Landing position prediction model for hydraulic monitors based on the genetic BP neural network

Ning Li, Wenrui Hao, Jiangming Kan

***Abstract*—**Automatic-orientating fire extinguishing is significant to the development of fire-fighting equipment, and the key issue is to accurately predict the landing position of the water jet. The landing positions of water jet are affected by multiple factors. A hydraulic jet experimental system was established to measure the landing positions under different conditions by changing the height of the hydraulic monitor, pitch angle, horizontal angle and hydraulic pressure. Meanwhile, data about the effect factors are collected, including the real-time flow, wind speed, wind direction and temperature. The BP neural network is widely used in prediction, which is good at addressing the non-linear data relationship. However, it has drawbacks such as the low convergence speed and the flaw of entering a local optimum. The genetic algorithm has a strong global searching ability, which is commonly used to optimize the weights and thresholds of BP neural networks. Therefore, the prediction model is proposed based on BP neural network, which was optimized by genetic algorithm. The simulation results demonstrate that the prediction model of GA-BP neural networks improve the prediction accuracy. The correlation coefficient between the output of GA-BP network and the target value was 0.97. Consequently, the prediction model well reflects the nonlinear relationship between the input factors and the landing position and is an effective method to predict the landing position of the water jets of hydraulic monitors.

***Keywords*—** neural networks; prediction model; genetic algorithms; landing position of water jets

I. INTRODUCTION

Fire can rapidly spread and is a strong destructive force, particularly in the fire-fighting process, which poses a great threat to the life safety of fire fighters. Developing remote-control fire-fighting equipment with an automatic positioning function is an effective method to solve these problems because firefighters can remotely control this type of equipment using electronic instruments. To satisfy the demand of high efficiency and accuracy of fire control, precise and fixed-point fire-fighting has become an important issue in the research of fire-extinguishing equipment, but how to accurately spray water to the ignition point is the precondition and key point. At present, most studies on fire-fighting equipment of water jets focus on the characteristics of the jet and identification of the jet trajectory. The main methods include image processing based on machine vision and jet trajectory model based on the motion equation. Chen Jing, Yang Jie et al identified the jet trajectory using image technology from the computer vision angle to achieve the positioning of the jet. The jet trajectory equation of the fire gun was deduced, and the theoretical model was established by Wan Feng [6] and Min Yonglin [7] et al. based on the particle kinematics, exterior ballistics theory and measured trajectory curve of the fire gun jet. By analyzing the force of the jet, the differential equation of the jet motion of the fire gun was calculated by Sun Jian [8], and the simulation model of the jet trajectory was built using Simulink.

BP neural network has unique advantages in addressing nonlinear relations and is a widely used prediction model[11-12].However, if the initial weights and thresholds of the BP neural network are not properly selected, the convergence speed will be slow, and the local optimum value will appear[13].Considering the complex nonlinear relationship among the equipment parameters, environmental factors and landing position of the water jet, this paper uses the genetic algorithm to optimize the BP neural network to establish a prediction model of the landing position. First, the experimental platform of water jet is set up to collect the coordinate of the landing point under different conditions and the data of influencing factors. Then, the BP neural network prediction model and BP neural network prediction model optimized by genetic algorithm are constructed, the prediction effect of the model is verified using experimental data, and the prediction results of the two models are compared and analyzed. This study provides a theoretical basis for the development of more accurate fixed-point fire-fighting equipment.

II. METHODS

A. Plantform

In the water jet experiment data acquisition, the fire-fighting equipment of LH400CUV fire vehicle, which was made by Jiangsu Linhai Power Machinery Company was selected as the research object. On this basis, the experimental platform was built. The structure of the experimental system is shown in Figure 1. Figure 1 (a) shows the direction of the water jet and information transfer of the experimental system. Figure 1 (b) shows the schematic diagram of the experimental platform. In Figure 1 (a), the black arrow indicates the direction of water jet.

This work is supported by the Fundamental Research Funds for the Central Universities (Grant No. TD2013-4) and Beijing municipal construction project special fund.

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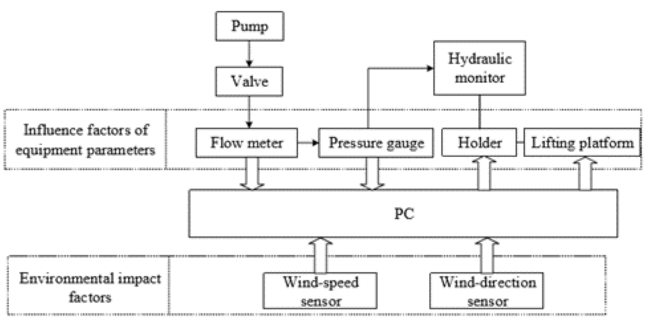
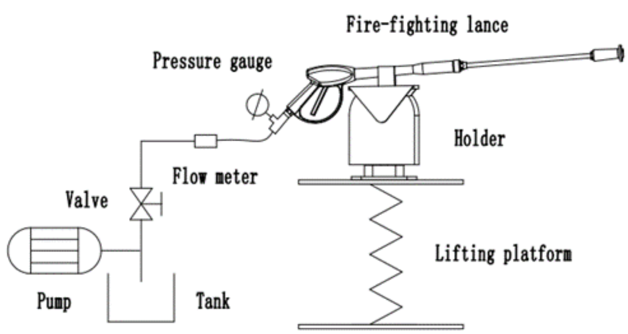
Water from the water tank enters the pipeline though the gasoline pump. The accessed pressure regulating valve is used to adjust the pressure to collect experimental data at different pressures; the flow sensor is connected to the pipeline to measure the flow information; the pressure sensor is installed at the water inlet of the hydraulic monitor to obtain the pressure signal. In the initial state, the hydraulic monitor is fixed on the pan tilt and parallel with the ground. In the experiment, the pitch angle and horizontal angle of the pan tilt were adjusted to perform the jet experiment under different postures of the hydraulic monitor. The bottom of the pan tilt was fixed on the lifting platform with an adjustable height. The height of the hydraulic monitor could be changed by adjusting the height of the lifting platform. The hollow arrow indicates the direction of information transmission. A PC terminal can send command to receive the real-time signal collected by the pressure, flow, wind speed, wind direction and temperature sensors to set or adjust the angle of the pan tilt. The lifting platform is driven by the motor, and its height is adjusted by controlling the motor.



(a)



(b)

Fig. 1 Structure of the experiment system

B. Data acquisition

In this paper, the selection of influencing factors mainly considers two aspects: equipment parameters and the environment. The former includes the height of the hydraulic monitor (h), horizontal angle (α), pitch angle (β), pressure (p), and flow (q). The latter includes wind speed (v) and wind direction (θ). In total, there are seven factors. The experiments are performed by changing height of hydraulic monitor, pitch angle, horizontal angle and pressure. Each experiment changed the value of one variable, and the other variables remained unchanged. The equipment parameters were adjusted to the expected value. We waited for the water jet to stabilize and record the landing position coordinate and real-time environmental impact variables. The values of experimental variables are shown in Table 1.

Table 1 Experiment parameters

Factors	Value										Level
Height (m)	1.5	1.75	2	2.25							4
Pitch angle (°)	-20	-10	0	10	20	30	40	45	50	60	10
Horizontal angle (°)	-15	0	15								3
Press (MPa)	0.5	0.6	0.7	0.8							4

This study used a complete experiment, where 480 sets of data were collected according to the product of the levels in the table. To conveniently record the landing position, the projection point of the hydraulic monitor outlet on the ground was selected as the origin. The orientation of the hydraulic monitor was in the positive y direction when the horizontal angle is zero. The water jet was decomposed into x and y components, i.e., each landing position corresponds to a coordinate (x, y).Therefore, each group of data contains nine values: seven factors and the coordinates of two landing positions. The wind direction was 0~5 electrical signal, which corresponds to 0-360 degrees in geographic azimuth from the north. Considering the wind effect, we had to use the difference in geographic azimuth corresponding to the wind direction angle and the initial status of the hydraulic monitor to obtain the angle (θ). The wind effect was also decomposed to x and y directions. The factors that define the variable wind are:

$$w_x = v \times \sin\theta$$
$$w_y = v \times \cos\theta \quad (1)$$

To weaken the effect of the dimension of experimental data on the network training and prediction, we normalized the raw data of each input and output variable and make them distribute in the range of [-1,1]. Thus, we obtained the required input variables (h, α, β, p, q, w_x, w_y) and output point (x, y) to build the model.

III. PREDICTION MODELS

A. BP neural networks

BP neural network is a multilayer feedforward neural network. The basic principle is to use the gradient descent method to correct the weights and thresholds to minimize the error between the network output value and the expected value [13].

In this study, the three-layer BP neural network model is used: the transfer function of the hidden layer is S tangent function tansig, and the output layer function is purelin. There are 7 input layer neurons, i.e., the seven described input variables. There are two neurons in the output layer: the coordinates of the two directions. The hidden layer determines the approximate value range according to the previous experience.

$$n = \sqrt{n_i + n_o} + a \tag{2}$$

Where n is the number of nodes in the hidden layer, n_i is the number of nodes in the input layer, no is the number of nodes in the output layer, and a is an integer between 1~10.

Because there is no explicit method to select the hidden nodes in the theory, a trial calculation was used to ensure the effect of the neural network prediction. According to Formula (2), we obtain the range of hidden nodes as 4~13. If the parameters of the BP neural network are not changed, the network is constructed with the number of hidden layer nodes in the range, and the same training set and test set are trained to calculate the prediction error. Table 2 shows the root mean square error of the test set of the neural networks with different hidden layer nodes after 3000 trainings. For comparison, the hidden layer takes 12 neurons to predict the minimum network error.

Table 2 Comparison of the mean square error with different hidden layers

B. BP neural network optimized by GA

BP neural network is a widely used prediction model, but it has many problems, for example, the speed of convergence is slow and the local minimum is easy to fall into. The GA does not easily fall into a local optimum in the search process, i.e., the global optimum can be obtained with a larger probability. Therefore, in this study, the GA is used to optimize the weights and thresholds of BP neural network to achieve better prediction results. The flow chart is shown in Figure 2.

Table 1 Experiment parameters

Hidden layers	4	5	6	7	8
MSE	0.0177	0.0128	0.0150	0.0149	0.0160
Hidden layers	9	10	11	12	13
MSE	0.0139	0.0154	0.0223	0.0124	0.0162

The specific steps of the GA to optimize the weights and thresholds of BP neural network are:

1) Individual coding and population initialization

All weights and thresholds in the BP neural network are arranged into a string in a certain order to form an individual. The randomly generated individuals can be obtained by coding; then, the initial population is obtained. In this paper, the actual coding is used to encode the individual. The length of coding S is the length of the chromosome, which can be obtained in Formula (3):

$$S = R \times S_1 + S_1 \times S_2 + S_1 + S_2 \tag{3}$$

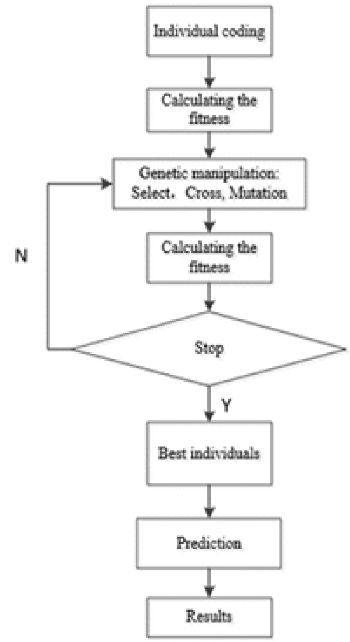


Fig. 2 Flow chart of the GA-BP algorithm

Where R is the number of nodes in the input layer, S1is the number of nodes in the hidden layer, and S2is the number of nodes in the output layer.

Generally, with a larger population size, the global optimum is more easily found, but the running time of each iteration is longer. The population size is generally in the range of 40-100, and this study set the population size at 50.

2) Setting of the fitness function

The fitness function plays an important role in the selection process, and the fitness value directly affects the probability of the individual being retained. In this paper, the fitness function is:

$$\mathrm{F} = \frac{1}{\mathrm{E}} \tag{4}$$

Where E is the root mean square error between the predicted output and the actual value of the network. According to this formula, a more accurate prediction result has a larger fitness value.

3) Individual choice

The purpose of the selection is to select the good individuals with good fitness to propagate the next generation from the current population, and the selection operation can improve the global convergence. The selection method in this study is the roulette selection method, where the individual fitness determines the probability of retention. The probability of individual selection is:

$$P_i = \frac{f_i}{\sum_{k=1}^{s} f_k} \quad (i = 1, 2, \ldots, s) \tag{5}$$

Where f_i is the fitness of the ith individual, s is the number of individuals in the population, and $\sum_{k=1}^{s} f_k$ is the sum of individual fitness of the population.

To not destroy the individuals of the best fitness in population because of the randomness of the crossover operation and mutation, we used the optimal preservation strategy in the GA: the individuals with the lowest fitness after the GA are replaced by individuals with the best fitness in the population.

4) Crossover

Crossover is the process of generating new individuals through the exchange of two pairs of paired chromosome genes in a parent population. Whether crossover is performed is determined by the crossover probability. In this study, the real coded arithmetic crossover method is used, and the crossover operation is shown in Formula (6):

$$X_A^{i\,'} = \alpha X_B^i + (1-\alpha) X_A^i$$
$$X_B^{i\,'} = \alpha X_A^i + (1-\alpha) X_B^i \qquad (5)$$

Where α is a random number in the range of 0-1; X_A and X_B are a pair of randomly selected chromosomes in one generation; X_A^i and X_B^i are genes on the cross positions, which are randomly selected on the chromosomes, $i \in [1, S]$ (S is the chromosome length); $X_A^{i'}$ and $X_B^{i'}$ are the new genes at the corresponding position after the crossover.

5) Mutation

Mutation is an indispensable step in the genetic algorithm, which can maintain the diversity of the population and prevent premature convergence. The non-uniform mutation operator can make the search step adaptively adjust with different evolutionary stages, and the search range decreases with the increase in evolutionary algebra; the principle is as follows:

$$\begin{cases} X_A^{i\,'} = X_A^i + \left(U_{max} - X^i\right) \times \gamma & \beta \ge 0.5 \\ X_A^{i\,'} = X_A^i - \left(X^i - U_{min}\right) \times \gamma & \beta < 0.5 \end{cases} \qquad (7)$$

where $\gamma = [r \times \left(1 - \frac{t}{t_{max}}\right)]^2$; r is a random number in the range of 0~1;t is the current evolutionary algebra; t_{max} is the maximum evolutionary algebra; β is a random number in the range of 0~1; X^i is a gene selected for mutation at the position of chromosome variation; $X^i \in [U_{min}, U_{max}]$; $X^{i'}$ is the new gene after mutation.

6)Loop

We determine whether the set of precision requirements or the number of iterations is reached; if not reached, we continue to cycle steps 2~5. If the termination condition of the loop is reached, we select and decode the best individual to assign values to the weights and thresholds of the BP neural network, and the prediction model of BP neural network after training is used to predict the test set samples and output the results.

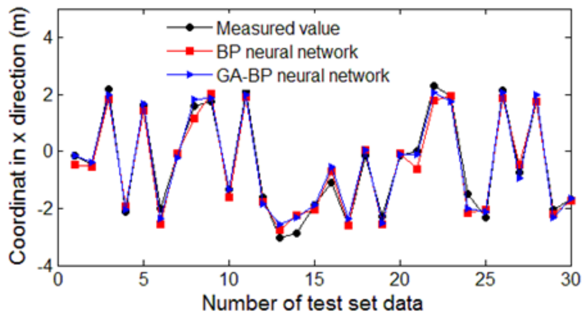
IV. PREDUCTION RESULTS AND ANALYSYS

In the Matlab2014b environment, the Matlab neural network correlation function was used to design the prediction model using the BP neural network and GA-BP neural network. Then, the former model is called BP neural network, and the latter model is called the GA-BP neural network. To conveniently compare the prediction effect of the two models, the network structure and part parameters of the GA-BP neural network are identical to those of the BP neural network. The maximum evolution algebra is 50, the crossover probability is 0.3, and the mutation probability is 0.05.The weights and thresholds of the BP neural network are obtained according to the genetic optimization steps in the previous section and shown in Table 3.

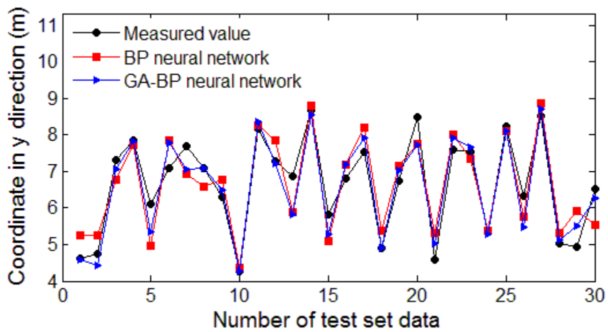
Table 3 Weights and thresholds of BP neural networks optimized by the genetic algorithm

Weights Between inputs and hidden layers							Thresholds
2.378	2.099	-1.952	-1.202	-0.370	-0.890	-1.029	1.537
2.123	2.307	-2.053	1.956	1.269	2.093	-2.448	0.040
1.806	1.889	1.284	-0.900	1.543	-1.629	0.887	2.234
1.656	0.232	1.677	-1.113	0.196	-1.229	-1.451	1.387
1.120	0.966	0.621	-1.988	1.473	0.175	0.998	-1.076
2.483	1.943	0.824	-1.897	1.549	0.490	2.033	1.105
-2.114	-1.144	1.005	-1.132	0.850	1.229	1.959	-1.510
-1.916	-0.996	-1.601	1.911	1.456	1.297	-1.294	-1.852
-0.641	-1.663	1.291	-1.388	-1.721	1.335	1.124	0.524
-0.558	1.127	1.677	1.307	-1.261	-2.016	1.974	-1.449
0.743	-2.464	-2.271	0.816	0.635	1.956	1.120	2.317
1.271	1.199	2.380	-1.853	1.993	0.017	-0.496	-0.759
-0.289	1.540	-1.396	-1.006	1.287	0.402	-0.532	-1.923
0.631	-1.739	-2.139	-2.399	-0.724	-1.873	-1.478	-0.659
-1.544	2.033	-2.383	-0.627	0.313	2.341	-2.311	
-2.317	0.617	-1.677					

The weights and thresholds obtained by the GA were substituted into the BP neural network to train the samples. In total, 450 groups were randomly selected from 480 sets of data as network training samples, and the other 30 groups were used as the test set. Two sets of prediction models were used to predict and contrast the landing position coordinates of the water jet in the same test set.



(a) Comparison of the landing position in the x direction



(b) Comparison of the landing position in the y direction

Fig. 3 Comparison of the predicted and measured landing positions of the water jet

The predicted results of the randomly selected test set data in two directions using two methods and the actual values are compared in Figures 3 (a) and (b).According to the selected factors, the predictive value of the prediction model established by GA-BP neural network in two directions is closer to the measured value. The error distance between the predicted landing position of the test set data and the actual landing position was calculated from the offset in two directions, as shown in Figure 4.

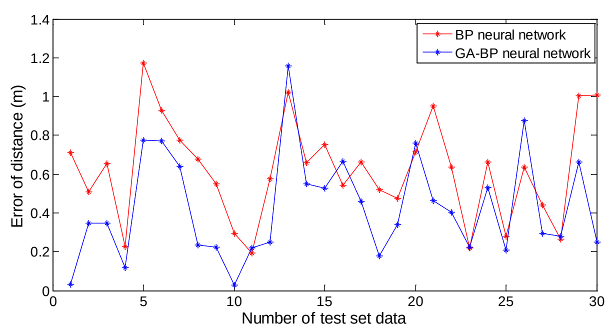


Fig. 4 Comparison of the error of distance

To evaluate the forecasting effect of the entire model, in this study, the mean error distance between the predicted landing position and the actual landing position of the test set data is used as an index to evaluate the prediction effect of the neural network, as shown in Formula (8):

$$\sigma_d = \frac{1}{m}\sum_{i=1}^{m}\sqrt{(x_{pi}-x_i)^2+(y_{pi}-y_i)^2} \quad (8)$$

where x_{pi} and y_{pi} are the neural-network-predicted landing position coordinates of the ith group experiment in the test set; and x_i are y_i the experimentally measured landing position coordinates; m is the test set sample number(30).

In addition, the ratio of the landing error distance and the distance from the actual landing position of water jet to the origin is used as the relative error. The average relative error of each group in the test set is used as the evaluation index, and its definition formula is as follows (9):

$$\delta_d = \frac{1}{m}\sum_{i=1}^{m}\frac{\sigma_{di}}{d_i}\times 100\% \quad (9)$$

where σ_{di} is the predictive error distance of the ith group experiment in the test set; d_i is the distance from the actual landing position of the water jet to the origin in the same group; $d_i=\sqrt{x_i^2+y_i^2}$ .The evaluation indices of the two models are shown in Table 4.

Table 4 Evaluation of two types of prediction models

Index	BP neural networks	neural networks
Relative error of distance	9．61%	6.30%
Mean error of distance(m)	0.624	0.427

Table 4 shows the index prediction results of the GA-optimized BP neural network are superior to those of the BP neural network model. Hence, the GA can optimize the BP neural network weights and thresholds, and the GA-BP neural network prediction model is more accurate. In combination with Figure 4, the BP network prediction has larger prediction errors at the regions with relatively more data points, whereas the GA-BP model prediction results basically remain at a small error level.

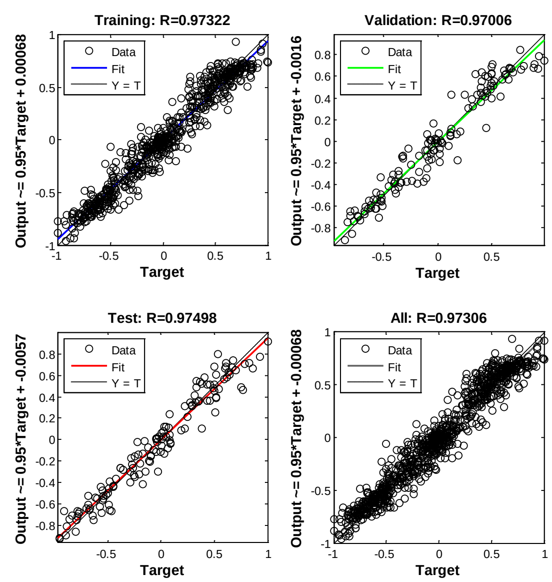


Fig. 5 Regression lines of the network output of training samples

Figure 5 shows the regression line of the output value Y and target value T of the GA-BP neural network model. The chart shows that the network output values on both sides of the distribution are in good linear regression. The regression coefficient R is 0.97, and the regression line coincides with the straight line with a slope of 1, which shows that the established GA-BP neural network prediction model in this paper has a notably small deviation between the output value and the target value and is an effective prediction method.

V. CONCLUSION

1) The BP neural network to predict the water jet landing position of the hydraulic monitor and the GA-BP neural network model based on GA to optimize the weights and thresholds of the BP neural network are established in this study. The prediction results of different models are experimentally compared and analyzed. The simulation results show that all evaluation indices of the GA-BP model are better than the BP neural network model, which shows that the GA effectively optimizes the BP neural network model.

2) Using the established model to predict the water jet landing position data of 30 randomly selected groups, the correlation coefficient of the output and target value of the GA-BP neural network model is 0.97, which shows that the model can effectively predict the landing position coordinates with high prediction ability and precision.

3) There are multiple influencing factors such as the water jet equipment parameters and external environmental factors. There is a complex nonlinear relationship between the influencing factors and the landing position. The prediction model of the water jet landing position based on the genetic BP neural network can be applied to the fire-fighting process to precisely adjust the attitude of the hydraulic monitor and provides a basis for further developments of automatic fix-point fire-fighting equipment.

REFERENCES

[1] Ma Yan, Zhang mingsong, Yang chunmei, et al. Analysis of forest fire hazards and important means of fighting fires. Forest Engineering, 2013, 29(6), 25-27. (in Chinese with English abstract)

[2] Zhang Yonggao, Li Yinling, Hu Aihua, et al. Design of a New Type of Control System for Free-swing Fire Monitor[J]. Industry and mine automation, 2010,4:33-35. (in Chinese with English abstract)

[3] Liu Shenyou, Yuan Hongyong, Su Guofeng, et al. Automatic orientating fire extinguishing Monitor[J].China safety science journal, 2001,11(2),38-41. (in Chinese with English abstract)

[4] Chen Jing, Zhao Min. Image segmentation and recognition algorithm for the fire cannon’s jet trajectory[J]. Electronic science and technology, 2010, 23(3),43-45. (in Chinese with English abstract)

[5] Yang Jie, Zhao Min, Su Hao, et al. Jet trajectory recognition method based on the fusion with vector search method and particle swarm optimization. Journal of electronic measurement and instrumentation, 2016:30(5),803-808. (in Chinese with English abstract)

[6] Wan Feng, Chen Xiaoyang, Min Yonglin, et al. Fitting equation of the fire monitor's jet track[J]. Fire Science and Technology,2007:26(6),657. (in Chinese with English abstract)

[7] Min Yonglin, Chen Xiaoyang, Chen chi, et al. Pitching Angle-based Theoretical Model for the Track Simulation of Water Jet out from Water Fire Monitors[J], Journal of Mechanical Engineering, 2011:47(11),135-138. (in Chinese with English abstract)

[8] Sun Jian. Study on the water jet track of water fire monitors[D]. Shanghai:Shanghai Jiaotong University，2009.

[9] Pang Yonggang. Simulation Research on Control System and ballistic of a remote Forest fire Fighting Cannon[C]. International Conference on Computer, Mechatronics, Control and Electronic Engineering, Changchun, China, 2010, 394-397.

[10] Liao Xiaodong, Liu Pingan, Cheng wenyu. The jet trajectory study of fire monitor based on MATLAB[J]. Fire Science and Technology, 2014:33(10),1169-1171. (in Chinese with English abstract)

[11] Zhang Hong, Ma Yan, Li Yong, et al. Transactions of the Chinese Society of Agricultural Engineering, 2014, 30(18), 78-82. (in Chinese with English abstract)

[12] Gao Yuming, Zhang Renjin. Analysis of House Price Prediction Based on Genetic Algorithm and BP Neural Network[J]. Computer Engineering,2014:40(4), 188-191. (in Chinese with English abstract)

[13] Wang Deming, Wang Li, Zhang Guangming. Short-term wind speed forecast model for wind farms based on genetic BP neural network[J]. Journal of Zhejiang University,2012: 46(5),838-841.

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