Application of PSO Algorithm to Gearbox Fault Diagnosis

Hongxia Pan Xiuye Wei Jinying Huang

School of Mechanical Engineering and Automation, North University of China, Taiyuan 030051, P. R. China

Abstract

After an introduction of the principle of particle swarm optimization (PSO) algorithm based on swarm intelligence, and of the modified version of the PSO algorithm, a neural network system for gearbox fault diagnosis has been established. After being trained by PSO algorithm, the neural network system is applied to fault diagnosis. Comparison of the diagnostic results between the PSO-based algorithm and the BP-based algorithm indicates that the network system based on PSO algorithm is of better training performance, and of less overall output error compared with those of the BP algorithm. It has been proved that the neural network system for fault diagnosis based on PSO algorithm is of higher probability of identifying multi-fault symptoms, and of rapid convergence and higher diagnosis accuracy, and that the neural network system for fault diagnosis expects a wide application in the field of mechanic fault diagnosis because of its higher searching efficiency.

Keywords: Partical swarm optimization(PSO), Fault diagnosis, Gearbox, Neural network

1. Introduction

Particle swarm optimization algorithm (hereinafter referred to as PSO algorithm)[1], proposed by J. Kennedy and R. C. Eberhart in 1995, is an optimization algorithm based on swarm intelligence principle: the algorithm optimizes searching by virtue of the swarm intelligence produced by the cooperation and competition among the particles of a species. Compared with evolution algorithm, PSO algorithm reserves all-dimension searching strategy based on a species, avoiding complicated genetic operation. In addition, PSO algorithm does not contain parameters to adjust nor does it need gradient information of target function; this makes the algorithm simple to operate and easy to realize. Since migration of particle group is directional, searching process can utilize feedback principle and parallel computation; this improves the searching efficiency. For this reason, PSO algorithm has been drawing researchers' attention and has been put into application in certain fields since it was proposed. In this paper, an attempt is made to diagnose gearbox fault by using the neural network system trained by PSO algorithm, and to compare the diagnostic performance of PSO algorithm with that of backward promulgating (BP) algorithm.

2. Principle of PSO Algorithm

Originated in simulation of a simplified social model, PSO algorithm bears a significant relation with artificial life theory and with bird's swarming phenomenon. Observed from social cognitive perspective, particle swarm optimization theory is primarily based on the following fundamental elements: 1) assessment on stimulus, 2) comparison with adjacent neighbor, and 3) imitation of leading adjacent neighbor. PSO algorithm is an optimized algorithm inspired by the flying of bird swarm.

In PSO algorithm, each solution to optimization problem is regarded as a bird flying at certain speed in a contraction pace; the flying speed is dynamically adjusted in accordance with the bird's flying experiences and with the flying experiences of its companions. In this algorithm, the bird is regarded as a particle without mass and volume.

In D-dimension searching space, the position of the ***i***th particle is $X_i = (x_{i1}, x_{i2}, \cdots x_{iD}), i = 1,2,\cdots,m$, and its speed is $V_i = (v_{i1}, v_{i2}, \cdots v_{iD},)$. Each particle has a fitness value determined by an optimised function, and each particle knows its present position X_i and the best position (pbest) that it has so far found; this can be regarded as the flying experiences of the particle. In addition, each particle knows the best position (gbest) that the whole swarm has so far found; this can be regarded as the flying experiences of the particle's companions. Each particle utilizes the following information to alter its present position: 1) its current position, 2) its current speed, 3) the distance between its current position and its best position, and 4) the distance between its best position and the best position of the whole swarm[2].

PSO is an optimization instrument based on iteration. For the kth times of iteration, each particle alters in accordance with formula (1) and formula (2) as follows:

$$v_{id}^{k+1} = v_{id}^{k} + c_1 rand\,(\;)(p_{id} - x_{id}^{k}) + c_2 rand\,(\;)(p_{gd} - x_{id}^{k}) \quad (1)$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \quad (2)$$

where, $i = 1,2,\cdots,m$, m being the total of all particles in a swarm; $d = 1,2,\cdots,D$; v_{id}^{k} represents the component of flying speed vector of particle ***i*** in the ***d***th dimension at the ***k***th times of iteration; x_{id}^{k} represents the component of positional vector of particle ***i*** in the ***d***th dimension at the ***k***th times of iteration; p_{id}^{k} represents the component of the best position (pbest) of particle ***i*** in the ***d***th dimension; p_{gd}^{k} represents the component of the best position (pbest) of particle swarm in the ***d***th dimension; learning factor c_1 and c_2 are positive constants; $rand()$ represents random function producing random numbers in the interval of [0,1].

PSO algorithm's memory enables the algorithm to adjust its searching strategy dynamically in accordance with the current contracting situation. Compared with evolution algorithm, PSO algorithm is a more efficient parallel searching algorithm.

3. Improvement on PSO Algorithm

Formula (1) shows that the right portion of the formula consists of three parts: the first part represents particle's speed before renewal; the latter two parts inflect the renewal of particle's speed. According to Shi and Elberhat's research[3], since v_{id} as in formula (1) is at random and lacks memory, it tends to enlarge searching space and to search new spaces; this endows the algorithm with the capability of global optimization. In practical optimization, researchers often than not expect to utilize global searching strategy so to make the searching space rapidly converge into a certain space, and then to utilize partial fine searching to improve searching accuracy.

In this situation, let v_{id} times inertia weight w: when w is greater, the PSO algorithm has stronger global searching capability; when w smaller, the PSO algorithm tends to search in partial spaces. Commonly used practices are to initially make w=0.9, and make it linearly decrease 0.4 as the times of iteration increases, so to reach expected optimization. In normal situation, weight function w is determined by the following formula:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \quad (3)$$

where, $w_{\max}$ represents the maximum value of w and $w_{\min}$ the minimum value; $iter$ represents current times of iteration and $iter_{\max}$ the maximum times of iteration.

4. Application of PSO Algorithm to Gearbox Fault Diagnosis

As a most frequently used algorithm for training neural network, backward promulgating (BP) algorithm is a gradient-based learning algorithm; this algorithm bears certain innate problems such as slow convergence and partial optimization, etc. To overcome the disadvantages of the algorithm, it is proposed to adopt PSO algorithm to adjust and optimize global network parameters such as weight value and threshold value, etc. for training neural network, and to adopt the method of neural network learning to optimize partial parameters. In this situation, particle-swarm optimization functions as a crude optimizing process or as an off-line learning process, whereas neural network learning functions as a fine optimizing process or as an on-line learning process[4]. Combination of the two methods can greatly improve the performance of the PSO algorithm when used for gearbox fault diagnosis.

4.1. Establishment of BP-Algorithm Based Neural Network

To thoroughly reflect practical gearbox fault modes and improve fault identification rate of neural network, the fault diagnosis system takes the following time-frequency dynamic characteristic parameters as diagnosis indexes: peak value, abruptness, abundant value, skewness, power spectral gravity center, frequency-domain variance, and harmonic factor. Take these seven indexes as the input of BP-algorithm based neural network so to reduce to unity the input symptom parameters, and take the following six commonly observed circumstances of gearbox as the output of BP-based neural network: gearbox under normal working condition, damages of bearing bracket, scratches of the inner/outer housing of bearing, occurrence of crushing pit, gear surface wearing, and gear tooth collapsing. The fault diagnosis system is a BP-algorithm based network, its topological structure being 7-12-6， its system error 0.001.

4.2. Application of Inertia-weight Model

When PSO algorithm is utilized to train BP network, define the element of the positional vector ***X*** as the total connecting power and threshold value. Initialise positional vector ***X***, and use PSO algorithm to search the optimal position so to minimize its mean square error (i.e. the fitness value)[5]. The purpose of thus formed PSO-algorithm based neural network is to obtain the minimum weight value and threshold value of ***J***.

$$J = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C}(y_{j,i}^{d} - y_{j,i})^2 \qquad (4)$$

where, N represents sample number in training collection; $y_{j,i}^{d}$ represents ideal output of the ***i***th sample at the ***j***th node; $y_{j,i}$ represents actual output of the ***i***th sample at the ***j***th node; C represents the number of output nerve cell of the network.

4.3. Parameter Setting

In present research, 5 sets of vibration acceleration signals of gearbox under the following 6 typical working conditions have been sampled: gearbox under normal working condition, damages of bearing bracket, scratches of the inner/outer housing of bearing, occurrence of crushing pit, gear surface wearing, and gear tooth collapsing. Randomly select three sets of data as the standard data of typical sample, and take the rest two sets of data as the data to be verified. This means that the research altogether takes 18 sets of samples as training sample, respectively corresponding to six working conditions, that takes the reduction of the input symptom parameters as the network input, and that takes 12 sets of samples to verify the output of the network.

In present diagnosis system, set 200 as the fixed number of PSO particles, ***c1=c2=2***; the times of iteration of w linearly reduces from 1.2 to 0.4, and number of iteration step is 20,000[6]. Train the neural network in training collection using PSO algorithm and BP algorism respectively, and use to-be-verified gearbox samples to test the neural network.

4.4. Analysis on Optimization Results

Apply the PSO-algorithm optimized connecting power values and threshold values (ignored) to BP-algorithm based neural network and diagnose the 12 sets of to-be-verified data of gearbox. Table 1 illustrates the diagnosis results of BP-algorithm based neural network, and Table 2 the diagnosis results of PSO-algorithm based BP neural network. The two tables show that the PSO-algorithm based neural network outputs as expected. Although actual outputs at fault nodes decrease slightly compared with their corresponding ideal outputs, these values are close to 1, and actual outputs at other nodes are close to 0. This proves that PSO-algorithm based neural network has sound identification capability.

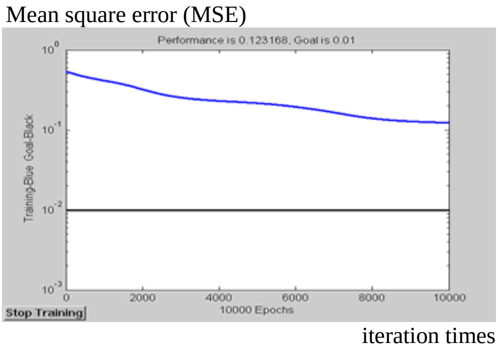

Fig. 1: The learning curve of BP algorithm.

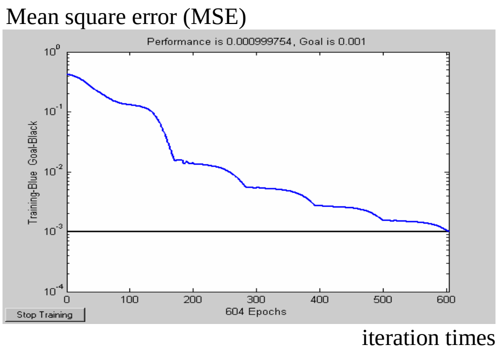

Fig. 2: The learning curve of PSO algorithm.

Fig. 1 and Fig. 2 illustrate the training curve of BP-algorism based neural network, and the training curve of PSO-algorithm based neural network. In these figures, the horizontal coordinate represents the number of training step, and the vertical coordinate the performance target, i.e., the fixed system error. These figures show that, when the times of iteration of PSO algorithm reaches 604, the system error reaches 0.001, and that when the times of iteration of BP algorithm reaches 10,000, the system error reaches 0.01, far away from the required system accuracy. Fig3a, 3b, 3c, and 3d show the error curves of BP-algorithm based neural network and PSO-algorithm based neural network under four working conditions: normal working condition, crushing pit in outer housing of bearing, gear surface wearing, and gear tooth collapsing. These error curves prove that the overall error of PSO-algorithm based neural network is less than that of BP-algorithm based neural network. It is obvious that PSO algorithm is of short training time, rapid convergence and high

Serial No.	Ideal output	Diagnosis Results						Diag.Error	Diagnosis Conditions
		F1	F2	F3	F4	F5	F6	E_{max}	
Z1	1，0，0，0，0，0	0.9994	0.0002	0.0011	0.0004	0.0706	0.0001	0.0706	Normal working condition
Z2	1，0，0，0，0，0	0.8194	0.0001	0.0018	0.0029	0.0300	0.0069	0.1906	Normal Working condition
Z3	0，1，0，0，0，0	0.0095	0.9618	0.0002	0.0376	0.0328	0.0003	0.0382	Crushing pit in outer housing of bearing
Z4	0，1，0，0，0，0	0.0071	0.8762	0.0001	0.1407	0.0298	0.0015	0.1407	Crushing pit in outer housing of bearing
Z5	0，0，1，0，0，0	0.2302	0.0002	0.9581	0.0113	0.0236	0.0165	0.2302	Gear surface wearing
Z6	0，0，1，0，0，0	0.0312	0.0003	0.9249	0.0835	0.2474	0.0719	0.2474	Gear surface wearing
Z7	0，0，0，1，0，0	0.0408	0.0118	0.0013	0.8262	0.0007	0.0040	0.0738	Damages of bearing bracket
Z8	0，0，0，1，0，0	0.0103	0.1060	0.0001	0.8176	0.0666	0.2326	0.2326	Damages of bearing bracket
Z9	0，0，0，0，1，0	0.0372	0.1764	0.0023	0.0002	0.9261	0.1532	0.1764	Scratches of the inner housing of bearing
Z10	0，0，0，0，1，0	0.0203	0.0033	0.0043	0.2733	0.8267	0.0360	0.2733	Scratches of the inner housing of bearing
Z11	0，0，0，0，0，1	0.0063	0.0278	0.0115	0.0390	0.0021	0.8991	0.2009	Gear tooth collapsing
Z12	0，0，0，0，0，1	0.0044	0.0425	0.0003	0.0001	0.0880	0.8537	0.1463	Gear tooth collapsing

Table 1: Actual diagnosis outputs of BP-algorithm based neural network.

Serial No.	Ideal Output	Diagnosis results						Diag.Error	Diagnosis Conditions
		F1	F2	F3	F4	F5	F6	E_{max}	
Z1	1，0，0，0，0，0	0.9998	0.0001	0.0001	0.0002	0.0016	0.0001	0.0016	Normal working condition
Z2	1，0，0，0，0，0	0.9189	0.0001	0.0013	0.0023	0.0270	0.0049	0.0821	Normal working condition
Z3	0，1，0，0，0，0	0.0085	0.9823	0.0001	0.0276	0.0128	0.0001	0.0982	Crushing pit in outer housing of bearing
Z4	0，1，0，0，0，0	0.0081	0.8962	0.0002	0.1187	0.0298	0.0014	0.1038	Crushing pit in outer housing of bearing
Z5	0，0，1，0，0，0	0.2167	0.0002	0.9617	0.0108	0.0236	0.0168	0.2167	Gear surface wearing
Z6	0，0，1，0，0，0	0.0232	0.0002	0.9439	0.0635	0.1979	0.0699	0.1979	Gear surface wearing
Z7	0，0，0，1，0，0	0.0368	0.0113	0.0001	0.8592	0.0018	0.0040	0.1408	Damages of bearing bracket
Z8	0，0，0，1，0，0	0.0113	0.1045	0.0002	0.8326	0.0366	0.0326	0.1674	Damages of bearing bracket
Z9	0，0，0，0，1，0	0.0272	0.1665	0.0019	0.0002	0.9378	0.0514	0.1665	Scratches of the inner housing of bearing
Z10	0，0，0，0，1，0	0.0104	0.1023	0.0028	0.0927	0.9071	0.0193	0.1023	Scratches of the inner housing of bearing
Z11	0，0，0，0，0，1	0.0055	0.0298	0.0002	0.0015	0.0021	0.9007	0.0298	Gear tooth collapsing
Z12	0，0，0，0，0，1	0.0048	0.0423	0.0013	0.0001	0.0880	0.8759	0.1241	Gear tooth collapsing

Table 2: Actual diagnosis outputs of PSO-algorithm based neural network.

Notes: In Table 1 and 2, ***F1-F6*** represent six working conditions of gearbox: normal working condition, damages of bearing bracket, scratches of the inner/outer housing of bearing, occurrence of crushing pit, gear surface wearing, and gear tooth collapsing. $\boldsymbol{E}_{max}$ represents maximum error.

training accuracy, meeting diagnosis and testing requirements. This proves that PSO-algorithm optimized connecting characteristics are closer to actual situation, thus greatly improving the network's information processing capability.

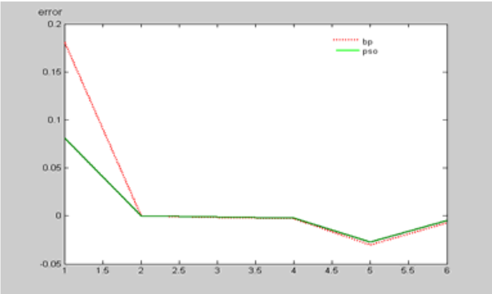

Fig. 3a: Error curve under normal working condition.

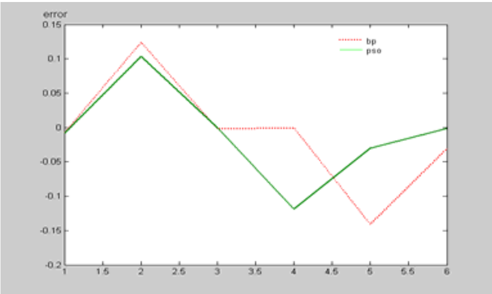

Fig. 3b: Error curve in case of crushing pit in outer housing of bearing.

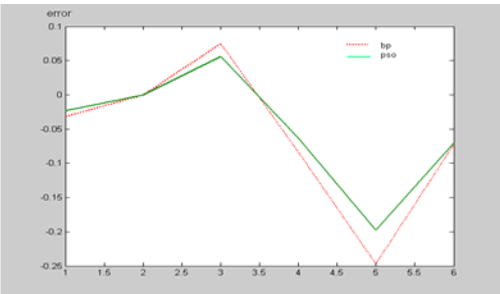

Fig. 3c: Error curve in case of gear surface wearing.

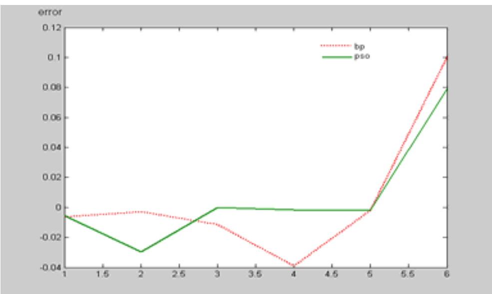

Fig. 3d: Error curve in case of gear tooth collapsing.

5. Conclusions

After being trained by weight-model based PSO algorithm, the neural network system has been applied to gearbox for fault diagnosis. Comparison of the diagnostic results between the PSO-based algorithm and the BP-based algorithm indicates that the network system based on PSO algorithm is of better output upon multi-fault symptom, less number of iteration, rapid convergence, and higher diagnosis accuracy compared with those of the BP algorithm. Experiments prove that PSO algorithm is an effective algorithm with a higher searching efficiency, and that the algorithm does not involve many parameters to adjust nor does it need the gradient information of target function, which makes the algorithm simple to operate and easy to realize. These advantages endow PSO algorithm great potential of application in the field of fault diagnosis.

Acknowledgement

The work described in this paper has been supported by National Natural Science Foundation of China under the grant No. 50575214 and Province Natural Science Foundation of Shanxi under the grant No. 2007011070. The authors would like to express their gratitude for the support of this study.

References

[1] J. Kennedy and R. C. Eberhart, Particle swarm optimization. Proc. IEEE Int'l. Conf. on Neural Networks, IV, 1995, pp.1942-1948. Piscataway, NJ: IEEE Service.

[2] J. Kennedy and R. C. Eberhart, A discrete binary version of the Particle swarm optimization algorithm. Proceeding of the IEEE international Conference on system, man and Cybernetics, Piscataway, 1997, pp.4104~4109.

[3] D. B. Cosmin , L. José and C. Sa da, Tuning the parameters of a classifier for Fault Diagnosis-particle swarm optimization vs genetic algorithms. ICINCO (1) 2004, pp. 157-162.

[4] C. D. Bocaniala, J. S. Costa and V. Palade, Refinement of the diagnosis process performed with a fuzzy classifier. Lecture Notes In Artificial Intelligence, 2004, 3215:pp. 365-372.

[5] Yu Liu and Zheng Qin, et,al. Training Radial Basis Function Networks with Particle Swarms. LNCS, 2004,3173: pp.317-322.

[6] G. Haibing and G. Liang, The research of neural network training algorithm based on particle swarm optimization," Electron Joural , 2004,(9):pp.1572-1574.