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ORIGINAL ARTICLE

A hybrid model using genetic algorithm and neural network for process parameters optimization in NC camshaft grinding

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Abstract Camshaft grinding is more complex comparing with the ordinary cylindrical grinding. Since its quality is mostly influenced by more factors, how to select process parameters quickly and accurately becomes the key to improve its quality and processing efficiency. In this paper, a hybrid artificial neural network (ANN) and genetic algorithm (GA) model is proposed to optimize the process parameters. In this method, a BP neural network model is developed to map the complex nonlinear relationship between process parameters and processing requirements, and a GA is used in order to improve the accuracy and speed based on the ANN model. The results show that the hybrid ANN/GA model is an effective tool for the process parameters optimization in NC camshaft grinding.

Keywords Genetic algorithm · Neural network · Camshaft grinding · Uniform design · Process parameters optimization

1 Introduction

Camshaft is a key part of the automobile engine and other internal combustion engines. Its quality and processing efficiency have a direct influence on the quality of automotive and the development of the entire automotive industry. Comparing with the ordinary cylindrical grinding, the camshaft's cam profile is usually complex, and the linear velocity of each point on the cam profile is variable when a camshaft rotates with a constant angular velocity. When machining, it is easy to form greater stress and metamorphic layer for the actual performance of fatigue cracks, wear, and parts failure in cam surface. Thus, ensuring the accuracy of a camshaft is difficult [1, 2]. Currently, many manufacturers are still using copying–grinding machines to product the camshaft. The accuracy of master form has a direct effect on the camshaft profile accuracy. Therefore, it is far from easy to ensure the consistency of the accuracy of the master forms.

As the merits of NC grinding and some requirements of the camshaft grinding including high accuracy, efficiency, and flexibility, it is an inevitable trend that traditional grinding methods are being replaced by NC grinding. However, more difficult technical problems have appeared in NC grinding; process parameters optimization is a particularly important one which is mainly achieved by the experience of skilled workers to ensure the accuracy of the camshaft.

Therefore, it is necessary to make further study about process technology of NC camshaft grinder. Because the characteristics of the camshaft grinding are different from other grinding methods, it is unpractical to use traditional methods for process parameters optimization in the camshaft grinding. With the powerful data processing capacity of computer and artificial intelligence technology, the camshaft grinding process will be better analyzed to meet its maximum technology characteristics.

Artificial neural network (ANN) and genetic algorithm (GA) are two of the most promising natural computation techniques. In recent years, ANN is widely applied, especially back propagation (BP) neural net-

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work [3–5]. BP algorithm has the advantage of optimization accuracy, but at the same time, there are some shortcomings, the most important of which is that it will easily fall into a local minimum, slow convergence, and oscillations [6]. As GA has strong macro-search capability and great probability in finding global optimal solution [7, 8], using GA to complete the initial search can better overcome the shortcomings of BP algorithm [9, 10]. The article combines the neural networks and the genetic algorithm to form a hybrid training algorithm to optimize process parameters in NC camshaft grinding. Nevertheless, this study was inspired by the very limited or no work on the application of genetic algorithm and neural network in this field.

2 The mathematical model of the camshaft grinding by constant linear velocity

The camshaft grinding is a special noncircular grinding. The typical machining motions are shown in Fig. 1. When the headstock drives the camshaft with rotation motion, the grinding carriage drives the grinding wheel with translational motion simultaneously. As the lift range is changing, the grinding conditions except the part of base circle are correspondingly changing. The linear velocities of grinding points on the cam profile and the material removal rates are variable when the camshaft rotates with constant angular velocity, which leads to grinding burn and waviness, so the camshaft grinding is totally different from the ordinary cylindrical grinding.

In the grinding process, the cam grinding depth b and width a_p are fixed variables, so the instantaneous linear velocity v_ω of the grinding point decides the material removal rate; v_ω can be made a constant value by

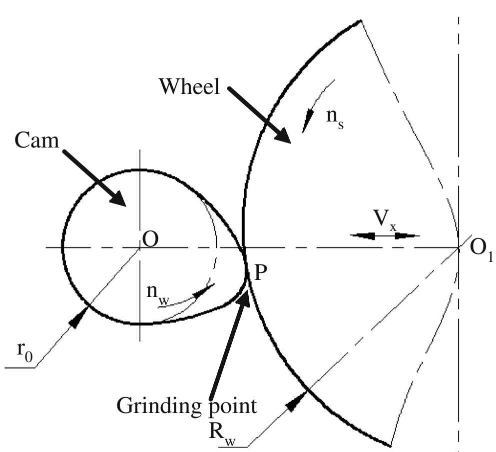

Fig. 1 The typical machining motions of camshaft grinding

controlling the headstock to achieve the constant material removal rate grinding.

From the literature [11], when grinding by constant linear velocity, the rotational velocity of the headstock ω_c and the translational velocity of the grinding carriage V_x are:

$$\omega_\varphi = \frac{r_0 \cdot \omega_0}{\sqrt{\rho^2 + \left[\frac{d\rho}{d\varphi}\right]^2}} \tag{1}$$

$$\omega_c = \omega_\varphi + \omega_\varphi^3 \cdot \frac{\rho \cdot \cos\beta + R_\mathrm{w}}{S_x^2} \cdot \frac{1}{(r_0 \cdot \omega_0)^2} \cdot \left(\frac{d\rho}{d\varphi} - \rho \cdot \frac{d^2\rho}{d\varphi^2}\right) \tag{2}$$

$$V_x = -\frac{\rho \cdot \sin\beta \cdot R_\mathrm{w}}{S_x^2} \cdot \omega_\varphi^3 \cdot \frac{1}{(r_0 \cdot \omega_0)^2} \cdot \left(\frac{d\rho}{d\varphi} - \rho \cdot \frac{d^2\rho}{d\varphi^2}\right) \tag{3}$$

$$\beta = \arctan\left(-\frac{d\rho}{\rho \cdot d\varphi}\right) \tag{4}$$

where r_0 is the base radius of the camshaft, R_w the base radius of the grinding wheel, ω_0 the rotational velocity of the base circle, $\rho(\phi)$ the polar equation of the cam profile, S_x the center distance between cam and grinding wheel when grinding.

By Eqs. 2 and 3, we can see that the rotational velocity of the headstock and the translational velocity of the grinding carriage are variable except the part of base circle when grinding by a constant linear velocity. In camshaft grinding process, the movement between the headstock and the grinding carriage is a coupling movement, so controlling the movement of headstock can achieve the grinding carriage's.

2.1 The model of camshaft grinding process parameters optimization

For the camshaft grinding, the process parameters optimization is influenced by a variety of factors. Using the nonlinear mapping capabilities of BP neural network and selecting the appropriate parameters affecting the characteristics of grinding, a neural network model was developed based on processing requirements and parameters. It can use past empirical data to study, automatically finding the governing relationships in the dataset by adjusting the weights between its nodes.

Genetic neural network combines the advantages of neural network with genetic algorithm, particularly applied to handling the models which are unknown or cannot be accurately described. If genetic neural network technology is applied to NC camshaft grinding process parameters optimization, it can analyze the relations among external factors, internal factors, processing accuracy, and surface quality. External factors include grinding wheel model, type of grinding, rotational velocity of cam, and feed rate. Internal factors include the properties of a camshaft to be processed. By the way, the more proper grinding process parameters, the more stable the camshaft process. Certainly the grinding burn and the error of lift range will be eliminated.

2.2 Experimental device

Grinding experiments were performed upon a NC camshaft grinder (Type CNC8312A) developed by the National Engineering Research Center for High Efficiency Grinding in China. The numerical control (NC) system of the grinder is siemens 840D, and 611D digital servo motor is used to control the grinding carriage-axis(X axis), the working table-axis (Z axis) and the headstock-axis (C axis). NC cam grinding without master form can be achieved through the linkage of X axis and C axis. Furthermore, coarse grinding, precision grinding, finish grinding, and no-spark grinding can be once finished after clamping the workpiece. The grinder whose spindle bearing stiffness is not less than 100 kg/μm is also equipped with an on-machine dynamic balancer (Type SBS4500). Thus, the camshaft machined by the grinder has the high precision including the error of adjacent point less than 0.01 mm, the maximum error of lift range no more than 0.04 mm, surface roughness $Ra \leq 0.4$ μm.

Surface roughness was measured by a surface coarseness profiling instrument (Type Homel18000) made in Germany. Grinding burn was detected by a metallographic microscope (Type 5 XB-PC) and a magnetic detector. Cam waviness and error of lift range were observed by visual detection and a cam error measuring instrument (Type TL500), respectively.

2.3 Grinding process parameters optimization

Because of the complexity of the process of camshaft grinding, the process parameters are affected by a lot of factors, such as dimensions of the camshaft, cam base circle diameter, cam surface roughness, accuracy, grinding allowance, size of grinding wheel, type of grinding wheel, depth of grinding wheel dressing, interval of dressing, number of dressing, linear velocity of dressing, translational speed of dressing and type of coolant, and so on. To simplify, when processing the same type of pieces, the other parameters are only considered except wheel type, depth of grinding wheel dressing, number of dressing, linear velocity of dressing, translational speed of dressing, interval of dressing, and type of coolant.

In order to reduce the complexity of network topology, experiments were conducted based on Table 1. Through qualitative analysis for the quality, "√" and "×" stand for the qualified and unqualified separately. After several rounds of tests, from Table 1, it can be seen that the best results of grinding will be achieved when depth of grinding wheel dressing, number of dressing, linear velocity of dressing, and translational speed of dressing are equal to 0.009 mm, 3, 50 m/s, and 600 mm/min, respectively. So at each stage, dressing depth will be set to 0.003 mm. Also, the conclusion can be proven by reference [12].

Among them, the rotational velocity of wheel and the camshaft and the feed rate of the grinding carriage have a great influence on its quality and processing accuracy [13]. Using a constant linear velocity to control grinding is to ensure that the material removal quantity is constant in unit interval. The material removal quantity in unit interval is defined as the material removal rate which is related to the rotational velocity and the feed rate of the camshaft. Certainly, a larger change of material removal rate is not conducive to improving the accuracy of the camshaft. To sum up, it can be initially set to the main process parameters reflecting the characteristics of the camshaft grinding: velocity of grinding wheel, rotational velocities of the camshaft in the three stages (coarse grinding stage, precision grinding stage, and finish grinding stage), feed rates in the three stages, grinding allowances in the three stages, and turns of no-spark grinding.

When using a constant linear velocity to control grinding, rotational velocity of the camshaft always changes by Eq.2, so it could not be accurately forecasted by the network. But when the grinding wheel radius, the base circle radius and cam lifts are the same; rotational velocities of points on the other parts can be obtained by converting rotational velocity of point on the base circle of cam profile.

After analyzing previous experimental data, there is an approximate ratio among the rotational velocities of point on the base circle of cam profile in the three stages. For example, in the actual production of a batch of camshafts, they were set to be 120, 80, and 60 rpm. So in this paper, the rotational velocities of the camshaft in other stages can be converted from rotational velocity of the camshaft in the finish grinding stage that is only set. During the machining course, a series of changes aroused from the effect caused by variable material removal rate are ignored. For the same camshaft to be processed, its total grinding allowance is a constant, so the grinding allowance in the coarse grinding stage can be calculated when grinding allowances in other stages are set.

Table 1 Different results of processing determined by different dressing parameters

Linear velocity of dressing (m/s)	Translational speed of dressing (mm/min)	Depth of dressing (mm)	Number of dressing	Surface roughness Ra	Degree of burn	Waviness	Maximum error of lift range	Maximum adjacent error
20	100	0.002	3	×	×	×	√	×
20	200	0.004	3	×	×	×	√	×
20	300	0.006	3	×	×	×	√	×
20	400	0.008	3	×	×	×	√	×
20	500	0.010	3	×	√	×	√	×
30	200	0.002	3	×	×	×	√	×
30	300	0.004	3	×	√	√	√	×
30	400	0.006	3	×	√	√	√	√
30	500	0.008	3	×	√	×	√	√
30	600	0.010	3	×	√	√	√	√
40	300	0.003	3	√	√	×	√	×
40	400	0.006	3	√	√	×	√	×
40	500	0.009	3	√	√	×	√	√
40	600	0.012	3	√	√	√	√	√
40	700	0.015	3	√	√	√	√	√
50	400	0.009	3	√	√	√	√	√
50	500	0.009	3	√	√	√	√	√
50	600	0.009	3	√	√	√	√	√
50	700	0.009	3	√	√	√	√	√
50	800	0.009	3	√	√	√	√	√
50	900	0.009	3	√	√	√	√	√
50	1000	0.009	3	√	√	√	√	√

In a word, in this paper, the network input parameters are simplified and only consist of: surface roughness, waviness, maximum error of lift range, degree of burn, and maximum adjacent error. The network output parameters consist of: linear velocity of wheel, rotational velocity of the camshaft in the finish grinding stage, feed rates in the three stages (coarse grinding stage, precision grinding stage and finish grinding stage), grinding allowances in the precision grinding stage and finish grinding stage, and turns of no-spark grinding. The network model is illustrated schematically in Fig. 2.

2.4 The samples of neural network based on uniform design

Establishing neural network model needs a series of samples. A reasonable sample size and distribution can accurately show the nonlinear mapping relations of the model. If using orthogonal experimental design, the number of experiments will be greater than the number n shown in the following equations:

$$n = s(q-1) + \frac{1}{2}s(s-1)(q-1)^2 \quad (5)$$

Where s is the number of experimental factors and q the number of experimental levels. For this experiment, when

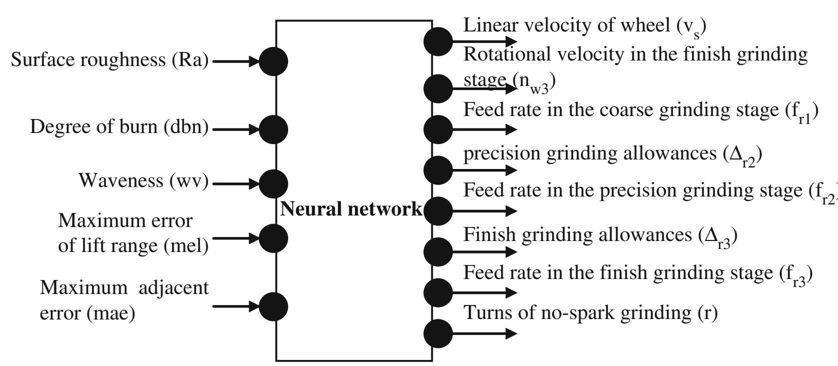

Fig. 2 Schematic model of neural network for camshaft grinding process parameters optimization

Table 2 The values of six levels

Factor	Levels					
v_s (m/s)	50	56	62	68	74	80
n_{w3} (rpm)	60	84	108	132	156	180
f_{r1} (mm/min)	0.005	0.405	0.805	1.205	1.605	2
$\vartriangle_{r2}$ (mm)	0.1	0.18	0.26	0.34	0.42	0.5
f_{r2} (mm/min)	0.005	0.325	0.645	0.965	1.285	1.6
$\vartriangle_{r3}$ (mm)	0.01	0.05	0.09	0.12	0.16	0.2
f_{r3} (mm/min)	0.005	0.205	0.405	0.605	0.805	1
r	0	2	4	6	8	10

choosing six testing levels for each of the eight factors, the total number of experiments is 740, that is, difficult in the sense of experimental data collection, performing, and analysis.

But the uniform design is another such efficient fractional factorial design. By using the uniform design of experiments, the number of experiments is substantially reduced on the premise of the experimental effect guaranteed [14].

In order to improve the pertinence of the experiments, the spans of eight experimental factors are appropriately enlarged on the basis of the earlier empirical data. Their spans and units are [50, 80] (m/s), [60,180] (rpm), [0.005, 2] (mm/min), [0.1, 0.5] (mm), [0.005, 1.6] (mm/min), [0.01, 0.2] (mm), [0.005, 1] (mm/min), [0, 10], respectively. The type of the uniform design table for these experiments is $U_{60}(6^8)$ [15]. The table is six levels for each of the eight factors and contains 60 samples. Table 2 shows the values of six levels for each of the eight factors.

2.5 Condition of the grinding experiments

Combining the above analysis, the condition of the grinding experiments was established on the choice of the following ways in CNC8312A camshaft grinder.

The grinding wheel whose specification is 14A1 500×24×160×5 CBN120A150 was dressed by an electroplated diamond roller dresser (Type S-DC-C-110×12×28) in down dressing mode with the way marked in Table 1. The interval of dressing was also set to 120 min. During grinding, a 3% solution of water-based coolant (Type W20) was applied. The properties of the camshaft to be processed are shown in Table 3. Its chemical compositions are given in Table 4.

3 Training model combining GA with BP

3.1 BP neural network

In theory, a three-layer BP model containing one hidden layer can realize any nonlinear mapping when the number of hidden layer is not limited. Neurons are located in the three types of layers: the input layer, the hidden layer, and the output layer. In this study, BP was used to achieve the nonlinear mapping relations between processing requirements (input) and process parameters (output), usually including a transfer function to calculate the output for each neuron except the input neurons. A tangent function was used for this transfer function. Each neuron's output was modified by the tangent transfer function, i.e., each hidden neuron's output was calculated using Eq.6 while the output neuron's output was calculated using Eq.7.

$$f(X_j) = \tan h\left(\sum_{i=1}^{n} X_i w_{ij} - \theta_{ij}\right) \tag{6}$$

$$f(X_k) = \tan h\left(\sum_{j=1}^{n} X_j w_{jk} - \theta_{jk}\right) \tag{7}$$

In Eqs.6 and 7, X_i is the value of the input variable, w_{ij} and w_{jk} connection weights between the input and hidden neuron and between the hidden neuron and output neuron, θ_{ij} and θ_{jk} bias terms for the jth and kth neuron respectively,

Table 3 The properties of the camshaft to be processed

Material	20CrNiMo	Total grinding allowance(mm)	2
Degree of hardness	HRC30~HRC37	Base radius(mm)	14.2
Maximum lift range of inlet cam (mm)	9.0882	Maximum lift range of exhaust cam (mm)	8.8823
Number of inlet cam	3	Number of exhaust cam	6
Total length (mm)	602.8	Total number of cam	9

Table 4 The chemical composition of the camshaft to be processed (wt%)

Element	C	Si	Mn	S	P	Cr	Ni	Cu	Mo
wt.(%)	0.21	0.32	0.84	0.021	0.027	0.65	0.72	0.30	0.28

and i, j, and k the number of neurons for the layers, respectively.

The training process was performed 2,000 epochs or until the test data's mean squared error calculated by Eq.8 is less than the error set by user.

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n} (O_i - T)_i^2}{n} \tag{8}$$

where O_i is the desired output for training data or testing data i, T_i the network output for training data or testing data i, and n the number of data in the training dataset or testing dataset.

There were no appropriate rules to determine the number of hidden neurons. According to experience, the number of hidden neurons can be designed referring to the following formula [16].

$$n = \sqrt{n_i + n_0} + a \tag{9}$$

where n is the number of hidden neurons, n_i the number of input neurons, n_0 the number of output neurons, a a constant between 1 and 10.

By Eq. 9 and compiling a program, the number of hidden neurons was optimized and its result was 12. By this way the neural network was established, which had five input neurons and eight output neurons. The structure of the neural network model was identified 5×12×8.

As the waviness and the degree of burn are described by the ambiguous words, they are unidentifiable if they are given to the network directly. So by using fuzzy compre-

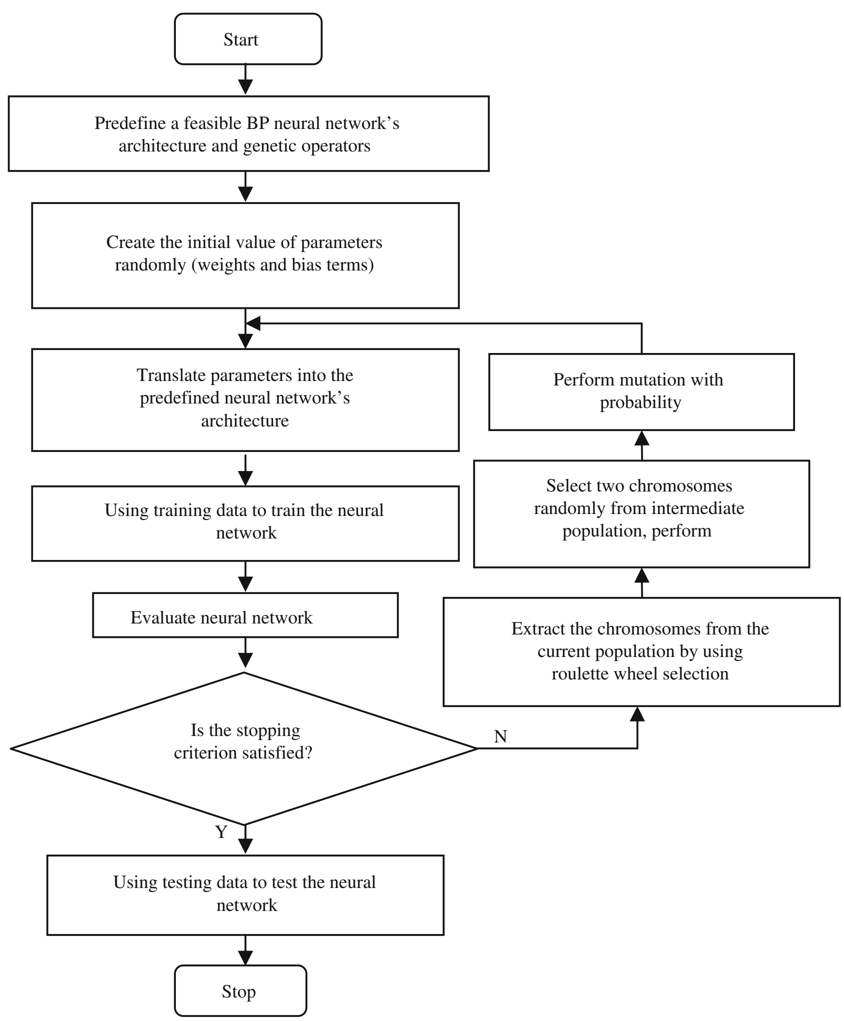

Fig. 3 The flowchart of GA-BP network

Table 5 Samples to test the network

Sample	Input					Output								
	Ra	dbn	wv	mel	mae	v_s	n_{w3}	f_{r1}	Δr_2	f_{r2}	Δr_3	f_{r3}	r
1	0.62	Infrequent	Mild	0.052	0.035	60	60	0.084	0.06	0.06	0.06	0.04	3
2	0.54	Infrequent	Infrequent	0.056	0.035	80	70	0.062	0.06	0.06	0.04	0.04	4
3	0.5	Infrequent	Infrequent	0.045	0.037	80	80	0.062	0.08	0.06	0.02	0.03	4
4	0.32	Infrequent	Infrequent	0.033	0.006	70	90	0.048	0.06	0.02	0.02	0.02	4
5	0.40	Infrequent	Moderate	0.034	0.071	60	100	0.062	0.12	0.04	0.04	0.04	4
6	0.20	Infrequent	Infrequent	0.015	0.002	80	80	0.048	0.06	0.02	0.04	0.01	3

hensive evaluation methods, it is defined as V={infrequent, mild, moderate, severe}, and they are replaced by the set {0, 0.3, 0.7, 1} in the network.

The spans of samples are too large especially the velocity of grinding wheel and the rotational velocity of the camshaft. So, the data normalization treatment was used to speed up the convergence.

3.2 The model of GA-BP network

GA algorithm is a kind of stochastic search algorithm inspired by the mechanics of natural evolution, including survival of the fittest, reproduction, crossover, and mutation. GA algorithm is based on Darwinian survival of the fittest strategy and works with a population of individuals, each of which represents a potential solution to a given problem. The basic operations in GA algorithm are selection (reproduction), crossover, and mutation. Although BP algorithm can surely obtain the final convergence of the network learning course, its evident weakness is that time of learning and training is too long and it is easy to converge on local optimal value. The capability of GA algorithm to obtain global optimal value is very great, but it is difficult to overcome the shortcomings of similar exhaustive search. However, the model combining GA with BP can effectively solve the above-mentioned problems. As the GA-BP network can easily select optimal point within the solution space. It is a fast, reliable method. Its algorithm steps are shown in Fig. 3 [17, 18].

The basis of GA is the continual improvement of the fitness of the population by means of genetic operators, as individuals are passed from one generation to the next. After a number of generations, the population evolves to a solution close to optimal. In this study, the roulette wheel selection based on ranking algorithm was applied in the reproduction. Chromosomes were selected in quantities according to their relative fitness after ranking in the roulette wheel operator, and then they were put into the intermediate population. The population size was 100. Uniform crossover and uniform mutation operators were used and the probability of crossover and mutation operators were 0.7 (Pc) and 0.03 (Pm), respectively.

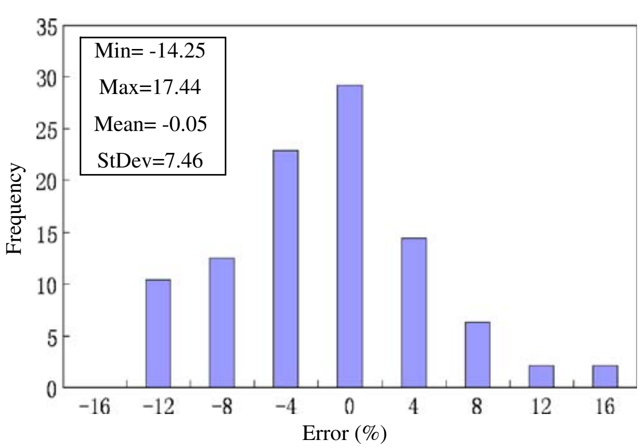

Fig. 4 Error distribution of the GA-BP network for mapping between the inputs and the outputs

4 Experimental results and discussions

After training the network using the samples that were designed by uniform design, six samples were collected from previous machining process to test the network. The details about six samples are given in Table 5.

The percentage error of the GA-BP network was calculated as the percentage difference between the experimental and predicted values (the network's relative inputs).

Table 6 The experimental and the network's relative inputs

Sample	Ra	dbn	wv	mel	mae
1	0.25	Infrequent	Infrequent	0.02	0.006
1′	0.24	Infrequent	Infrequent	0.018	0.007
2	0.32	Infrequent	Mild	0.025	0.008
2′	0.30	Infrequent	Mild	0.027	0.006

The error distribution of the GA-BP network for mapping between the inputs and the outputs shown in Table 5 is presented in Fig. 4. The error has a uniform distribution pattern about zero with a mean value and standard deviation of −0.05% and 7.46%, respectively. The absolute maximum error is less than 17.44%. The result shows that 85.42% of the predicted values have the percentage error ranging between ±10%. It can be seen that the network can achieve better mapping between the inputs and the outputs.

On this basis, the following two samples generated randomly like samples 1 and 2 were entered into the network. Then the outputs of the network were used to control the camshaft grinding and the results of measurements like sample 1′and 2′are shown in Table 6 by comparing with the network's relative inputs.

By Table 6 it can be seen that the errors between the experimental and predicted value are small. GA-BP network model provides a powerful tool in process parameters optimization in NC camshaft grinding, and has the ability of optimizing grinding process parameters.

Through the above analysis, it is obvious that applying the GA-BP network model in process parameters optimization in NC camshaft grinding is correct and effective in this paper. It is a reference for other grinding of multi-parameters.

5 Conclusions

In this study, the GA-BP network in process parameters optimization in NC camshaft grinding is modeled and experimentally tested. This hybrid approach is aimed to find an integrated solution to the existing problem of analyzing camshaft grinding processes for which using traditional methods for process parameters optimization is not straightforward. The nonlinear mapping relations between processing requirements (input) and process parameters (output) were achieved with a $5\times12\times8$ configuration. The errors to test the network by six testing data have a uniform distribution pattern about zero with a mean value and standard deviation of −0.05% and 7.46%, respectively. The result shows that 85.42% of the predicted values have the percentage error ranging between ±10%. It can be seen that the network can achieve better mapping between the inputs and the outputs. So the hybrid ANN/GA model is an effective tool for the process parameters optimization in NC camshaft grinding.

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