Motor Health Status Prediction Method Based on Information from Multi-sensor and Multi-feature Parameters

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Abstract

Health status prediction is of great significance for a motor system's safe operation and lifecycle management. The object of this work is to achieve better information fusion performance for information obtained from X-, Y-, and Z-axial and existed in the multi-feature parameter, and therefore gain more comprehensively and effectively prediction results of health status. First, a UAV power motor is chosen as the test item to obtain the original vibration data. Then, the multi-feature parameters are fused and chosen based on quality and quantity method considering the diagnosis results and degradation path descriptive ability. Next, the health status prediction is achieved with Bayesian updating algorithm. Finally, a DS theory and information entropy weight-based granulation fusion method of multi-source health status information for the electric motor is proposed. The method can achieve the fusion of multiple prediction results obtained from multi-feature parameters to gain the optimal health status prediction result for the motor. The result is compared with actual data and also verified by information entropy. Meanwhile, according to the prediction results, its application in risk assessment and maintenance planning were discussed.

Keywords Health status · Prediction · Motor · Multi-sensor · Multi-feature parameters

1 Introduction

With the development of industrial technology, motor products have been widely applied in emerging and traditional

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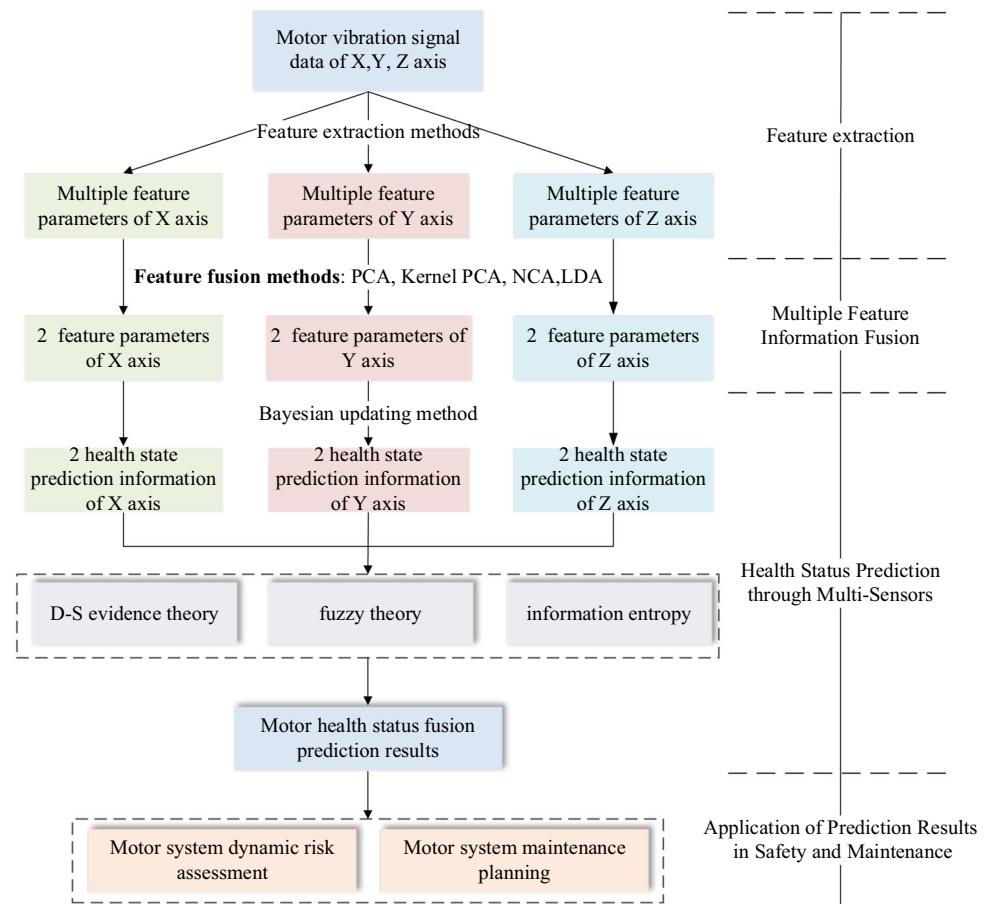 zhaoxuejiao@buaa.edu.cn

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areas. To reduce the harm of motor faults, increase the system's safe operation, economic efficiency, and lifecycle operational capability, it is increasingly urgent to accurately acquire and anticipate a motor's health status. For bulleted lists.

The key solution of the foregoing problems is to accurately extract health-related features from the signal of motor. Vibration signals are the most effective one due to the extensive and mature information it contains [1]. So, it has considerable applications, including time-domain-analysis-based methods (involving parameters such as mean, variance, mean–variance, peak value, skewness, kurtosis, and waveform [2], frequency-domain-analysis-based methods (involving parameters such as gravity frequency, mean-square frequency, and frequency variance [2], as well as the Hilbert–Huang transform (HHT) based on time–frequency-domain analysis [2, 3]. Different feature-extraction methods reflect product health status from different aspects, which both intersect and complement with each other. The fusion of information from different feature-extraction methods can be realized using principal component analysis (PCA) [4], kernel PCA [5], neighborhood components analysis (NCA) [6], and linear discriminant analysis (LDA) [7], etc. However, multi-feature

Fig. 1 Flowchart

parameters usually exist while fusing information without sacrificing useful ones. Meanwhile, the existing health status prediction methods mainly include physical models [8], the nonlinear degradation model [9, 10], Neural Network and Bayesian network model [11]. Predicting the health status of the motor, most researchers are based on uniaxial information [12, 13] or reduce a multiaxial status to an equivalent uniaxial one [14]. While a motor's vibration signal obtained from the X, Y, and Z axes are somewhat different, but also displays intersectionality and complementarity. Ignoring such information may cause accuracy loss of prediction results. Therefore, information extracted from X-, Y-, and Z-axial and the effective utilization of multi-feature parameters information are both considered in this paper to obtain more accurate and more useful health-related information of motor. The technical flowchart is shown in Fig. 1

First, we design a lifetime test on an electric motor to obtain the original vibration data gained from X-, Y-, and Z-axial. Second, we conducted feature-extraction methods on the original data and fused the multi-feature information based on quality and quantity method considering the diagnosis results and degradation path descriptive ability to obtain the feature parameters of X-, Y-, and Z-axial for health state prediction. Third, health status prediction model is built using

Bayesian updating algorithm based on the obtained parameters and prediction results are got accordingly. Next, known from the ability to fuse information from multiple sources of DS theory [15, 16], a health status information granulation fusion method for the electric motor is proposed by combining DS theory, Fuzzy theory and Information entropy. The proposed method considers the information from X-, Y-, and Z-axial and can achieve the fusion of multiple prediction results which obtained from multi-feature parameters to gain the optimal health status prediction result for the motor.

The rest of the paper is structured as follows: the test motor, experimental process, and data are introduced in Sect. 2. The multi-feature information is fused in Sect. 3. The prediction model and multi-sensor information fusion method are described in Sect. 4. In Sect. 5, examples of the application of predicted results in risk assessment and maintenance planning are given. Section 6 concludes the paper.

2 Experiment and Original Data

To obtain the vibration signal from three axials during the life cycle of electric motor, a set of test system is established. A T-MOTOR U8 brushless DC motor (which used in multi-rotor
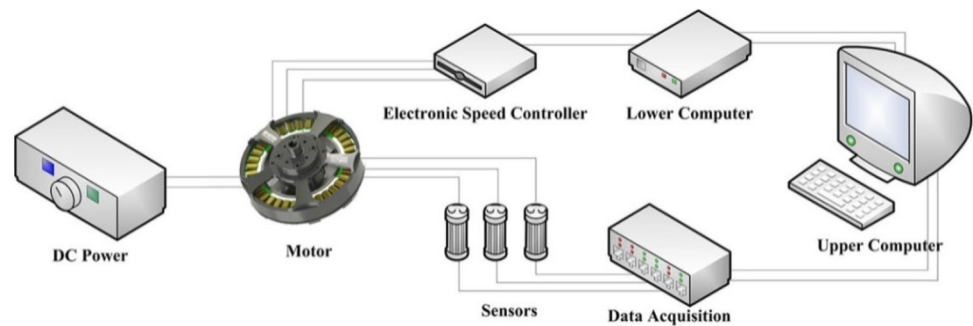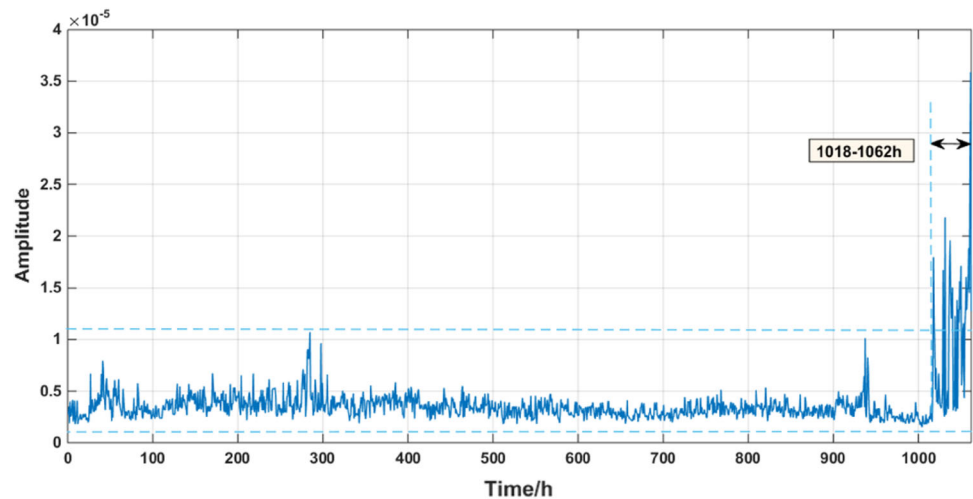
Fig. 2 Experimental equipment

Fig. 3 Motor running status

UAVs) was chosen as the test object. The test system is shown in Fig. 2. The control program of the upper computer was realized by LabVIEW (2014) software, and the control of the electronic governor by the lower computer was accomplished using a Pulse Width Modulation (PWM) signal. The vibration signals of X, Y, and Z axes were collected by an accelerometer and transmitted to the computer for monitoring and storage.

The degeneration test lasted for 1062 h. The sample ran stable for 0–1017 h. Characteristic quantity during 1018–1062 h exhibited a sudden change in amplitude (as shown in Fig. 3), which continued to occur without any tendency to decrease or disappear. Bearing wear and motor fault were proved after sample testing as shown in Fig. 4 [17].

3 Feature Extraction and Fusion

3.1 Feature Extraction

The objective of feature extraction is to obtain a motor's status feature information hidden in the vibration signals for status diagnosis, and, thereafter, to carry out the status prediction accordingly. Common feature-extraction methods are based on time-domain analysis, frequency-domain analysis,

and time–frequency-domain analysis, each of which focuses on different aspects.

In this section, 9 methods based on time-domain analysis(include mean, variance, root mean square, peak value, skewness, kurtosis, pulse, margin, and waveform) [2], 3 methods based on frequency-domain-analysis(include gravity frequency, mean-square frequency, and frequency variance) [2], and 1 method based on time–frequency-domain analysis (HHT), are selected to extract the original data of the motor degeneration experiment in Sect. 2 to obtain the corresponding status feature parameter. Taking the kurtosis, gravity frequency, and HHT method as examples, the extracted status feature parameters are shown in Fig. 5.

According to the data, a motor's general condition, to a certain extent, can be described by the status feature parameters obtained using different feature-extraction methods. However, the details embodied in the information are slightly different, and the status of the motor is explained from only one aspect.

3.2 Multiple Feature Information Fusion

Currently, the methods of multi-feature information fusion commonly applied to motors or similar products are PCA [4], kernel PCA [5], NCA [6], and LDA [7], which have been usu-

Fig. 4 Sample test results captured by scanning electron microscope: **a** inner side of outer race and **b** bearing ball
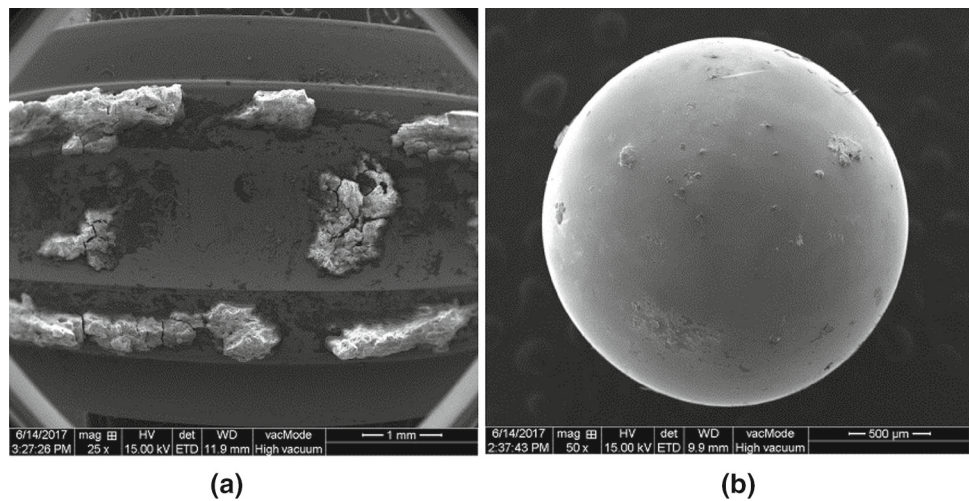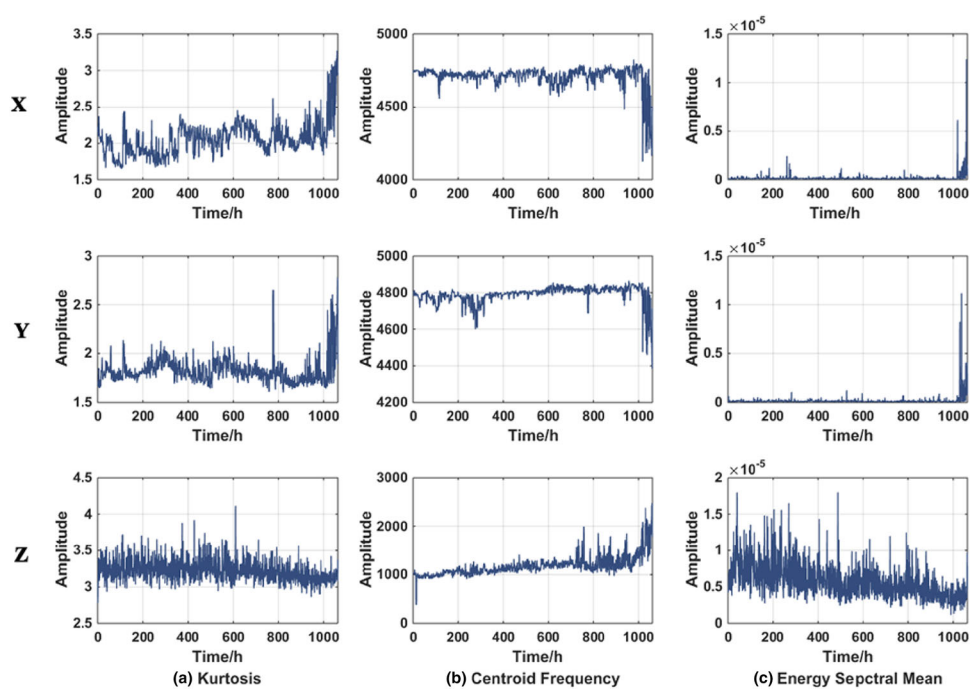

(a)   **(b)**

Fig. 5 Feature parameters obtained using kurtosis, gravity frequency, and HHT of each axis

(a) Kurtosis   (b) Centroid Frequency   (c) Energy Septral Mean

ally used for motor fault diagnosis. However, selecting the method of motor status prediction is slightly different from that of fault diagnosis. The method should effectively distinguish the states of motor degeneration and well describe the degeneration process. Therefore, PCA, kernel PCA, NCA, and LDA methods were applied to the feature fusion of actual data and the first and second principal components derived from each method are chosen. Then, the results of which were analysed to select the most suitable method.

Since the X- and Y-axial data are similar, mainly the X- and Z-axial data are described. In this paper, the first two feature parameters fused using PCA, kernel PCA, NCA, and LDA methods were studied, since the main feature information can be covered with 2 feature parameters obtained by the fusion

of multi-feature information. The results are shown in Figs. 6 and 7.

It can be seen from Fig. 6a, the health-fault status of motor can be effectively distinguished by PCA, Kernel PCA, LDA method for X-axial data. As for Z-axial data PCA, Kernel PCA, NCA methods are proved useful (see Fig. 7a). Then, Cluster evaluation index D is introduced to make a quantitative evaluation of the above methods and utilize the effective one to further conduct multi-feature information fusion. The Cluster evaluation index D can be written as:

$$D = \frac{tr\left(S_{w_1}\right) + tr\left(S_{w_2}\right)}{tr\left(S_b\right)} \tag{1}$$
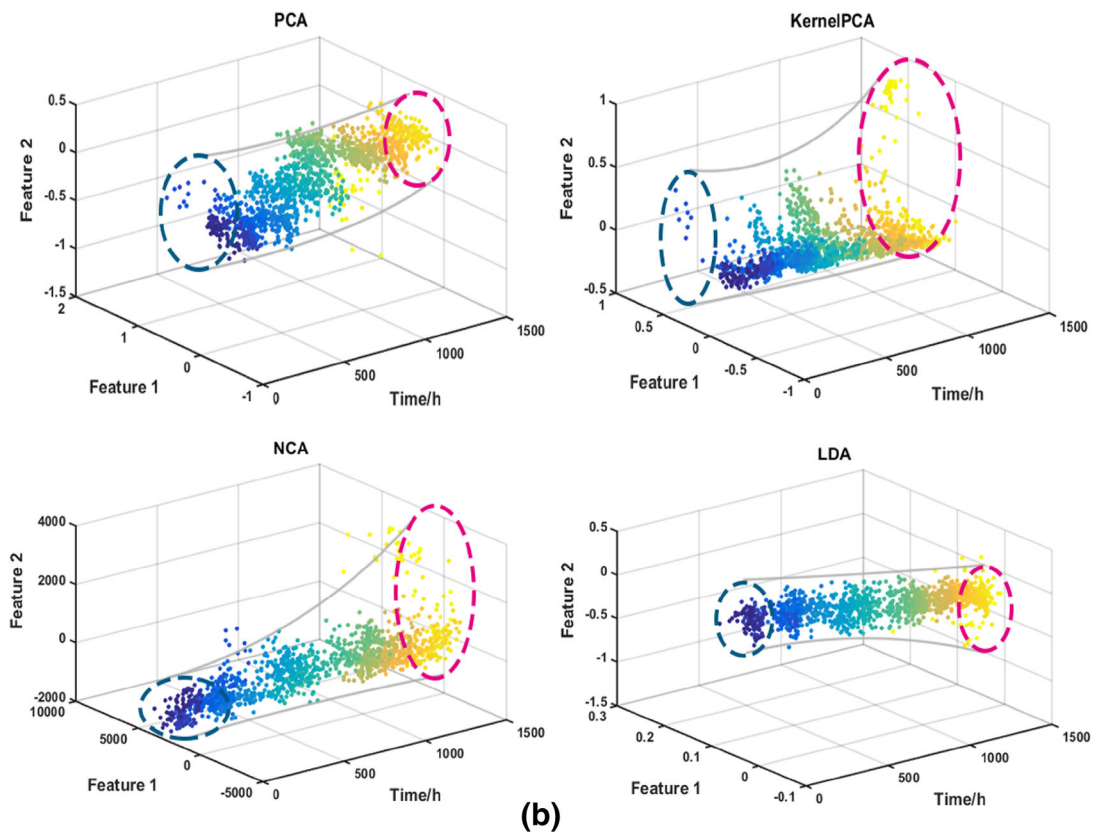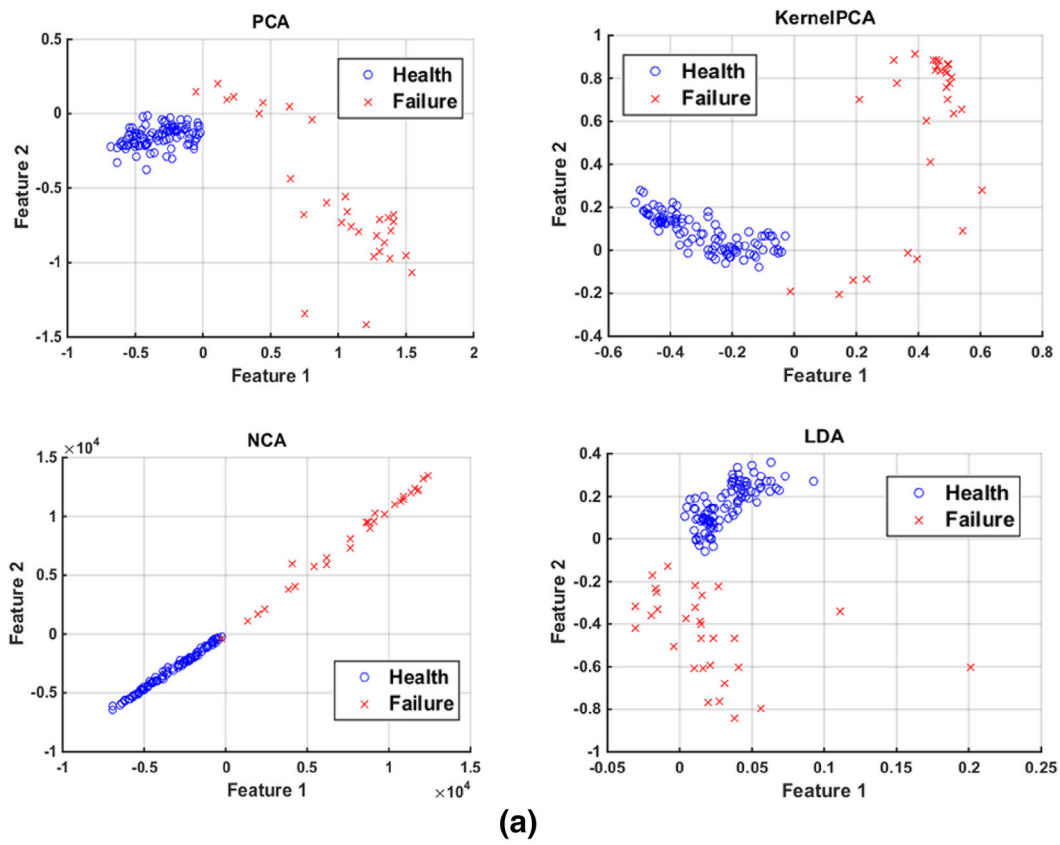
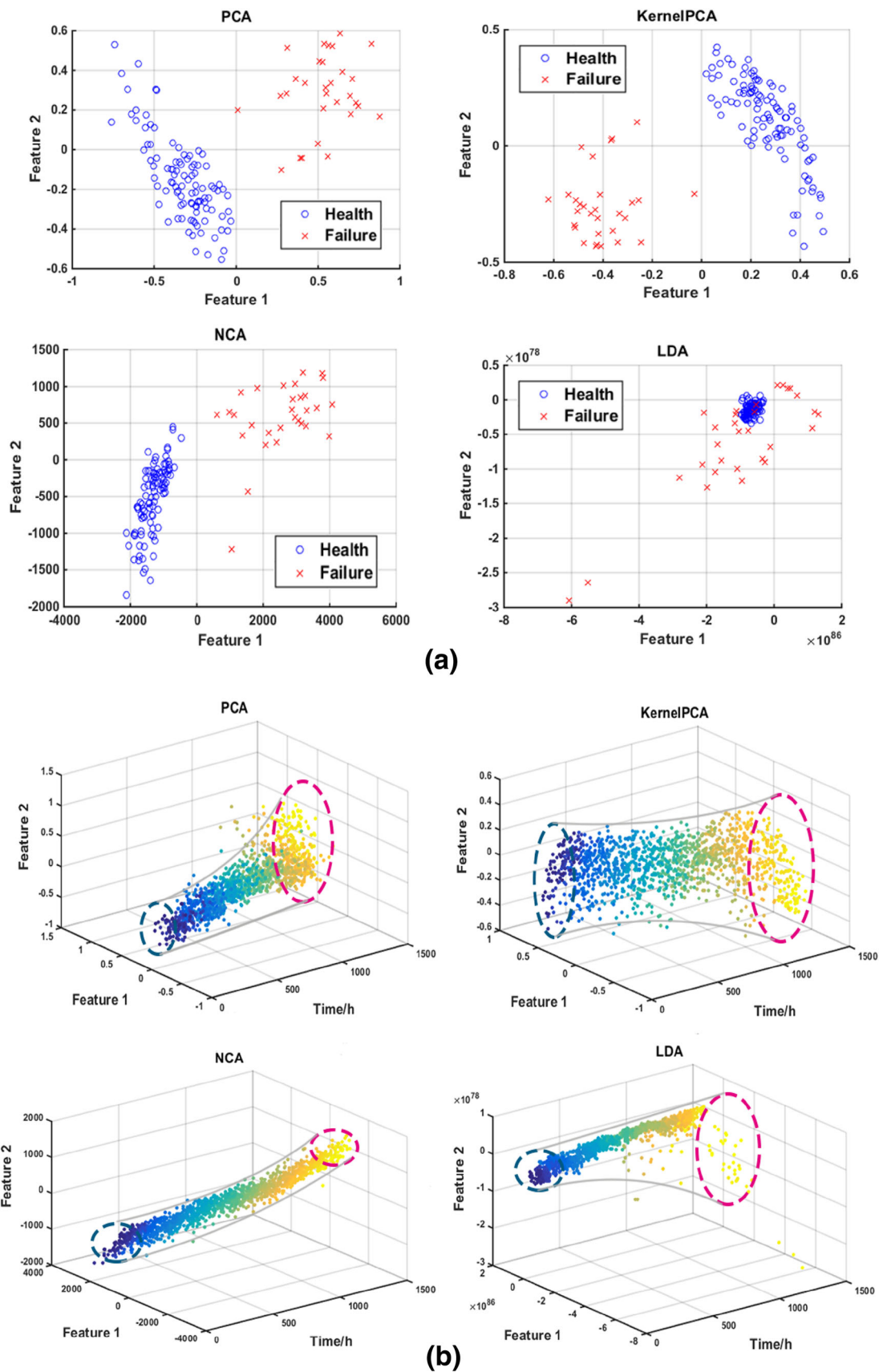**Fig. 6** Results of X-axial feature fusion

(a)

(b)

Fig. 7 Results of Z-axial feature fusion

Table 1 The Cluster evaluation indexes of health-fault status

	PCA	Kernel PCA	LDA
X-axial			
	1.3766	1.5432	0.7773
Z-axial			
	0.8765	0.8133	0.5386

Where S_{w_1} and S_{w_2} is the within-class scatter matrix of the sample of health and fault status [18], respectively, which denotes the dispersion of the mean of the sample points in each state. $tr(S_{w_1})$ and $tr(S_{w_2})$ are the trace of the scatter matrix which denotes the aggregation of the sample (the smaller the better). S_b is the between-class scatter matrix of the sample of health and fault status which denote the distribution of each state sample in space. It can be given as:

$$S_b = \sum_{i=1}^{c} P(i)(\vec{M}_i - \vec{M}_0)(\vec{M}_i - \vec{M}_0)^T \qquad (2)$$

Where $P(i)$ and $\vec{M}_i$ are the prior probabilities and the Mean vector of the sample of class i state, respectively. $\vec{M}_0$ is the overall mean vector of all C class state samples $\left(\vec{M}_0 = \sum_{i=1}^{c} P(i)\vec{M}_i \right)$. $tr(S_b)$ is the trace of scattering matrix between two class state samples which denotes the distribution of each state sample (the bigger the better). Therefore, the smaller the Cluster evaluation index D of the health-fault state is, the better distinguish performance the dimensionality reduction method can achieve over the health-fault status of the motor. The Cluster evaluation indexes of Figs. 6a and 7a are shown in Table 1.

Known from Table 1, LDA method achieves the best distinguish performance in quantity. And as one can see in Fig. 6b, LDA methods can better describe the degeneration trajectory and have less volatility compare to PCA and kernel PCA methods. Hence, the LDA method was used for X- and Y-axial data, and similarly the NCA method for Z-axial data, thus realizing the fusion of multi-feature information. The obtained feature parameters were then used to predict the motor's health status.

4 Health Status Prediction Through Multi-sensors

4.1 Prediction Method Based on Bayesian Updating Method

The status degeneration models mainly include regression-based [19], random process-based [20, 21], machine-learning-based [22], and failure physics-based models [23],

which were used to construct the degeneration model of feature parameters in accordance with the product's actual condition. In this paper, the Wiener process model is utilized to build the degradation model which can be expressed as [24]:

$$Y(t) = \sigma B(t) + d(s) \cdot t + y_0 \qquad (3)$$

where $Y(t)$ denotes the degeneration process of feature parameters; $B(t)$ denotes the standard Brownian motion, $B(t)–N(0, t)$; σ denotes the diffusion coefficient; y_0 denotes the initial value of feature-parameter degeneration; and $d(s)$ denotes the drift coefficient, which is a function of stress and reflects the product's degeneration rate. If l is the failure threshold of the feature parameters, the product will cease to be effective when $y(t) - l < 0$. The time (t) that $y(t)$ passes through l for the first time is subject to inverse Gaussian distribution, so the distribution of health status probability is as follows:

$$H(t) = \Phi\left[\frac{l - y_0 - d(s)t}{\sigma\sqrt{t}}\right]$$
$$- \exp\left(\frac{2d(s)(l - y_0)}{\sigma^2}\right)\Phi\left[-\frac{l - y_0 + d(s)t}{\sigma\sqrt{t}}\right] \qquad (4)$$

In the prediction model, accuracy drops with increasing distance. Therefore, Bayesian theory was applied to the reconstruction of the prediction process, as well as the update and fusion of historical data and new data, so that the model can be updated in real time with the actual data, thereby ensuring a high prediction accuracy (as shown in Fig. 8, the prediction accuracy keeps on a higher level due to the update).

Three kinds of information are included in Bayesian theory, namely the general, sample, and prior information. According to the nature of the Wiener process, the degeneration increment Δy in unit time Δt is subject to normal distribution with the mean value of $d(s)\Delta t$ and the variance of $\sigma^2 \Delta t$; that is,

$$\Delta y \sim N\left(d(s)\Delta t, \sigma^2 \Delta t\right) \qquad (5)$$

Therefore, formula (5) is the general information, $p(\theta)$, where θ is the parameter of the model, i.e., $d(s)$ and σ. If the number of data is n in total, the latest m data can be defined as the sample information y_2, and the former $n - m$ data as the prior information. The corresponding Bayesian formula of y_1 is as follows:

$$p(\theta|y_1) \propto p(\theta)l(\theta|y_1) \qquad (6)$$

As the sample information y_2 is obtained, it can be inferred that

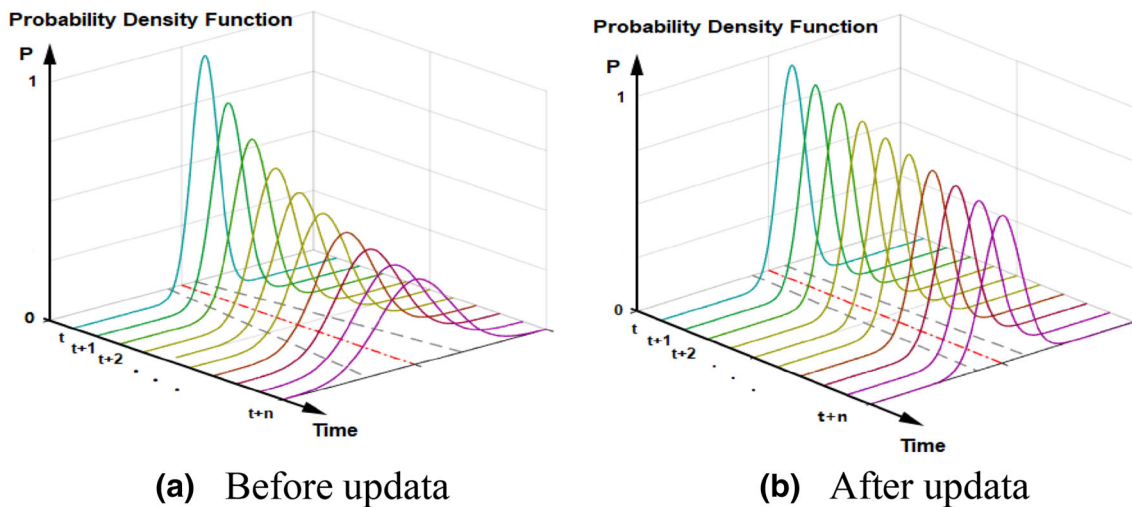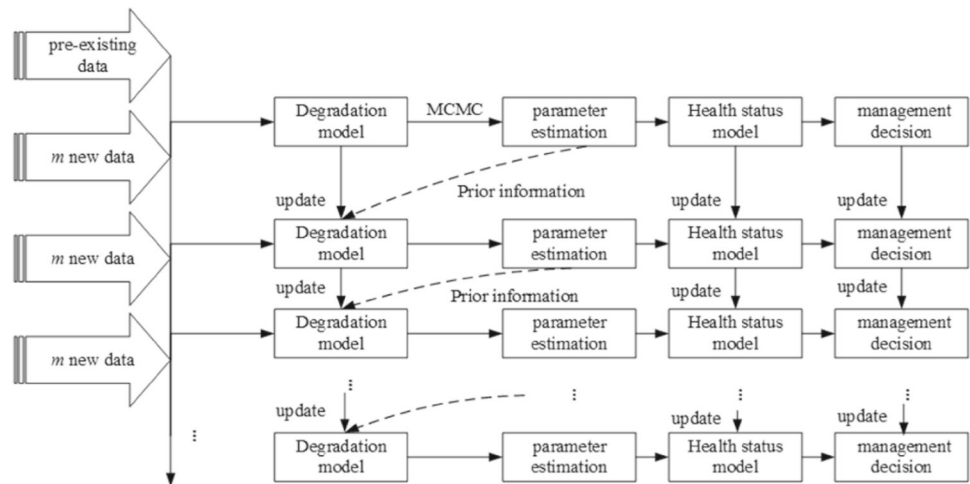$$p(\theta|y_2, y_1) \propto p(\theta)l(\theta|y_1)l(\theta|y_2) \propto p(\theta|y_1)l(\theta|y_2) \qquad (7)$$

(a) Before updata   **(b)** After updata

Fig. 8 Variation of predictive accuracy over time

Fig. 9 Updating process

This means that the posterior distribution of θ under y_1 plays the role of the prior distribution of θ under y_2. If the expression of $d(s)$ is $d(s) = \exp[A - B/s]$, the posterior distribution of formula (1) can be expressed as follows:

$$\pi(\Theta|D) = \pi\left(A, B, \sigma^2|\Delta y_1, s, \Delta t\right) \propto \prod_{i=1}^{m} \left(\frac{1}{\sigma^2 \Delta t_i}\right)^{1/2}$$

$$\exp\left(-\frac{(\Delta y_{1i} - \exp(A + B/s_i)\Delta t_i)^2}{2 \cdot \sigma^2 \Delta t_i}\right)$$

$$\cdot \pi\left(A, B, \sigma^2|\Delta y_2\right) \tag{8}$$

Where A and B are the two model parameters in the model $d(s)$, their values can be obtained by the motor degradation data. For the posterior distribution model, the Markov Chain Monte Carlo (MCMC) method was used to infer the parameters to obtain the assessed value of parameters $d(s)$ and σ. Then, the health status of product at each time was predicted using formula (4). The specific update process is shown in

Fig. 9. Next, based on the above method, the modeling of each axial parameter and each feature parameter was carried out. Finally, using all the characteristics in chapter 3.2, the health status probability is calculated and demonstrated in Fig. 10.

4.2 Multi Sensor Health State Information Granulation Fusion Method Based on Information Entropy Weight

According to Sect. 4, a motor's future health status can be predicted based on the feature parameters of the X, Y, and Z axes extracted and fused in Sect. 3. The prediction results given by different information sources provide evidence for a motor's future status from different perspectives, but it is not able to describe the entire picture of the incident, as there are some limitations in the above evidence. How to effectively fuse the above evidence is the key to making an effective prediction and the obtaining accurate prediction results. In this

respect, DS theory is an effective solution to the uncertainty caused by randomness and ambiguity, so it was used for the fusion of three-axial information.

DS theory has two main characteristics. First, it provides a more flexible approach to describe uncertainty than probabil-

of full support for proposition A, and can also be referred to as the degree of precise belief of proposition A.

For the same recognition framework Θ, if the evidence of the basic belief assignment functions $m_1, m_2, \ldots, m_n$ from n different information sources is $E_1, E_2, \ldots, E_n$, respectively, it can be inferred that

$$
\begin{cases}
m(\phi) = 0 \\
m(D) = (m_1 \oplus m_2 \oplus \cdots \oplus m_n)(D) = \dfrac{\displaystyle\sum_{\cap_{i=1}^n E_i = A} m_1(E_1) m_2(E_2) \cdots m_n(E_n)}{1-K} \forall D \subseteq \Theta, D \neq \phi
\end{cases}
\tag{10}
$$

ity theory (basic belief assignment function). Second, it also provides a combination rule for combining different items of evidence.

4.2.1 Basic Belief Assignment Function and Combination Rule

Θ is set as a finite non-empty set of elements that are mutually exclusive and exhaustive, which is called as a recognition framework. Any proposition A belongs to the set 2^Θ. In 2^Θ, the basic belief assignment function m (mass function) can be defined as $2^\Theta \to [0,1]$, which satisfies

$$
\begin{cases}
\displaystyle\sum_{A \subseteq \Theta} m(A) = 1 \\
m(\phi) = 0
\end{cases}
\tag{9}
$$

$m(A)$ is recognized as the basic belief assignment function of event A. Here, ϕ is an empty set. $m(A)$ represents the degree

where

$$
K = \sum_{\cap_{i=1}^n E_i = \phi} m_1(E_1) m_2(E_2) \cdots m_n(E_n) > 0
\tag{11}
$$

K can be used as a measure of the contradiction degree among the data sources. The larger K is, the more intensive the contradiction of evidence. The coefficient $1/(1-K)$ is called the regularization factor, the function of which is to avoid assigning non-zero trust to the empty set Φ during synthesis.

4.2.2 Fuzzy Granulated Description of Health State

To effectively describe the status of the motor, three propositions $A, B,$ and C existing in the recognition framework Θ are defined, among which A represents that the motor is in good status, B a recession status, and C a near-failure status. Fuzzy theory is adopted to define the basic belief assignment function. By selecting appropriate fuzzy numbers, the entire decreasing process of health status is divided. In addition, the corresponding fuzzy membership functions are given, including the common fuzzy numbers, such as triangular, trapezoidal, bell-shaped fuzzy numbers, etc. The triangular fuzzy numbers are adopted in this study to define the basic belief assignment function under each status. If there are n feature parameters $y_1, y_2, \ldots, y_n$ in the three axes of the motor, the probability models of their health status are $H_1(t), H_2(t), \ldots, H_n(t)$, respectively. With the health status H_b as an example, the membership degree of the motor in proposition B is $\tilde{\mu}_B(H) = 1$. As $H(t)$ gradually changes towards H_a or H_c, the probability of belonging to this status is reduced to zero and its corresponding membership function is

Fig. 10 Health status probability of single-feature parameter

$$
\tilde{\mu}_B(H_i) = \begin{cases}
\dfrac{H_i - H_a}{H_b - H_a} & (H_a \leq H_i < H_b) \\
\dfrac{H_c - H_i}{H_c - H_b} & (H_b \leq H_i \leq H_c) \\
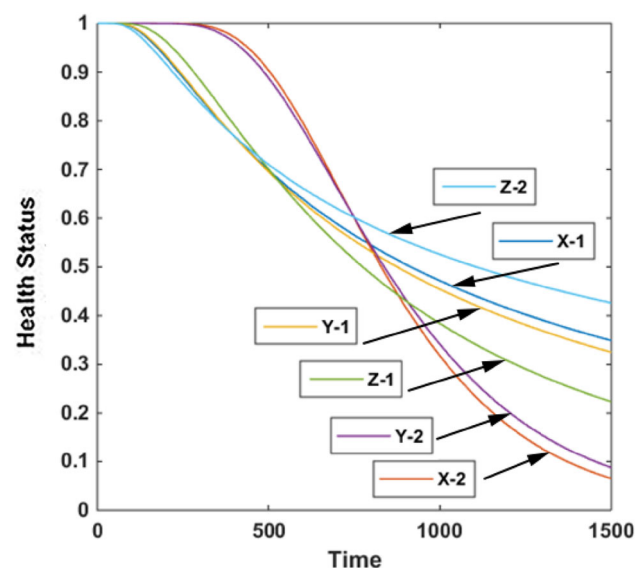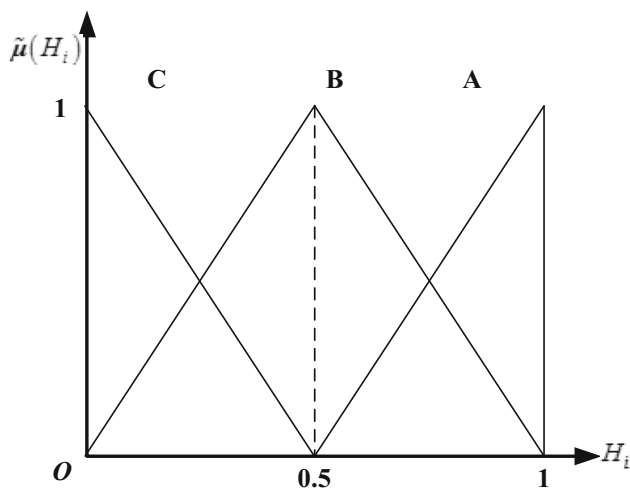0 & (\text{others})
\end{cases}
\tag{12}
$$

Fig. 11 Membership functions of propositions A, B, and C

For propositions A, B, and C, their trapezoidal membership functions can be defined as (Fig. 11):

At a certain time point, the relationship among the membership degrees of the motor under each status, $\tilde{\mu}_v(H_i)$ ($v = A, B, C$), is

$$\tilde{\mu}_A(H_i) + \tilde{\mu}_B(H_i) + \tilde{\mu}_C(H_i) = 1 \tag{13}$$

On this basis, according to the construction principle of evidence, the information provided by n kinds of feature parameters at time t was taken as n kinds of evidence in DS theory, represented by $m_{t1}, m_{t2}, \ldots, m_{tn}$. In this case, the corresponding basic probability assignment function is

$$m_{ti}(A) = \tilde{\mu}_A(H_i) \tag{14}$$

$$m_{ti}(B) = \tilde{\mu}_B(H_i) \tag{15}$$

$$m_{ti}(C) = \tilde{\mu}_C(H_i) \tag{16}$$

4.2.3 Evidence Combination Based on Information Entropy Weight

Because the credibility of information contained in each evidence is different, we endowed with information entropy weight to each feature parameter to make more accurate and effective use of source information. Since Entropy originates from statistical thermodynamics which is an expression of the disorder, or randomness of a system. Its increase often corresponds to an increase in the disorder of system. In information theory, entropy is the measure to define the uncertainty of random variable value and it is sometimes referred as Shannon entropy, If X represents a random variable, and the proba-

bility when X equals x is $p(x)$, the information entropy of X, $E(X)$, is defined as:

$$E(X) = -\int_x p(x) \log p(x) dx \tag{17}$$

Thus, information entropy can be the basis of weight assignment. The information entropy of feature parameter of X-, Y-, and Z-axial is shown in Table 2. Take A status as example, the information entropy of its feature parameter can be calculated by:

$$w_{Ai} = \frac{1/E_{Ai}}{\sum\limits_{j=1}^{6} (1/E_{Aj})} \tag{18}$$

Then, adjust the distribution function of the credibility based on weight. Which is:

$$\begin{cases} m'_k(A_i) = \dfrac{[m_k(A_i)]^{w_k/w\mathrm{max}}}{\sum\limits_{j} [m_k(A_j)]^{w_k/w\mathrm{max}}} \\ m'_k(\phi) = 0 \end{cases} \tag{19}$$

where $w_{\max}$ is the maximum value of all feature parameters under all status. Next, we can adjust the evidence with less weight.

4.2.4 Results Analysis

After the fusion of the frame combination using DS theory, the motor's health status D combining 6 kinds of three-axial parameter information was obtained. Its basic probability assignment function at time t is

$$m_t(D) = m_{t1} \oplus m_{t2} \oplus \cdots \oplus m_{tn}(D), \tag{20}$$

Based on the above method, the fusion of X-, Y-, and Z-axial information was carried out. Evidence of all information sources was combined to obtain the probability function of a motor in good condition (status A), which is as shown in Fig. 12.

Figure 12a is the confidence distribution function of a motor in good condition obtained by multi-feature parameters. Figure 12b is the confidence distribution function after fusion (namely the probability of a motor being in good condition).

A motor's health status function $H_i(t)$, $i = A, B, C$ (as shown in Fig. 13) was obtained by the fusion of probability functions of motor health status acquired by multi-feature parameters using the proposed method. As shown in Fig. 13, B status meets its peak value at 829 h and then gradually reduces. C status reaches 0.5 at 892 h (the sum of the value of A status and B status) and reaches 0.9 at 1071 h. by that time point the failure status is reached with a high probability

Table 2 Information entropy

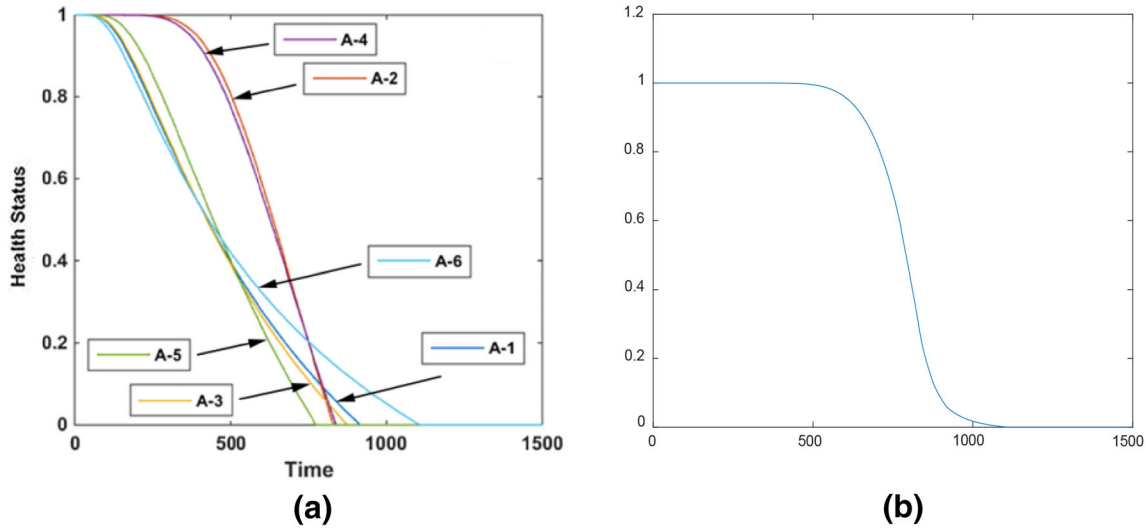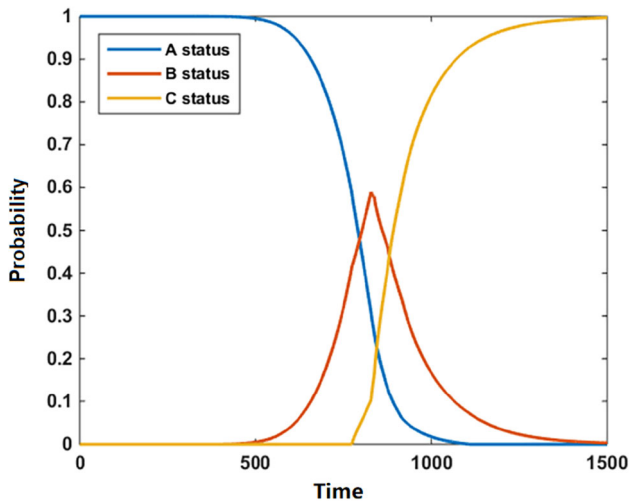| Information source	X-1 1	X-2 2	Y-1 3	Y-2 4	Z-1 5	Z-2 6
A status	2.6068	2.2105	2.5453	2.2677	2.3651	2.8358
B status	2.9759	3.0632	3.0407	3.1048	3.1697	2.9505
C status	2.0792	2.2572	2.1789	2.2484	2.4042	1.5573

Fig. 12 Information fusion of status A

Fig. 13 Prediction results of motor health status using multi-sensor information

Table 3 Information entropy

Information source	A status	B status	C status
Information entropy	1.5251	2.3672	1.442

As seen in Tables 2 and 3, the proposed method owes the least information entropy, so we can see the proposed method is more credible since it can integrate multi-source information while reduce information uncertainty.

5 Application of Prediction Results in Safety and Maintenance

5.1 Risk Assessment

Based on the prediction results, the dynamic risk assessment of the system was realized in accordance with the motor's probability of being in different states, thereby guiding the formulation of relevant safety decisions in a timely and effective manner.

Known from the property of basic quantitative risk assessment which describe risk with risk severity and risk probability, the risk value of the motor at each state can be assessed [25]. According to the prediction results given in Sect. 4, the motor's statuses (Fig. 13) can be divided into three risk lev-
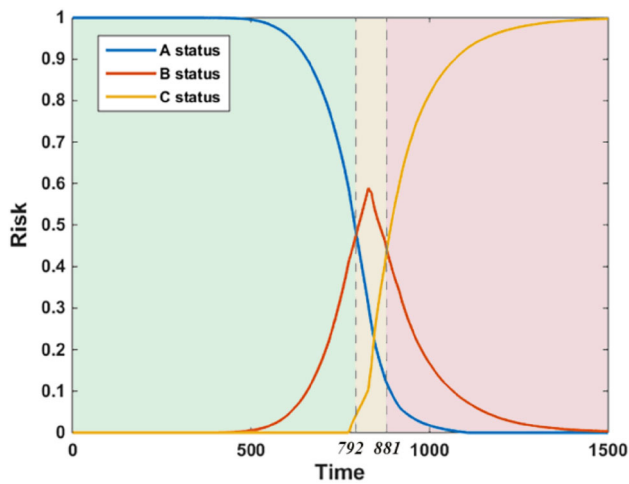
for motor. So, one can infer that the status transition point of motor is between 892 h and 1071 h which is matched with test result (1018 h).

Furthermore, information entropy method is conducted to verify the effect of the proposed method by assessing the information of multi-feature parameter calculated above. Table 3 shows the obtained information entropies of the multi-sensor fusion parameter (the proposed method).

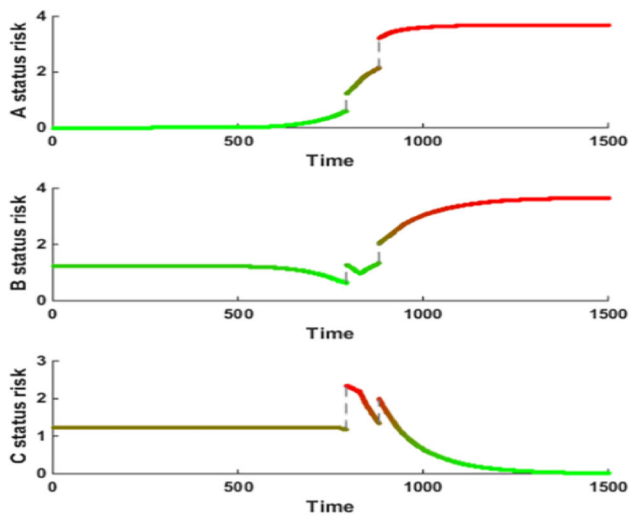**Fig. 14** Risk Level of motor health status

Fig. 15 Risk value of motor

els, also named the severity of the risk, and can be shown in Fig. 14. The risk probability is related to health status. Therefore, the assessed risk value of the motor at each state can be calculated. The risk value of motor is shown in Fig. 15.

5.2 Maintenance Planning

Motor maintenance planning can be carried out in accordance with the health status functions $H_A(t)$, $H_B(t)$, and $H_C(t)$. If the near-failure status function $H_C(t)$ is taken as the criterion by which motor failure is determined, with given preventive maintenance cost C_p and corrective maintenance cost C_c, the preventive maintenance cost $TC(T_p)$ at time T_p is [26]:

$$TC(T_p) = C_p \cdot (H_A(T_p) + H_B(T_p)) + C_c \cdot H_C(T_p) \quad (21)$$

the expected lifecycle $L(T_p)$ is expressed as

$$L(T_p) = T_p \cdot (H_A(T_p) + H_B(T_p)) + M(T_p) \cdot H_C(T_p) \quad (22)$$

and the cost per unit time $EC(T_p)$ is expressed as

$$EC(T_p) = \frac{C_p \cdot (H_A(T_p) + H_B(T_p)) + C_c \cdot H_C(T_p)}{T_p \cdot (H_A(T_p) + H_B(T_p)) + M(T_p) \cdot H_C(T_p)} \quad (23)$$

where $M(T_p)$ denotes the timeframe of the failure period estimated by the truncated expected value of the failure distribution at T_p, which is expressed as

$$M(T_p) = \int_0^{T_p} \frac{tc(t)dt}{C(T_p)} \quad (24)$$

where $c(t)$ denotes the failure probability density function and $C(T_p)$ the cumulative failure probability of the motor at T_p.

By optimizing the preventive maintenance time T_p, the optimal preventive maintenance cost per unit time $EC(T_p)$ at T_p can be obtained, and the corresponding T_p is the preventive maintenance time corresponding to the minimum maintenance cost. It is known that the preventive maintenance cost C_p of this motor is 1000 CNY and that the corrective maintenance cost C_c is 7000 CNY, which includes the cost of motor and potential loss.

Figure 16a shows the relationship between the motor's preventive maintenance time T_p and the total maintenance cost $TC(T_p)$. The probability of motor failure has been gradually increasing since the 558th hour. The relationship between the motor's preventive maintenance time T_p and the maintenance cost per unit time $EC(T_p)$ is shown in Fig. 16b. In the early stage, the dominant factor for $EC(T_p)$ is the motor's expected lifecycle $L(T_p)$, so $EC(T_p)$ decreases with time. After 852 h, the corrective maintenance cost C_c caused by failure becomes the dominant factor for $EC(T_p)$, so $EC(T_p)$ increases gradually with increasing failure function value $C(t)$. In other words, it grows with time. Therefore, the motor's preventive maintenance cost per unit time $EC(T_p)$ reaches the minimum at the 852nd hour, which is 1.261 CNY/h.

6 Conclusions

In order to acquire motor health status information more comprehensively and effectively and solve the information fusion problems between X-, Y-, and Z-axial information and multi-feature parameter information of motor. This paper takes a UAV power motor as the test item and studies this problem with its life cycle vibration data. The problem is solved
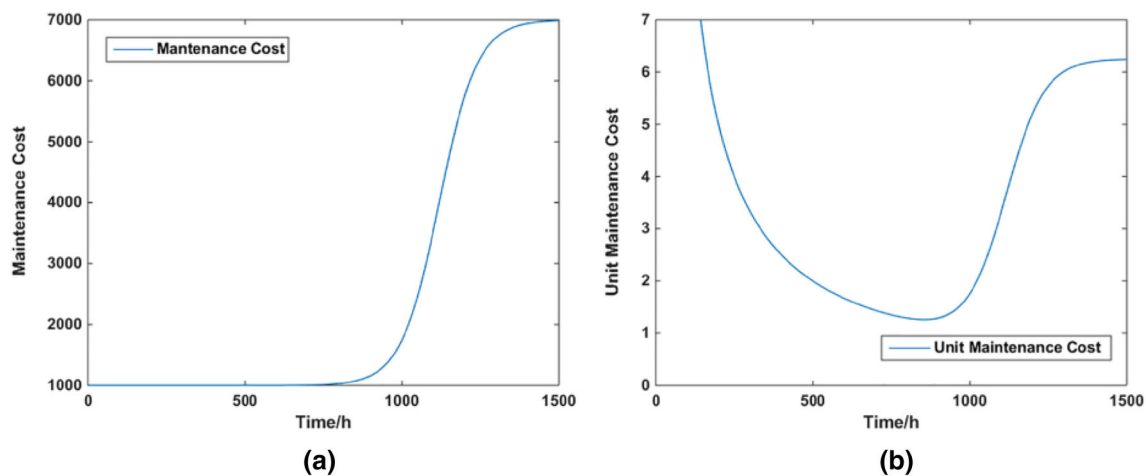
Fig. 16 Maintenance cost optimization analysis: Relationship between **a** T_p and $TC(T_p)$ and **b** T_p and $EC(T_p)$

based on quality and quantity method considering the diagnosis results and degradation path descriptive ability. Then, the health status prediction is achieved with Bayesian updating algorithm. Next, a DS theory and information entropy weight-based health status information granulation fusion method for the electric motor is proposed to fuse information obtained from the X-, Y-, and Z-axial. The method can achieve the fusion of multiple prediction results obtained from multi-feature parameters to gain the optimal health status prediction result for the motor. The analysis results show that the prediction results are in conformity with the actual situation, and the proposed method is more credible since it can integrate the multi-source information while reducing information uncertainty. Meanwhile, according to the prediction results, its application in risk assessment and maintenance planning were discussed, which indicates that it can be used as data support for lifecycle management, thereby ensuring the high reliability, safety, and economic efficiency of motor products and their systems. However, given the limited amount of experimental data in this paper, the details of this method should be optimized gradually with the expansion of sample size. Moreover, the implementation of the proposed method will also be affected by different motor types and sensor-assembly methods, which will be studied in follow-up research.

Compliance with Ethical Standards

Conflicts of interest The authors declare no conflict of interest.

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