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PREDICTION MODEL OF LIQUID HOLDUP BASED ON SOA-BPNN ALGORITHM

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ABSTRACT

In the actual operation of wet gas pipeline, liquid accumulation is easy to form in the low-lying and uphill sections of the pipeline, which leads to a series of problems such as reduced pipeline transportation efficiency, increased pipeline pressure drop, hydrate formation, slug flow and intensified corrosion in the pipeline. Accurate calculation of liquid holdup is of great significance to the research of flow pattern identification, pipeline corrosion evaluation and prediction, and gas pipeline transportation efficiency calculation. Based on the experimental data of liquid holdup in horizontal pipeline, a commonly used BP neural network (BPNN) model is established in this paper. In order to improve the accuracy of BPNN model, Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Seeker Optimization Algorithm (SOA) are used to optimize the initial weights and thresholds of BPNN model, and GA-BPNN model, PSO-BPNN model and SOA-BPNN model are established. By comparing the model accuracy, the average absolute error of SOA-BPNN prediction model is 3.7351%, and the root mean square error is 0.0113. This model has high prediction accuracy and wide application range, which is obviously superior to other algorithms, and provides a new method for accurate prediction of liquid holdup of wet gas pipeline.

Keywords: *Wet gas pipeline, Liquid holdup, Seeker Optimization Algorithm, BP Neural Network, Model accuracy*

1.INTRODUCTION

The technology of long-distance mixed transportation of wet natural gas has been widely used in practical production. However, due to the change of pipeline temperature and pressure, condensate and water in wet gas pipeline are easy to gather in low-lying areas of pipeline, which accelerates corrosion in pipeline (Surkov *et al*., 2000; Liu *et al*., 2017). Liquid holdup refers to the actual liquid volume fraction in the pipeline, which is the most important parameter in calculating pressure loss, and is also very important for predicting hydrate formation and wax deposition (Shao *et al*., 2019).

For the prediction of liquid holdup, scholars at home and abroad have put forward a large number of mechanism models and empirical models. Nsidibe Sunday et al analyzed the numerical heat transfer of two-phase flow in horizontal and inclined flowline using OpenFOAM (Sunday *et al*., 2022). The model is able of calculating velocity distribution, pressure gradient, liquid holdup, and temperature variation at the flowline cross-sections (Sunday *et al*., 2022). Some of which are widely used, while the other part has a narrow application range. Most of the methods begin with the prediction of flow patterns, and each flow pattern has its own method for predicting liquid holdup, but this method depends on the accuracy of flow pattern prediction. With the rise of computer science, intelligent algorithms are gradually applied to liquid holdup prediction. Chen Xing et al established the calculation model of liquid holdup in horizontal pipeline based on ACE algorithm (Chen *et al*., 2018). Xiao Rongge et al applied BP neural network algorithm to predict liquid holdup of horizontal pipeline (Xiao *et al*., 2020). Shao Mengliang et al, Xiao Rongge et al and Qi Mingjun et al optimize the weights and thresholds of BP neural network by Genetic Algorithm(GA), Whale Optimization Algorithm(WOA) and Improved Salp Swarm Algorithm(ISSA) respectively, and the prediction accuracy of the model is further improved (Shao *et al*., 2018; Xiao *et al*., 2022; Qi *et al*., 2022).

But the current neural network method for liquid holdup prediction has some problems, such as over-learning, long training time, low generalization ability and easy to fall into local minimum, so this paper optimizes BP neural network by using seeker optimization algorithm. Seeker optimization algorithm is a new meta-heuristic algorithm proposed by Dai et al (Dai *et al*., 2010). The results show that the seeker optimization algorithm (SOA) has faster convergence speed and optimization accuracy than the traditional swarm intelligence optimization algorithm (Xiao *et al*., 2021).

Based on the experimental data of liquid holdup in horizontal pipeline, the BPNN model is initially established in this paper. Genetic algorithm (GA), particle swarm optimization (PSO) and seeker optimization algorithm (SOA) are used to optimize the initial weights and thresholds of BPNN, and then the optimized model is used to predict the liquid holdup in horizontal pipeline. In order to prove the feasibility and superiority of SOA-BPNN model in predicting liquid holdup.

2. BPNN AND OPTIMIZATION MODEL

2.1 BPNN Model

There are dozens of artificial neural network models, among which BPNN model is the most widely used (Yan *et al*., 1900). BPNN generally adopts a three-layer network structure: an input layer for inputting

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relevant data information, a hidden layer for intermediate process calculation, and an output layer for outputting operation and simulation results. Its network structure diagram is shown in Figure 1. In Fig. 1, X_1, X_2,..., X_m denote m actual inputs; ω_{ij} represents the connection weights between the input layer and the hidden layer; Z_1, Z_2, …, Z_l denote l hidden layers; ω_{jk} represents the connection weight between the hidden layer and the output layer; Y_1, Y_2, …, Y_n denote n predicted outputs; T_1, T_2,..., T_n denote n desired outputs.

When the sample data is input, the neuron is activated and propagates along the path of input layer→ hidden layer→ output layer, while the output error is fed back to the input layer along the opposite path. At this time, the forward propagation of variables and the back propagation of errors alternate. If the prediction is unreasonable, the weights and thresholds of the hidden layer are revised and iterated continuously until the prediction results meet the requirements.

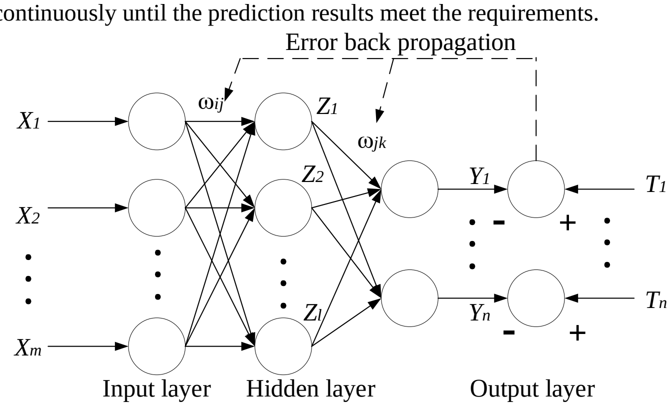

Fig. 1 Schematic diagram of BP neural network structure

2.2 GA Optimization Algorithm

Genetic algorithm is an evolutionary algorithm, and its basic principle is to imitate the evolutionary law of "natural selection, survival of the fittest" in the biological world (Ji., 2004), which mainly includes six parts.

①Coding. GA expresses the solution data in solution space as genotype string structure data in genetic space before searching, and different combinations of these string structure data constitute different points.

②Generation of initial population. N initial string structure data are randomly generated to form a group.

③ Fitness assessment. Fitness indicates the advantages and disadvantages of an individual or solution.

④Choose. The excellent individuals in the current population are selected as parents to breed the next generation.

⑤Cross. Crossover operation is the most important operation of genetic algorithm. By crossing, new individuals combine the characteristics of their parent individuals.

⑥Mutation. Randomly select an individual in a population to randomly change the value of a string in the string structure data with a certain probability.

2.3 PSO Optimization Algorithm

PSO algorithm was proposed by Kennedy and Eberhart in 1995. It originated from the study of bird predation behavior and is an evolutionary computation technique (Clerc., 2006). Its core idea is to create N particles in a limited space, each particle has only two attributes: speed and position, speed represents the speed of movement, and position represents the direction of movement. Each particle searches for the optimal solution separately and the optimal solution is shared by the whole particle swarm, so as to achieve the purpose of optimization. The speed iteration of the algorithm is shown in Equation 1.

$$v_i(t+1)=\omega v_i(t)+c_1r_1(X_i^{pb}(t)-x_i(t))+c_2r_2(X_i^{gb}(t)-x_i(t)) \quad (1)$$

Where, i=1,2,…, N, N is the total number of particles; t is the number of current iterations; ω is inertia weight; v_i is the velocity of particles; r_1 and r_2 are random numbers; x_i is the current position of particle i; X_i^{pb} is the current individual optimal position of particle i; X_i^{gb} is the current optimal position of particle swarm; c_1 and c_2 are learning factors, usually taking 2.

2.4 Seeker Optimization Algorithm

Seeker optimization algorithm is a new heuristic random search algorithm based on population. In this algorithm, the search direction is selected according to the empirical gradient by evaluating the response of the corresponding position change, and the step size is determined by uncertain reasoning based on fuzzy rules (Xiao *et al*., 2021). Seeker optimization algorithm has the characteristics of clear concept, easy to understand, fast convergence speed and high precision, and its calculation steps are as follows.

(1) The determination of search step

In SOA algorithm, the optimum values of individuals are arranged in descending order, and the individuals are assigned the sequence number from 1 to N as the input of fuzzy reasoning. Gaussian membership function is used to express the fuzzy variables of searching step size, that is,

$$u_A(x)=\exp\left[-\frac{(x-u)^2}{2\delta^2}\right] \quad (2)$$

In Equation 2, u_A is Gaussian membership degree; x is the input variable; u and δ are parameters of membership function.

Membership degree of other positions can be expressed as

$$u_i=U_{\max}-\left[N-I(i)\right]\frac{U_{\max}-U_{\min}}{N-1} \quad (3)$$

$$u_{ij}=rand(u_i,1) \quad (4)$$

Where, u_i is the membership degree corresponding to the i-th individual; $I(i)$ denotes the serial number of the best fitness values of the i-th individual after being arranged in descending order; N is the population size; U_{max} is the maximum membership degree, U_{min} is the minimum membership degree; u_{ij} is the membership degree corresponding to the objective function value i of the j-dimensional search space; the function $rand(u_i,1)$ produces real numbers uniformly and randomly distributed on [u_i,1].

The search step size formula is

$$a_{ij}=\delta_{ij}\sqrt{-\ln u_{ij}} \quad (5)$$

In Equation 5, a_{ij} is the search step size of the j-dimensional search space; δ_{ij} is the parameter of Gaussian membership function, and the calculation formula is

$$\delta_{ij}=\omega(t)\left|zbest-10rand(1,3)\right| \quad (6)$$

$$\omega(t)=\frac{\text{MaxIter}-t}{\text{MaxIter}} \quad (7)$$

Where, *zbest* means global optimum; *rand*(1,3) denotes generating real numbers that are uniformly randomly distributed over [1,3]; $\omega(t)$ is the weight function value of the t-th iteration, which linearly decreases from 0.9 to 0.1 with the increase of iteration times, and t is the current iteration times; MaxIter is the maximum number of iterations.

(2) Determination of search direction

After determining the search step size, it is determined whether the search direction is the egoistic direction $d_{i,ego}$, altruistic direction $d_{i,alt}$ or the preactive direction $d_{i,pro}$ by comparing the i-th individual with the individual best and the global best, which is expressed as

$$d_{i,ego}(\text{t})=\text{g}_{i,best}-x_i(\text{t}) \quad (8)$$

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$$d_{i,alt}(t) = z_{i,best} - x_i(t) \tag{9}$$

$$d_{i,pro}(t) = x_i(t_1) - x_i(t_2) \tag{10}$$

Where, $g_{i,best}$ represents the historical optimal position of the group in the field where the i-th search individual is located; $z_{i,best}$ denotes the optimal position of the i-th search individual; $x_i(t)$ is the current position of the individual.

The search direction is determined by using the random weighted geometric mean of three directions as the standard, and the calculation formula is

$$d_i(t) = sign(\omega d_{i,pro} + \varphi_1 d_{i,ego} + \varphi_2 d_{i,alt}) \tag{11}$$

$$\omega = \omega_{\max} - t\,\frac{\omega_{\max -}\omega_{\min}}{\text{MaxIter}} \tag{12}$$

Where, ω is the inertia weight; φ_1 and φ_2 are constants, and their value ranges are uniformly distributed constants within [0,1]; t is the number of current iterations, and the value is an integer between [2,MaxIter], with the maximum weight ω_{max} and the minimum weight ω_{min}.

(3) Renewal of individual position

After determining the search step size and direction, the individual position should be updated, and the position update formula is

$$\Delta x_{ij}(t+1) = \alpha_{ij}(t) d_{ij}(t) \tag{13}$$

$$x_{ij}(t+1) = \Delta x_{ij}(t+1) + x_{ij}(t) \tag{14}$$

3. CONSTRUCTION OF LIQUID HOLDUP PREDICTION MODEL

3.1 Model Building

Combined with the theoretical basis of each algorithm, GA, PSO and SOA algorithms are used to optimize the initial weights and thresholds of BPNN models, and the liquid holdup prediction models BPNN, GA-BPNN, PSO-BPNN and SOA-BPNN are constructed. The specific model construction process is shown in Figure 2.

The main steps of optimizing BP neural network with SOA algorithm are as follows:

Step 1: Preprocess the sample data, determine the structure of BP neural network and initialize the connection weights and thresholds of each layer of BP neural network.

Step 2: initializes the population size, population individuals, iteration times, maximum and minimum membership degrees and the maximum and minimum values of weights of the population search algorithm.

Step 3: uses the error between the predicted value and the real value obtained by the trained BP neural network as the fitness value, substitutes the sample data into the fitness function, and calculates the global optimum, the individual optimum, the individual optimum fitness and the global optimum fitness.

Step 4: initializing the empirical gradient direction, determining the search step size and the search direction, determining the search strategy, updating the position of the calculated step size and the direction, updating the individual and global optimum and optimum fitness values until the iteration satisfies the termination condition, and outputting.

Step 5: assigning the optimal network weight value and threshold value to the initial weight value and threshold value of BP neural network.

Step 6: BP neural network training, initializing network parameters, calling Levenberg-Marquardt function as training function, after training, input sample data into the model for prediction, obtain prediction accuracy value, analysis results.

3.2 Model Validation Indicators

In order to validate the prediction effect of the model, two evaluation parameters, RMSE and MAPE are introduced to evaluate the prediction performance of the model. Among them, the closer the root mean square error is to 0 and the smaller the average absolute percentage error value is, the higher the prediction accuracy of the model is proved. The calculation formula is:

$$RMSE = \sqrt{\frac{1}{M}\sum_{i=1}^{M}\left(y_i - f\left(x_i\right)\right)^2} \tag{15}$$

$$MAPE = \frac{1}{M}\sum_{i=1}^{M}\left|\frac{y_i - f(x_i)}{y_i}\right| \times 100\% \tag{16}$$

Where, M represents the number of sample sets; y_i is the actual value; $f(x_i)$ is the predicted value.

4. EXAMPLE CALCULATION

4.1 Collection and Processing of Sample Data

In order to establish a high-precision and widely adaptable liquid holdup calculation model, it is an important prerequisite to establish a rich indoor experimental database, which follows the following data screening principles: (1) the parameter change range is as large as possible to ensure that the established liquid holdup calculation model has strong adaptability and good calculation accuracy under different working conditions; (2) There are as many factors influencing the liquid holdup as possible, so as to ensure good learning effect in the data training stage. Based on the above principles, the experimental data of gas-liquid two-phase flow research by scholars at home and abroad are widely counted, and some independent experimental data are obtained (Beggs *et al*., 1973; Payne *et al*., 1979; Van *et al*., 1977; Andrisos., 1986; Guler., 1991; Abdul *et al*., 1996; Badie *et al*., 2000; Wang *et al*., 2015; Xu *et al*., 2009; Minami *et al*., 1987). The results are shown in Table 1.

Taking horizontal pipeline as an example, Six factors, such as pipe diameter, gas phase velocity, liquid phase velocity, pressure, viscosity and temperature, which have the greatest influence on liquid holdup of horizontal pipeline, are selected as influencing variables. Based on SOA optimized BP neural network algorithm, a prediction model of liquid holdup of gas-liquid two-phase flow is established. Where, 32 groups of data are randomly selected as training samples, and the remaining 5 groups are used for accuracy verification.

4.2 Model Parameter Setting

Under the condition of AMD Ryzen 7 4800U CPU @ 1.80 GHz, memory 16.0 GB and windows 10 operating system, the mathematical model is simulated and solved by Matlab R2020a software. The training times of BP neural network is 1000 times, the learning rate is 0.01, the minimum error of training target is 0.00001, the initial SOA algorithm population size is 20, and the maximum iteration times is 20. The Levenberg-Marquardt function is selected to train BP neural network, and the weights and thresholds of BP neural network are continuously optimized through iterative calculation. In this model, the input layer has 6 parameters, which are pipe diameter, gas phase conversion velocity, liquid phase conversion velocity, pressure, viscosity and inclination angle. Because the output layer is liquid holdup, the output layer is set to 1. The number of neurons in hidden layer is determined according to Equation 17. The number of neurons in the optimal hidden layer is determined by the trial value, and the results are shown in Table 2.

$$m = \sqrt{n + l} + \alpha \tag{17}$$

Where m is the number of hidden layer nodes, n is the number of input layer nodes, l is the number of output layer nodes, and α is a constant between 1 and 10.

As can be seen from Table 2, the optimal number of hidden layer nodes is 3, and the corresponding mean square error is 0.0171. Therefore, set the network structure of the model to 6-3-1.

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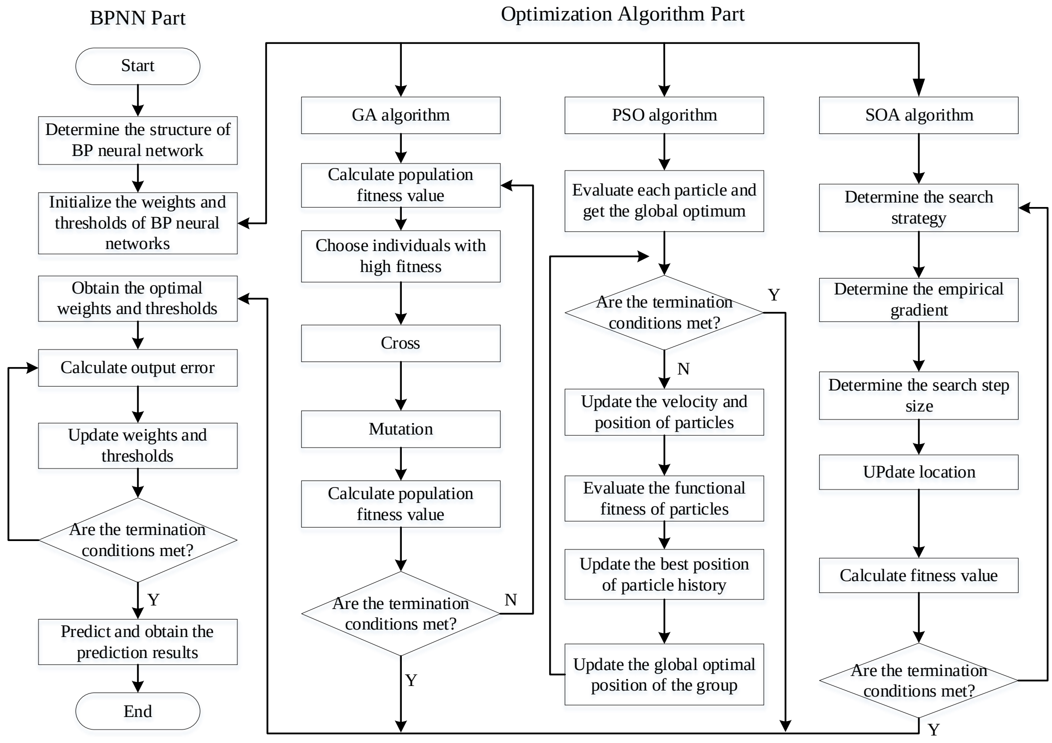

Fig. 2 Flow chart of each prediction model

Table 2 m Mean square error of training with different values

m Value	Mean Square Error	m Value	Mean Square Error
3	0.0171	8	0.0572
4	0.0809	9	0.0208
5	0.0539	10	0.0572
6	0.0397	11	0.0265
7	0.0321	12	0.0220

4.3 Forecast Results and Error Test

The prediction results of BPNN, GA-BPNN, PSO-BPNN and SOA-BPNN for liquid holdup are shown in Table 3, and the relative errors are shown in Figure 3. It can be seen from Tab. 3 that the predicted value of SOA-BPNN liquid holdup prediction model is the closest to the experimental value, and the prediction effect is the best. Compared with the single BPNN model, the prediction accuracy has been greatly improved, and it is better than PSO-BPNN and GA-BPNN prediction models.

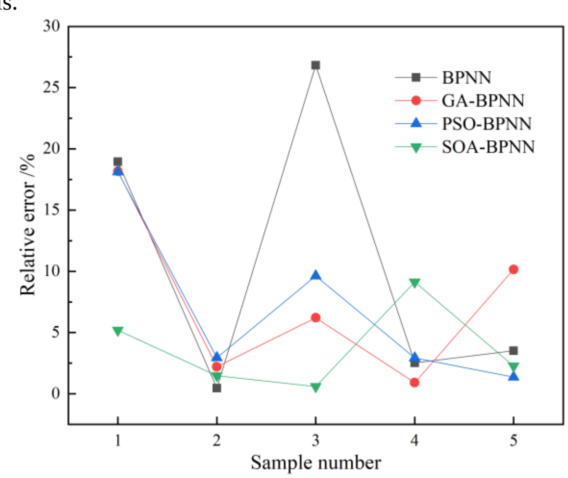

Fig. 3 Error curve of prediction result

It can be seen from Table 3 that the maximum relative error of liquid holdup predicted by BPNN model is 26.8196%, and the average relative error is 10.4545%; The maximum relative error of GA-BPNN model is 18.1689%, the average relative error is 7.5305%; The maximum relative error of PSO-BPNN model is 18.1293%, the average relative error is 7.0027%; The maximum relative error of SOA-BPNN model is 9.1373%, and the average relative error is 3.7351%.

In order to evaluate the accuracy and superiority of the precision prediction model constructed in this paper more intuitively, two error indexes, Root Mean SquareError (RMSE) and Mean Absolute Percentage Error (MAPE), are selected to measure the difference between the predicted value and the real value, and compared with WOA-BPNN. The results are shown in Table 4. It can be seen from Table 4 that the average absolute percentage error and root mean square error of SOA-BP model are 3.7351% and 0.0113, respectively, which are far lower than other models, and the prediction results are ideal.

Table 4 Error analysis table of each model

Model	MAPE（%）	RMSE
BPNN Model	10.4545	0.0208
GA-BPNN Model	7.2918	0.0234
PSO-BPNN Model	7.0052	0.0135
SOA-BPNN Model	3.7351	0.0113
WOA-BP Model (Xiao *et al*., 2022)	4.50	0.0121

Therefore, using SOA-BPNN model to predict liquid holdup has certain feasibility and superiority. Because this paper randomly selected experimental data from the gas-liquid two-phase real data, the data do not affect each other, and the data coverage is wide, which provides help for future model prediction. Therefore, the prediction model in this paper can be applied to the calculation of liquid holdup of gas-liquid two-phase flow in pipe under any conditions.

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5. CONCLUSIONS

1) There is a complex nonlinear relationship between liquid holdup and its influencing parameters. In view of the advantages of BP neural network in the field of regression prediction, this paper combines SOA algorithm with BP neural network and applies it to the liquid holdup prediction of horizontal pipeline, and establishes a liquid holdup prediction model based on SOA-BP algorithm. The predicted results by this model are in good agreement with the experimental results, which provides a new idea for the prediction of liquid holdup.

2) BPNN, GA-BPNN, PSO-BPN and SOA-BPNN models are used to train and predict the experimental data of liquid holdup in horizontal pipeline. The Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) of SOA-BP model are 3.7351% and 0.0113, respectively, which are better than those of other models. It is proved that SOA-BPNN model has high accuracy in predicting liquid holdup.

Table 1 Part of liquid holdup data of horizontal pipe

Number	*Pipe Diameter /mm*	*Gas Phase Velocity /m.s^{-1}*	*Liquid Phase Velocity /m.s^{-1}*	*Pressure /mPa*	*Temperature /℃*	*Liquid Phase Viscosity /mPa.s*	*Liquid Holdup*
1	50.8	0.459	0.102	0.7688	42.2	1.49	0.5225
2	38.1	1.259	1.177	0.225	47.78	1.33	0.5
3	77.9	13.4469	0.1676	0.3123	40.56	1.37	0.0866
4	50.8	1.064	0.109	0.5474	46.7	1.36	0.3655
5	95.3	12.65	0.1676	0.102	15	1.82	0.2096
6	25.2	10.25	0.0017	0.0987	26	1.61	0.1121
7	50.8	3.085	0.7	0.9142	43.3	1.46	0.2742
8	38.1	0.454	1.155	0.115	47.22	1.35	0.71
9	95.3	9.3	0.1097	0.0996	15	1.82	0.1928
10	50.8	1.951	1.321	0.5902	41.1	1.52	0.402
11	95.3	24.03	0.175	0.177	15	1.82	0.1477
12	25.2	4.94	0.0018	0.0986	26	1.61	0.0494
13	38.1	0.677	1.137	0.129	47.78	1.33	0.62
14	25.2	12.62	0.0018	0.0989	26	1.61	0.06
15	77.9	14.54	0.0335	0.2827	37.78	1.41	0.0253
16	77.9	11.9	0.3024	0.4875	40	1.37	0.1112
17	50.8	0.315	0.004	0.9101	35	1.72	0.3527
18	77.9	13.54	0.0978	0.2979	37.78	1.41	0.0614
19	25.2	3.51	0.0017	0.0986	26	1.61	0.1464
20	50.8	16.621	0.555	0.3289	45	1.41	0.0714
21	50.8	10.291	0.301	0.3365	27.8	1.99	0.1191
22	50.8	6.149	0.35	0.7757	35	1.72	0.157
23	38.1	1.524	2.213	0.172	50	1.27	0.6
24	38.1	0.613	2.231	0.15	47.78	1.33	0.79
25	95.3	3.65	0.1052	0.0994	15	1.82	0.3336
26	77.9	7.6654	0.5307	0.3489	41.11	1.36	0.178
27	38.1	1.948	1.158	0.239	47.22	1.35	0.41
28	25.2	7.12	0.0018	0.0986	26	1.61	0.1221
29	38.1	0.396	2.231	0.143	47.78	1.33	0.87
30	95.3	6.45	0.11	0.0994	15	1.82	0.2367
31	95.3	9.78	0.031	0.766	44.4	1.43	0.3364
32	50.8	0.733	0.128	0.7529	37.8	1.63	0.4619
33	95.3	4.49	0.1122	0.0994	15	1.82	0.3105
34	38.1	1.082	2.231	0.279	48.89	1.3	0.66
35	77.9	10.3739	0.5118	0.4151	40	1.37	0.1372
36	25.2	2.15	0.0017	0.0986	26.5	1.6	0.157
37	50.8	0.787	0.1597	0.0996	15	1.82	0.236

Table 3 Analysis of relative error results

Number	*Experimental value*	*BPNN*		*GA-BPNN*		*PSO-BPNN*		*SOA-BPNN*	
		Predicted value	*Relative error /%*	*Predicted value*	*Relative error /%*	*Predicted value*	*Relative error /%*	*Predicted value*	*Relative error /%*
3	0.0866	0.1030	18.9522	0.1023	18.1689	0.0709	18.1293	0.0911	5.1864
13	0.6200	0.6171	0.4651	0.6063	2.2112	0.6383	2.9516	0.6109	1.4727
19	0.1464	0.1071	26.8196	0.1373	6.2072	0.1323	9.6311	0.1473	0.6019
25	0.3336	0.3420	2.5180	0.3366	0.9103	0.3434	2.9376	0.3641	9.1373
32	0.4619	0.4781	3.5175	0.4150	10.1546	0.4682	1.3639	0.4514	2.2771

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