Prediction of Maximum Outlet Velocity of Auxiliary Nozzle with Six Orifices Based on PSO-BP

Yalong He[1, a], Junqing Yin[1, b*], Yongdang Chen[1, c], Xingxuan Yang[1, d], Jianxin Ma[1, e], Keyu Ni[1, f], Chen Zhang[1, g]

[a]heyalong@stu.xpu.edu.cn, [b]jqyin@xpu.edu.cn, [c]chenyd@xpu.edu.cn, [d]xxyang@stu.xpu.edu.cn, [e]majianxin610@stu.xpu.edu.cn, [f]fushengnky@stu.xpu.edu.cn, [g]mengyi@stu.xpu.edu.cn

[1]School of Mechanical and Electrical Engineering, Xi’an Polytechnic University, Shaangu avenue, Xi’an, China

Abstract: In view of the complexity of the auxiliary nozzle structure of air-jet looms, a prediction model between the auxiliary nozzle structure parameters and the maximum exit velocity was established based on PSO-BP. Firstly, the finite element model of the auxiliary nozzle was established by using Ansys software. Secondly, 500 sets of structural parameters were sampled using Latin hypercube sampling, and the corresponding maximum outlet velocity was obtained using the finite element model. Finally, 450 groups of samples are used as the training set, and the remaining 50 groups are used as the test set to establish the PSO-BP prediction model. The results show that the PSO-BP model is effective and accurate to predict the maximum exit velocity of the auxiliary nozzle.

Keywords: auxiliary nozzle, structural parameters, maximum outlet velocity, PSO-BP model, prediction introduction

1 Introduction

As an important textile machine, the auxiliary nozzle is an important part of the air-jet loom. There is a nonlinear relationship between the structural parameters of the auxiliary nozzle and the comprehensive performance evaluation index, and each parameter has an important influence on the comprehensive performance evaluation index of the auxiliary nozzle. A reasonable structure can not only reduce energy consumption, improve productivity, but also achieve a better weft insertion effect [10].

Researchers have carried out a large number of numerical and experimental studies on flow field characteristics, injection performance and energy consumption of auxiliary nozzles [3] [5] [13], including the influence of structural parameters of auxiliary nozzles, nozzle shape, nozzle number and flow parameters on flow field characteristics. Relevant scholars have studied the nozzle shape of single-hole nozzle [4], the diameter of single-round hole [1] and its taper value [2], the optimal aspect ratio of rectangular nozzle [12], and the cross-sectional area of nozzle

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outlet [11]. The flow field characteristics of the auxiliary nozzle with different shapes of single orifices, different orifices of single circular orifices and their taper values, and the optimum aspect ratio of the rectangular orifices were obtained. It was proved that the cross-section area of the nozzle outlet has a great influence on the jet velocity and persistence. Li *et al*.[5] analyzed three typical auxiliary nozzle structures of single circular hole, equilateral hole and star hole under different air supply pressures, and carried out corresponding three-dimensional flow field numerical simulation. The results show that under the same air supply pressure, the star hole auxiliary nozzle has the best air flow concentration, weft insertion smoothness, the lowest gas consumption and the best comprehensive performance.

The influence of the structural parameters of the auxiliary nozzle on its injection performance was studied by means of experiment and numerical simulation. But few people use intelligent optimization algorithm to optimize the structural parameters of the auxiliary nozzle to make the overall performance optimal. The relationship between the structural parameters and the comprehensive performance evaluation index of the auxiliary nozzle is a nonlinear problem, which is difficult to be expressed by common methods. BP neural network algorithm has strong nonlinear mapping ability, self-learning and self-adaptation ability, and can deal with many complex nonlinear problems [8] [9]. However, since the weight and threshold of BP neural network are updated by gradient descent method, it is easy to obtain local extreme values instead of global extreme values by updating parameters in the direction of negative gradient of the target. Particle Swarm Optimization (PSO) is widely used in the Optimization of various models because it can avoid the process of Optimization falling into local extreme values and has good robustness and easy convergence [6] [7].

This paper aims to establish an accurate model between structural parameters and comprehensive performance evaluation indexes. The nozzle diameter, nozzle taper, nozzle position and nozzle center distance of the central annular six-hole auxiliary nozzle were selected as structural parameters, and the maximum outlet velocity was selected as the performance evaluation index. BP neural network was used to establish the relationship model between the four structural parameters and the maximum outlet velocity, and then PSO was used to optimize the network weights and thresholds iteratively in the process, in order to get the relationship model with as little error as possible, which could provide reference for practical production.

2 Six round hole auxiliary nozzle model

2.1 Geometric Model

The central annular six-hole auxiliary nozzle model shown in Figure 1 was selected as the research object. Figure 2 shows the 3D flow field model, whose outward drawing angle is 80°, and the length, diameter and drawing depth of the external far flow field are 80 mm,24 mm and 2 mm respectively.

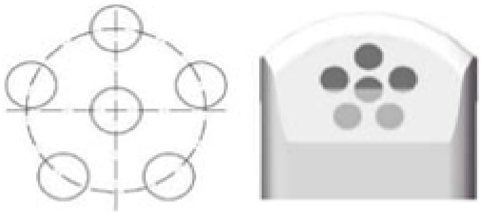

Figure 1: Schematic diagram of the arrangement of the nozzle holes of the auxiliary nozzle with six round holes and its three-dimensional characteristics.

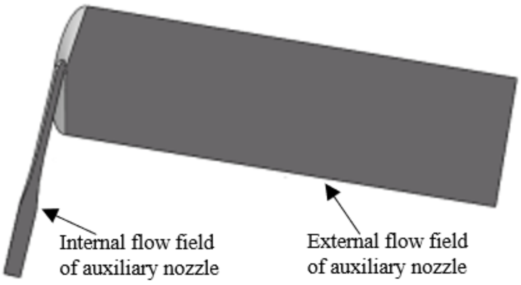

Figure 2: 3D flow field model of auxiliary nozzle.

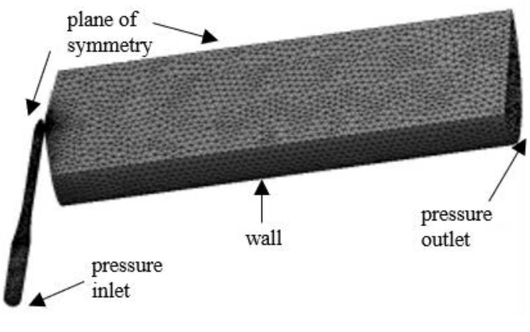

Figure 3: Mesh division and boundary condition setting of flow field model.

2.2 Numerical Simulation Model

Mesh plug-in in finite element software Ansys was used to conduct mesh division for the three-dimensional flow field model of the auxiliary nozzle. Figure 3 shows mesh division and boundary condition setting of the flow field model. Free tetrahedral mesh was adopted with mesh density of 100 and mesh quality of Fine, and the number of meshing is about 840,000. Four boundary conditions of pressure inlet, symmetrical surface, pressure outlet and wall surface are set respectively after the mesh is generated.

Density-based hermit solver in Fluent was used to calculate the grid files. Other simulation parameter settings refer to Table 1. Density-based hermitage solver was used to calculate. RNG K-ε biequation model was used for turbulence model. Ideal gas is selected as the fluid medium. Using mixed initialization conditions. The number of iterations is 500, and then the solution is performed. Figure 4 shows the cloud diagram of the maximum outlet velocity of the six-hole auxiliary nozzle with a diameter of 0.6124 mm, a center distance of 0.76 mm and a taper of 9°. In the figure, the maximum outlet velocity is 453 m/s. The flow field has very good bundling and the weft insertion effect is excellent.

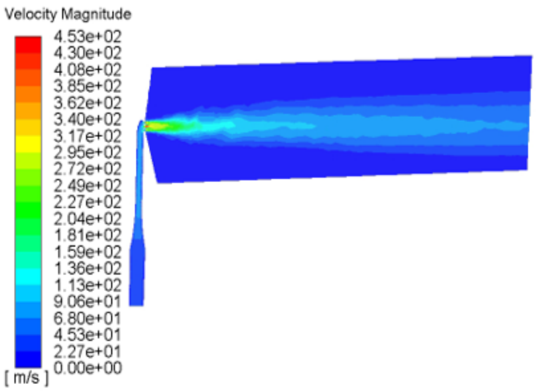

Figure 4: Cloud map of the maximum exit velocity of the auxiliary nozzle with six round holes.

Table 1: Flow field boundary condition setting in Fluent.

Parameter setting	parameter value
Inlet air supply pressure/(MPa)	0.3
Turbulent dissipation rate at the entrance /(m^2/s^3)	8428.8
Turbulent kinetic energy /(m^2/s^2)	5
temperature/(K)	293
Pressure outlet total pressure/(Pa)	101325
Static pressure/(Pa)	297510

After comprehensive consideration of engineering practice, requirements of relevant process specifications and errors in actual processing, the value range of the auxiliary nozzle's jet hole aperture, jet hole taper, jet hole position and jet hole center distance is determined to be 0.55-0.67 mm, 0°-9°, 0°-72°, 0.76-0.86 mm, respectively. The reference position of the annular nozzle location distribution is the vertical center line in Figure 1.

3 PSO-BP prediction model

3.1 PSO-BP Algorithm

BP neural network is a multilayer feedforward error back propagation neural network. When the actual output value is different from the expected output value, the error will be propagated back, and the weights and thresholds of each layer will be adjusted along the gradient direction to achieve the target accuracy. The number of nodes in the input layer and output layer is determined by the number of input and output variables, while the number of nodes in the hidden layer is usually determined by the empirical formula. M and L are the number of neurons in the input layer and output layer respectively. In this paper, N =10 and the value range of ρ is 0-10. The activation functions of the hidden layer and output layer are tansig function and purelin function respectively. Newff function is called to create the network, and train function is used to train the network.

$$N = \sqrt{L+M} + \rho \tag{1}$$

Particle swarm optimization (PSO) is a parallel optimization algorithm based on swarm intelligence. Its basic principle is that each particle is a potential solution of optimization problem, corresponding to a fitness value, by the fitness function to calculate the fitness values, each particle has a speed determine their movement direction and distance, and the optimal particle particle are to follow the current search in the solution space, so as to realize the optimization of the whole space. Therefore, particle swarm optimization is used to optimize the weight and threshold of BP neural network model, so that it can better approximate the global extreme value. Using Latin hypercube sampling method from the given parameter values range from 500 groups of data, each group of structure parameters in Ansys combinations corresponding to maximum exit velocity, randomly selected 450 groups of data is used to set up auxiliary nozzle structure parameters and the biggest export rate of relational model, the remaining 50 sets of data used for testing the relational model. The specific steps of PSO-BP neural network optimization algorithm are as follows:

Step1: As the range of some input data may differ greatly, resulting in slow convergence of neural network and long training time, the input sample data is normalized and the topological structure of BP neural network is determined according to the input and output samples. The normalization formula is shown as follows:

$$y = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{2}$$

Where, x are the mapping values, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values.

Step2: After initializing the network weight, threshold, population position and speed, update the speed and position according to the individual extreme value and population extreme value, the formula is as follows:

$$V^{k+1} = \omega V^k + c_1 r_1 (P_{id}^k - X^k) + c_2 r_2 (P_{gd}^k - X^k) \tag{3}$$

$$X^{k+1} = X^k + V^{k+1} \tag{4}$$

Where, c_1 and c_2 are constants, also known as acceleration constants. r_1 and r_2 are the uniform random number within the range of [0,1], which is used to increase the randomness of particle flight. k is the current iteration number. P_{id}^k is the individual optimal particle position. P_{gd}^k is the global optimal particle position. V is the particle velocity. X is the particle position.

Step3: calculate the fitness value with the fitness function, and then update the individual extreme value and the population extreme value according to the fitness value. The fitness function is shown as follows:

$$E = \frac{1}{n}\sum_{j=1}^{n}(X_{id}^{k+1} - X_{id}^{k})^2 \tag{5}$$

Where, n is the total number of particles, X_{id}^{k+1} is the updated value of the id particle, and X_{id}^{k} is the initial value of the id particle.

Step4: PSO algorithm is used to optimize the weight and threshold of BP neural network model, and then training and testing are carried out. If the error conditions are met, the prediction results are output. Otherwise, step2 is returned to continue execution until the error requirements are met.

The training fitting and optimization process based on PSO-BP is shown in Figure 5.

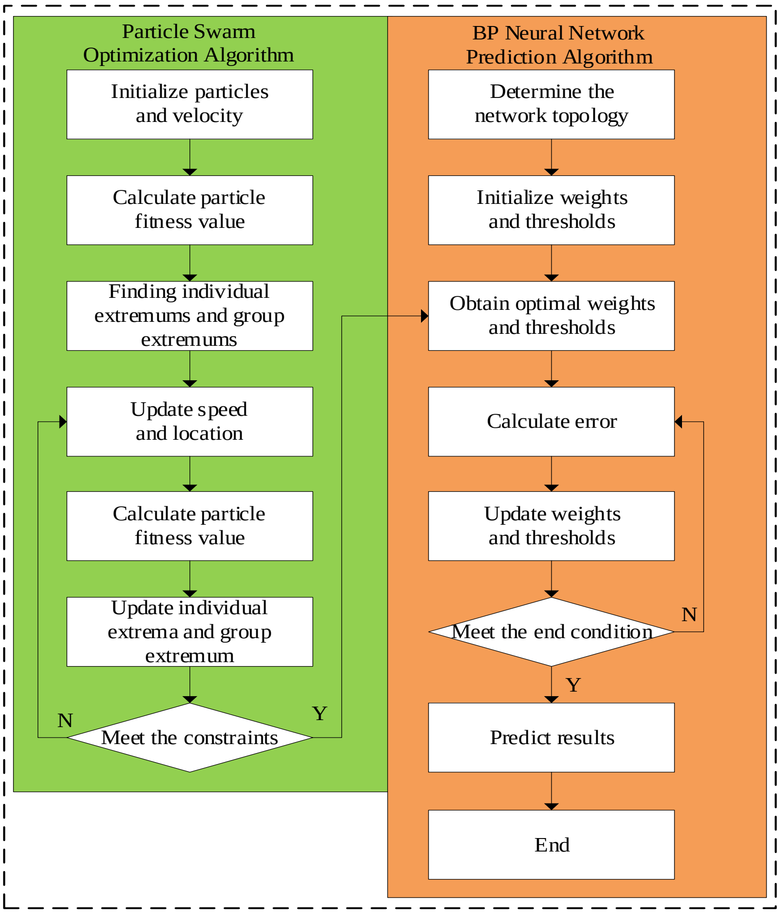

Figure 5: The training, fitting and optimization process based on PSO-BP.

3.2 Evaluation of the Model

The established network was used to calculate the input test set, and the actual output value and predicted value of the test set were analysed for error. The results used mean square error (MSE) and mean absolute percentage error (MAPE) as the performance evaluation indexes of the model. The smaller the two, the higher the prediction accuracy of the model. The specific calculation formulas are as follows (6) and (7):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{6}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{7}$$

In the formula, y_i is the actual value and $\hat{y}_i$ is the predicted value of the neural network model.

3.3 Analysis of Results

The actual value and predicted value of the PSO-BP model test set are shown in Figure 6, with an average relative error of 0.00886. According to formulas (6) and (7), the mean square error of the test set is 0.0299, and the mean absolute percentage error is 0.00045%. Through calculation and analysis, the accuracy of PSO-BP neural network is very high, and the maximum outlet velocity of six-hole auxiliary nozzle can be predicted well.

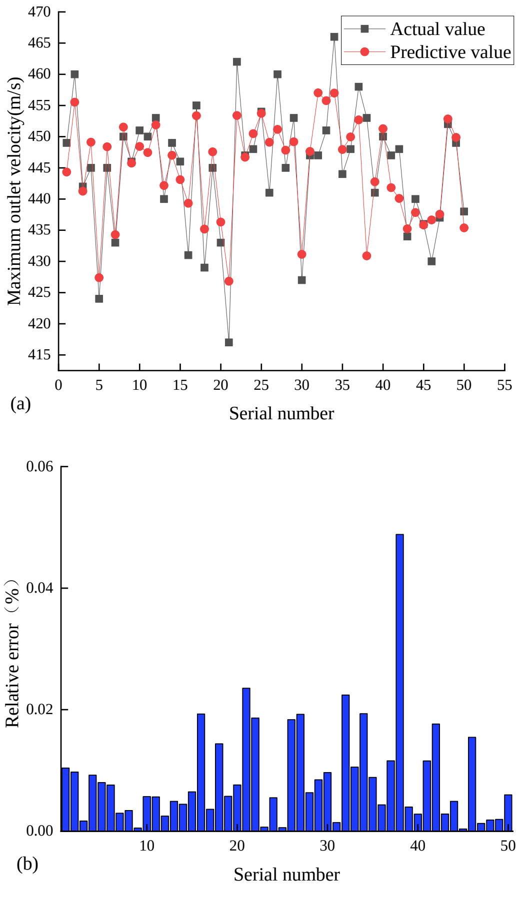

Figure 6: Prediction results of PSO-BP neural network.

4 Conclusions

BP neural network optimized by particle swarm optimization algorithm was used to establish a model between the four structural parameters of the auxiliary nozzle (nozzle aperture, nozzle taper, nozzle location and nozzle center distance) and the maximum outlet velocity, so as to predict the maximum outlet velocity of the six-hole auxiliary nozzle. The results show that the mean square error and mean absolute percentage error of the proposed method are both lower than 5%, which indicates that the prediction accuracy is very high and can meet the actual demand of engineering. This enlightens us that there are certain deficiencies in single prediction models, and these deficiencies are inherent. However, combined with the optimization algorithm, the prediction results will be more reliable, even if it makes the algorithm a little more complicated.

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