International Journal of u- and e- Service, Science and Technology
Vol.6, No.6 (2013), pp.71-82
http://dx.doi.org/10.14257/ijunesst.2013.6.6.08

Reliability Prediction Model of the CNC System

Yan Gu[1,2], Yiqiang Wang[2*], Xiaoqin Zhou[1], Xiuhua Yuan[2] and Mingyang Ma[1]

[1]College of Mechanical Science and Engineering, Jilin University
Changchun, Jilin (China)
[2]Ningbo Institute of Technology, Zhejiang University
Ningbo, Zhejiang(China)
pcik001@qq.com, jluwang@gmail.com, xqzhou@jlu.edu.cn, yxhjlu@163.com, mamingyang-1986@163.com

Abstract

In order to guarantee the effectiveness of the CNC system and reach expected reliability level, reliability prediction model was established for the CNC system by BP neural network algorithm based on the particle swarm optimization. The weight and threshold value of BP neural network were optimized with the particle swarm optimization algorithm, the three-layer BP neural network prediction model was established, and practical failure data verification was conducted for the model established. Through the simulation verification, the result suggested that this scheme is accurate and effective. The improved algorithm improves the convergence rate and BP network learning ability, carries out successful prediction for the reliability of the CNC system, and provides basis for the design decision of the CNC system.

Keywords: *CNC system, Reliability prediction model, Particle swarm optimization, BP neural network*

1. Introduction

The reliability prediction takes the product structural model as the foundation, and it will predict the accessible reliability level of the product in the future application or predict the reliability of the improved products according to the related design and failure data acquired from the same type of products [1-2]. The optimal design scheme can be found out through the reliability prediction for the products. After the design scheme was determined, the vulnerable spot in the design can be discovered, and improvement approach will be provided, which can also provide significant basis for such studies as the reliability growth test, verification test and expense budget of the newly developed products [3-4]. Correct reliability prediction for the products was first premised for guaranteeing the product quality. Therefore, substantial efforts have been input by the domestic and foreign scientific research personnel. The study on the reliability prediction was brought by the reliability of the electronic valves [5]. After realizing the significance of reliability prediction in the reliability study, other countries also take abundant efforts in scientific research. At present, the study on the reliability prediction mainly gathers in the approaches and standards of the reliability prediction [6-9]. The BP forward network can realize the highly-nonlinear mapping from the input to the output state space [10-13], and it can solve the above mentioned reliability

*Corresponding Author

ISSN: 2005-4246 IJUNESST

prediction problem. Since there is a certain kind of nonlinear mapping relationship in the reliability index of both the sub-system of the numerical control system and the whole numerical control system, it is equipped with inherent non-linear characteristics as the neural network, as well as the characteristics that can be learnt though training. Based on these characteristics, as well as the special prediction and learning ability of neural network, the reliability of the numerical control system can be predicted better. Although quite a few scholars have studied the approaches for optimizing the neural network structure and improving the generalization of the neural network [14-15], there hasn't been a practical and effective one till now. Meanwhile, among all the approaches, the long computing time is a widespread problem, and especially confronted by a large scale, it will be difficult to be practical in time of a large scale. It can effectively prevent the network from falling into the local minimum and guarantee the accuracy of the results by integrating the global optimization ability of the particle swarm optimization algorithm and local searching advantages of BP neural network algorithm.

2. Establishment of the Reliability Prediction Model for CNC System

The reliability prediction of the CNC system mainly includes two aspects of contents. One is the overall reliability prediction for the CNC system according to the reliability of each component of the CNC system. It is a computing process from locality to entirety, and only when the reliability of each component reaches the standard, can the overall reliability of the CNC system satisfy the demands. The other is the reliability prediction for the next working period according to the known reliability data of the numerical control system, which can be used for guiding the design and application of the CNC system. The two aspects of contents are about the typical non-linear mapping relationship, and the BP neural network can just solve this problem.

The main thought of predicting the reliability of the CNC system with BP network is that the CNC system is divided into hardware and software according to the structures, and both the software and hardware are divided into relatively independent component according to the functions. And then failure data will be collected according to the corresponding component and unit, and counted according to the stated statistical method. The failure rate of the CNC system will be taken as the input and the failure rate of the CNC system in the next statistical period as the output. Three-layer BP neural network will be established for training the network. Finally, the well trained network will be used to conduct the reliability evaluation and prediction for the same series of the CNC system.

In the practical application, if a function is continuous in a certain closed interval, it can be approximated with a BP neutral network with a hidden layer. Figure 1 shows the established reliability prediction model. The model consists of three layers which named input layer, hidden layer and output layer. X_i in the established model corresponding to the input value of the network input neuron and y is the theoretical output of the network.

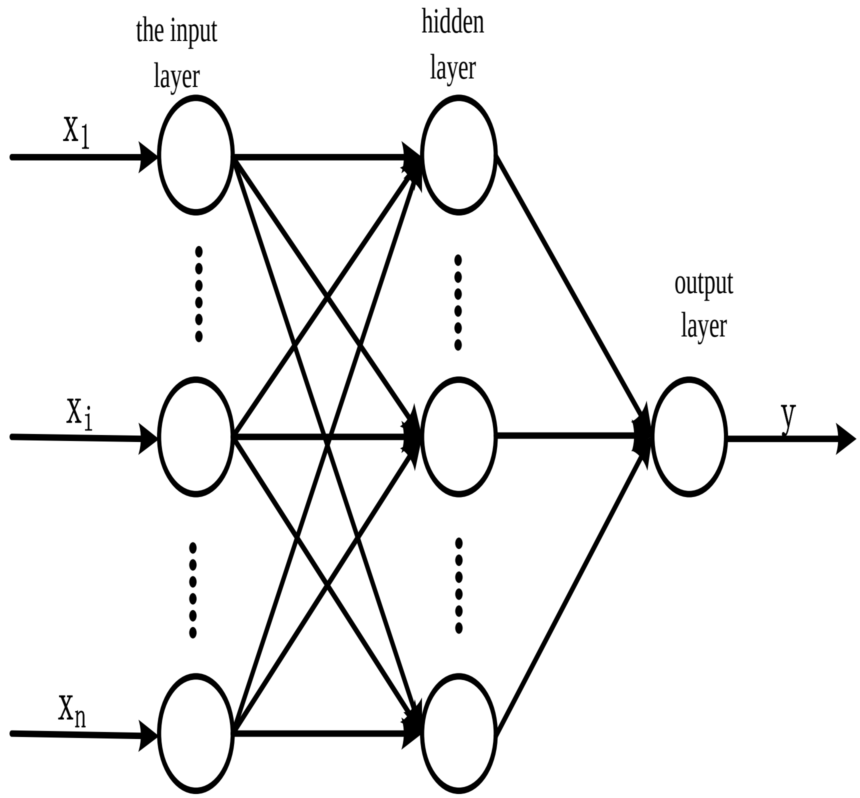

Figure 1. The Reliability Prediction of the CNC System

3. Improved BP neural Network Algorithm

3.1. BP Neural Network

BP neutral network refers to a kind of neutral network adopting the error back-propagation algorithm, and it overcomes the shortcoming that the simple neutral network can't adjust the network connecting weight, and is capable of realizing any nonlinear mapping. The common BP network often has three layers, among which the corresponding neural elements of the two adjacent layers are realized through full join, and there is a connection in every neural element between the previous layer and next layer, but the neural elements of the same level are independent from each other. BP neural network trains the network with the tutor-type learning approach, responding to the comprehensive effecting results of the corresponding neural element output to each input value in the network output layer. And then, the gap between the actual input and expected output will be calculated, the output layer of the error signal with network will be transmitted backward to the input layer, and the network will be trained after modifying the connecting weight of each layer until it reaches the required precision. Although BP neural network is equipped with relatively high fitting ability, there is still certain error in the prediction result. In order to obtain more accurate prediction output, the particle swarm optimization has been introduced into the BP neural network for predicating the reliability of the numerical control system. That means the particle swarm optimization is used to train the BP neural network, which can improve the precision of the prediction for the BP neural network and reduce the prediction error.

3.2. Improved BP Neural Network based on the Particle Swarm Optimization

The unit of the group in the PSO algorithm is a particle. Each particle flies in multiple searching spaces [16]. In addition, the particle updates its speed and location in line with its experience, neighbor experience and group experience [17]. It is assumed that particle j flies in the searching space n, the location and speed are updated as follows:

$$x_{jk}(t+1) = x_{jk}(t) + v_{jk}(t+1) \tag{1}$$

$$v_{jk}(t+1) = \omega \cdot v_{jk}(t) + c_1 \cdot r_1[p_{jk} - x_{jk}(t)] + c_2 \cdot r_2[p_{gk} - x_{jk}(t)] \tag{2}$$

$$(k = 1, 2, \cdots, n, j = 1, 2, \cdots, m)$$

Where m is population size, ω is size inertial factor, p_{jk} is K-th component of the vector, p_j in partially optimum position of the particle j, p_{gk} is K-th component of the vector, p_g in global optimum position of the particle, c_1, c_2 is cognitive coefficient and society coefficients, r_1, r_2 is a random value between 0 and 1.

Particle inertial factor ω used to control the speed of the current speed beforethe impact, direct impact on global and local search particles capable [18], set as follows:

$$\omega = \omega_{max} - (\omega_{max} - \omega_{min}) \times \frac{t}{T_{max}} \tag{3}$$

Where ω_{max} is maximum inertial factor, ω_{min} is minimum inertial factor, t is current iteration T_{max} total number of iterations.

The particle swarm optimization is one of the advanced algorithms, which starts from the random solution and seeks for the globally optimal solution through iteration. It has a good global searching ability, but it is relatively incompetent in precise local searching[19-20]. However, the local optimization ability of BP algorithm is strong relatively, and the two can complement each other's advantages. The particle swarm optimization neural network algorithm optimizes the initial weight and threshold value of the neutral network with particle swam algorithm, and it can reach the point near the global optimal point after the end of the algorithm. Based on the particle swarm algorithm, the BP algorithm with strong local optimization ability has been used to conduct the local searching by starting from this point, thus to reach the training targets. The process of optimizing the BP neural network with improved particle swam optimization can be described as follows.

(1)Set the particle dimension of the search space D, each particle position vector component corresponds to the dimensions of a neural network weights or threshold value, particle dimension equal neural network weights and thresholds value:

$$D = R \times L + L \times M + L + M \tag{4}$$

Where R is input nodes, L is hidden layer nodes, M is output nodes.

(2)Set the fitness function of the particle swam, select the mean square error of the BP neural network as the fitness function of the particle swam.

$$E = \frac{1}{F}\sum_{i=1}^{F}\left[\sum_{j=1}^{M}(y'_{ij} - y_{ij})^2\right] \tag{5}$$

Where F is training sample, M is output nodes, y'_{ij} is desired output value, y_{ij} is actual output value.

(3)The network weight and threshold of the particle swam optimization were optimized by the improved particle swam algorithm.

(4)Regard the optimized weight and threshold value as the initial weight and threshold value of the BP algorithm, and replace it into the neutral network for training.

The algorithm flow chart designed was shown as follows:

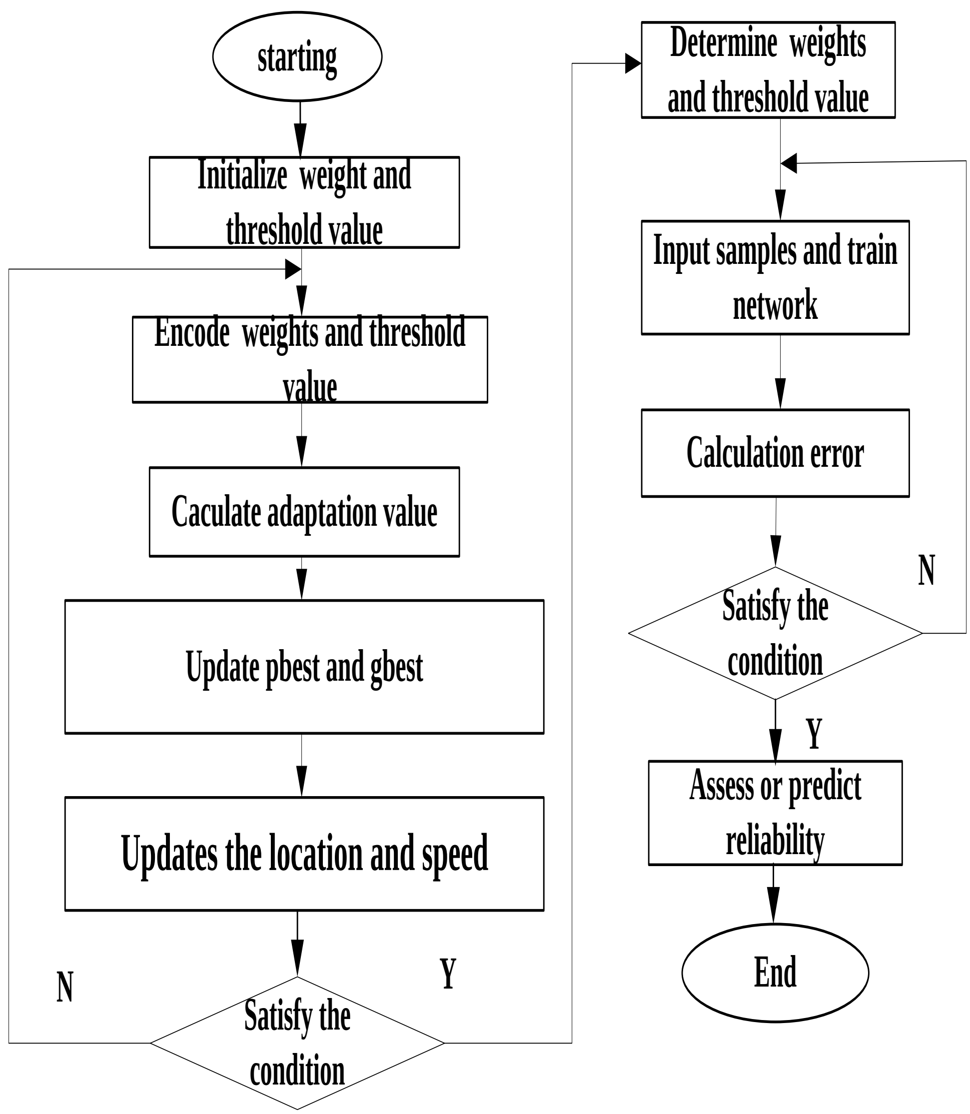

Figure 2. Algorithm Flowchart

4. Application Example

The primitive failure data of a certain type of numerical control system will be counted every three months to calculate the mean time between failures (MTBF) and failure rate (λ). MTBF refers to the average operation time between two failures, as the mathematical expectation of the time between the failures, and the observed value can be calculated according to equation (6).

$$MTBF = \frac{1}{N}\sum_{i=1}^{N} t_i = \frac{T}{N} \tag{6}$$

Where N is The cumulative number of failures CNC system in the statistical period, t_i is CNC working time, T is CNC working total time.

λ refers to the probability of the products that are still effective till a certain moment but are ineffective later. In this paper, the average failure rate of every statistical cycle was employed, and it could be calculated according to equation (7).

$$\lambda = \frac{1}{MTBF} \tag{7}$$

The calculation result was shown in Table 1:

Table 1. A Type of the CNC System Fault Statistics

Sample Number	Number of Failures	Total working time	MTBF	λ（10^{-4}）
1	2	1835	917.5	10.8991
2	1	1850	1850	5.4054
3	2	1755	877.5	11.3960
4	1	1755	1755	5.6980
5	2	1845	922.5	10.8401
6	1	1845	1845	5.4200
7	1	1835	1835	5.4496
8	2	1815	907.5	11.0193
9	1	1755	1755	5.6980
10	2	1850	925	10.8108
11	1	1800	1800	5.5556
12	2	1750	875	11.4286
13	1	1835	1835	5.4496
14	1	1815	1815	5.5096
15	3	1750	583.3	17.1438
16	2	1800	900	11.1111

In order to get the input data matching the distribution of the output variables better, the test data should be pre-processed. Normalization processing was employed to turn the test data to be within in this paper[0, 1], and the calculation equation can be shown as follows:

$$\bar{x} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{8}$$

Normalization processing will be conducted for the failure rate λ in table 1, and the data will be divided into 13 groups by classifying three failure rates into one group. Taking the data in each group as a sample, the input of the nth group will ben+1, n+2 and n+3, while the output will be n+4. And then, it will be classified according to the selection principle of the input and output neutral element to determine the training sample set and verification sample of the BP neutral network (as shown in Table 2), in which the front 11 groups are the training samples, while the rest 2 groups are the verification samples.

Table 2. Training Sample and Verification Sample

Sample Number	Input			Output
1	0.4680	0	0.5103	0.0249
2	0	0.5103	0.0249	0.4630
3	0.5103	0.0249	0.4630	0.0012
4	0.0249	0.4630	0.0012	0.0038
5	0.4630	0.0012	0.0038	0.4783
6	0.0012	0.0038	0.4783	0.0249
7	0.0038	0.4783	0.0249	0.4605
8	0.4783	0.0249	0.4605	0.0128
9	0.0249	0.4605	0.0128	0.5131
10	0.4605	0.0128	0.5131	0.0038
11	0.0128	0.5131	0.0038	0.0089
12	0.5131	0.0038	0.0089	1
13	0.0038	0.0089	1	0.4861

The decline curve of the network model training error shows in Figure 3, and the network training will be stopped after the network training steps reach the 22 step and satisfy the requirements. And at this moment, the error of mean square of the network model reaches the accuracy preset. The fitting diagram and error changing curve of the measured value and predicted value are shown in Figure 4 and Figure 5.

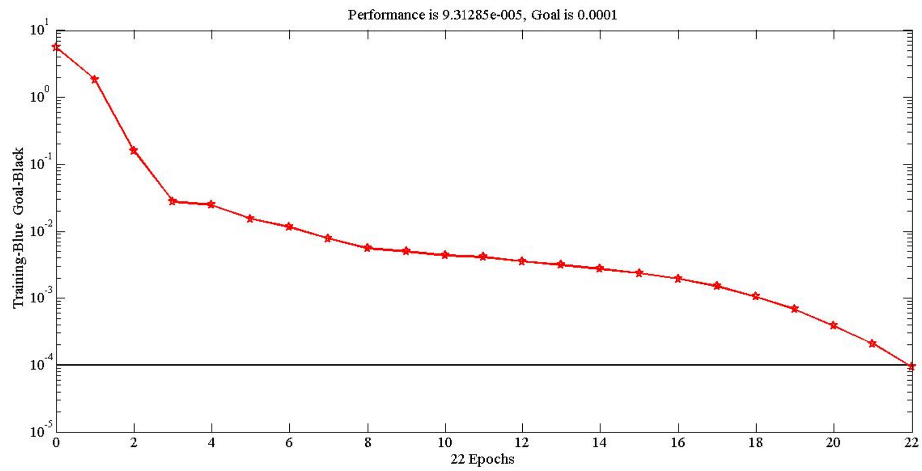

Figure 3. The Decline Curve of the Network Model Training Error

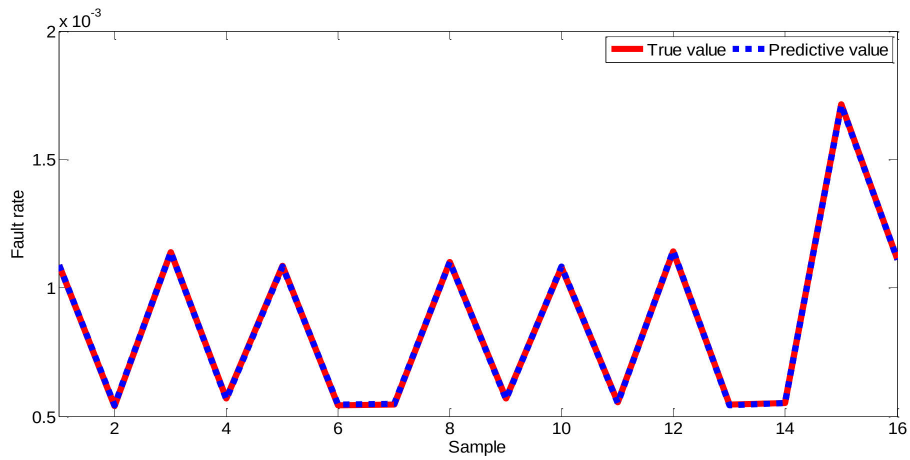

Figure 4. The Fitting Diagram of the Measured Value and Predicted Value

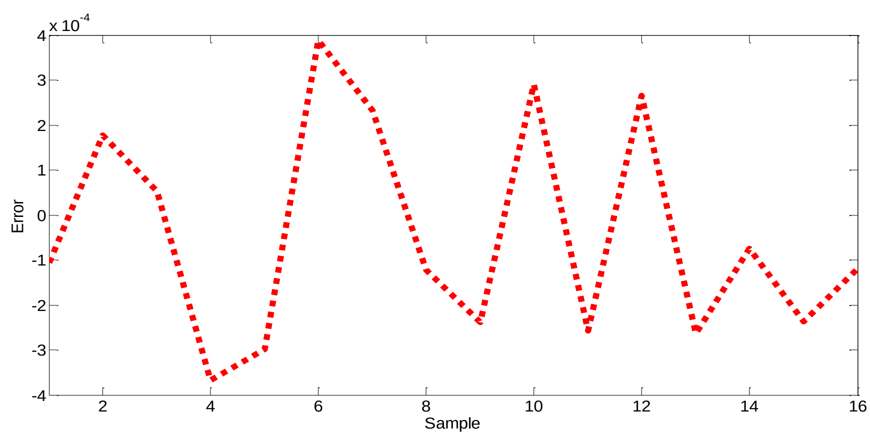

Figure 5. Error Changing Curve of the Measured Value and Predicted Value

5. Result Analysis

The training error curve of the BP neutral network is shown in the Figure 4, in which the black heavy line stands for the preset precision, the red heavy line stands for the changes of training error, and the horizontal ordinate stands for the training cycle of the network. It can be seen from the figure that it can satisfy the precision demands after 22 cycles. The fitting diagram of the measured value and predicted value is shown in the Figure 5, neural network work based on particle swarm optimization are well fitting. After the training, the test sample will be input for predicating the network, and error changing curve of the measured value and predicted value will be obtained through Matlab simulation. Compared to the actual value, the error is from 0 to 0.0004, which is acceptable in the practical production. Therefore, it can testify that the BP neutral network based on the particle swarm optimization can be applied into the practical production.

In the end, the neutral network prediction will be employed to predicate the failure rate of this type of numerical control system within the next three months. The result of the simulation calculation with Matlab is 0.4134, and it is 10.2582 after normalization processing. Namely, the possible failure rate of this type of numerical control system within this period will be 10.2582×10^{-4}.

6. Conclusion

The reliability prediction model for the CNC system of the BP neutral network algorithm has been proposed based on the particle swarm optimization. It turns out that the improved algorithm overcomes the slow convergence speed of the traditional BP neutral network and the limitations of easily falling into the local weight, and enhances the convergence speed and precision of the BP neutral network. Three-layer neutral network prediction model has been established according to the design requirements of the numerical control system. Meanwhile, the data acquired in the on-spot test has been counted to establish the training sample set and test sample for the training prediction of the neutral network. Successful prediction of the reliability of this numerical control system in the next time period has been carried out as soon as the network reaches the required errors.

Acknowledgements

This paper is supported by state key science and technology special projects for advanced CNC machine tools and basal manufacturing equipments (2012ZX04011021), and natural science foundation of Zhejiang province (No. Y1110708).

References

[1] I. D. Lins, M. d. C. Moura, E. Zio and E. L. Droguett, “A paricle swarm-oprimized support vector machine for reliability prediction”, Quality and Reliability Engineering International, vol. 2, no. 28, **(2012)**.

[2] I. D. Lins and E. L. Droguett, “Redundancy allocation problems considering systems with imperfect repairs using multi-objective genetic algorithms and discrete event simulation”, Simulation Modelling Practice and Theory, vol. 1, no. 19, **(2011)**.

[3] S. W. Lee and H. K. Lee, “Reliability prdiction system based on the failure rate model for electronic components”, Journal of Mechanical Science and Technology, vol. 5, no. 22, **(2008)**.

[4] M. D. C. Moura and E. L. Droguett, “Mathematical formulation and numerical treatment based on transition frequency densities and quadrature methods for non-homogeneous semi-Markov processes”, Reliability Engineering and System Safety, vol. 2, no. 94, **(2009)**.

[5] S. Y. Yang, W. S. Kwon and S. B. Lee, “Chip warpage model for reliability prediction of delamination failures”, Microelectronics Reliability, vol. 4, no. 52, **(2012)**.

[6] M. Yu, Z. He and Q. Qian, “Reliability analysis combined hardware/software system based on markov

process", Acta Electornica Sinica, vol. 2, no. 38, **(2010)**.
[7] G. Ren, D. Wang and X. Miao, "Research on CNC reliability prediction based on grey system theory", Machinery Design& Manufacture, vol. 5, no. 5, **(2010)**.
[8] A. Z. Al-Garni and A. Jamal, "Artificial neural network application of modeling failure rate for Boeing 737 tires", Quality and Reliability Engineering International, vol. 2, no. 27, **(2010)**.
[9] W. C. Hong and P. F. Pai, "Predicting engine reliability by support vector machines", The International Journal of Advanced Manufacturing Technology, vol. 2, no. 28, **(2006)**.
[10] Z. Man and H. Wu, "A new adaptive backpropagation algorithm based on Lyapunov stability theoryfor neural networks", IEEE Trans on Neural Networks, vol. 6, no. 17, **(2006)**.
[11] W. K. Wong, C. W. M. Yuen, D. D. Fan, L. K. Chan and E. H. K. Fung, "Stitching defect detection and classification using wavelet transform and BP neural network", Expert Systems with Applications, vol. 2, no. 36, **(2009)**.
[12] K. W. Chau, "Reliability and performance-based design by artificial neural network", Advances in Engineering Software, vol. 3, no. 38, **(2007)**.
[13] S. Ch and S. Mathur, "Particle swarm optimization trained neural network for aquifer parameter estimation", KSCE Journal of Civil Engineering, vol. 3, no. 16, **(2012)**.
[14] R. B. Chinna and P. Baruah, "A neuro-fuzzy approach for estimating mean residual life in condition-based maintenance systems", International Journal of Materials and Product Technology, vol. 1, no. 20, **(2004)**.
[15] P. Pai and K. Lin, "Application of hybrid learning neural fuzzy systems in reliability prediction", Quality and Reliability Enginnering International, vol. 2, no. 22, **(2006)**.
[16] G. He and N. Huang, "A modified particle swarm optimization algorithm with applications", Applied Mathematics and Computation, vol. 3, no. 219, **(2012)**.
[17] Y. G. Petalas, K. E. Parsopoulos and M. N. Vrahatis, "Memetic particle swarm optimization", Annals of Operations Research, vol. 1, no. 156, **(2007)**.
[18] K. Tang and T. Li, "Comparison of different partial least-squares methods in quantitative structure–activity relationships", Analytica Chimica Acta., vol. 1, no. 476, **(2003)**.
[19] H. Wang, S. Yang, W. H. Ip and D. Wang, "A Memetic Particle Swarm Optimization Algorithm for Dynamic Multi-Modal Optimization Problems", International Journal of Systems Science, vol. 7, no. 43, **(2012)**.
[20] H. Wang, S. Yang, W. H. Ip and D. Wang, "A particle swarm optimization based memetic algorithm for dynamic optimization problems", Natural Computing, vol. 3, no. 9, **(2010)**.

Authors

Yan Gu, he is currently a doctor at Jilin University, China. His current research interests include different aspects of software reliability and quality control.

Yiqiang Wang, he received his PhD in Mechanics(1999) from Jilin University, China. Now he is a professor and PhD candidate supervisor at Zhejiang University, China. His current research interests include different aspects of quality control and digital manufacturing technology.

Xiaoqin Zhou, he is a professor and PhD candidate supervisor at Jilin University, China. His current research interests include different aspects of advanced optical Manufacturing and digital manufacturing technology.

Xiuhua Yuan, he received his M.Sc. in Mechanics (2008) and PhD in Mechanics (2011) from Jilin University. Now he is a post doctor at Zhejiang University, China. His current research interests include different aspects of man-machine system and intelligent robotics.

Mingyang Ma, she received her M.Sc. in Mechanics (2012) from Jilin University. Now she is a technician of AVIC Shenyang Liming Aero-engine (Group) Corporation LTD. Her current research interests include digital manufacturing technology and virtual manufacturing.