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Optimization of Technical Parameters for Making Plant Fiber Composite Pencil Board Based on PSO-BP

Bu Chiwu

College of Light Industry, Harbin University of Commerce, Harbin 150028, P. R. China
buchiwu@126.com

Abstract

Wood plastic composites (WPCs) were prepared and used as pencil board. The primary raw materials were corn straw fiber powder, high-density polyethylene, and polystyrene. The tensile strength, surface roughness, hardness, and roll cutting performance of the prepared composites were tested and compared with those of linden wood, which is typically used for pencil board. A back propagation (BP) neural network was adopted to build the prediction model of process technical parameters of the composite. An improved particle swarm (modified particle swarm optimizer, MPSO) was adopted to optimize the BP neural network, and the advantages of the PSO algorithm's global optimization ability and the BP neural network algorithm's high processing speed were realized. The results show that the composite had the best performance, with a mass ratio of 3.8 (corn straw fiber powder): 47.6 (high-density polyethylene): 28.6 (polystyrene). The composites can be used as a substitute for linden wood in the production of pencil board.

Keywords: *Corn straw fiber, Wood plastic composites, Pencil board, BP neural network, Improved particle swarm optimization*

1. Introduction

China produces about 10 billion pencils annually and must fell over 30,000 cubic meters of trees to do so. In recent years, the use of wood flour-, wood fiber-, and plant fiber-filled thermoplastic polymer materials, known as wood plastic composites (WPCs), have been increasingly used as substitutes for timber. The experiments in this study use plant fibers and thermoplastics as raw materials to prepare a plant fiber-composite pencil board to replace linden plate, which has economic and environmental significance [1].

Many factors affect the performance of wood-plastic composites, including coupling agents, process parameters, and interface compatibility. In recent years, much research around WPC has been carried out regarding topics including wood glue-interface modification and performance, the impact of different coupling agents on properties, and processing and mechanical properties [2-8]. To determine the relationship between the performance of WPCs and process parameters, more experiments are needed. Raw material mass proportion has an impact on the performance parameters of WPCs, including the elastic modulus, tensile strength, and roll cutting performance. There is a complex, nonlinear relationship between the mass ratio and the performance of WPCs. With the continuous development of computer technology, intelligent modeling technology is becoming important in various types of modeling. Artificial neural networks have adaptive, self-organizing and self-learning abilities. A group of mutually corresponding input and output data can be provided by analyzing the neural network in advance to obtain the potential between the two laws; then based on the obtained law and using new input data to calculate a result, the data prediction can be obtained.

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Back propagation (BP) neural networks have the capacity for self-learning and storage and distribution of non-linear information; they have been used in the modeling of complex systems [9-10]. Particle swarm optimization (PSO) is a swarm intelligence method based on evolutionary computing techniques used to search for a global collaboration by assessing the interactions between the individual optimal solutions. The concept is simple and easy to implement, both for scientific research and for engineering applications [11-12]. Considering the advantages and disadvantages of BP neural networks and particle swarm optimization, an algorithm model combining a modified particle swarm optimizer (MPSO) and the BP neural network was proposed. The MPSO-BP neural network hybrid algorithm is used here to build the process parameter prediction model of pencil composite board.

2. Pencil Composite Plate BP Neural Network Modeling and Algorithms

The composite materials used for pencil board include corn stalk fiber powder, high-density polyethylene (HDPE), and polystyrene (PS). Board material performance factors include pencil elastic modulus, tensile strength, surface hardness, roll cutting performance, and surface roughness. There are complex links between the mass ratio of each raw material and the composite performance factors. The adaptive, self-organizing, and self-learning abilities of artificial neural networks can analyze the links to obtain the corresponding law of the mass ratio of each raw material and the composite performance factors. Artificial neural networks have become an important modeling method.

2.1. BP Neural Network Model

The error back propagation algorithm based on the BP neural network is currently the most widely-used feed forward network. The BP network is built by the input layer, the hidden layer, and the output layer. The number of neurons in the input layer depends on factors affecting the performance of the pencil board composite. There are many factors that affect the performance of WPC, but this work mainly considered the raw material mass ratio. The mass ratio of corn stalk fiber powder, HDPE, and PS is set as the input unit of the BP neural network. The main performance measures, including elastic modulus, tensile strength, surface hardness, roll cutting performance, and surface roughness, are set as the output unit. The hidden neurons number in the hidden layer is set at six. Thereby, the BP neural network model is built with a 3-6-5 structure (Figure 1)

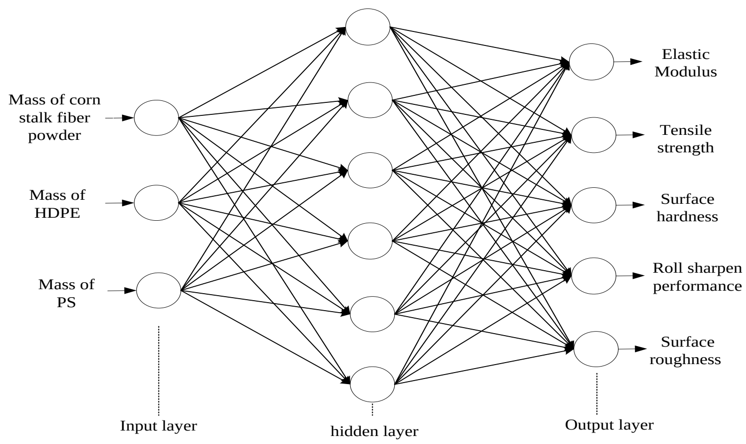

Figure 1. Network Structure of the Prediction Model

2.2. BP Neural Network Algorithm Analysis

The BP neural network algorithm process consists of two parts: forwarding and reversing the spread of propagation. An input signal from the input layer through the hidden layer to the output layer is the process of forward propagation; once the error network output and the actual output exceeds a predetermined range, the system enters the next part: the back-propagation. In this link, the error signal is assigned back to the system and the system will adjust from there and threshold layers of neurons, thereby improving the system's performance.

The BP neural network algorithm has a simple structure as well as minimal computation, parallelism, and other advantages. Meanwhile, the BP algorithm has some disadvantages: (1) it is looked upon as an optimized nonlinear problem and difficult to obtain the optimal solution; (2) slow learning of convergent velocity; (3) low precision. it is difficult to obtain the optimal solution.

3. Improved Particle Swarm Optimization and MPSO-BP Neural Network Hybrid Algorithm

The particle swarm optimization algorithm (PSO) has a few parameters that are dependent on experience and can converge rapidly, *etc.*, but there are also congenital deficiencies. The PSO is an efficient parallel optimization method, as the direct encoding of the decision variables as operands does not rely on specific areas that are asking the question. It is simple to operate, converges rapidly, and uses multiple search points of information for solving some of the non-linear, non-differentiable, and complex multi-objective optimization problems. However, the PSO algorithm has the following disadvantages: (1) the global convergence ability is poor; (2) it converges slowly, and it is difficult to quickly find the optimal solution [13-15]. An improved particle swarm (modified particle swarm optimizer, referred to as MPSO) was adopted here to optimize the BP neural network and to realize the advantages of the PSO algorithm's global optimization ability and BP algorithm local search.

Suppose that there is a group composed of n particles in a d-dimension; the i-th particle is $x_i = (x_{i1}, x_{i2}, \cdots, x_{id})$, $i = 1, 2, \cdots, n$, and the position of every particle is a partial solution. A fit output can be calculated if x_i is put to a target function; the output will be evaluated by the output. The "fly speed" of the i-th particle is expressed by $v_i = (v_{i1}, v_{i2}, \cdots, v_{id})$. The best search position of the i-th particle is $p_i = (p_{i1}, p_{i2}, \cdots, p_{id})$, and the best search position of all the particles is $p_g = (p_{g1}, p_{g2}, \cdots, p_{gd})$.

The speed and position of each particle was updated by the following formula (Eq. 1) [11]:

$$\begin{cases} v_{id}^{k+1} = \omega v_{id}^{k} + c_1 r_1 \left(p_{id}^{k} - x_{id}^{k} \right) + c_2 r_2 \left(p_{gd}^{k} - x_{id}^{k} \right) \\ x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \end{cases} \tag{1}$$

where ω is the inertia factor, r_1 and r_2 are random numbers between 0 and 1, c_1, c_2 is the acceleration factor, v_{id}^{k} is the search velocity component of the i-th particle, x_{id}^{k} is the search location component of the i-th particle, and k is the iteration.

With almost no increase in the amount of computation, we attempted to overcome the lack of the particle swarm algorithm by using the asynchronous methods of non-linear inertia weight strategies and diminishing the value of the acceleration factor to achieve the standard PSO algorithm improvements.

3.1. Decreasing Nonlinear Inertia Weight Strategy

The standard PSO algorithm is reduced through the linear inertia weight ω , which easily leads to premature convergence, increasing the difficulty of global optimization. To overcome these drawbacks, the Sigmoid function was decremented using strategies of improved inertia weight (Eq. 2):

$$\omega = \frac{\omega_{max} - \omega_{min}}{1 + \eta^{2\eta k / k_{max}} - \eta} + \omega_{min} \tag{2}$$

where ω_{max} and ω_{min} are the maximum and minimum inertia weights, respectively, k and k_{max} are the current iteration and the maximum iteration, respectively, and η is the adjustment of the speed of change in the speed factor.

3.2. Asynchronous Changes in the Value of the Acceleration Factor

Such particles are quickly approaching the global optimal solution, therefore accelerating factors c_1 and c_2 should not take the constant value, but should optimize the projected changing values as follows (Eq. 3):

$$\begin{cases} c_1 = \left(c_{1f} - c_{1i}\right) \dfrac{t}{T_{max}} + c_{1i} \\ c_2 = \left(c_{2f} - c_{2i}\right) \dfrac{t}{T_{max}} + c_{2i} \end{cases} \tag{3}$$

where c_{1i} , c_{1f} , c_{2i} , and c_{2f} are constants.

Through the inertia weight and acceleration improvement factor, this paper proposes an improved particle swarm optimizer (MPSO) algorithm to optimize the BP neural network.

4. Experiment Research

By WPC production process analysis and comparison, the study identified additional sample preparations made by a single screw extrusion die method (Figure 2).

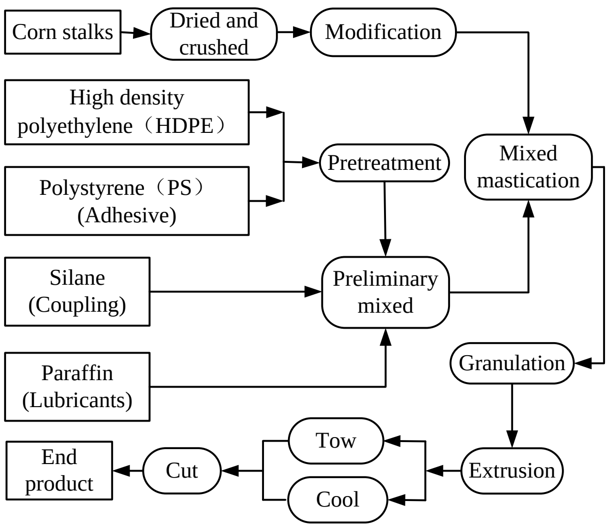

Figure 2. Preparation Technology of WPC Pencil Board

4.1. Design Variables

The mass ratio of corn stalk fiber powder, HDPE, and PS were selected as the three independent variables. Pencil board requirements include texture integrity; minimal scar defects; lower resin content; ease of deformation; dense, soft, or slightly soft fiber; slightly brittle; easy to cut; and smooth surfacing. Of all the different types of wood, linden is the most appropriate and most commonly used for pencil plate. The WPC prepared in this study was an isotropic rigid material, so there were no texture or integrity issues and fewer restrictions from scar defects. This made it a more favorable material than wood composite. Wood and composite material does not contain oily resins. Elastic modulus, tensile strength, surface hardness, roll cutting performance, and surface roughness were considered to be the main performance factors and were analyzed.

4.2. Process Temperature

The melting temperatures of PS and HDPE are 180 °C and 140 °C, respectively, so the experiment was carried out between 190 and 200 °C.

5. Result and Discussion

The performances of the prepared WPC according to 15 prescriptions with different mass ratios were measured and are shown in Table 1.

Table 1. Experiment Results

No.	Corn Stalk Fiber Powder (%)	HDPE (%)	PS (%)	Roll cutting Performance (qualitative)	Surface Roughness (μm)	Tensile Strength (MPa)	Surface Hardness (N)	Elastic Modulus (GPa)
1	26.0	37.0	37.0	M	4.038	24.46	3572.0	0.43
2	30.4	43.5	26.1	E	2.641	22.22	3763.5	0.36
3	30.4	26.1	43.5	E	5.426	19.31	4229.0	0.30
4	36.8	31.6	31.6	E	5.768	20.21	3069.5	0.31
5	20.0	40.0	40.0	G	3.555	20.95	4472.5	0.34
6	23.8	47.6	28.6	E	3.351	20.58	3568.5	0.32
7	23.8	28.6	47.6	E	4.486	20.11	4454.5	0.31
8	29.4	35.3	35.3	E	3.941	20.20	3961.5	0.28
9	27.3	36.4	36.4	M	4.843	20.32	3860.0	0.29
10	23.7	31.5	44.8	G	4.112	22.60	4341.0	0.38
11	32.2	42.9	24.9	G	5.594	22.07	3124.0	0.28
12	23.7	44.8	31.5	E	3.882	21.66	3374.0	0.28
13	32.2	24.9	42.9	E	5.364	22.26	3621.0	0.34
14	32.4	33.8	33.8	E	6.116	19.42	3862.5	0.35
15	21.3	39.4	39.4	G	4.706	23.46	4610.0	0.42

M=Medium; E=Excellent; G=Good

The priority order of pencil board performance is roll cutting, surface roughness, tensile strength, surface hardness, and elastic modulus. The best comprehensive performance was prescription No. 6, and the mass ratio of corn stalk fiber powder, HDPE, and PS was 23.8:47.6:28.6. The performance comparison between the WPC pencil board (the selected prescription of No. 6) and linden pencil board was carried out and is shown in Figure 3 and Table 1.

The chips of WPC pencil board and linden pencil board are shown in Figure 3. The roll cutting performance of WPC pencil board was better than that of linden pencil board. The main performance parameter comparisons are shown in Table 1. It is clear that the comprehensive performance of WPC pencil board is better than that of linden pencil board.

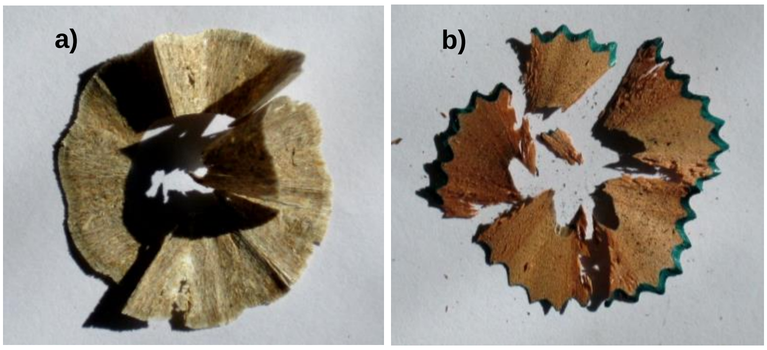

Figure 3. Roll Cutting Performance Comparison between WPC Pencil Board (the Selected Prescription of No. 6) and Linden Pencil Board: (a) Chips of WPC Pencil Board (the Selected Prescription of No. 6); (b) Chips of Linden Pencil Board

Table 2. Main Performance Parameter Comparisons between WPC Pencil Board (The Selected Prescription of No. 6) and Linden Pencil Board

Material	Elastic Modulus (GPa)	Tensile Strength (MPa)	Surface Hardness (N)
WPC pencil board (the selected prescription of No. 6)	0.32	20.58	3568.50
Linden pencil board	0.49	31.83	2580.00

To avoid network convergence problems and shorten network training time, first the different scales on the sample data in Table 1 were normalized. Among them, the composite volume machinability ratings of "excellent, good, fair, and poor" were digitally read as "1, 0.5, 0, and －0.5", respectively. Then the first 12 groups of test data normalization were input as sample networks after training. The BP neural network hidden layer and output layer transfer functions were selected as: tangent function " tansig," S-type linear function " purelin," and training function " trainlm."

To avoid network convergence problems and shorten network training time, the need for sample data on various scales were normalized following a formula treatment using the following normalization method:

$$x_{ij}' = (x_{ij} - \min(x_i)) \frac{x_{N\max} - x_{N\min}}{\max(x_i) - \min(x_i)} + x_{N\min} \tag{4}$$

where x_{ij} is the j-th value of the i-th input/output parameter, $\max(x_i)$ and $\min(x_i)$ are the up and down bound values, respectively, $x_{N\min}$ and $x_{N\max}$ are the threshold values of the normalized data, and $0 < x_{N\min} < x_{N\max} < 1$, let $x_{N\min} = 0.1$, $x_{N\max} = 0.9$. x_{ij}' is one of the normalized values. The particle number of the PSO algorithm was set to 30, with inertia factors of ωmax = 0.9 and ωmin = 0.1, C1 = C2 = 2.

Part of the test data (three groups) using Table 1 on BP neural network testing error analysis is shown in Figure 4. As can be seen from Figure 4, the neural network model used to predict the test results with the relative error was below 6%, therefore the network created by the neural prediction model showed the best prediction ability.

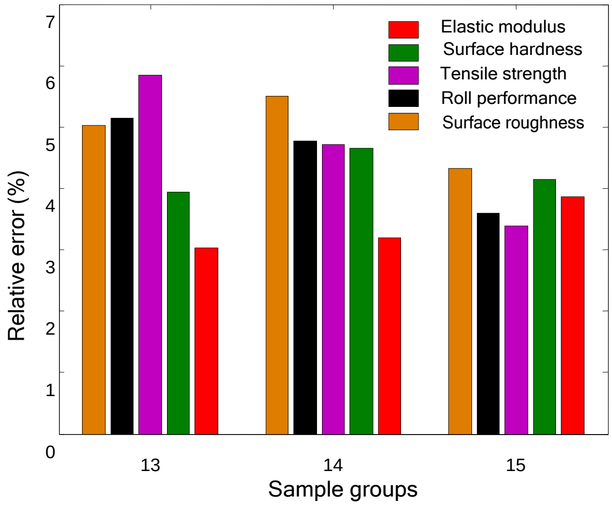

Figure 4. The Relative Error of Model Prediction Results Compared with Experimental Results Conclusions

Composites with principal components of corn straw fiber powder, HDPE, and PS were produced. The physical and mechanical property differences depend on raw materials and mixing ratio.

The preparation prediction model of the composite built up with the BP neural network has certain predictive abilities; particle swarm optimization BP neural network can improve these abilities.

The composite with the selected preparation and raw material ratio has the most desirable properties and can be used for pencil board.

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References

[1] J. L. Xie, X. G. Kang, Z. W. Gong and Y. Li, “Analysis of global industry round wood production and major end products in 1961-2009”, Zhejiang A & F Univer., vol. 28, no. 2, **(2011)**, pp. 287-292.

[2] W. H. L. Chiu and C. Chang, “Relationship between extrusion condition and mechanical properties of FRPP,” J. of Applied Polymer Sci., vol. 43, **(1991)**, pp. 1335-1341. DOI:10.1002/app.1991.070430716.

[3] B. H. Liang, L. Mott, S. M. Shaler and G. T. Caneba, “Properties of transfer-molded wood-fiber/polystyrene composites”, Wood and Fiber Science, vol. 26, no. 3, **(1994)**, pp. 382-389.
[4] B. D. Park and J. J. Balatinecz, “A comparison of compounding processes for wood-fiber/thermoplastic composites”, Polymer Composites, vol. 18, no. 3, **(1997)**, 425-431. DOI:10.1002/pc.10294.
[5] K. Jayaraman and D. Bhattacharya, “Mechanical performance of woodfibre–waste plastic composite materials”, Resources, Conservation and Recycling, vol. 41, **(2004)**, pp. 307–319. DOI:10.1016/j.resconrec.2003.12.001.
[6] A. Ashori and A. Nourbakhsh, “Reinforced polypropylene composites: Effects of chemical compositions and particle size”, Bioresour. Technol, vol. 11, **(2010)**, pp. 2515-2519. DOI:10.1016/j.biortech.2009.11.022.
[7] S. Bajwa, G. Holt, T. Coffelt and F. Nakayama, “Properties of thermoplastic composites with cotton and guayule biomass residues as fiber fillers”, Ind. Crops Prod., vol. 33, **(2011)**, pp. 747-755. DOI:10.1016/j.indcrop.2011.01.017.
[8] O. O. Isiaka, A. O. Joseph and P. B. Mayowa, “Mechanical properties of mahogany (Swietenia macrophylla) and araba (Ceiba pentandra) dusts reinforced polyester composites”, Leonardo Electronic Journal of Practices and Technologies, vol. 23, **(2013)**, pp. 1-18.
[9] K. Schindler and M. Fischer, “An incremental algorithm for parallel training of the size and the weights in a feed forward neural network”, Neural Processing Letters, vol. 11, **(2000)**, pp. 131–138.
[10] Z. Y. Li and L. H. Peng, “An exploration of the uncertainty relation satisfied by BP network learning ability and generalization ability”, Science in China Ser. F Information Sciences, vol. 47, no. 2, **(2004)**, pp. 137-150, DOI:10.1360/02yf0331.
[11] J. Kennedy and R. C. Eberhart, “Particle swarm optimization,” IEEE International Conference, Neural Networks, Piscataway, **(1995)**, pp. 1942-1948.
[12] C. W. Jiang and B. Etorre, “A self adaptive chaotic particle swarm algorithm for short term hydroelectric system scheduling in deregulated environment,” Energy Conversion and Management, vol. 46, **(2005)**, pp. 2689-2696, DOI:10.1016/j.enconman.2005.01.002.
[13] R. C. Eberhart and Y. Shi, Comparing inertia weights and constriction factors in particle swarm optimization”, Proc. of congress on Evolutionary Computing, vol. 1, **(2000)**, pp. 84-88. DOI:10.1109/CEC.2000.870279.
[14] D. W. Boeringer and D. H. Werner, “Particle swarm optimization versus genetic algorithms for phased array synthesis,” IEEE Trans. Antennas Propagation, vol. 52, no. 3, **(2004)**, pp. 771-779, DOI:10.1109/TAP.2004.825102.
[15] Y. Da and X. R. Ge, “An improved PSO-based ANN with simulated annealing technique”, Neurocomput. Lett., vol. 63, **(2005)**, pp. 527-533, DOI:10.1016/j.neucom.2004.07.002.

Author

BU Chiwu received the B.S. and M.S. degrees from the Harbin University of commerce, Harbin, China, in 2003 and 2006, respectively, and the Ph.D. Degree from Harbin Engineering University, Harbin, China, in 2012.

He is currently a Research Engineer in Industry School of Harbin University of Commerce His research interests lie in the area of materials science, robotics, and industrial control.

