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SOLID LUBRICATED BEARINGS PERFORMANCE DEGRADATION ASSESSMENT: A FUZZY SELF-ORGANIZING MAP METHOD

OCENA OBNIŻENIA CHARAKTERYSTYK ŁOŻYSK ZE SMAREM STAŁYM: METODA ROZMYTYCH SAMOORGANIZUJĄCYCH SIĘ MAP

Solid lubricated bearings are common components in space mechanisms, and their reliability and performance degradation assessment are very crucial. In this study, a fuzzy self-organizing map method is used to perform performance degradation assessment. Feature vectors are constructed by indices of vibration as well as friction torque signal. Self-organizing map is then used to perform performance degradation assessment and the subjection of each feature vector to normal cluster on output layer is used as degradation indicator. Accelerated life test results show that this method can make effective performance degradation assessment and describe degradation degree in the whole life time.

Keywords: *solid lubricated bearings, performance degradation, fuzzy self-organizing map.*

Łożyska ze smarem stałym to powszechnie stosowane elementy urządzeń, a ich niezawodność i ocena degradacji charakterystyk są bardzo istotne. W przedstawionej pracy wykorzystano metodę rozmytych samoorganizujących się map do oceny obniżenia charakterystyk. Wektory cech skonstruowano za pomocą wskaźników wibracji, jak również sygnału momentu tarcia. Następnie dokonano oceny obniżenia charakterystyk z wykorzystaniem samoorganizującej się mapy, a za wskaźnik degradacji przyjęto przynależność każdego wektora cech do normalnej grupy w warstwie wyjściowej. Wyniki badań przyspieszonych pokazują, że przy użyciu omawianej metody można dokonywać skutecznej oceny obniżenia charakterystyk a także opisywać stopień degradacji w całym okresie eksploatacji.

Słowa kluczowe: *łożyska ze smarem stałym, obniżenie charakterystyk, rozmyta mapa samoorganizująca się.*

1. Introduction

Solid lubricated bearings are widely used in space mechanisms and other appliances, due to their characteristics of negligible vapor contamination, wide operating temperature and ignorable surface migration [17, 25]. Their failure might cause severe economic loss, or even catastrophic consequences. For this reason, reliability and performance degradation assessment of solid lubricated bearings have drawn more and more attention in this research field.

Many studies of failure mechanism and its influencing factors of solid lubricated bearings have been carried out. Early in 1980s, several researches by simulation methods were reported. These studies mainly focused on the tribological performance of solid lubricated bearings, including impact factors of wear rate [2, 6], influence of geometry and motion forms on dynamic performance [4, 5]. In 1990s and later, more experimental as well as simulation studies were carried out, aiming at investigating the process of particle generation [23], relationship between fault mechanism and outer stress and some other tribological behaviour [7, 17, 22, 29, 30]. These studies made further research on fault mechanism of solid lubricated bearings, as well as its relationship with environments and working conditions.

However, for the research of solid lubricated bearings, scholars merely concentrate on the fault mechanism analysis, while performance degradation assessment that can better meet the need to improve machine uptime and near-zero breakdown productivity has been scarcely studied [11]. Usually performance degradation assessment consists of two steps. Firstly, features which can reflect operating status should be extracted. And secondly, an assessment needs to be generated, describing degradation degree of the system. For solid lubricated bearings, several studies on their performance degradation assessment have been performed. Using wear rate as a feature reflecting operating status, Meeks and Bohner studied prediction of bearing life by creating semi-empirical wear equations [15]. This assessment method is built based on data acquired when failure mode is known. However, in actual situation, this is not always the case, which makes this method not very practical. Later several experimental researches were carried out by NASA and ESA, assessing degradation degree of solid lubricated bearings by carefully dismantling and observing [1, 3, 9, 16]. Assessing methods in these studies may not be appropriate for performance degradation assessment of other solid lubricated bearings, because dismantling is not easy to perform. Moreover, these methods did not consider working condition and environment factors. A comprehensive and effective method which can realize real-time monitoring of operating status of solid lubricated bearings is emergently needed.

Signal processing has been extensively used for condition monitoring [14]. Based on feature vectors extracted from different kinds of signals by relevant signal processing methods, various researches on performance degradation assessment have been performed [8, 18–21, 32, 33]. These researches mainly focused on intelligent assessment methods, and self-organizing map (SOM) is one of them. Being a topology-preserving mapping from a high-dimensional input to a lower-dimensional output space, SOM is a prominent tool for data analysis and clustering [13]. Application of SOM in performance degradation assessment is mainly based on trajectory method, which observes the trajectory of the best matched unit (BMU) for the data of life tests [21]. This method can provide the time when a test object goes into a certain status, but for each input vector of SOM, only the BMU is considered, which makes it not accurate enough. Meanwhile, in this method only the time of status transition can be observed, while degradation degree corresponding to each input vector is not illustrated.

In this study, a performance degradation assessment method for solid lubricated bearings based on fuzzy analysis of SOM output layer is proposed. Based on analysis of the consuming process of lubrication film in solid lubricated bearings, certain metrics of vibration and friction torque signal of solid lubricated bearings are selected to compose feature vectors. Then the fuzzy SOM which can quantitatively illustrate the degradation degree is used to describe the degradation process. Accelerated life test of solid lubricated bearings is conducted to evaluate the effectiveness of this approach under different working stresses.

This paper is organized as follows. In Section 2, consuming process of lubrication in solid lubricated bearings is analyzed, and feature vectors are composed based on processing of vibration and friction torque signal. Basis of SOM is then briefly presented and the proposed fuzzy SOM method is introduced. In Section 3, accelerated life test of four groups of solid lubricated bearings is conducted and performance degradation assessment is carried out based on the proposed fuzzy SOM method. Conclusions are in Section 4.

2. Technical background and methodology

2.1. Consuming of lubricant film and feature extraction

Different from bearings lubricated with oil or grease, solid lubricated bearings have their particular fault mechanisms. The structure of a solid lubricated bearing is shown in Figure 1.

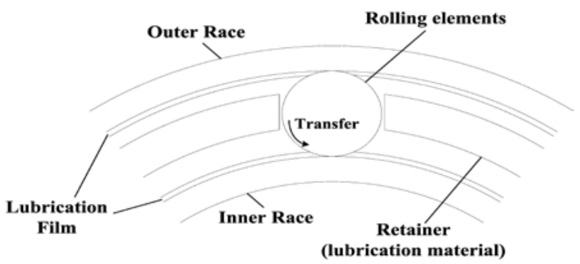

Fig. 1. Structure a solid lubricated bearing

When a solid lubricated bearing is working, no outer oil supply system is needed. As a result, solid lubricated bearings are also called self-lubricating bearings. In most cases, inner and outer races of solid lubricated bearings are coated with lubrication film, and retainer is made of lubricating material. Rolling elements are usually made of steel or ceramics, which are not lubrication material.

In solid lubricated bearings, lubrication film on inner and outer races as well as lubrication material of the retainer plays as lubricants. When a solid lubricated bearing is put into use, at first lubrication film on inner and outer races plays as lubricant and this part of lubricant gradually consumes. Meanwhile, lubrication material of retainer is transferred onto inner and outer races by the rotating and spinning of rolling elements and plays as complementary lubricant.

Due to different working condition, transfer rate of retainer lubricant can be different, and this will cause different effect on the performance degradation process of solid lubricated bearings. If the transfer rate is fluctuating within an appropriate range, a solid lubricated bearing might work for a relatively long time, and turns into failure after both two parts of lubrication film completely consumes. If this rate is small, the consumed lubricant of inner and outer races cannot be replenished in time, and a solid lubricated bearing might turn into failure in a faster speed. In these two cases, the bearing fails due to wear caused by lack of lubricant. This failure mode is called 'Failure Mode 1' in the rest of this paper.

However, if the transfer rate is big, transferred film will accumulate on inner and outer races, and in this case the bearing might not work smoothly. Excessive transferring of retainer lubrication material will make cage pockets become large and collision of balls on cage pockets will be stronger and aggravate the instability of retainer [26]. Both the accumulation and the instability will accelerate the degradation process and eventually cause the bearing to failure. This failure mode is called 'Failure Mode 2' in the rest of this paper.

As mentioned before, signal processing has been widely used in condition monitoring, as different kinds of signals contain large quantity of information of system operating status. For bearings, vibration signal has been most commonly used [24]. Compared with bearings lubricated with oil or grease, vibration signal of solid lubricated bearings should have its specific characteristics owing to the different failure mechanism. When a solid lubricated bearing is running, small particles and pits are gradually generated due to the wear of lubricants on inner and outer races as well as the transferred film. As the bearing is continuously running, each time a rolling element runs over a particle or a pit, an impulse is generated. As the number of particles and pits is increasing, more impulses are expected to occur. Therefore, impulses in vibration signal can be used as indication of performance degradation of solid lubricated bearings.

However, impulses caused by the rolling of rolling elements over particles and pits are weak, because the size of particles and pits is usually very small. Vibration signal measured by vibration sensor experiences a series of modulation process, and due to inherent deficiency of measuring system, much noise will be inevitably introduced into the acquired vibration signal [31]. Hence effective signal processing method is required to extract these impulses which are almost entirely buried in acquired signal from vibration sensor. Taking the similarity of the shape between an actual impulse and the well-known Morlet wavelet into account, the adaptive Morlet wavelet filter proposed in [12] is used here. RMS, Kurtosis and crest factor of each filtered signal are selected to construct feature vectors, following the method in [8].

Friction torque signal can also reflect the operating status of solid lubricated bearings [25]. If there is no liquid lubricant, bearing friction torque can be largely accounted for by Coulomb friction between opposing surfaces [27]. So far no quantitative relationship between indices of friction torque signal and performance degradation of solid lubricated bearings has been reported. Only in [15], C. R. Meeks qualitatively pointed out that transferred film could increase friction torque. In this study, RMS, crest factor and variation value of each friction torque signal, together with RMS, Kurtosis and crest factor of each filtered vibration signal are used to construct feature vectors.

With constructed feature vectors, an efficient performance degradation assessment method is needed. In the following sections, background of SOM is briefly introduced, and the proposed degradation assessment method is given in detail.

2.2. Theoretical background of SOM

The SOM is an artificial neural network developed by Kohonen in [10]. It is an unsupervised neural network which just has two layers and can organize itself according to the nature of the input training data. Basic structure of SOM is shown in Figure 2.

The number of nodes on the input layer equals the dimension of each input vector. On the output layer, neurons are connected with neighboring neurons and usually form a two dimensional regular lattice hexagonally. Each neuron on the output layer is represented by n-dimensional weight, and n also equals the dimension of each input vector. Before training, weight of each neuron of the output layer is stochasticallly determined. In the training process, this weight is continuously adjusted at a gradually decreasing rate, and neurons on the output layer gradually form into clusters.

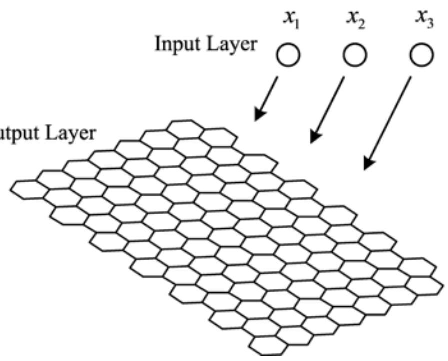

Fig. 2. Structure of SOM

After training, each neuron on the output layer has certain value of weight, and for each input vector, a distance of it and each neuron on the output layer can be calculated. The neuron with the minimum distance is called BMU. If data from normal, degradation and typical failure state are used to train the SOM, clusters representing different states of solid lubricated bearings would appear on the output layer. For a run-to-failure test of solid lubricated bearings, BMUs of extracted feature vectors at different time of the test should form into a trajectory, which can be used to describe the performance degradation process of solid lubricated bearings [21].

2.3. Fuzzy SOM

In the above trajectory method, for each input vector, the position of its BMU on the output layer is used to indicate the corresponding status. However, there exists two problems in this method. Firstly, in certain cases, the distance between the input vector and its BMU might be close to that between it and the neuron with the second smallest distance to it. Here this neuron is called the second BMU. If the BMU and the second BMU of an input vector do not belong to the same cluster, it might not be accurate enough to analyze the status of tested bearing just by observing the position of its BMU.

Secondly, dividing output layer into clusters by training result is a subjective process, and in certain cases, this subjectivity might lead to some problems. Figure 3(a) shows the output layer of a trained SOM and here the color of a neuron represents the distance between its neighboring neurons, as shown in the corresponding diagram on the right of the trained SOM in Figure 3(a). Thus neuron with color standing for bigger value can be treated as dividing line. A preliminary clustering result is shown in Figure 3(b), and it can be seen that it is not easy to determine whether the two neurons marked with a black square belong to cluster B or C here. In this case, the accuracy of trajectory method would be affected.

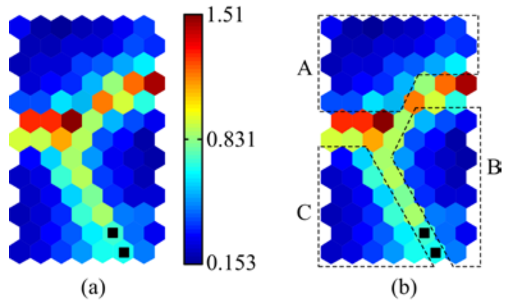

Fig. 3. A trained SOM and its clustering

To solve these two problems, a fuzzy analyzing method based on SOM is proposed in this study. Assuming that for certain type of solid lubricated bearing, there are typical data of normal state, degradation state and failure state. An SOM is trained based on typical data, and there are clusters formed on output layer. Here l is used to represent the number of clusters on output layer and l can be determined using Davies-Boulding clustering index [28]. Normally, there will be one cluster corresponding to normal state. Specify normal state as the 1st state. For a run-to-failure test of the same type of bearing, a group of data is obtained, denoted as $x_1, x_2, \ldots, x_m$, and m is the number of sampling points. Use n to represent the dimension of input vector.

For each input vector, the distance between it and each neuron in each cluster is calculated. Use $d_{j,k}^{(i)}$ to represent the distance between xi, the ith input vector, and wj,k, the jth neuron in the kth cluster. Here i=1,2,…,m, k=1,2,…,l, j=1,2,…,s_k, and s_k represents the number of neurons in the kth cluster. And $d_{j,k}^{(i)}$ can be expressed by

$$d_{j,k}^{(i)} = \left\| x_i - w_{j,k} \right\| \tag{1}$$

where $\|\cdot\|$ means Euclidean norm.

Use $D_{i,k}$ to represent the average distance between the ith input vector and each neuron in the kth cluster, as shown in

$$D_{i,k} = \frac{1}{s_k} \sum_{j=1}^{s_k} d_{j,k}^{(i)} \tag{2}$$

As the normal state has been specified as the 1st state, use (3) to define the subjection of the ith input vector to normal state.

$$S_i = \frac{\dfrac{1}{D_{i,1}}}{\sum_{k=1}^{l} \dfrac{1}{D_{i,k}}} \tag{3}$$

It can be seen from this derivation process that compared with conventional SOM method, the proposed fuzzy SOM method take the distance between an input vector and all neurons in all clusters into consideration. It uses the objection of an input vector to normal state as performance degradation indicator and is intuitionistic. For a run-to-failure test of solid lubricated bearings, following the curve of the subjection of each feature vector to normal state, the performance degradation assessment can be carried out. The method proposed in this paper is depicted in Figure 4.

3. Experimental results and analysis

3.1. Experiment rig

Accelerated life test was conducted to validate the effectiveness of the proposed method. Experiment rig is shown in Figure 5. Four groups of bearings were tested and Figure 5 only shows two of them. Each group had three pairs of bearings and was driven by a DC brushless motor. Vibration and friction torque signal for each group were obtained by corresponding sensors.

Before the test, each pair of bearings was preloaded axial loads. Vibration and friction torque signal were collected at the sample rate of 25.6 kHz and 50 Hz, respectively. Data collection was conducted every four hours, i.e. six times a day. Each collection lasted for 4 seconds. The test lasted for 47 days and at the end of the test, three of the four groups of bearings were in failure state. Note that this test was performed in nitrogen environment. Parameters and operating condition of tested bearings are shown in Table 1 and Table 2, respectively.

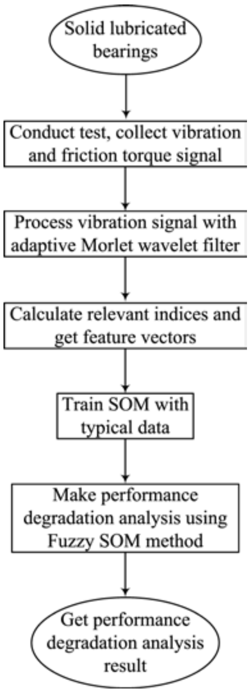

Fig. 4. The proposed performance degradation assessment method

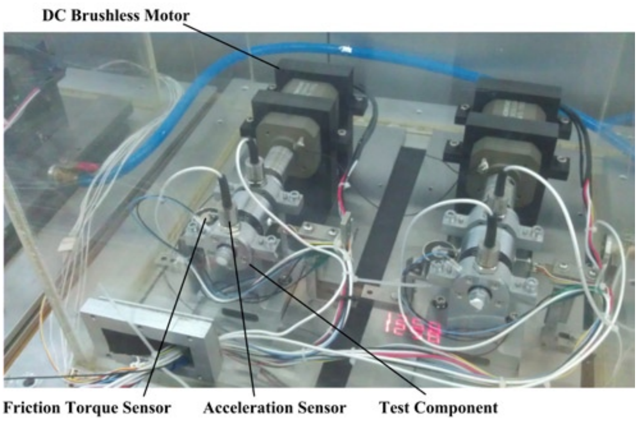

Fig. 5. Accelerated life test of solid lubricated bearings

Table 1. Parameters of tested bearings

Inner diameter (mm)	Outer diameter (mm)	Width (mm)	Ball number	Ball diameter (mm)
7	22	7	7	4.0

Table 2. Operation condition of tested bearings

Group Number	Rotation Velocity (rpm)	Axial Load (N)	Temperature (°C)
1	1500	20	20
2	1000	30	20
3	1500	30	20
4	1000	50	20

3.2. Results and analysis

Group 4 and Group 3 ended up at the 9th and the 31st day of the test, respectively. Group 2 ended up at the 45th day of the test. At the end of the test, Group 1 was still working. Dismantling results showed that there was large quantity of debris on inner and outer races of Group 4. For Group 3 and Group 2, a number of cracks and debris on inner and outer races as well as balls were observed. Group 1 was also dismantled after test and only small amount of debris and cracks were observed on inner and outer races. Combining with the observed results of the amplitude of vibration and friction torque signal, it can be concluded that Group 4 ended up in 'Failure Mode 2' and Group 3 and Group 2 ended up in 'Failure Mode 1'. For Group 1, certain degrees of performance degradation also took place.

Before the accelerated life test, a life test of the same type of solid lubricated bearings had been conducted. In this life test, the number of specimen is two, and both of them work under normal condition. Vibration and friction torque signal were also obtained. At the end of this test, one of the two specimen ended up in 'Failure Mode 1' and the other one ended up in 'Failure Mode 2'. Data acquired in this life test at typical status, i.e. normal, degradation and faiure, are used to train an SOM and the trained SOM is then used to conduct the performance degradation assessment of solid lubricated bearings in the accelerated life test.

As mentioned above, for every time of signal acquisition, both in the previous life test and the accelerated life test, vibration signal is propossed by adaptive Morlet wavelet filter. Then RMS, crest factor and kurtosis of the filtered vibration signal as well as RMS, crest factor and vatiation value of friction torque signal are calculated and used to construct feature vectors. These obtained vectors act as the input of SOM. Input dimension of SOM here is six. Number of neurons on the output layer and the ratio of side lengths are automatically determined by the SOM toolbox.

In final assessment of performance degradation of the four tested groups of bearings, trajectory method and the proposed fuzzy SOM method are adopted and results come out from these two methods are compared with each other. The SOM toolbox developed by Helsinki University of Technology is used. Firstly, SOM is trained by specified data, which consist of five groups, i.e. normal data, degradation and fault data of 'Failure Mode 1', and degradation and fault data of 'Failure Mode 2', respectively. These five groups are later labeled as 'N', 'D1', 'F1', 'D2' and 'F2' in SOM, respectively.

U-matrix of the trained SOM is shown in Figure 6(a). A preliminary clustering is made, judging by the color difference, and the result is also illustrated in Figure 6(a), and it can be seen that there are three clusters, marked with '1', '2' and '3' , respectively. Figure 6(b) shows the Davies-Boulding clustering index curve. On this curve three gets minimum value, which shows that three is the optimal number of clusters. The labeled map is shown in Figure 6(c). It can be seen that cluster '1' corresponds to normal state, cluster '2' corresponds to degradation state and cluster '3' corresponds to failure state. Though in cluster '3', 'Failure Mode 1' and 'Failure Mode 2' can be further classified, here they are treated as the same cluster as we only consider the degradation degree, not specified failure mode.

Degradation trajectory of the four groups of tested bearings is shown in Figure 7. For Groups 1, 2 and 3, each point stands for the status in two days. For Group 4, each point represents the status in one day. It can be seen that Group 1 moves from normal state to degradation state at the 29th day. Group 2 moves from normal state to degradation state at the 25th day, then to failure state at the 43rd day. Group 3 moves from normal state to degradation state at the 13rd day, then to failure state at the 29th day. Group 4 moves from normal state to degradation state at the 3rd day, then to failure state at the 9th day. For Group 2, 3 and 4, time falling into failure state is broadly in line with judgments of test operators. However, degradation degree in degrada-

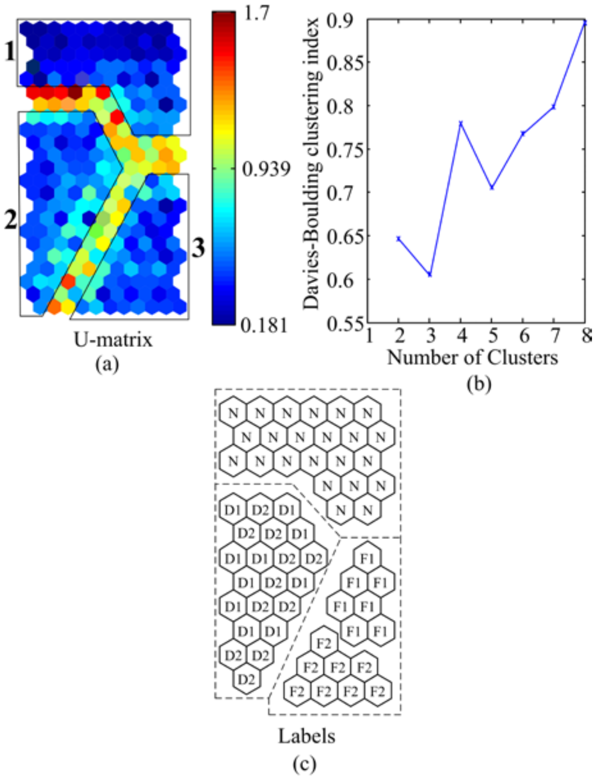

Fig. 6. Trained SOM with typical data (a) U-matrix and clustering, (b) Davies-Boulding clustering index curve, (c) Labeled map

tion state, corresponding to Cluster 2 in Figure 6(a) cannot be seen with trajectory method.

Then, with the method proposed in Section 2.3, performance degradation assessment of four tested groups is carried out, and the result is shown in Figure 8. 0.5 is selected as failure state threshold. Failure date of Group 2, 3 and 4 judged by trajectory method and fuzzy SOM method, as well as actual test result is compared in Table 3.

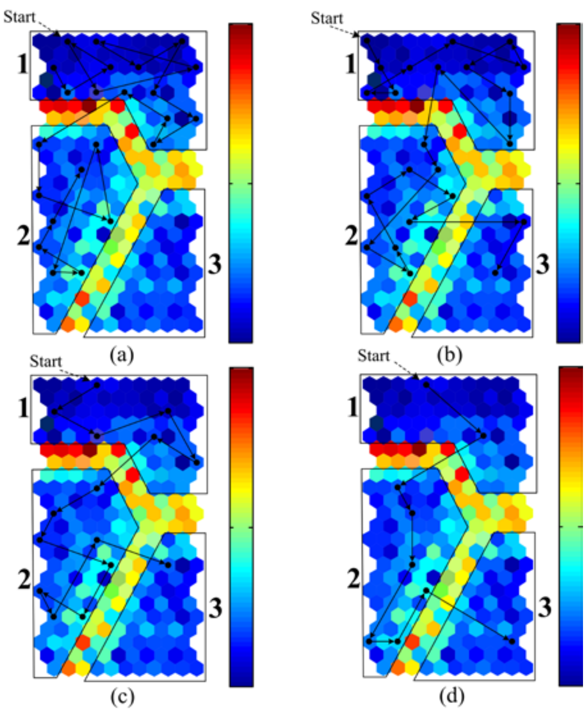

Fig. 7. Degradation trajectory of tested bearings (a) Group 1, (b) Group 2, (c) Group 3, (d) Group 4

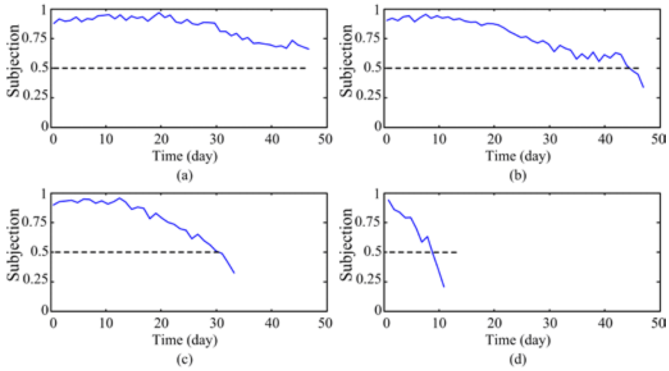

Fig. 8. Degradation curve of test bearings (a) Group 1, (b) Group 2, (c) Group 3, (d) Group 4

Table 3. Results comparison

Group Number	Actual Failure Date	Failure Date by Trajectory Method	Failure date by Fuzzy SOM Method
2	45	43	45
3	31	29	31
4	9	9	9

It can be seen that failure time of the four tested groups by fuzzy SOM method is in full accordance with test results. Moreover, before failure, degradation degree of the four groups of bearings can be clearly seen. In reality, this can give operators more time to conduct maintenance or replacement.

4. Conclusion

In this study, a new method for performance degradation assessment of solid lubricated bearings is proposed. After feature extraction based on vibration as well as friction torque signal, a fuzzy SOM is used to make performance degradation assessment. After training SOM with typical data, clusters are formed on output layer, and the subjection of an input vector to the cluster corresponding to normal state is used as performance degradation indicator. Accelerated life test results show that this method can give the time of transition to failure state as well as describe the degradation degree in the whole lifetime. Future studies should focus on the effect of training data selection on clustering forming of trained SOM and its accuracy of performance degradation assessment.

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