and energy consumption

From the experiments, 246 groups of data were obtained, and 60 representative groups of data were selected as samples. The former 50 groups of training data were used to establish the models, while the latter 10 groups of data were chosen to validate the model. The model structures were obtained based on the experimental data and "ANFIS-SCM."

The inputs for the QF fuzzy model were SR, CH, OV, and CP, and the output was QF. To decrease the number of fuzzy rules, the SCM was applied to optimize them. A cluster radius of 0.5 was determined to sort the data. The initial step size was 0.1, the training error goal was 0, and the number of epochs was 100. The smallest value of the checking data error occurred at the 35th epoch. The ANFIS model structure generated from the subtraction clustering method is shown in Fig. 5. Each type of input parameter was divided into 6 fuzzy partitions, and the fuzzy system acquired 6 fuzzy rules based on the experimental data.

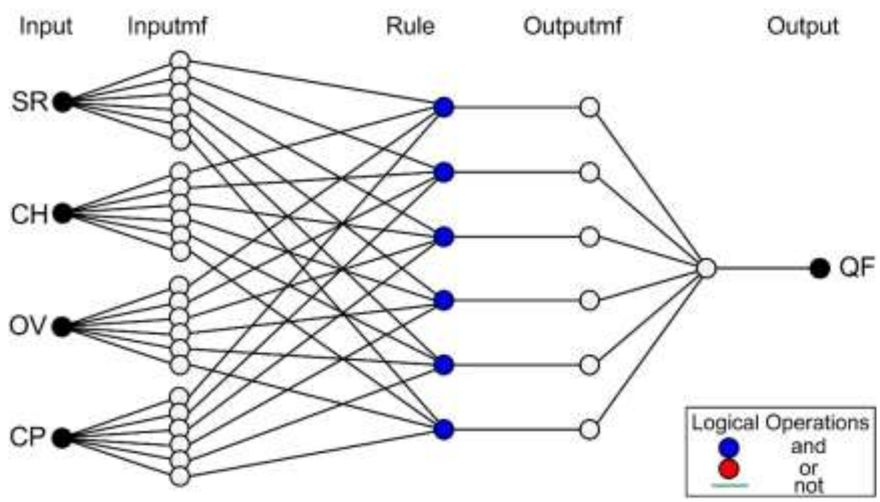

Fig. 5. QF ANFIS model structure generated by SCM

The inputs of the SEC model were the same as those used for the QF model. The output was SEC. A cluster radius of 0.5 was determined to sort the data. The initial step size was 0.15, the training error goal was 0, and the number of epochs was 100. The smallest value of the checking data error occurred at the 32nd epoch.

The SEC ANFIS model structure generated by the SCM is shown in Fig. 6. Each type of input parameter was divided into nine fuzzy partitions, and the fuzzy system acquired nine fuzzy rules based on the experimental data.

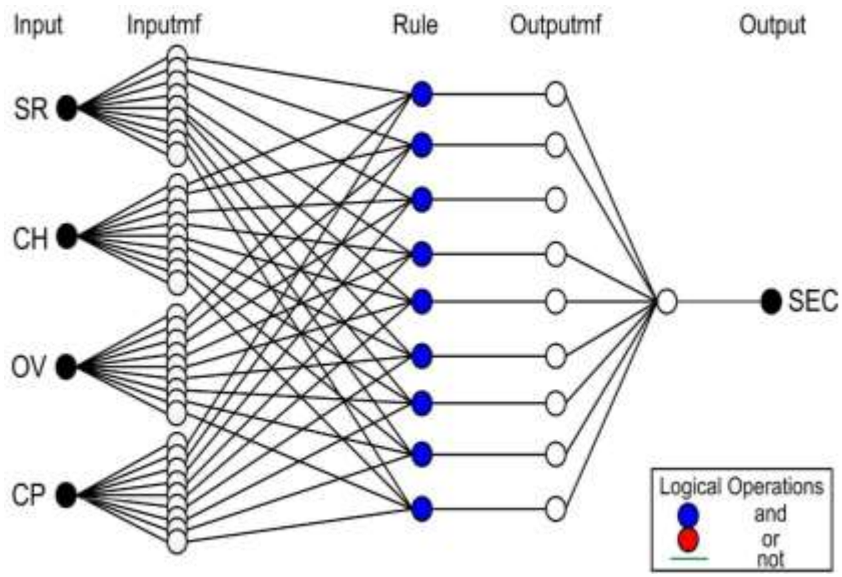

Fig. 6. SEC ANFIS model structure generated by SCM

Optimization of refining based on the models

Not all of the fibers were qualified in the practical production. When the qualified fiber content is more than 50% of the total fiber, the total fiber can be considered as qualified (Chen 2012). The production parameters can be optimized based on the energy consumption predicted by the model. Therefore, the minimum energy consumption was determined as the energy consumption meeting the minimum requirements of the fiber quality to decrease energy consumption in practical production.

To achieve the target quality, the quality errors (*QE*) were set as the target function. The quality errors can be defined as the square of the difference between the qualified fibers and the minimum requirements of the fiber quality (50%). The quality errors were determined as follows (Eq. 3),

$$QE = (QF - 50)^2 \tag{3}$$

where *QF* is the qualified fibers (%), and 50 is the minimum percentage of required qualified fiber.

To avoid local optimization termination, a large number of candidate solutions were tested, and the best solutions were obtained. Of a number of programs, the simulated annealing method had better performance in the global optimization. Thus, the simulated annealing method was used in this study. The minimum and maximum critical values supplied by experts were chosen as constraint conditions (Runkler *et al.* 2003).

RESULTS AND DISCUSSION

Conclusion Functions of the Models

The nonlinear ANFIS global model was synthesized from local models represented by lineal conclusion functions. The liner subsystems can approximate to a complex nonlinear system using a nonlinear mapping function of the fuzzy logic system to an arbitrary precision.

The conclusion function for the fiber quality fuzzy model can be linearly described by *OV*, *CH*, *SR*, and *CP* as following (Eq. 4),

$$QF = a_iOV + b_iCH + c_iSR + d_iCP + e_i \qquad (i = 1, 2, \ldots, 6) \qquad (4)$$

where *QF* is the qualified fibers (%), *OV* is the opening ratio of the valve in the discharge pipe (%), *CH* is the chip height in the pre-heater (m), *SR* is the feeding screw revolution speed in the chip feed pipe (rpm), *CP* is the content of Chinese poplar (%), and a_i, b_i, c_i, d_i, and e_i (i = 1,2,…, 6) were extracted model parameters for the conclusion functions of the fiber quality model (Table 1).

Table 1. Extracted Model Parameters for the Conclusion Functions of the Fiber Quality Model

i	1	2	3	4	5	6
a_i	-5.126	-0.319	-6.617	7.728	-15.960	-1.279
b_i	-46.780	-2.669	-64.120	-276.100	-637.600	-160.000
c_i	0.139	-1.292	1.176	-1.902	-20.630	7.892
d_i	-0.960	2.481	0.275	2.769	-9.039	3.354
e_i	591.60	52.98	784.30	1177.00	5173.00	631.00

The conclusion function for the energy consumption fuzzy model can be linearly described by *OV*, *CH*, *SR*, and *CP* as the following (Eq. 5),

$$SEC = A_iOV + B_iCH + C_iSR + D_iCP + E_i \qquad (i = 1, 2, \ldots, 9) \qquad (5)$$

where *SEC* is the specific energy consumption (kWh/t), *OV* is the opening ratio of the valve in the discharge pipe (%), *CH* is the chip height in the pre-heater (m), *SR* is the feeding screw revolution speed in the chip feed pipe (rpm), *CP* is the content of Chinese poplar (%), and A_i, B_i, C_i, D_i, E_i (i = 1, 2,…, 9) are extracted model parameters for the conclusion functions of the energy consumption model (Table 2).

Table 2. Extracted Model Parameters for the Conclusion Functions of the Energy Consumption Model

i	1	2	3	4	5	6	7	8	9
A_i	3.090	1.958	-2.577	10.170	-15.150	3.664	15.180	10.280	14.120
B_i	32.290	-170.500	38.290	144.500	247.700	-0.435	-113.700	-126.500	-141.100
C_i	-9.099	6.036	-0.246	3.960	1.807	-8.276	-12.610	3.235	-12.740
D_i	-1.937	-6.802	-1.397	-0.760	-4.742	-2.085	-0.734	2.592	9.601
E_i	29.58	726.70	151.60	-1071.00	-177.80	-0.09	340.80	151.10	85.84

Based on the models, accurate values of the fiber quality and energy consumption can be obtained online by controlling the inputs. The models were used as soft sensors that provided the operator with an online estimate of the fiber quality, which saved a lot of time required by experiments and labor costs.

Training Results

To assess the results of the fiber quality and energy consumption models, the performance of the multiple linear regression (MLR) with the ANFIS-SCM was compared. Assessment indicators were the relative error, mean absolute error (MAE), mean relative error (MRE), and root mean square error (RMSE), and they are defined according to the following formulas, respectively,

1. Relative error:

$$\delta = \frac{\left|y_i - \hat{y}_i\right|}{y_i} \times 100\% \tag{6}$$

2. Mean absolute error:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{7}$$

3. Mean relative error:

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

4. Root mean square error:

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

where y_i are the actual outputs and $\hat{y}_i$ are the FIS outputs.

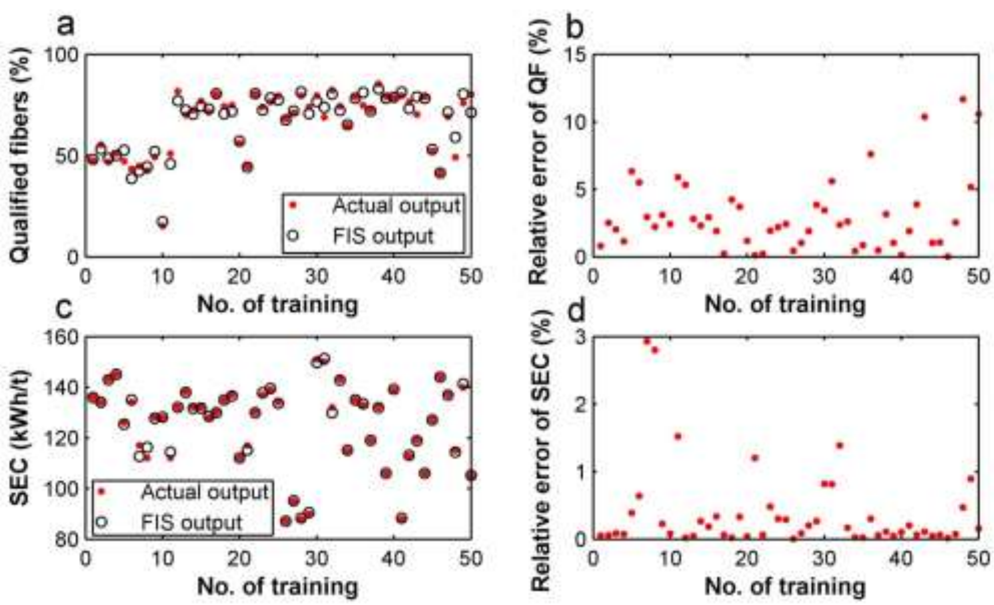

Fig. 7. Comparison of the actual outputs to the FIS outputs based on the training data: (a) qualified fibers, (b) relative error of QF, (c) SEC, and (d) relative error of SE

Based on the training data, the comparison of the actual outputs and the FIS outputs are shown in Fig. 7. The actual outputs are similar to the FIS outputs for both QF (Fig. 7a) and SEC (Fig. 7c). As described by Fig. 7b, the maximum relative error for fiber quality was 11.68%. The maximum relative error for SEC was 2.92% (Fig. 7d). It can be concluded that the built ANFIS-SCM models had good prediction effect.

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We compared the errors of ANFIS-SCM with that of MLR based on the training data, and the detailed results are listed in Table 3. In Table 3, we can see that, on the basis of MAE, the ANFIS-SCM achieved decreases of 67.05% and 95.66% compared to the MLR, respectively. Similar results can be obtained from the other errors such as MRE with decreases of 85.90% and 95.80% and RMSE with decreases of 75.57% and 93.25%. The ANFIS-SCM has better performance than MLR in prediction.

Table 3. Comparison of Errors between ANFIS-SCM and MLR based on the Training Data

Models	Algorithms	MAE	MRE (%)	RMSE
Fiber quality	ANFIS-SCM	2.5558	2.3800	2.8084
	MLR	7.7564	16.8762	11.4963
Energy consumption	ANFIS-SCM	0.5718	0.4800	1.0925
	MLR	13.1833	11.4212	16.1837

The results indicated that the fiber quality and energy consumption models through ANFIS-SCM during refining could satisfy the modeling accuracy because of their small predictive errors. Accurate values of the fiber quality and energy consumption can be obtained online by controlling the production parameters.

Validation of the Accuracy of the Models

To validate the accuracy of the fiber quality and energy consumption models, checking data was used at each epoch. The checking data also prevents over-fitting and verifies the ANFIS models (Nilashi *et al*. 2016).

The FIS outputs of the checking data were obtained based on the models. Based on the checking data, a comparison of the actual outputs and the FIS outputs is shown in Fig. 8. The actual outputs are similar to the FIS outputs for both qualified fibers (Fig. 8a) and SEC (Fig. 8c). As depicted in Fig. 8b, the maximum relative error for fiber quality was 8.57% (Fig. 8b). The maximum relative error for SEC was 12.90% (Fig. 6d). It can be known that the built ANFIS-SCM models have good generalization performance.

Errors were also compared for the ANFIS-SCM relative to MLR based on the checking data, and the detailed results are listed in Table 4. From Table 4, one can see that on the basis of MAE, the ANFIS-SCM achieved decreases of 34.93% and 31.83% compared to the MLR, respectively. Similar results can be obtained from the other errors such as MRE with a decrease of 69.56% and 34.79% and RMSE with a decrease of 70.99% and 75.12%. The ANFIS-SCM exhibited better performance than MLR in generalization.

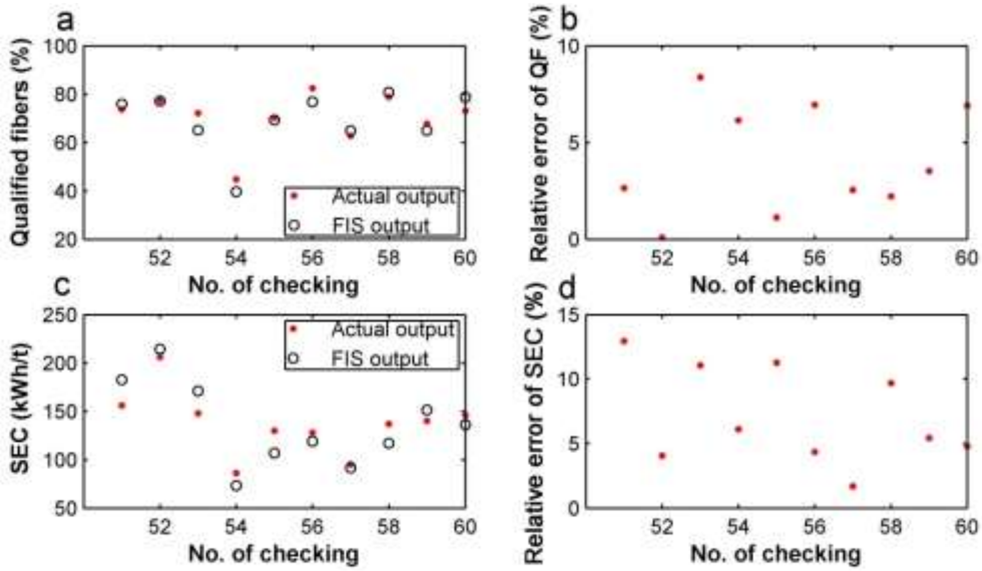

Fig. 8. Comparison of the actual outputs to the FIS outputs based on the checking data: (a) qualified fibers, (b) relative error of QF, (c) SEC, and (d) relative error of SEC

Table 4. Comparison of Errors among ANFIS-SCM and MLR based on the Checking Data

Models	Algorithms	MAE	MRE (%)	RMSE
Fiber quality	ANFIS-SCM	5.9123	4.1400	4.0052
	MLR	9.0866	13.6017	13.8083
Energy consumption	ANFIS-SCM	9.7060	6.7200	4.1568
	MLR	14.2389	10.3053	16.7093

The validation demonstrated that the predictive errors of the fiber quality and energy consumption fuzzy models based on ANFIS-SCM were small enough to precisely predict the practical production.

Minimum of Energy Consumption

The optimization results are shown in Table 5.

Table 5. Optimization Results of Quality Errors

i	1	2	3	4	5	6
Fval	0	0	0	0	0	0
SR (rpm)	62	40	74	53	74	72
CH (m)	4.6	5.0	5.7	5.4	4.6	4.6
OV (%)	40	26	97	49	37	13.5
CP (%)	17	23	21	18	26	42

On the premise of guaranteeing that the content of qualified fiber reached 50%, parameters were input into the fiber energy consumption fuzzy model as shown in Table 6.

Table 6. Energy Consumption for Qualified Fiber Reaching 50%

i	1	2	3	4	5	6
SR (rpm)	62	40	74	53	74	72
CH (m)	4.6	5.0	5.7	5.4	4.6	4.6
OV (%)	40	26	97	49	37	13.5
CP (%)	17	23	21	18	26	42
SEC (kWh/t)	129.16	84.67	126.04	41.51	182.83	186.67

Table 6 illustrates that, when SR was 53 r/min, CH was 5.4 m, OV was 49%, and CP was 18%, the minimum energy consumption was 41.51 kWh/t.

The modeling and optimization of fiber quality and energy consumption are beneficial to the improvement of fiber production efficiency, and revealed a promising trend on potential energy savings in MDF production.

CONCLUSIONS

1. The fiber quality and energy consumption fuzzy models were developed based on the ANFIS and subtraction clustering. The models can be used to predict fiber quality and energy consumption during the refining process.
2. The predictive mean relative errors of the fiber quality and energy consumption were 2.38% and 0.48%, respectively, using the training data, indicating that the models had a high predictive accuracy. The predictive mean relative errors of the fiber quality and energy consumption were 4.14% and 6.72%, respectively, using the checking data, also indicating that the models had a high accuracy and reliability.
3. The simulated annealing was used to optimize the refining process, and the input parameters were obtained on the premise of meeting the minimum requirement of fiber quality. Based on the fuzzy model for energy consumption, the minimum energy consumption was determined as 41.51 kWh/t, which can satisfy the requirements of fiber quality at the cost of the minimum energy consumption.

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