Research on improving the basis weight measurement accuracy of tissue paper based on PSO-BP neural network

LIANHUA HU, YUXIU FENG, AND JIN MA

ABSTRACT: The near-infrared (NIR) sensor can be used for measuring the basis weight and moisture of tissue paper, but the measurement accuracy is not ideal for this paper grade. The weight range of the tissue is 10~30 g/m², indicating that it is a low gram weight paper. The temperature and humidity of the production environment significantly impact an NIR sensor.

This paper focuses on improving the measurement accuracy of tissue paper basis weight. In order to reduce the influences of temperature and humidity, a mathematical model based on a particle swarm optimization back propagation (PSO-BP) neural network is proposed. In comparison with multiple linear regression measurement models, the basis weight measurement error with the PSO-BP model is within ± 0.5 g/m². This model can effectively improve the measurement accuracy and has a good effect on overcoming the basis weight nonlinear effect caused by the changes in ambient temperature and humidity.

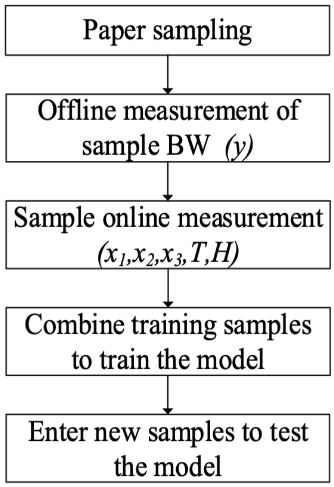
Application: The PSO-BP neural network model can eliminate the nonlinear effects of temperature and humidity on basis weight, which provides a new idea for online measurement of paper basis weight for mills in the future.

For tissue paper, basis weight (BW) is an important quality indicator [1]. Higher quality requirements are put forward for the accuracy of online detection [2]. As a green measurement technology, the near-infrared (NIR) sensor has a fast measurement speed, no radiation, no damage, and can analyze and measure multiple components at the same time [3]. Many studies have been focused on NIR for measurement of paper BW and moisture of paper [4-7]. When paper moisture absorbs NIR light, NIR light of different wavelengths will absorb in different components of the paper [8]. In the IR, 1.94 µm is the specific absorption wavelength for water, the signal at 1.83 µm is unaffected by water, the wavelength at 2.10 µm is absorbing fibers, and the wavelength at 2.29 µm is influenced by lignin and latex [9]. According to the above relationship and the reference technology, the paper basis weight can be obtained. However, the temperature and humidity in the environment will have a nonlinear effect on the basis weight of the paper [10,11]. Tissue paper is also more affected by these two factors because of its thinness.

At present, many fields use multi-sensor data fusion to increase information input to predict power generation, rainfall, wind, etc. [12-17]. In order to solve the influences of temperature and humidity on measurement accuracy, this paper uses a particle swarm optimization algorithm (PSO) [18,19] to optimize a back propagation (BP) neural network [20,21] model by combining an IR sensor and temperature and a humidity sensor to reduce measurement error. According to relevant data, the detection accuracy of high basis weight paper-type sensors both in China and overseas is only ±1 g/m² [22]. Multiple linear regression is a commonly used measurement model in engineering. Compared with the model in this paper, the results show that the measurement error of the PSO-BP model is within ±0.5 g/m², which confirms the validity of the model proposed in this paper.

EXPERIMENTAL

The experiment is divided into offline measurement and online measurement. The BW obtained by offline measurement of the sample is used as the output y of model training. The voltage, temperature, and humidity values are measured online when the sample is placed in the sensor. The NIR sensor is used to measure the voltage values of different wavelengths. According to the voltage values and Eq. 1 and Eq. 2 in the “Online data collection and processing” section below, the products x_1, x_2, and x_3 of the mass absorption coefficient and the BW are obtained. The measured temperature and humidity fusion x_1, x_2, and x_3 are used as the input of PSO-BP measurement model, and the actual BW of tissue paper is used as the output to train the neural network. Then, new sample inputs are selected, the paper BW is measured using the trained network, and errors are analyzed in combination with the actual measured values. **Fig. 1** shows the experimental flow.



1. Experimental flow chart.

Experimental equipment

The equipment for the experiments included:

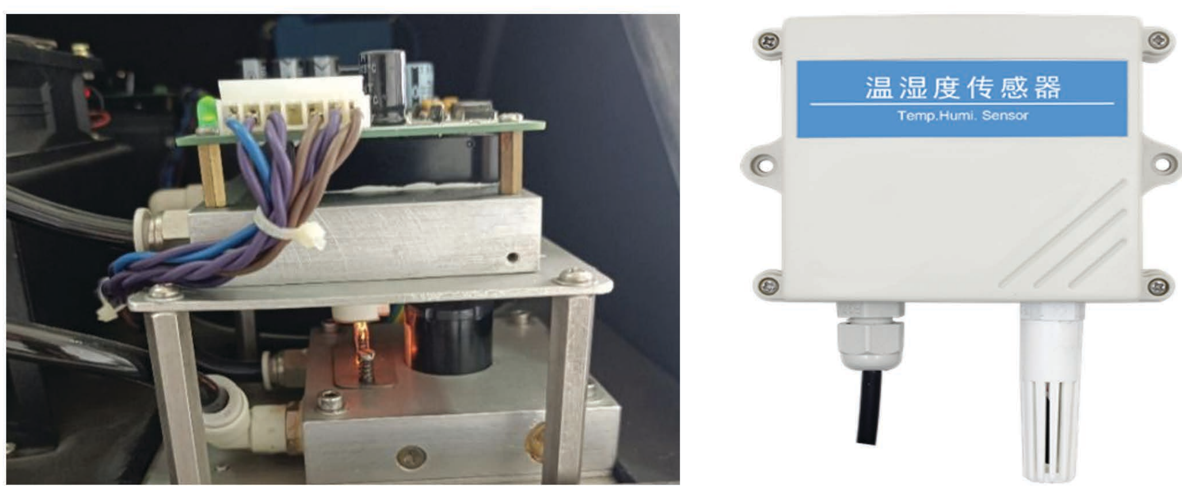
1. Paper and paperboard circular BW sampler (TST-A518-1, Dongguan Texter Testing Instrument Co., Ltd.; Guangdong, China).
2. Electronic balance (accuracy of 0.0001 g)
3. Paper sample container (polyvinyl chloride [PVC] plastic releasable bag is generally selected)
4. Oven
5. Dryer
6. The NIR sensor mainly consists of an IR light-transmitting part and a detector (**Fig. 2a**). The main IR light source of the transmitting part is a halogen bulb, and the output signal of the detector receiving part is the voltage signal of four wavelengths, which is the original data from the experiment.
7. The temperature and humidity sensor (Fig. 2b) has a stable signal and measurement accuracy of ± 3% relative humidity (RH) and ± 0.5°C, and can dynamically measure the temperature and humidity of the working environment online.

Offline measurement of experimental samples

As this research primarily studies the BW measurement of tissue paper, the BW of one layer of tissue paper is between 10~20 g/m², so the sample with the BW range of about 16 g/m² was primarily selected as the research object. In order to ensure the measurement accuracy, paper samples of 6 g/m², 10 g/m², 13 g/m², and 18 g/m² were selected for experiments. In the measurement process, the first step was sampling and sample treatment. Sampling and temperature and humidity treatment are carried out according to GBT 24328.5-2009 [23], a National Standard of the People's Republic of China for tissue paper and its products. In order to ensure the uniformity of sampling size, the sampling size of the sampler was 0.01 m² in the experiment [24], and the area deviation was within ±1%. After sampling, electronic balance with an accuracy of 0.0001 g was used to measure each sample, and the value was taken after the balance was stable. During the measurement, the balance was operated according to specifications and to prevent the airflow from affecting the balance. All experimental results were obtained in a laboratory environment with a constant temperature and humidity range. The temperature was 27°C~29°C, and the humidity was 69%~71%. Figure 3 shows samples of the different grams of tissue paper selected for study.

Online data collection and processing

The sample was measured online using an NIR sensor, and according to the characteristics of different wave-



a) b)

2. Experimental equipment: a) near-infrared sensor and b) temperature and humidity online sensor.

3. Paper samples.

lengths, it was converted into the input x through voltage calculation. When the paper moisture absorbs NIR light, other components in the paper also absorb NIR light to varying degrees. In order to avoid the influence of other components on the measurement results during moisture measurement, the NIR light measurement technology adopts the reference method. Reference technology uses different substances to have different absorption characteristics for NIR light. The 1.83 μm wavelength signal is not affected by moisture in the paper, and can be used as a reference signal for moisture measurement. The measurement of moisture in paper is based on the specific absorption properties of water in the 1.94 μm wavelength NIR light. At this wavelength, the radiation transmission is comparable to the 1.8 wavelength intensity for obtaining moisture content.

Tissue paper mainly includes components such as moisture, fibers, and chemical additives that have one or several characteristic absorption wavelengths in the NIR band. The fiber in the paper has better absorption characteristics at the wavelength of 2.10 μm, and the wavelength of 2.29 μm is mainly affected by the lignin and chemical additives in the paper. The wavelength signals at these two locations can be used to correct moisture measurement errors caused by changes in lignin or chemical additive content. The calibration algorithms all calculate the ratio of the signal at 1.83 μm to each of the other three signals, taking the natural logarithm of these three ratios, temperature, and humidity as inputs to the quantitative model for PSO-BP prediction.

According to the measured voltage signal, it can be concluded that:

$$\begin{aligned} T_R &= V_{183}/V_{183-0} \\ T_W &= V_{194}/V_{194-0} \\ T_F &= V_{210}/V_{210-0} \\ T_C &= V_{229}/V_{229-0} \end{aligned} \tag{1}$$

where T is the standard signal at different wavelengths of NIR light. Subscripts in T_R, T_w, T_F, and T_c represent reference, water, fiber, and chemicals. The V represents the voltage signal, the subscript of the voltage signal represents the wavelength, and the subscript "0" is the voltage in the case of no paper.

According to the Beer-Lambert absorption law:

$$\begin{aligned} x_1 &= \ln\left(T_R/T_W\right) \\ x_2 &= \ln\left(T_R/T_F\right) \\ x_3 &= \ln\left(T_R/T_C\right) \end{aligned} \tag{2}$$

where x_1, x_2, and x_3 are the products of mass absorption coefficient and BW.

Since the main components of tissue paper are fiber and moisture and they contain small amounts of chemical additives, lignin, and other components, the paper BW can be obtained as follows:

$$BW = ax_1 + bx_2 + cx_3 \tag{3}$$

In Eq. 3, a, b, and c are constants that can be obtained by calibration of measured values.

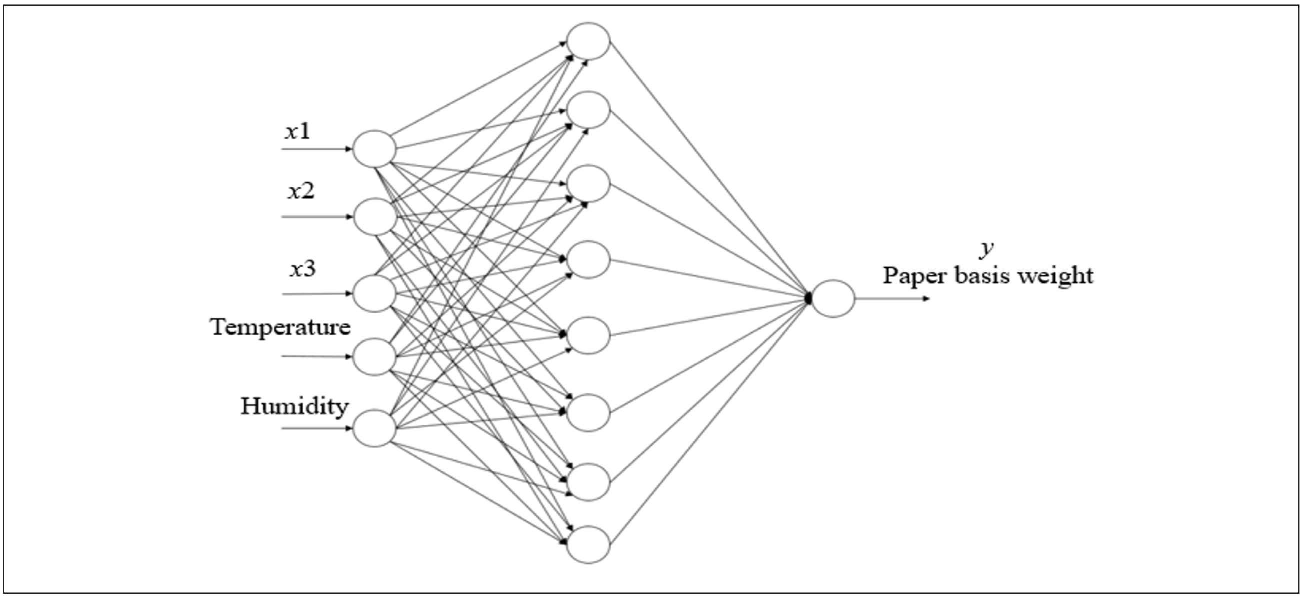
Equation 3 shows that the inputs x_1, x_2, and x_3 have a linear relationship with the paper BW. In practical application, multiple linear regression analysis is usually used in problem analysis with multiple independent variables. The three independent variables in the model are the parameter x. The dependent variable is the actual BW of paper.

Let the multiple linear regression be:

$$y = d_0 + d_1x_1 + d_2x_2 + d_3x_3 \tag{4}$$

In this model, y is BW, x is input, and d is the coefficient of the linear model. The coefficients of the transmission characteristics were determined by linear regression modeling analysis using the experimental data measured by NIR light. Solving the system of equations in MATLAB (MathWorks; Natick, MA, USA), the linear regression equation between input and output is:

$$y = 146.03x_1 - 168.65x_2 - 78.92x_3 + 27.5691 \tag{5}$$



4. Back propagation (BP) neural network structure.

Establishment of PSO-BP prediction model

The structure of the BP neural network includes the input layer, hidden layer, and output layer. The BP neural network is trained according to the method of error back propagation calculation. The principle is to correct the weights of each layer from back to front by collecting the errors generated each time. When the learning error and learning times of the network reach the specified target, the output value can be predicted through the input.

The three important parameters x_1, x_2, and x_3 are measured by the sensor, and the temperature and humidity in the air are used as inputs for the neural network, so the input layer sets five nodes. The actual weighing value of tissue paper is the output value y of the model, and the number of nodes in the output layer is 1. In the selection of the number of hidden layers, one hidden layer is selected to avoid overfitting and computer over operation. In general, the number of nodes in the hidden layer is positively correlated with the nonlinear degree of the network. The more the number of nodes, the higher the nonlinear degree. However, if the number of nodes is too large, the network operation will increase and the network operation efficiency will decrease. If the number of nodes is too small, it is difficult to judge the nonlinear relationship between the input value and the output value, which leads to a larger error. The number of nodes that selects the hidden layer in the neural network is generally less than twice the input. In practical problems, the selection of the number of hidden layer nodes first determines the approximate range and then uses the trial-and-error method to determine the optimal number of nodes. Therefore, the range of hidden layer nodes in this study was less than 10, and eight nodes were selected through comparison.

Figure 4 shows the BP network structure of the algorithm model. When establishing the measurement model, y is the actual BW value.

The basic idea of the BP network is to correct the network weights w_{ij} and T_{li} and the thresholds θ_i and θ_l, to minimize the mean square error.

The input of the hidden layer node is:

$$net_i = \sum_j w_{ij} x_j - \theta_i \tag{6}$$

where x_j denotes the input, w_{ij} denotes the network weight between the input layer and the hidden layer, and θ_i denotes the network threshold between the input layer and the hidden layer.

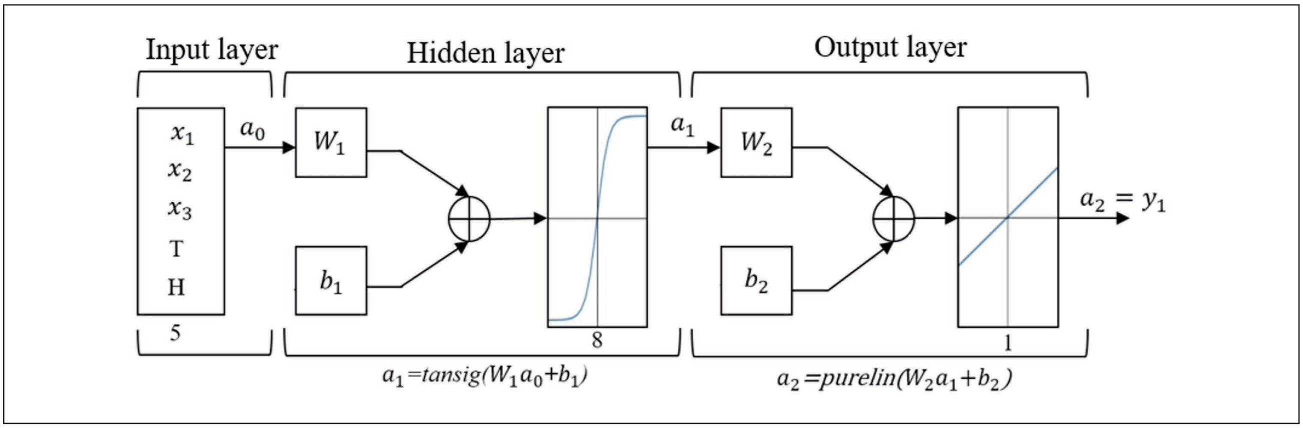
The input to the output layer node is:

$$net_l = \sum_i T_{li} x_i - \theta_l = a_1 \tag{7}$$

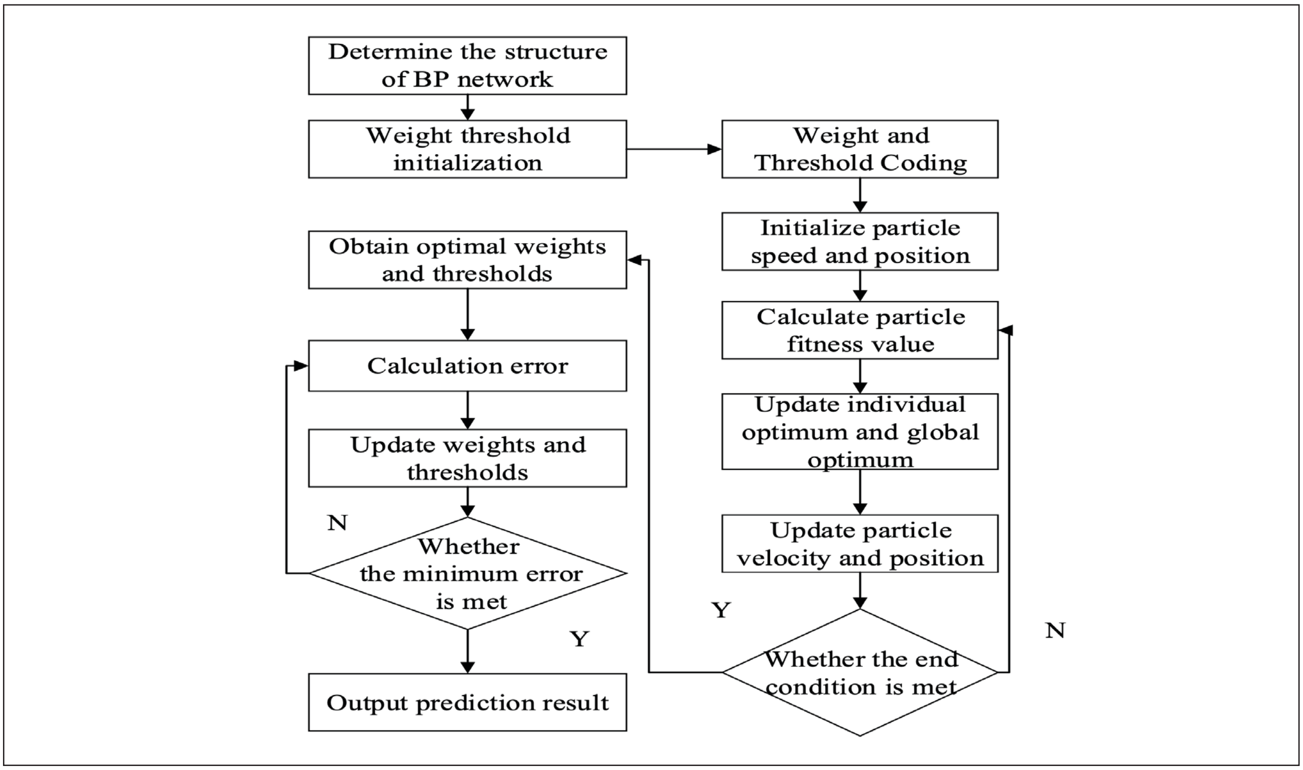
where x_i denotes the hidden layer node, T_{li} denotes the network weight between the hidden layer and the output layer, and θ_l denotes the network threshold between the hidden layer and the output layer.

The network structure of the final prediction model is shown in **Fig. 5**. It can be seen that the structure has five input nodes, eight hidden nodes, and one output node; a_0 is the input, a_1 is the hidden layer output, and a_2 is the output. The W and b denote the weight and bias between different layers, respectively. In this model, the tansig hyperbolic tangent sigmoid transfer function in MATLAB was selected for the hidden layer, and the purelin linear transfer function in MATLAB was selected for the output layer.

However, the initial weights and thresholds of the BP neural network model need to be selected. It is difficult to select the suitable parameters at one time, which can cause poor training results. Debugging training parameters many



5. Neural network model.

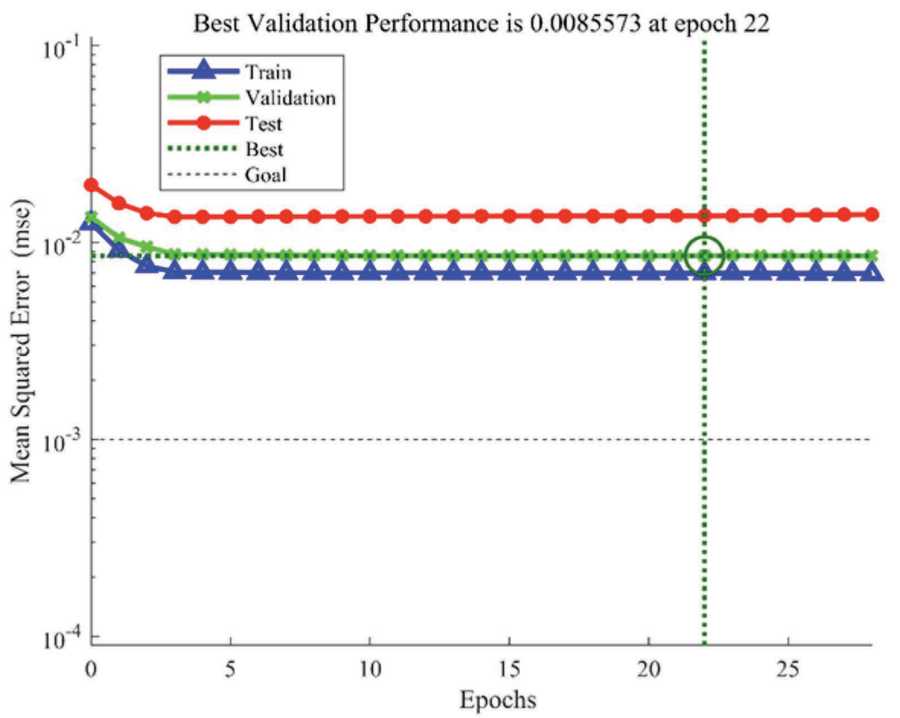


6. Flow chart of particle swarm optimization back propagation (PSO-BP) neural network.

times not only wastes time but also leads to overfitting of training. The PSO algorithm can automatically adjust and match the optimal parameters of the BP neural network through its strong global search ability and can rapidly improve the learning performance and global convergence speed of the network [25].

The essence of particle swarm optimization is a random search algorithm. The trajectory of each particle is mainly determined by the current position of the particle itself, the historical optimal position of the particle itself, and the historical optimal position of the particle swarm. Through these three factors, the particle can adjust the movement speed and position in real time, and can repeatedly iterate to find the optimal solution. The process of the PSO algorithm optimizing BP network is shown in **Fig. 6**.

The adjustment of several parameters in a PSO optimization algorithm has a great impact on the performance of the algorithm, including population size, inertia weight, acceleration coefficient, maximum speed of particles, etc. In the particle swarm optimization model, the particle swarm size is generally set between 20 and 50, and the difficulty gradually increases according to the specific problem. The model training based on different swarm sizes shows that when the swarm size is 20 and 50, the running effect is better than when the swarm size is 30 and 40. When the swarm size is 20, the running time is faster than when the swarm size is 50. Considering the running speed and running effect, the number of particle swarm size is



7. The PSO-BP training network paper basis weight measurement error.

selected as 20. The inertia weight controls the ability of global optimization and local optimization, and the value range is between 0.8 and 1.2. The acceleration constant is used to adjust the maximum step size of the search, and 1.5 is usually chosen to make the individual experience as important as the group experience and to avoid falling into a local optimum. The maximum speed range is tuned and between -0.5 and 0.5 to avoid getting stuck in local optima.

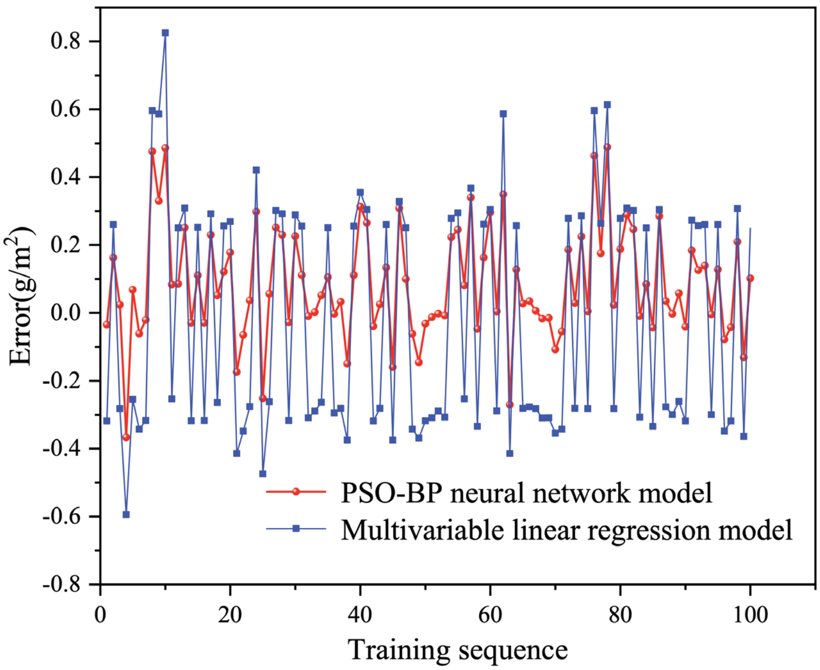
During the training process of the PSO-BP neural network in MATLAB, the PSO algorithm stops running when the desired goal is reached. Once the mean square error reaches the desired value, the BP network will stop learning to complete the model training.

RESULTS AND DISCUSSION

When selecting training samples, 1000 groups of raw data of 10 g/m², 13 g/m², 16 g/m², and 18 g/m² were selected for PSO-BP neural network training. The trained model can

Sequence	x_1	x_2	x_3	Temperature, °C	Humidity, %	Actual Basis Weight, g/m²
1	0.1171	0.0481	0.2983	18.2292	35.7083	15.92
2	0.1119	0.0261	0.2700	18.2986	35.6215	15.61
3	0.1121	0.0375	0.3177	18.2292	35.5637	15.91
4	0.1204	0.0612	0.2727	18.2292	35.5637	16.33
5	0.1199	0.0620	0.2766	18.2292	35.4190	15.55
6	0.1222	0.0536	0.3015	18.1944	35.4190	16.24
7	0.1124	0.0489	0.2681	18.1944	35.3322	15.86
8	0.1104	0.0299	0.3104	18.2986	35.1586	15.65
9	0.1189	0.0356	0.2970	18.2292	35.1586	15.53
10	0.1197	0.0369	0.3070	18.2986	35.0139	15.42

I. Data from training samples.



8. Error comparison of two model algorithms.

be applied in the BW range of 10~20 g/m². **Figure 7** shows the process from start of training to model convergence. Epoch is the number of times the neuron weights and thresholds are adjusted based on the output error return during computation. It can be seen that the model training speed is fast and reaches the best state after 22 iterations. The input and output of some training samples are shown in **Table I**.

One-hundred groups of sample data were selected as the PSO-BP neural network test data, and the prediction results of the model were compared with the results of the multiple linear regression model. **Figure 8** indicates that the PSO-BP neural network model can improve the measurement accuracy in the NIR light tissue quantitative measurement system. The BW fluctuation of the product BW measurement standard is ±1 g/m². The measurement deviation of PSO-BP is controlled within ±0.5 g/m². Compared with the measurement deviation of multivariate linearity of ±0.9 g/m², the measurement accuracy is significantly improved.

The 100 sets of test data show that the PSO-BP neural network model can improve the measurement accuracy of the NIR light tissue BW measurement system. Compared with the linear model, the PSO-BP neural network model takes into account the nonlinear effects of ambient temperature and humidity on the measurement results, so the measurement accuracy is higher and the error is lower.

Hence, in the NIR light paper BW measurement system, the intelligent BW measurement model based on adaptive PSO-BP neural network technology can effectively overcome the nonlinear drift in the measurement process and solve the nonlinear problem in the measurement system.

CONCLUSION

This research focused on the problem of measurement error caused by the interference of ambient temperature and humidity in the BW of tissue paper. The offline and online measurement of toilet paper produced by 10 different papermaking enterprises was carried out in the laboratory, and the BW measurement mathematical model was established according to the measurement results. Drawing on the idea of multi-sensor data fusion and adding the input of temperature and humidity, the paper BW measurement model based on the PSO optimized BP algorithm is proposed to further improve the accuracy of the measurement results. As a nonlinear model, the PSO-BP neural network model effectively solves the problem of BW measurement of tissue paper caused by the nonlinear drift of temperature and humidity changes in the air. At the same time, the acquisition speed and processing speed of the PLC control system of the paper mill meets the hardware requirements of the model. Therefore, combined with measurement accuracy and usability, the model represents a positive development trend for paper mills in the future. **TJ**

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About this journal

ABOUT THE AUTHORS

As an important indicator of paper quality, paper basis weight is easily affected by the nonlinear effects of temperature and humidity in the environment. A method is needed to overcome nonlinear effects to improve measurement accuracy.

There are currently no studies applying machine learning and smart algorithms to paper measurement. This study draws on the idea of multi-sensor data fusion and solves the nonlinear effect of temperature and humidity through a PSO-BP network to improve the measurement accuracy.

This is the first time that the intelligent algorithm has been applied to the basis weight measurement of paper. The establishment and debugging of the mathematical model were difficult. The offline weighing value and online measurement value were combined as a sample set, and the model was debugged based on experience.

Through this study, we discovered a new method to improve the measurement accuracy of infrared sensors. The proposed model effectively overcomes the nonlinear change of temperature and humidity, and it improves the accuracy of the infrared sensor.

The acquisition speed and processing speed of paper mill PLC control systems meets the hardware requirements of the model. The training speed and measurement accuracy of the model are suitable for online measurement in paper mills. The next step is to improve the applicability of the algorithm and make the model suitable for other types of paper in addition to tissue. The model was successfully tested in the laboratory paper machine scanner, and the next step is to realize online measurement in paper mills.

Hu

Feng

Ma

Hu is associate professor, Feng is a Master's student and Ma is a Master's student in the College of Mechanical and Electrical Engineering, Shaanxi University of Science and Technology, Xi'an, Shaanxi, China. Email Hu at hulianhua@sust.edu.cn

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