

# BP Neural Network based on PSO Algorithm for Temperature Characteristics of Gas Nanosensor

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**Abstract**—To comprehensively understand the characteristics of gas nanosensor between temperature and sensitivity, this paper has developed a Backward Propagation (BP) neural network based on Particle Swarm Optimization (PSO), which is applied to fitting the temperature-sensitivity characteristic of the  $S_nO_2$  gas nanosensor mixed with benzene. The simulation results show the PSO can well optimize the structure of the BP network, and the fitting accuracy of the temperature of nanosensor using the acquired BP model is improved greatly and the optimized BP network has better generalization performance than the traditional BP network, and the acquired curve is both smooth and accurate, so the study shows that BP-PSO neural network is effective for fitting the temperature characteristics of gas nanosensor.

**Index Terms**—gas nanosensor, temperature characteristics, neural network, PSO

## I. INTRODUCTION

With the development of the electronic and communication technique, sensor technique has been improved greatly and sensor has become an indispensable equipment, which has found widespread applications in industry, agriculture, transportation and so on. As one of the most important branches of sensor, nanosensor has been under research by many institutions and a great number of researchers for as long as ten years. A nanosensor is a sensor built on the atomic scale based in measurements of nanometers, which are any biological, chemical, or surgical sensory points used to convey information about nanoparticles to the macroscopic world. Their use mainly include various medicinal purposes and as gateways to building other nanoproducts, such as computer chips that work at the nanoscale and nanorobots [1, 2]. Presently, there have been a number of advances in the research and development of nanosensor for a number of different applications. Some of the major applications are the medical field, national security, aerospace, integrated circuits, and many more. Along with many different applications for nanosensor, there are also many different types of nanosensor, and a number of ways to manufacture them [3]. Nanotechnology offers the

promise of improved gas sensors with low-power consumption, fast response time which will enable portability for a wide range of applications. Indeed, nanostructured materials such as nanotubes and nanowires have been shown to be suitable for sensing various gases [4]. Gas nanosensor is mainly used for testing gas density and humidity [5], currently, the majority of nanosensors are made of nano  $S_nO_2$  film, which is mixed with different heavy metal particles, it greatly enhance its freedom and flexibility. In recent years, many nanosensor researches and applications show that gas nanosensor has various advantages such as good stability, high sensitivity, fast responsibility, and high accuracy and so on. But the sensitivity of gas nanosensor is very sensitive to the temperature of environments tested, so sensitivity is considered as a impairment parameter for gas nanosensor and the measurement system simulation [6, 7].

There exists a nonlinear relationship between temperature and sensitivity in gas nanosensor, but many applications was also based on a linear computation, which resulted in big nonlinear error. So, to eliminate or compensate the nonlinear error and have a thorough understanding of the relation between temperature and sensitivity, there are some fitting models established based on test data. Liu Haiyan [8] proposed the comparison of the cubic polynomial method and the spline polynomial fitting in least square method for gas nanosensor, the simulation results show the accuracy of the cubic polynomial method is better than that of the spline polynomial fitting in least square method, and its fitting curve is smooth without any break in connections; ZENG Zhezhaoh [7] introduced the neural network algorithm with Fourier basis functions for fitting the temperature characteristics of gas nanosensor, the experiment involved inferring that the method is both smooth and accurate.

In recent decades, as a good nonlinear model, Artificial Neural Network (ANN) is widely applied to many complex nonlinear questions, and the BP neural network is one of the widest network types, which has a powerful capability to generalize the nonlinear relationship between input and desired output, but the traditional BP network can trap into local minimum and has inherent searching rate slowly when training. Guo Wenxian[9] proposed BP neural network model based on PSO was

Manuscript received Sept. 10, 2011; revised Oct. 17, 2011; accepted Oct. 28, 2011.

Project number: 2011138 and E2010001026

applied to predict river temperature of the Yangtze River, the study proved that PSO-BP neural network model was effective in river temperature prediction. Wang Ping [10] established an improved algorithm called PSO-BP, the new algorithm fully shows the ability of nonlinear approach of multilayer feedforward network, improves the performance of ANN, and provides a favorable basis for further on-line application of a comprehensive model, it is applied to mechanical property prediction of strip model, inferring excellent performance.

So, to overcome the shortcomings, in this paper, a combination of Particle Swarm Optimization is used to train and optimize the BP network structure including its weights and thresholds, it can overcome the over-fitting problem and the local minima problem of the BP neural network, and then the established BP network is applied to fitting the relationship between temperature and sensitivity in the SnO<sub>2</sub> gas nanosensor, the simulation results show the fitting curve is accurate and the BP network based on PSO is practical and effective.

## II. BP NEURAL NETWORK

As is a type of complex system, artificial neural network is made up of plenty of nerve cells, which can simulate the way that human deals with the problem, parallel process information and make nonlinear transformation. Artificial neural network handling information first is train to neural network, then composes linear functions and gain fit weight, finally completes the nonlinear processing about variety information. Under the situation of loosing of sample and parameters drifting, it can also guarantee the stable output. This characteristic of artificial neural network has been successfully used in many fields, including pattern recognition, image processing, intelligent control, optimal calculation, artificial intelligence and so on [11].

Back propagation was proposed by generalizing the Widrow-Hoff learning rule to multiple layer network and nonlinear differentiable transfer function. Input vectors and corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined in this study. The back propagation algorithm consists of two paths; forward path and backward path. Forward path contain creating a feed forward network, initializing weight, simulation and training the network. The network weights and biases are updated in backward path [12]. A typical three layers BP neural network with 4 inputs is shown in Fig. 1

In general, the implementation of the training algorithm makes use of the followed sigmoid as the output function of each node whose value is in (0, 1),

$$f(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

The error margin of the actual output  $Y$  of the BP network and expectation output  $T$  is:

$$E = \frac{1}{2} \sum_{i=1}^n (y_i - t_i)^2 \tag{2}$$

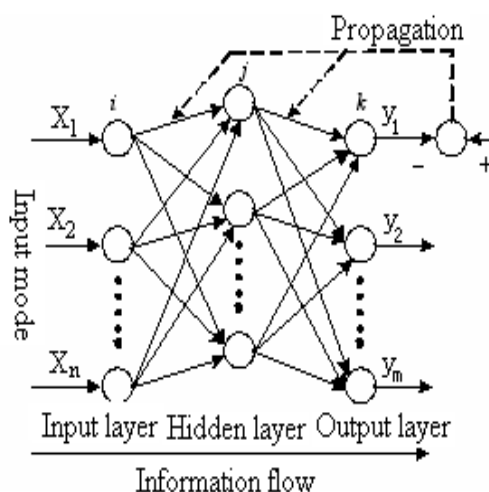


Figure 1. Structure of BP neural network

When we train a neural network with a gradient and descent method based on back propagation [13] the network is provided with a set of training samples along with their target outputs. One by one, each sample is placed into the inputs of the neural network. The resulting outputs are then compared to the target values and an error is calculated for each node, starting with nodes in the output layer and propagating backward toward nodes in the input layer. The error at an output node  $i$ , with respect to its target  $t$  and output  $o$ , is

$$\delta_i = \dot{o}(t - o) \tag{3}$$

The error at hidden node  $i$ , with respect to each of its downstream connections  $j$ , is

$$\delta_i = \dot{o} \cdot \sum_{j \in \text{Downstream}(i)} w_{ji} \cdot \delta_j \tag{4}$$

Each weight  $w_{ji}$  between nodes  $i$  and  $j$  is adjusted based on a learning constant  $\eta$ , the calculated error  $\delta_j$  at the target node  $j$  and the output  $x_i$  of the source node  $i$ .

$$\Delta w_{ji} = \eta \cdot \delta_j \cdot x_i \tag{5}$$

## III. PSO ALGORITHM

PSO is a method for performing numerical optimization without explicit knowledge of the gradient of the problem to be optimized [14, 15]. PSO is basically developed through simulation of bird flocking and fish schooling in two-dimension space which is based on a simple concept, so the computation time is short and requires few memories, and then it was originally developed for nonlinear optimization problems with continuous variables so that it is easily expanded to treat a problem with discrete variables.

The position of each individual (agent) is represented by  $XY$  axis position and also the velocity is expressed by  $v_x$  (the velocity of  $X$  axis) and  $v_y$  (the velocity of  $Y$  axis). Modification of the agent position is realized by the position and velocity information.

An optimization technique based on the above concept can be described as follows: namely, bird flocking optimizes a certain objective function. Each agent knows

its best value so far (*pbest*) and its *XY* position. Moreover, each agent knows the best value so far in the group (*gbest*) among *pbests*. Each agent tries to modify its position using the following information: the current positions (*x,y*), the current velocities (*vx,vy*), the distance between the current position, *pbest* and *gbest*.

This modification can be represented by the concept of velocity. Velocity of each agent can be modified by the following equation:

$$v_i^{k+1} = wv_i^k + c_1rand \times (pbest_i - x_i^k) + c_2rand \times (gbest - x_i^k) \tag{6}$$

where,

$v_i^k$ : velocity of agent *i* at iteration *k*,

*w*: inertia weight,

$c_j$ : weight factor,

*rand*: random number between 0 and 1,

$x_i^k$ : current position of agent *i* at iteration *k*,

*pbest<sub>i</sub>*: *pbest* of agent *i*.

Using the above equation, a certain velocity, which gradually gets close to *pbest* and *gbest* can be calculated. The current position (searching point in the solution space) can be modified by the following equation:

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{7}$$

### VI. BP NETWORK BASED ON PSO

BP network has excellent characteristics of nonlinear approximation and has been widely used in many fields, but it has the disadvantages of inherent slowly searching rate and partially leading to minimum. To improve the performance of BP network, we use PSO to optimize all weights and thresholds in BP network. So, we adopt the global searching for the optimum weights and thresholds instead of BP itself, the method will improve the solution of results and increase the convergence speed of the BP network, the flowchart of the BP based on PSO is shown in Fig. 2 and the procedure is summarized as follows:

Step 1: Normalize the training samples and test samples into [-1, 1].

Step 2: Define the network structure of BP network according to the input samples and the output samples.

Step 3: Initialize parameters *m*, *w*,  $c_1$ ,  $c_2$ ,  $\theta$ , where:

*m*: number of population,

*w*: inertia weight,

$c_i$ : weight factor,

$\theta$ : parameter of identification (coefficient of nonlinear rectification equation), the velocity and position of each particle are initialized randomly.

Step 4: Each particle's velocity is updated according to (6) and each particle's position is updated according to (7).

Step 5: Each particle's fitness is evaluated. The Mean square Error (MSE) of BP neural network is used as the fitness function to guide the particle population for searching for the optimum solution, we use all the training samples to calculate in forward propagation for

each particle, so as to generate the training error of particles with training samples.

Step 6: The personal best position *pbest* and the global best position *gbest* are updated.

Step 7: If the maximum of the iteration is achieved or the optimum solution is acquired, then the algorithm is stopped, else return to Step 4.

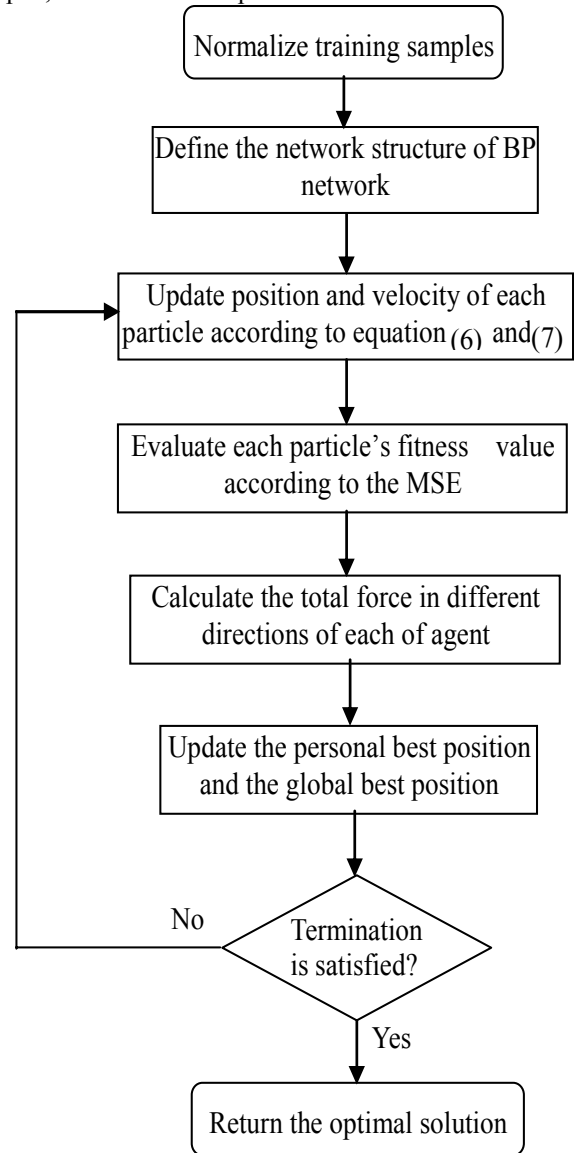


Figure 2. The flowchart of the BP network based on PSO

### V EXPERIMENT AND RESULTS

We put  $S_nO_2$  gas nanosensor with mixed with different concentration of benzene into a testing equipment whose gas density and pressure is constant, then the temperature is changed every 10°C and the sensitivity of nanosensor is recorded. The experimental results between temperature and sensitivity are list in [8].

In this paper, the BP network based on PSO is applied to fit the temperature characteristics of gas nanosensor [16], firstly, we need to determine the involved parameters, which is given as follows [9]:

$$a = 2 \times i + 1 \tag{8}$$

$$b = x \times \frac{k(m-1)}{i+k-1} \tag{9}$$

Where  $x$  is set to 2 constantly,  $k$  is the number of neurons of output layer,  $i$  is the number neurons of input layer,  $m$  is the size of the training samples, and the number of the neurons of the hidden layer  $h$  is searched in range  $[a, b]$ , so the number of parameters to be optimized by the PSO in the BP network is  $i \times h + h + h \times k + k$ . Then, the PSO algorithm we used is the standard global version with inertia weight, the population sizes the particles is set at 50, the maximum iteration is 100, the acceleration factors  $c1$  and  $c2$  are both 2.0, a decaying inertia weight  $w$  starting at 0.9 and ending at 0.2 is used.

For the comparison, the standard BP network and the BP network based PSO are both applied to the temperature characteristics of gas nanosensor, the training parameters are set as follows: learning rate is 0.02, and Momentum constant is 0.9, the weights and biases are initialized randomly. The two methods are trained with the same training samples, and the same test samples are used too in testing. The 30 sensitivity values corresponding to different temperatures are used as a dataset as shown in Table 1, of which 25 samples are as training samples, the remaining 5 samples randomly selected as test samples as validation data.

We use the training samples to train the BP network based on PSO, the final number of the hidden layer is 5, so the BP structure of the two methods is 1-5-1. Fig. 3 and Fig. 4 demonstrate the convergence process using the two methods respectively when training, Fig. 5 and Fig. 6 show the fitting results for the two methods, Table 2 summarizes the training results of the two methods using the training samples. It can be seen that the BP optimized using PSO achieve the optimal error at the iteration of 26 and the MSE is 0.00239, while the BP network achieve the optimal error at the epoch of 802 and the MSE is 0.00526. It is clear that the BP network based on PSO requires fewer training time and has faster convergence speed than the BP network, moreover, the training accuracy of the former is better than that of the latter. So, we has established a good prediction model based on the BP optimized using PSO, which is applied to predict the Sensitivity of nanosensor corresponding to the desired temperature.

TABLE I.  
THE PERFORMANCE COMPARISON OF TWO METHODS

Method	Epoch(Iteration)	Training error(MSE)
BP	802	0.00526
BP based on PSO	26	0.00239

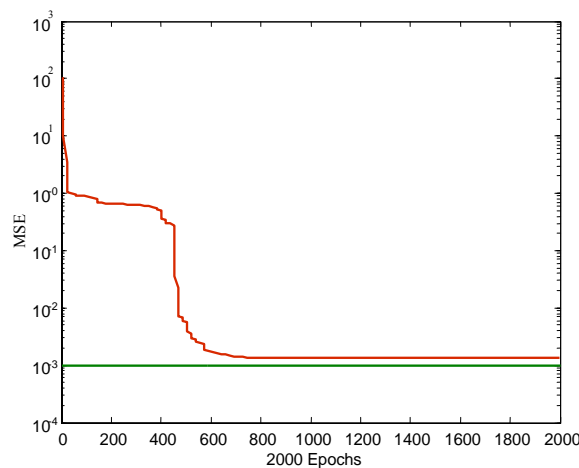


Figure 3. Convergence process of BP network

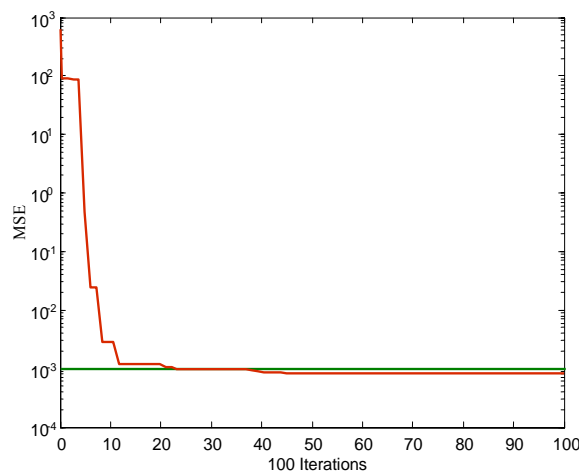


Figure 4. Convergence of BP network based on PSO

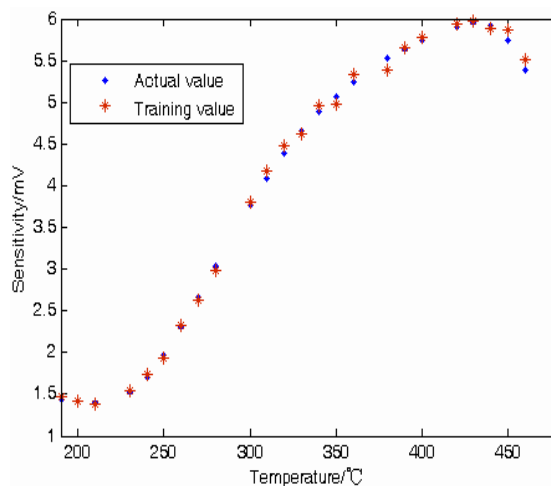


Figure 5. Fitting result of BP network

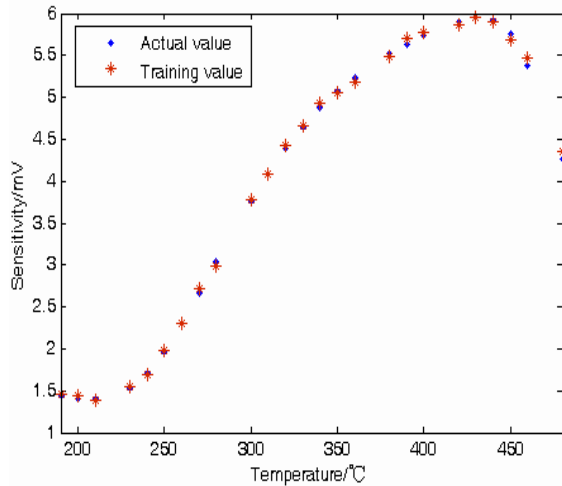


Figure 6. Fitting result of BP based on PSO

The prediction results of the remaining 5 samples using the two methods are depicted in Fig. 7 and Fig. 8 respectively, they show the prediction value of the BP network based on PSO is nearer to the diagonal line inferring its higher prediction accuracy than that of its counterpart, Fig. 9 illustrates the comparison of relative error of the test samples for the two method, it is obvious that the relative error of most of the test samples using the BP-PSO is smaller than that using the BP network except for the fifth test sample, the average relative error of BP network is 0.0126 and the average relative error of BP-PSO is only 0.0093, it proves that the proposed method has a better prediction ability than its counterpart.

We can see that the BP-PSO has a better generalization performance, whether its convergence speed or its prediction ability, this results shows the fact that the PSO has a good generalization performance and global searching for the optimum, it can refine the optimal parameters of the BP network structure, which can better reflect the nonlinear relationship between the temperature and the sensitivity of nanosensor.

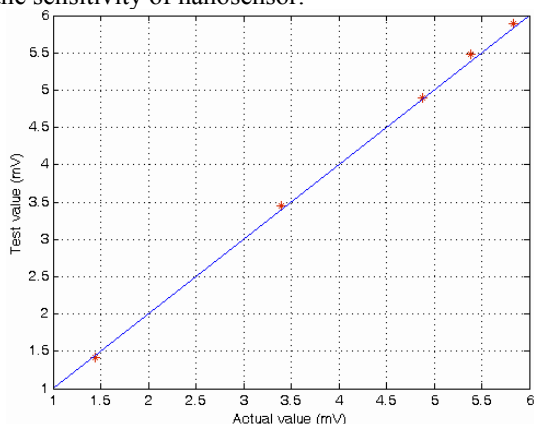


Figure 7. Predicted value versus actual value for BP network

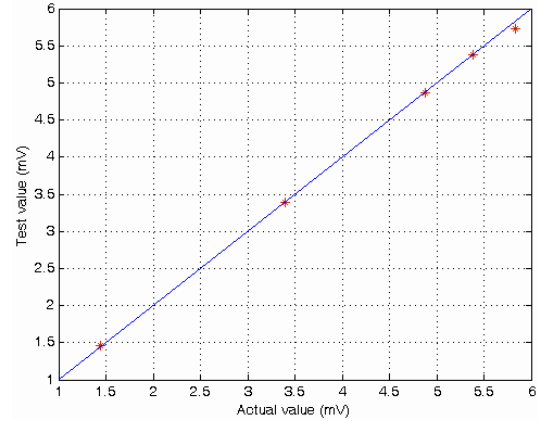


Figure 8. Predicted value versus actual for BP-PSO

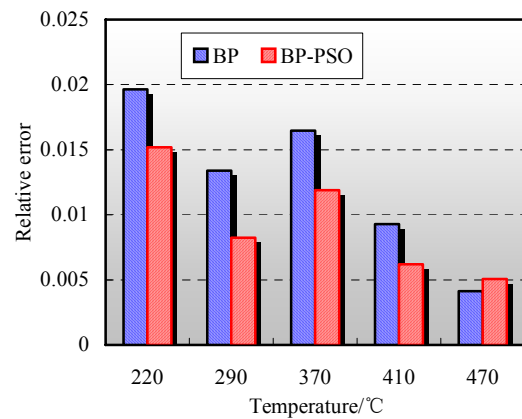


Figure 9. Comparison of relative error for two methods

#### IV. CONCLUSIONS

In this paper, we have proposed a BP neural network model whose struct is optimized using the PSO, and it is applied to fitting the temperature characteristics of the  $S_nO_2$  gas nanosensor mixed with benzene. The simulation results show the PSO can well refine the structure of BP neural network, the proposed method has greater improvement in both accuracy and convergence speed for the traditional BP neural network, so it provide a practical and effective method for gas nanosensr. Our future research is to investigate the fitting model based on on-line and apply it to gas nanosensor.

#### ACKNOWLEDGEMENTS

This work is supported by the Science and Technology Research Project of University of Hebei Province No. 2011138, and the Natural Science Foundation of Hebei Province of China No. E2010001026.

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