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Parameter Optimization Method of Screw Axis with Variable Diameters and Different Pitches Based on PSO-BP NN

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Abstract. Parameter optimization of screw axis with variable diameters and different pitches is very important to improve the performance of material conveying equipment. But it is a trouble thing with classic theory modeling because of the complexity of material fluidity and screw structure. A PSO-trained BP algorithm is applied to establish the screw axis parameter optimization neural network (NN) model.Taking asphalt transfer vehicle as an example, PSO-BP NN is applied to set up the relationship between input parameters and aim parameter. Practical example shows that the PSO-BP NN has faster convergence and higher computational precision than the other three investigated algorithms, and it provides a powerful parameter optimization approach for screw axis with variable diameters and different pitches.

Introduction

Traditional screw axis structures are easy to form flow dead zone, lead to material segregation or caking, and increase power consumption of material conveying equipment. The structure of variable diameters and different pitches is an effective way to solve the above problems[1]. While traditional parameter optimization methods including analysis experiment and numerical simulation are trouble things because of the complexity of material fluidity and screw structure[2]. With the development of computer technology, intelligent modeling technology including Neural Network(NN) gradually becomes a new direction in structure parameter optimization[3]. However, the standard Back Propagation (BP) NN is easy to fall in the local minimum and its convergence speed is slow.

Particle Swarm Optimization (PSO) is a swarm intelligence algorithm proposed by Kennedy and Eberhart, which searches for the optimal value by sharing the cognitive and social information among the individuals (particles) in the global solution space[4]. PSO has many advantages over other evolutionary computation techniques like faster convergence rate, fewer parameters to adjust, simpler implementation, etc. [5]. PSO is successfully applied to various optimization problems[6,7].Taking asphalt transfer vehicle as an example, PSO-trained BP NN is applied to establish the relationship model between working parameters of screw axis and ratio of asphalt mixture separation. Practical example shows that the PSO-BP NN provides a powerful optimization approach for screw axis with variable diameters and different pitches.

Modeling based on Neural Network

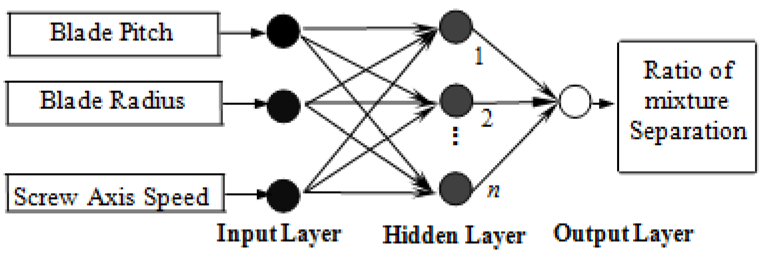

Fig. 1 Screw axis parameter optimization NN model

Three factors, blade pitch, blade radius and screw axis speed, are the most important factors that affect ratio of mixture separation[8]. There are much complex relationships among them. Due to NN quick modeling ability for complex nonlinear problem, we set up the NN model of screw axis with

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variable diameters and different pitches for asphalt transfer vehicle is shown in Fig. 1.The number of input neutrons depends on related factors affecting ratio of mixture separation.the three outstanding factors pitch, blade radius and screw axis speed are defined as inputs of the NN. The amount of hidden neuron is commonly adjusted according to practical operation. The output layer is constituted of one nerve cell which represents ratio of mixture separation.

PSO-optimized BP NN

The standard NN With BP algorithm has some shortcomings such as slow convergence speed, easily getting stuck in the local extreme point and the instability of network. PSO algorithm with better global search ability is introduced to improve the modeling capability of BP NN.

PSO Algorithm. In PSO, There are a number of pbests for the respective agents in the swarm and the agent with greatest fitness is called the global best (gbest) of the swarm. Each particle is treated as a point in a D-dimensional space. The ith particle is represented as $X_i = (x_{i1}, x_{i2} \ldots x_{iD})$, $i = 1, 2 \ldots N$, where N is the swarm size. The best previous position of the ith particle (pbest$_i$) that gives the best fitness value is represented as $P_i = (p_{i1}, p_{i,} p_{iD})$. The best particle among all the particles in the population is represented by $P_g = (p_{g1}, p_{g2} \ldots, p_{gD})$. The velocity, i.e., the rate of the position change for particle i is represented as $V_i = (v_{i1}, v_{i2} \ldots, v_{iD})$. The searching procedure can be described by (1).

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

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{1b}$$

In (1a,b), c_1 and c_2 are acceleration constants, r_1 and r_2 are random number between 0 and 1 ,V_i^k is current velocity of agent i at iteration k, V_i^{k+1} is modified velocity of agent i at iteration k +1, , X_i^k is current position of agent i at iteration k, p_{id} is the pbest of agent i, p_{gd} is gbest of the group, k is current iteration number, ω is inertia weight which can be set according to the following equation:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} \times k \tag{2}$$

Where ω_{max} is the initial weight, ω_{min} is the final weight, $iter_{max}$ is maximum iteration number.

PSO-BP Algorithm. Bp algorithm has merits in accuracy, but has weaknesses such as the low learning convergence speed and the easily appearing local minimum. PSO algorithm, which is of properties of the good global searching, can effectively avoid the local minimum. Neural network is optimized by PSO algorithm can fully exert each advantage. And the objects (particles), which need to be optimized by PSO algorithm, are the weights and the thresholds of BP NN. The PSO-BP algorithm procedure can be expressed as follows:

Step 1: Initialize the positions and velocities for a group of particles randomly.

Step 2: Evaluate fitness value of each particle (Here, MSE function is chosen as fitness function.), and P_b is set as the positions of current particles, while P_g is set as the best position of particles.

Step 3: If the $iter_{max}$ is arrived, go to *Step 8*, else, go to *Step 4*.

Step 4: The best particle of the current particles is stored. The positions and velocities of all the particles are updated according to Eqs. (1a,b), then a group of new particles are generated, If a new particle flies beyond the boundary[X_{min}, X_{max}], the new position will be set as X_{min} or X_{max}; if a new velocity is beyond the boundary[V_{min},V_{max}],the new velocity will be set as V_{min} or V_{max} .

Step 5: Evaluate each new particle fitness value, and the worst particle is replaced by the stored best particle. If the *i*th particle new position is better than P_{ib}, P_{ib} is set as the new position of the *i*th particle. If the best position of all new particles is better than P_g, then P_g is updated.

Step 6: Reduce the inertia weights ω according to Eqs. (2).

Step 7: If the current P_g is unchanged, then go to *Step 8*; else, go to *Step 3*.

Step 8: Use the BP algorithm to search around P_g for some epochs, if the search result is better than P_g, output the current search result; or else, output P_g.

Here , we introduced a constant σ with positive values close to zero, to judge whether current P_g is unchanged. If the phenomena that absolute value of change of P_g between two adjacent generations is less than σ, appears ten times in rapid sequence, then we deduce the current P_g is unchanged. And parameterσgenerally is adjusted to an appropriate value by several repeated experiments.

Experimental Validation and Result Analysis

Experimental Data Acquistion. The effects of Pitch(S, mm), blade radius (r, mm), and screw axis speed(n, $r \cdot min^{-1}$) on ratio of mixture separation(ξ) are investigated. The investigated parameters and their test levels are listed in Table 1. The orthogonal array $L_9(3^4)$ is selected to arrange the test program, and each trial of nine experiments is performed once. Measuring position is shown in Fig. 2. Data from the measuring position in Fig.2 have representation of complete appliance, because the structure of test apparatus is of properties of axial symmetry.

Table 1. The investigated parameters and their test levels

	S(mm)	r (mm)	n (r•min^{-1})
Zero level	165	95	40
High level	185	110	20
Lower level	145	80	60
Level space	20	15	20

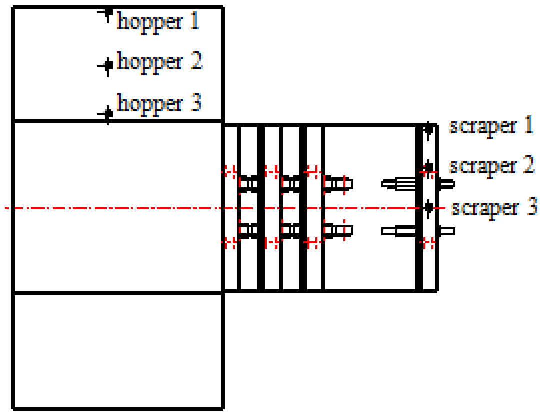

Fig. 2 Sample point distribution for test measurement

Validation Test and Result Analysis. the correlative parameters of the network are set as follows: x_{Nmin}=0.1, x_{Nmax}=0.9; C_1=C_2=2, $iter_{max}$=1000; ω_{max}=0.9, ω_{min}=0.3, N=40.The data is normalized in order to make it suitable for the training process firstly. Close to 80% of the test data are used in NN learning procedure and the remaining ones used in testing the achieved optimal NN. The same training data are respectively used to train the following NN model: Standard BP, Resilient BP, BP-LM, and PSO-BP. The error goal are used as 0.001. Training performances of the four algorithms are illustrated in Table 2. The mean relative error with PSO-BP is 1.72%. Comparison of relative error of the four algorithms are showed in Fig. 3.From Fig. 3 and Table 2 , it can be seen that the fitting precision and training times of PSO-BP algorithms are superior to those of Standard BP and Resilient BP , but has no significant advantage over those of BP-LM.

However, when used to simulate unknown samples, PSO-BP NN has obvious advantages over the other three NN models, shown in Fig.4. The mean relative error in this testing process with PSO-BP NN model is 2.76%, and those with the other three NN models are more than 20%. Namely, PSO-BP NN has remarkably better prediction ability than others.

Table 2. Training performances of the four algorithms

NN model	Iteration number	MSE	mean relative error (%)
PSO-BP	23	9.8e-5	1.72
Standard BP	1000	9.1e-3	12.22
Resilient BP	65	3.3e-4	3.16
BP-LM	3	1.2e-4	1.74

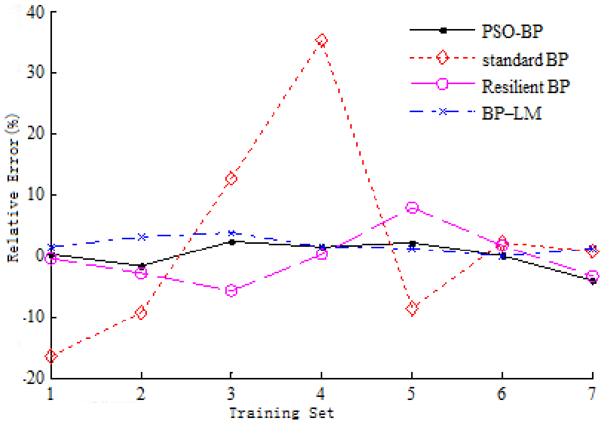

Fig. 3 Relative error of training set.

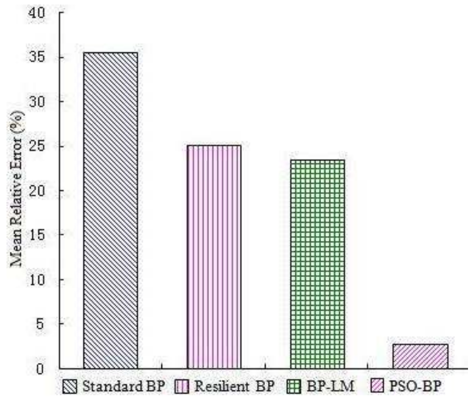

Fig. 4 Relative error of validation set.

Conclusions

(1) The test result shows that PSO-BP NN has faster convergence and higher computational precision than the other three investigated algorithms.

(2) the PSO-BP NN can gain the best parameter combination by modeling and simulation, it provides a powerful parameter optimization approach for screw axis with variable diameters and different pitches.

Acknowledgments

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