Equipment Quality Condition Assessment Based on Improved PCA-BP

Jin An¹⁺, Ting-xue Xu¹, Xiang Zeng¹, Zhi-qiang Li¹ and Gui-fang Zhu^{1,2}

¹ Naval Aeronautical and Engineering University Department of Ordnance Science and Technology ² Shandong High-tech Institute

Abstract. Development of monitoring technologies and computer equipment makes test data acquisition be more real-time and complete, which provides better qualification to obtain the real-time equipment condition. In this paper, research status of equipment quality condition assessment is analyzed. Two aspects are expounded from dimensionality reduction and the selection of index system to the choice of assessment methods. Firstly, the condition level is divided and the raw test data is standardized. Then the PCA method is used to select the vectors to be evaluated and reduce the dimension. After that, the improved BP neural network algorithm is applied to assess the equipment quality condition. Finally, the applicability and advancement of the method are verified by an example.

Keywords: test data, quality condition assessment, PCA, BP neural network.

1. Introduction

With the digitization promotion of test equipment, the digitized test parameters result can be recorded and compared with the standard quantitative values. The mastery of equipment quality condition and keeping the equipment in good condition are of great importance. Aiming at the research status defects, two aspects are expounded in this paper: index system dimensionality reduction and the choice of assessment methods. The fundamentals are condition level dividing and the raw test data standardizing. On the one hand, the PCA method is used to select the vectors to be evaluated and reduce the dimension. On the other hand, the improved BP neural network algorithm is applied to assess the equipment quality condition. Finally, an example is showed to verify the applicability and advancement of the method.

2. Research Status of Quality Assessment

The concept of quality condition assessment is coming from technology condition assessment and the Prognostics and Health Management (PHM). As one of the most important parts of Condition-Based Maintenance (CBM), condition assessment has been widely studied and applied [1]. Differently from the qualitative assessment of traditional quality assessment based on expert experience, the quality condition assessment mainly focuses on the comprehensive evaluation based on the monitoring and test data.

Quality assessment has always been a hot spot in the field of integrated logistics support and quality management [2, 3]. Respectively, E. Li [4], S. Zhao [5], W. Liu [6] and L. Duan [7] have discussed quality assessment methods for various stages of equipment life cycle. what's more, the allocation of weight, the built up of evaluation model and the assessment methods covering qualitative, quantitative and comprehensive ones have been explained. On the basis of evaluation theory and methods research, Y. Ma [8] offered the theory and method applicable to the military field.

⁺ Corresponding author. Tel.: 15165736930; fax: 0535-6635043. *E-mail address*: 137331253@qq.com

At present, most of the equipment is equipped with test equipment. But in the operation of equipment, only two conditions (failure and non-failure) are based on to determine the equipment condition. The collection and analysis of deviation from the standard test data and the trend of information changes are not complete. Also, expert experience is excessive depended on. In this regard, a more impersonal and comprehensive assessment system is demanded.

3. Quality Level Division and Data Pre-processing

3.1. Quality level division

In order to describe the equipment quality condition better, the existing classification method and the health management concept and method are used for reference to divide the equipment quality condition into five levels: "good", "normal", "useful", "deteriorated" and "faulty" as shown in Table 1.

Table 1: levels of quality condition						
Levels	Level description					
good	The test data of all the performance parameters are within the specified threshold, and all the performance characteristic parameters are close to the standard value, away from the threshold upper and lower boundary.					
normal	The test data of all the performance parameters in the test are within the specified threshold, and the test data of some performance characteristic parameters fluctuate in the vicinity of the standard value, but still far from the upper and lower thresholds.					
useful	All the performance parameters of the test data are within the specified threshold, and some performance characteristics of the test data far from the standard value, but still did not reach the upper and lower boundaries.					
deteriorated	The test data of all performance characteristic parameters are in the specified threshold range, and the test data of some performance characteristic parameters are close to or even reach the upper and lower thresholds.					
Faulty	The test data for one or several performance characteristic parameters during the test is outside the specified threshold. The performance of the test is often a frequent occurrence of multiple parameters of the phenomenon of ultra-threshold.					

3.2. Data preprocessing

3.2.1 Normalization

The equipment condition can be characterized by the corresponding test results away from the size of the specification given by the industrial sector. Also, for performance characteristics, the dimension and threshold value are not basically the same. Assuming there are *n* test parameters, the normalized value λ_i of the test parameter $i(i = 1, \dots, n)$ is shown in equation (1).

$$\lambda_{i} = \begin{cases} \left| \frac{x_{i} - x_{s}}{x_{u} - x_{s}} \right|^{k} & x_{s} \leq x_{i} \leq x_{u} \\ \left| \frac{x_{i} - x_{s}}{x_{l} - x_{s}} \right|^{k} & x_{l} \leq x_{i} < x_{s} \end{cases}$$

$$(1)$$

In the formula, x_i is the measured value of performance characteristic parameter *i*, x_s is the standard value, x_u is the upper threshold value, x_l is the lower threshold value, and *k* is the influence degree of the parameter changes on the performance characteristic parameter state, which is generally numbered 1. From the expression of the normalized value, we can see that the state of the performance characteristic parameter is deteriorated with the increase of the normalization value. When the measured value of the performance characteristic parameter is equal to the standard value, the normalized value is equal to 0, and the performance characteristic parameter is in the optimal state. When the measured value of the performance characteristic parameter is 1, and the performance characteristic parameter is in the worst state.

3.2.2 Time correction

In general circumstances the characteristics of the equipment can only get the quality of each test state, while the equipment quality condition and its changes in the law between every two tests can't be reflected. Assuming that the equipment has not suffered an instantaneous stress failure, its quality condition is the firstly slow and then gradually degenerate process. Modify the test data for time correction according to the formula (2).

$$\begin{cases}
S_{2} = 1 & T < T_{1} \\
S_{2} = \frac{b-a}{T_{2} - T_{1}} (T - T_{1}) + a & T_{1} \le T < T_{2} \\
S_{2} = \frac{-b}{T_{3} - T_{2}} (T - T_{3}) & T_{2} \le T < T_{3} \\
S_{2} = 0 & T \ge T_{3}
\end{cases}$$
(2)

 (T_1,T_2) is the slow failure time for the equipment, (T_2,T_3) is the rapid failure time, *a* and *b* are degradation coefficient, all the value can be determined based on the actual degradation of data and expert experience.

4. Condition Assessment Model

4.1. Index optimization based on PCA

Many experts and scholars have done a lot of research with regard to the optimization of indicators. In addition to subjective preference screening, most of the theoretical research results are focused on eliminating the relevance of indicators. Among the various methods, the principal component analysis (PCA) method is widely used because of its simple principle, high optimization efficiency and easy software realization. PCA is a multivariate statistical analysis method that transforms multiple indicators into a few unrelated composite indicators. Assuming that there is *n* samples, that is, the *n* test results of the equipment, each sample can be described by the *p* factors $\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_p$, the original data matrix can be obtained:

$$\mathbf{X} = (\mathbf{X}_{1}, \mathbf{X}_{2}, \dots, \mathbf{X}_{p}) = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1p} \\ x_{21} & x_{22} & \dots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{np} \end{pmatrix}$$

$$\mathbf{X}_{j} = \begin{pmatrix} x_{1j}, x_{2j}, \dots, x_{nj} \end{pmatrix}^{T} (j = 1, 2, \dots, p)$$
(3)

Do a linear combination for p vector of data matrices $\mathbf{X}: \mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_p$.

$$= a_{1i} \mathbf{X}_{1} + a_{2i} \mathbf{X}_{2} + \dots + a_{pi} \mathbf{X}_{p}, \quad (i = 1, 2, \dots, p)$$

$$a_{1i}^{2} + a_{2i}^{2} + \dots + a_{pi}^{2} = 1, \quad i = 1, 2, \dots, p$$
(4)

The coefficients are determined by the following principles:

 F_i

- $Cov(F_i, F_j) = 0 \ (i \neq j; i, j = 1, 2, \dots, p)$.
- $Var(F_i) \ge Var(F_2) \ge \cdots \ge Var(F_p)$.
- $\sum_{i=1}^{p} Var(x_i) = \sum_{i=1}^{p} Var(F_i)$

The comprehensive indicator F_1, F_2, \dots, F_p above is called the first principal component, the second principal component, \dots , the *p* th principal component of the original index. With the front part of the principal components F_1, F_2, \dots, F_k ($k \le p$), you can reflect the original index contains a large part of the amount of information, and the principal components are irrelevant. So that you can use a few of the irrelevant principal components to take the place of the original indicators to analyse and solve the problem.

To get the required principal component of the original index, the core is the combination coefficient. Supposing that the covariance matrix of $\mathbf{X} = (\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_p)$ is \mathbf{S} , the eigenvalues in order from large to small are $\lambda_1 > \lambda_2 > \dots > \lambda_p > 0$.

Mathematical statistics have shown that the combined coefficient $a_{1i}, a_{2i}, \dots, a_{pi}$ of the *i* th principal component F_i of the original index is the normalized eigenvector corresponding to the *i* th eigenvalue λ_i , and there is:

$$Cov(F_i, F_j) = \begin{cases} \lambda_i & i = j \\ 0 & i \neq j \end{cases}$$
(5)

Thus, the variance contribution rate of the previous k principal components is:

$$a(k) = \frac{Var(F_i)}{Var(F_j)} = \frac{\sum_{i=1}^{n} \lambda_i}{\sum_{j=1}^{p} \lambda_j}$$
(6)

In this way, to find the p principal components of the original index, we only need to find the eigenvalue of the covariance matrix **S** of the original index and the corresponding normalized orthogonal eigenvector. The principal component can be expressed as the original indicator:

$$F_i = a_{1i}\mathbf{X}_1 + a_{2i}\mathbf{X}_2 + \dots + a_{pi}\mathbf{X}_p, \quad (i = 1, 2, \dots, k)$$

$$\tag{7}$$

And then use the weighted arithmetic average to synthesize, and the principal component of the variance contribution rate as the weight, that is,

$$F = \frac{\lambda_1 F_1 + \lambda_2 F_2 + \dots + \lambda_k F_k}{\sum_{i=1}^p \lambda_i}$$
(8)

So as to get the comprehensive evaluation of each sample, which can be compared and sort analysis.

4.2. Condition assessment based on BP neural network

For the optimized index, the structure of the factors is complex and non-linear, and it is difficult to determine the influence degree of each evaluation index on the quality and the mutual influence by using the traditional analytic hierarchy process (AHP) and the fuzzy comprehensive evaluation method.

BP neural network has been widely used in the field of system evaluation and simulation prediction because of its good nonlinear mapping approximation ability and generalization ability and easy realization. ^[9-10]. The use of BP neural network can be a good way to avoid the subjective factors, through the BP algorithm on the evaluation of the various indicators of objective decentralization, which can reasonably arrive at the true level of quality condition. Therefore, this paper chooses BP neural network algorithm to assessment equipment quality condition based on test data.

BP neural network is a three-layer or more neurons of the one-way propagation multi-layer forward neural network. Learning samples are in accordance with the "error inverse propagation algorithm" ^[11] for neural network learning and training. As the error correction in the algorithm continues, the correct rate of the network is rising. The process is divided into network learning process and network assessment and output process.

Experiments show that the three-tier BP network can be approximated to any continuous function ^[12], so a three-tier network can be used to assess the equipment quality condition based on test data.

The calculation is divided into two steps:

1. Network learning process

The form and basic meaning of the symbols used in this section can be seen in references [9-12].

2. Network working process

Input the predicted sample, that is, the actual equipment test parameters. Calculate the output of the forecast sample (equipment quality condition level based on the test data) according to the training process of the inter-layer connection weights and thresholds.

5. Simulation Example

5.1. Index optimization

In this paper, eight performance parameters are selected for 4 times, and PCA is used to optimize the analysis. First of all, deal with the original index data for standardization and time series processing, to get the normalized test data as shown in Table 2.

Table 2: Normalized test data								
	T1	T2	T3	T4				
V1	0.823	0.756	0.881	0.913				
V2	0.640	0.705	0.861	0.804				
V3	0.602	0.806	0.759	0.922				
V4	0.811	0.698	0.908	0.712				
V5	0.651	0.816	0.944	0.825				
V6	0.732	0.806	0.608	0.855				
V7	0.764	0.609	0.802	0.924				
V8	0.884	0.793	0.838	0.826				

The variables and constraints are input to the SPSS software. Since the PCA method requires that the variables are positive, the positive correlation test is carried out. The coefficient correlation matrix results show that the set of data can be analyzed by PCA. Set the maximum convergence iteration number to 25, and start the PCA in SPSS. According to the "total variance explained" shown in Table 3, it can be seen that the cumulative contribution rate of the first three principal components reaches 100%, and the matrix formed can explain the initial evaluation index.

Table 3: Total variance ex	plained

	Initial Eigenvalues				Extraction Sums of Squared Loadings			
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %		
1	3.374	42.170	42.170	3.374	42.170	42.170		
2	2.889	36.107	78.277	2.889	36.107	78.277		
3	1.738	21.723	100.000	1.738	21.723	100.000		
•••••	•••••					•••••		
Extraction Method: Principal Component Analysis.								

The coefficient matrix of the three principal components can be further obtained, as shown in Table 4.

	Component ^a							
	1	2	3					
V1	.815	.221	.535					
V2	.980	019	198					
V3	.621	779	.087					
V4	.340	.898	279					
V5	.828	144	542					
V6	253	822	.510					
V7	.672	.163	.723					
V8	216	.838	.500					
Extraction Method: Principal Component Analysis.								
a. 3 components extracted.								

Table 4: Principal component matrix

5.2. Condition assessment

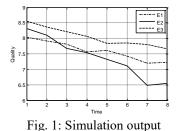
According to the above method, PCA analysis of 360 test parameters of five subsystems of the equipment was carried out, and 24 principal components of five groups were obtained. A three-layer BP neural network is established. The output layer is the assessment result S_1 , the membership degree matrix of each grade. The number of neurons in the middle layer is calculated to be 50 according to empirical formula, and the data of the normalized network training were obtained by simulation and expert experience, as shown in Table 5. The evaluation criteria are used as the evaluation data in the first 25 groups, and the 26th group is the data to be assessed.

	Input					Output					
	U ₁	U ₂	U3		U ₂₃	U ₂₄	good	normal	useful	deteriorated	Faulty
1	0.98	0.98	0.95		0.95	0.95	1	0	0	0	0
2	0.85	0.85	0.80	•••••	0.80	0.80	0	1	0	0	0
3	0.60	0.60	0.50		0.60	0.60	0	0	1	0	0
		•••••		•••••		•••••	•••••	•••••	••••	•••••	•••••
25	0.40	0.40	0.20		0.10	0.20	0	0	0	1	0
26	0.74	0.87	0.92	•••••	0.93	0.77	0	1	0	0	0

Table 5: Data set

In MATLAB, call the neural network toolbox, set the corresponding parameters, and do network training and evaluation of the simulation. It is evaluated that indicators membership matrix is (0.16, 0.72, 0.10, 0.02, 0).

Through the assessment we can see that the state of the equipment is "normal". In accordance with the above steps, the three equipment of the same batch are taken for continuous state evaluation, and the levels are assigned to the results shown in Fig. 1. It can be seen that the quality condition and quality condition of the same batch of equipment are basically the same, and with the advance of the time axis, the quality condition is declining. Wherein the quality level of the equipment 2 is reduced rapidly and should be of interest.



6. Suggestions

The equipment quality condition assessment based on test parameters can provide technical support for equipment maintenance work, technical support work, preventive maintenance and extended life work. The results of the equipment quality condition based on the improved PCA-BP are consistent with the actual condition of the equipment, while it can be realized by computer conveniently and fast. In the future, the condition assessment hardware and software system can be established and the system can be connected with the test equipment through the port to form a perfect condition management system. Further refinement of the model and its application to the actual quality management work will be the next step in the research direction.

7. References

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