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A Double Layer BRB Model for Health Prognostics in Complex Electromechanical System

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ABSTRACT The health of a complex electromechanical system is dynamic and is accompanied by a full life cycle. Due to the complexity and coupling of complex electromechanical systems, the establishment of a dynamic and accurate model for the health state is difficult. A belief rule base (BRB) shows outstanding performance in modeling complex systems because it can combine both quantitative information and expert knowledge. In this paper, a double-layer BRB model is proposed to predict the health state of a complex electromechanical system. The two layers achieve different functions: BRB_layer1 is used to establish the dynamic change of the time series of features, BRB_layer2 is employed to combine the features for predicting the health state of the complex electromechanical system. During this process, the infinite irrelevance method is utilized for feature selection in reducing the scale of the BRB model. Considering the initial parameters are given by experts, which may have boundedness and may not be appropriate for engineering practice, the projection covariance matrix adaption evolution strategy (P-CMA-ES) is chosen as the optimization algorithm to train the initial parameters. To verify the rationality and effectiveness of the proposed model, the low-frequency vibration fault of a certain aero-engine is taken as an example. The results show that the proposed method can predict the health state of a complex electromechanical system precisely according to current and historical data.

INDEX TERMS Belief rule base (BRB), complex electromechanical system, double layer BRB, health prognostics, projection covariance matrix adaption evolution strategy (P-CMA-ES).

I. INTRODUCTION

Complex electromechanical systems are integrated systems whose features consist of the mechanics, electronics, hydraulics and controls, such as those found in aero-engines, rail vehicles and CNC machine tools. They play an important role in national development. The health of a complex electromechanical system is necessary to be predicted because it is also regarded as a dominant basis for safety, reliability and economy [1], [2]. A reasonable health prognostic can achieve optimum maintenance decision-making and effectively reduce the casualties and economic losses caused by system failure [3], [4].

The methods of health prognostics for complex electromechanical systems can be divided into three categories: analytical-based models, data-driven-based intelligent learning models, and qualitative knowledge-based models [5]–[7]. In a complex system with an accurate mathematical model, the analytical-based model has been widely used, such as Kalman Filter and improved Kalman Filter [8], [9]. However, the results of these methods are less accurate because they depend on the modeling of the analytic model for complex electromechanical systems, and the establishment of the analytic model is very difficult. In addition, for a complex electromechanical system, such as aero-engine gas path system, the prognostic is not completely reliable because the measurable parameters are less than the parameters to be estimated in this system [10]. Recently, data-driven-based intelligent learning models have been rapidly developed and extensively applied [11]–[13]. These intelligent methods can address nonlinear models for complex systems and predict the health state based on a large amount of data. Researches that are recently appeared in using data-driven approach give effective results. For example, the literature [14] studied a nonlinear process monitoring based on data-driven approach. In this work, the locally weighted projection regression is used to improve test statistics. The literature [15] researched an improved incremental learning approach for prognosis of dynamic fuel cell system. This method has a high accuracy by using an overlapped algorithm which combines locally weighted projection regression with partial least squares. However, their principle in processing is called ''black boxes'', which means that the parameter setting of the model lacks reasonable explanation. Thus, it inevitably causes fuzzy descriptions for the mechanism connection in the prognostic results during the dynamic changes. The expert system method is the most employed as a typical qualitative knowledge-based model. Due to the lack of quantitative knowledge on the basis of the qualitative knowledge, the traditional expert system brings less precise prediction results [16]. Therefore, it is difficult to make highly accurate prognostics for a complex electromechanical system using no more than a simple expert system method.

For most complex electromechanical systems, accurate analytic models are difficult to be constructed. Due to the characteristics of complexity and coupling with the system, it is also hard to establish an accurate health predictive model to reflect the dynamic change of the future behavior. Moreover, considering the failure data with small-scale in engineering practice, it is hard to get enough effective data to ensure the accuracy of prediction by using the data-driven method. Furthermore, to address the limitation that the existing methods only consider single knowledge of information, it is necessary to combine the data-driven method with qualitative knowledge to improve the accuracy of health prognostics in complex electromechanical systems. The BRB model is a nonlinear model based on semi-quantitative information proposed by *Yang et al*. [17]. It can address both qualitative knowledge and quantitative information. This model can make full use of the quantitative knowledge especially combined with expert knowledge to reflect the behavior of the complex system [18], [19]. After taking the expert knowledge into account, this method shows excellent performance in dealing with problems with small-scale samples [20], [21]. It is also has the effectiveness on nonlinear dynamic modeling [22]. In this paper, the BRB model is employed to predict the health state for a complex electromechanical system. A double-layer BRB model is proposed to dynamically predict the health state of a complex electromechanical system. With the proposed model, the future behavior of the system is objectively described, and the health state is accurately predicted. In this process, the P-CMA-ES [23] algorithm is used to update the initial parameters.

The proposed double layer BRB model is an advantage hybrid method that is suitable for the characteristic of small-scale samples appeared in complex electromechanical system. The modeling approach can address the information contains both quantitative and qualitative knowledge that the data-driven method cannot be qualified. Moreover, the model can also reflect the dynamic change in a complex electromechanical system with history and current data.

This paper is organized as follows. In Section II, the problem is formulated. In Section III, a double layer BRB model is established, and the detailed steps are described. Section IV presents a case study for the vibration problem in an aero-engine. Finally, the conclusions are given in Section V.

II. PROBLEM FORMULATION

For complex electromechanical systems, which lack accurate analytic models, there are features that can reflect the health state of the human body system, such as temperature, blood pressure and blood glucose [24]. During the full life cycle, the change of the health state can be reflected by the changes of these features. Thus, the key problem in this paper is how to build a health predictive model by using reasonable features. The health prognostics can be known as the health estimation for the system's future behavior. Thus, the process of the model contains two steps: a time series of features prediction and health estimation for future behavior.

It is assumed that the health state of a complex electromechanical system is represented by $y(t)$ in the time instant t. The health state of a complex electromechanical system with features can be described as:

$$y(t) = f(x_{1t}, x_{2t}, \cdots, x_{Nt}, \mathbf{V}) \tag{1}$$

where $x_{nt} (n = 1, 2, \ldots, N)$ is one of the features reflecting the health state, $f(\bullet)$ is a nonlinear BRB model, and $\mathbf{V}$ is the set of parameters in this model.

Therefore, the prognostics of the health state in a complex electromechanical system can be expressed as:

$$\hat{y}(t+p) = f(\hat{x}_{1(t+p)}, \hat{x}_{2(t+p)}, \cdots, \hat{x}_{N(t+p)}, \mathbf{V}) \tag{2}$$

where p is the step of the prognostics.

$\hat{x}_{n(t+p)}$ represents the time series prediction, which can be described as:

$$\hat{x}_{n(t+p)} = h\left(x_{nt}, x_{n(t-1)}, \ldots, x_{n(t-\tau)}, \mathbf{G}\right) \tag{3}$$

where $\mathbf{G}$ is the set of parameters in the model.

Therefore, the health prognostics of a complex electromechanical system can be expressed as:

$$\hat{y}_{(t+p)} = f\left(h\left(\mathbf{X}_t, \mathbf{X}_{t-1}, \mathbf{X}_{t-\tau}\right), \mathbf{V}, \mathbf{G}\right) \tag{4}$$

where, $\mathbf{X} = [x_1, x_2, \cdots, x_N]$.

This paper focuses on how to establish a nonlinear model, which contains f and h, and determines the model parameters $\mathbf{V}$ and $\mathbf{G}$.

III. THE HEALTH PROGNOSTICS BASED ON DOUBLE LAYER BRB

The BRB model is effective at nonlinear dynamic modeling. After considering the related features of the system,

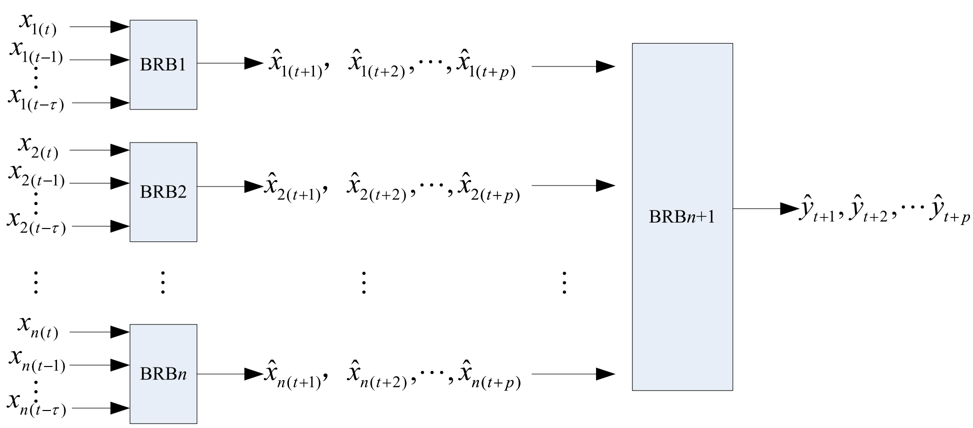


FIGURE 1. **The proposed double layer model.**

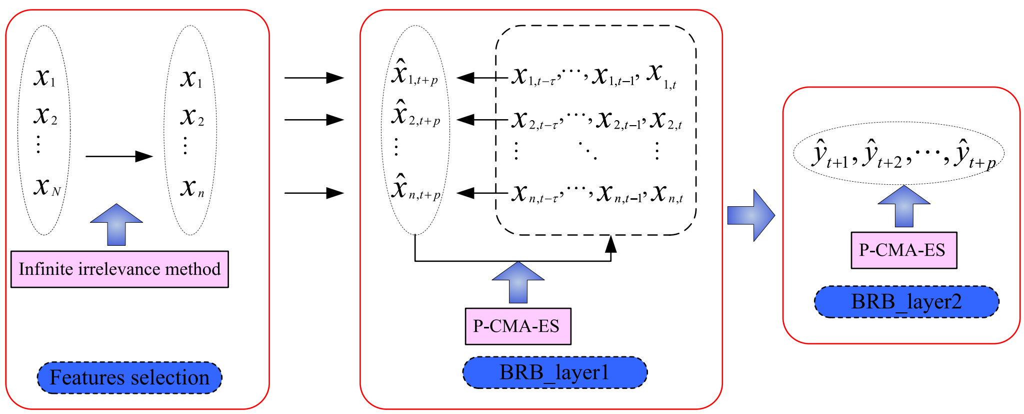


FIGURE 2. **Health state prediction model based on the double layer BRB.**

a BRB-based health prognostics model is proposed. In this paper, we propose a double-layer BRB to dynamically predict the health state of a complex electromechanical system. BRB_layer1 is used to establish the dynamic change of features in a time period, followed by prediction. BRB_layer2 is employed to combine the features to evaluate the future health state. The structure of the double-layer BRB is shown in Fig. 1.

In the process of health prognostics, the features selection and parameters updates are used to build a more compact and accurate model. The infinite irrelevance method and P-CMA-ES are applied to select features and update parameters, respectively. The process of modeling is detailed as follows. The modeling process of health prognostics based on double-layer BRB is shown in Fig. 2.

A. FEATURE SELECTION BASED ON INFINITE IRRELEVANCE METHOD

There are many features that can reflect the health state in a servo system. Some of them have less influence on the health of the servo system. And the number of features determines the complexity of the BRB model. The computation complexity of BRB is based on the number of rules which is calculated by the number of features and references. Feature selection can ensure the accuracy of BRB model in reducing the computation complexity. Thus, the infinite irrelevance method [25] is used to reduce the scale of the features. The specific steps are shown in Fig. 3 [25].

According to the three steps in Fig. 3, the complex correlation coefficient ρ_i is obtained. A greater value of ρ_i means that the correlation of $\mathbf{x}_i$ has a major relevance with the others. Thus, the features can be selected on the basis of ρ_i.

B. BRB_LAYER1: TIME SERIES PREDICTION MODEL

In the double-layer BRB health predictive model, dynamic time series prediction is first performed to characterize the feature of the complex electromechanical system. The time series prediction model is developed in accordance with the basic BRB, which contains the current and historical data of the feature as well as some expert knowledge. The time series BRB prediction model of the feature is established as follows:

$$\begin{aligned} &R_{k\text{BRB\_layer1}}: \\ &\quad \text{If } x_n(t) \text{ is } A_1^k \wedge x_n(t-1) \text{ is } A_2^k \wedge \cdots \wedge x_n(t-\tau) \text{ is } A_{\tau+1}^k \\ &\quad \text{Then } x_n(t+p) \text{ is } \left\{(D_1, \beta_{1,k}), \cdots, (D_N, \beta_{N,k})\right\} \end{aligned} \tag{5}$$

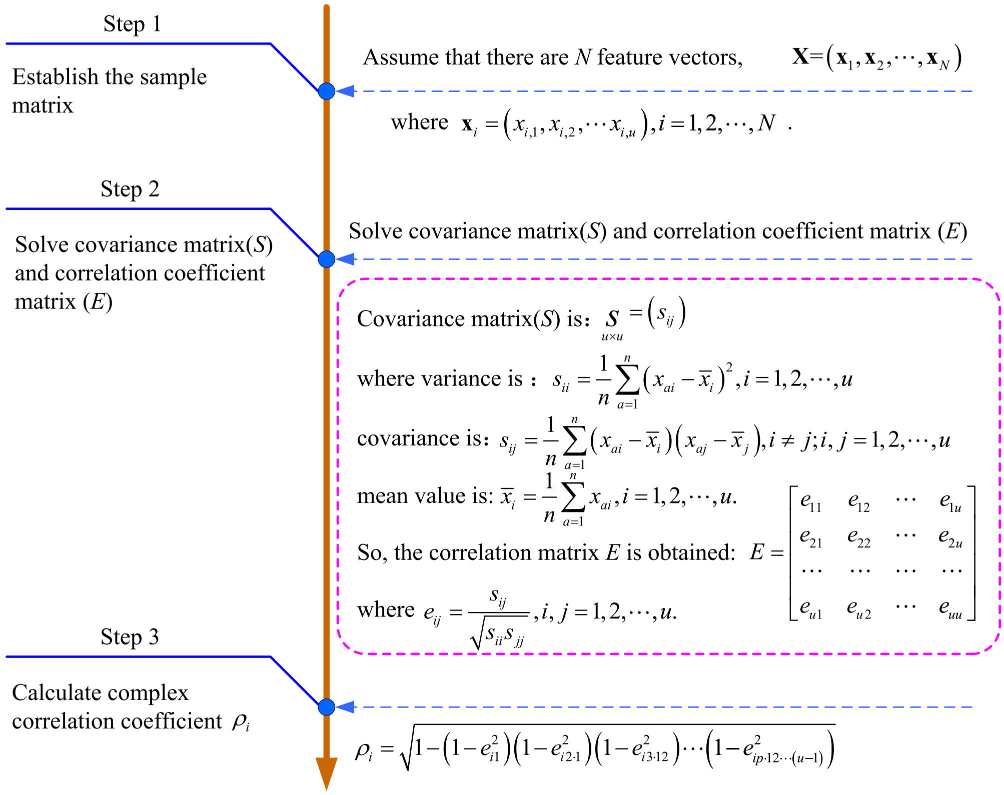


FIGURE 3. He steps of infinite irrelevance method.

where R_k is the kth belief rule of x_n in BRB_layer1 and x_n is the input. τ is the delay step. $A_m^k\,(k = 1, 2, \cdots, L)$ represents the reference value of antecedent attribute in the kth rule. p is the step of prediction in BRB_layer1. $D = \{D_1, D_2, \cdots, D_N\}$ is the set of value of consequent; $\beta_{j,k}\,(j = 1, 2, \cdots, N, k = 1, 2, \cdots, L)$ is the belief degree of jth results D_j, where $D_j \in D$.

Therefore, the time series BRB prediction model of x_n as BRB_layer1 is established in a complex electromechanical system, which is h in (4).

C. BRB_LAYER2: HEALTH ESTIMATION MODEL

It is assumed that a total of n features can be used to express the health state of a complex electromechanical system. The health assessment model of the system can be established as:

$$\begin{aligned}&R_{k'}\ \text{BRB\_layer2:}\\ &\quad \text{If } x_1(t+p)\ \text{is}\ A_1^k \wedge x_2(t+p)\ \text{is}\ A_2^k \wedge \cdots \wedge x_n(t+p)\ \text{is}\ A_n^k\\ &\quad \text{Then } \left\{\left(H_0, \beta_{1,k}\right), \cdots, \left(H_B, \beta_{N,k}\right)\right\}\\ &\quad \text{With a rule weight}\theta_k \text{ and attribute weight}\bar{\delta}_1, \bar{\delta}_2, \cdots, \bar{\delta}_n\end{aligned} \tag{6}$$

where $R_{k'}$ is the k' th belief rule in BRB_layer2, x_n is the input, and n is the number of features in the complex electromechanical system. $A_n^k\,(k = 1, 2, \cdots, L)$ is a set of reference value antecedent attribute, where $A_n^k \in H$. $H = \{H_0, H_1, \cdots, H_B\}$ is the set of consequents; $\beta_{b,k}\,(b = 1, 2, \cdots, B, k = 1, 2, \cdots, L)$ is the belief degree of H_b in the results, where $H_b \in H$.

D. OPTIMIZATION MODEL FOR THE DOUBLE LAYER BRB BASED ON P-CMA-ES ALGORITHM

In the double-layer BRB, the initial parameters in the model are set by the experts. Because the expertise is limited by the lack of prior knowledge, the initial parameters cannot accurately reflect the true working state. Thus, it is necessary to build an optimization model to train the initial parameters of the double-layer BRB.

In BRB_layer1, the optimized objective function can be built as follows:

$$\begin{aligned}&\min\ \xi(\mathbf{G})\\ &\text{s.t.}\ \sum_{n=1}^{N}\beta_{n,k} = 1\\ &\qquad 0 \le \beta_{n,k} \le 1, \quad k = 1, 2, \cdots, L\end{aligned} \tag{7}$$

where $\xi(\mathbf{G})$ is the mean squared error (MSE), and $\xi(\mathbf{G}) = \frac{1}{T-\tau}\sum_{t=\tau+1}^{T}\left(x(t) - \hat{x}(t)\right)^2$, where T is the amount of data.

As with the optimized model presented in BRB_layer1, the optimized objective function of BRB_layer2 can also be

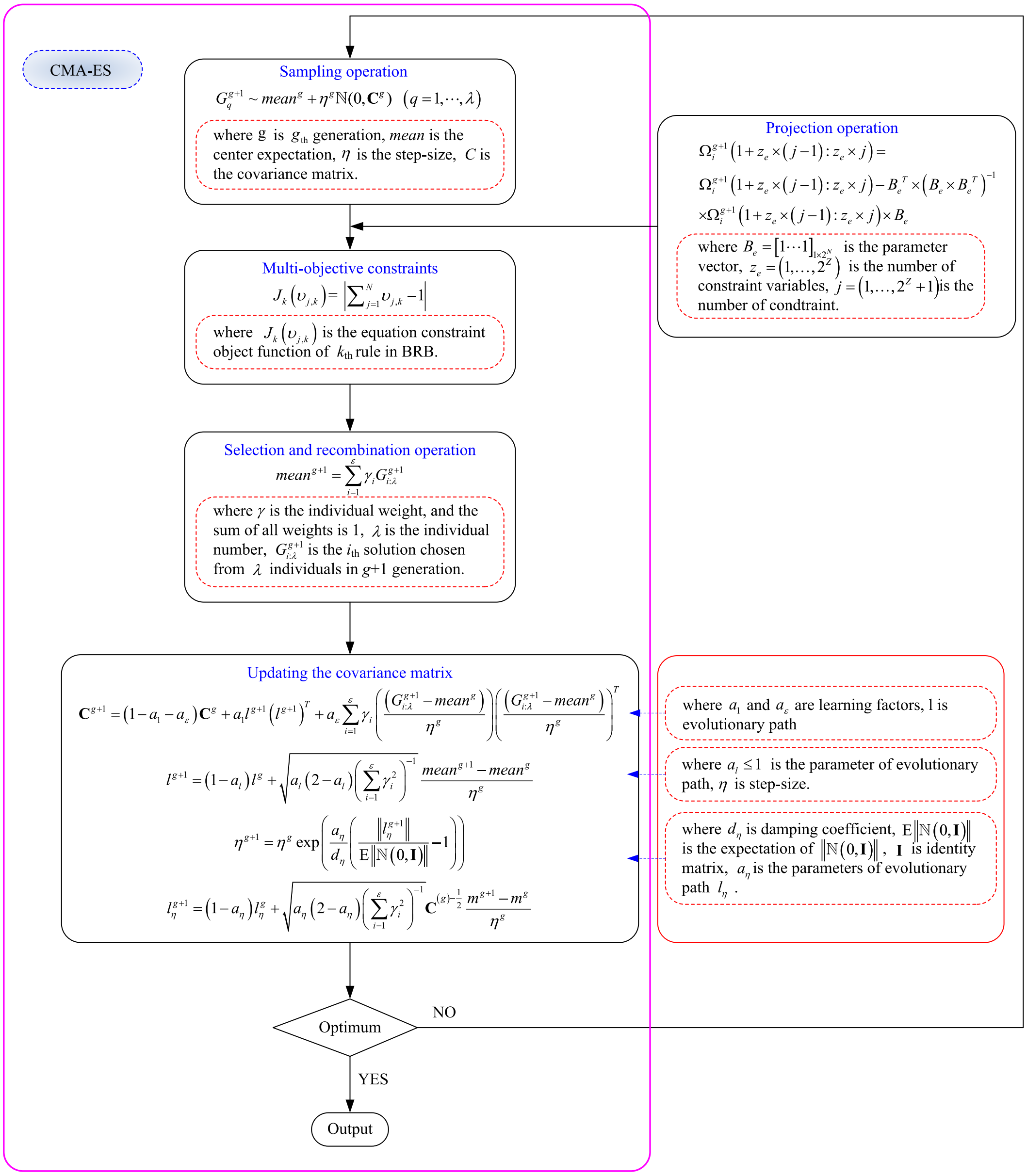


FIGURE 4. **The process of P-CMA-ES.**

built as:

$$
\begin{aligned}
&\min\ \xi(\mathbf{V}) \\
&\text{s.t.} \sum_{n=1}^{N} \beta_{n,k} = 1, \\
&\quad 0 \le \beta_{n,k} \le 1, \quad k = 1, 2, \cdots, L \\
&\quad 0 \le \delta_i \le 1, \quad i = 1, \ldots, M \\
&\quad 0 \le \theta_k \le 1
\end{aligned} \tag{8}
$$

where $\xi(\mathbf{V})$ is the mean squared error (MSE), and $\xi(\mathbf{V}) = \frac{1}{T-\tau} \sum_{t=\tau+1}^{T} \left(y(t) - \hat{y}(t)\right)^2$, where T is the amount of data.

In the double-layer BRB, the P-CMA-ES algorithm is used to optimize the proposed model. It was proposed by Hu [23] in 2016 based on the CMA-ES algorithm. This algorithm has the advantage of reducing complexity and subsequently improving the effectiveness of optimization. The detailed steps for optimization are shown in Fig. 4, and **G** as the parameter set of BRB_layer1 taken as an example.

IV. CASE STUDY

To verify the proposed model of health prognostics for complex electromechanical systems, the test bed for a type of aero-engine is taken as an example to carry out the experimental study for health prognostics. The data of aero-engine vibration are collected, and the vibration sensor is the original part of the aero-engine. In the condition of engine speed of 6500 r/min, the vibration signal of the aero-engine under three states is collected, and 3000 groups are collected

TABLE 1. The referential points and values of *Kurtosis*.

Referential points	L	M	H	VH
Referential values	1.1444	2.0000	3.0000	4.6809

for each state. These three health states are Normal (high-altitude valve spring pressure is normal), Medium Serious (high-altitude valve spring pressure is decreased by 10%), and Serious (high-altitude valve spring pressure is decreased by 20%). The vibration signal of the aero-engine is shown in Fig. 5.

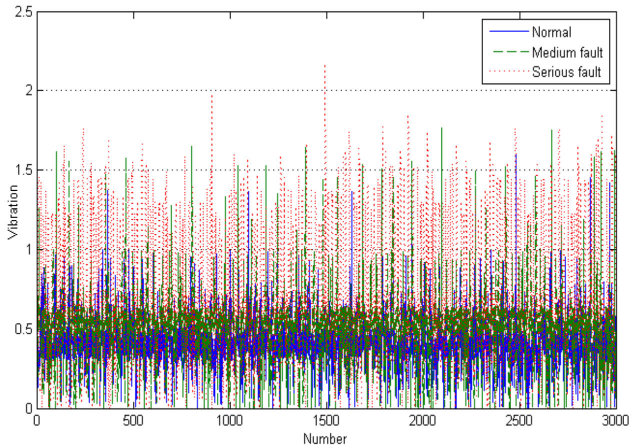


FIGURE 5. The vibration signal of aero-engine under three states. (a) Kurtosis. (b) Skewness.

A. FEATURES SELECTION BASED ON INFINITE IRRELEVANCE METHOD

Due to the complexity of its structure and the diversity of the vibration excitation of the aero-engine, a single vibration quantity cannot make an accurate prognosis for the health state of the aero-engine. Time-domain characteristics have physical meanings that can be easily explained, so five dimensionless time-domain features are extracted from the vibration signal [21], [26]. The extracted features are Mean, Mean square value, Variance, Skewness and Kurtosis. Their calculation method and physical meaning are presented as:

Mean:

$$\bar{x} = \frac{1}{n}\sum_{n}^{T} x_n \tag{9}$$

Mean square value:

$$\xi = E(x_n^2) \tag{10}$$

Variance:

$$\sigma^2 = E[(x_n^2 - \bar{x})^2] \tag{11}$$

Skewness:

$$\psi = E[(x_n^2 - \bar{x})^3]/\sigma^3 \tag{12}$$

Kurtosis:

$$\eta = E[(x_n^2 - \bar{x})^4]/\sigma^4 \tag{13}$$

The results of filtering are shown in Fig. 6.

From the feature selection method introduced in part A of section III, the complex correlation coefficients of five dimensionless features are obtained, which are 0.999, 0.999, 0.992, 0.790 and 0.592. Thus, *Skewness* and *Kurtosis* are selected as the most representative features and then are used as the input attributes in the BRB model. Theoretically, the value should be stabilized in the same health state. However, in the measurement environment, the vibration data not only contain vibration data but also contain environmental noise. To obtain the actual vibration data, the vibration data are screened to accurately evaluate the health by cleaning some error data. The results of data cleaning are shown in Fig. 7.

B. ESTABLISHING BRB_LAYER1 MODEL

After determining the features of an aero-engine vibration machine health state, which are *Kurtosis* and *Skewness* denoted by x_1 and x_2 respectively, the two features of the time series prediction model, named BRB1 and BRB2, are shown below:

$$\begin{aligned} &R_{1k}: \\ &\quad \text{If } x_1(t) \text{ is } A_1^k \wedge x_1(t-1) \text{ is } A_2^k \wedge \cdots \wedge x_1(t-\tau) \text{ is } A_{\tau+1}^k \\ &\quad \text{Then } x_1(t+p) \text{ is } \left\{\left(D_{11}, \beta_{1,k}^1\right), \cdots, \left(D_{1N}, \beta_{N,k}^1\right)\right\} \end{aligned} \tag{14}$$

$$\begin{aligned} &R_{2k}: \\ &\quad \text{If } x_2(t) \text{ is } A_1^k \wedge x_2(t-1) \text{ is } A_2^k \wedge \cdots \wedge x_2(t-\tau) \text{ is } A_{\tau+1}^k \\ &\quad \text{Then } x_2(t+p) \text{ is } \left\{\left(D_{21}, \beta_{1,k}^2\right), \cdots, \left(D_{2N}, \beta_{N,k}^2\right)\right\} \end{aligned} \tag{15}$$

Four referential points are chosen for *Kutrosis*, which are Low, Middle, High and Very High, abbreviated as L, M, H and VH. The referential points of *Skewness* are also set as L, M, H and VH. The referential points and attributes value in BRB1 and BRB2 are shown in Table 1 and Table 2.

In the time series prediction model, the delay steps are 2, that is $\tau = 1$, and the prediction steps are 1, that is $p = 1$. Because the *Kurtosis* $x_1(t)$ has 4 referential values, the delay of *Kurtosis* $x_1(t - \tau)$ also is set with 4 referential values. Therefore, there are 16 belief rules in BRB1 and BRB2. The initial parameters in BRB1 and BRB2 are set as the same values and are shown in Table 3.

In the parameter training of BRB1 and BRB2, 300 data are selected from the dataset respectively. The P-CMA-ES algorithm is chosen as the optimization algorithm, and its population size is set to 82 and the generation number is

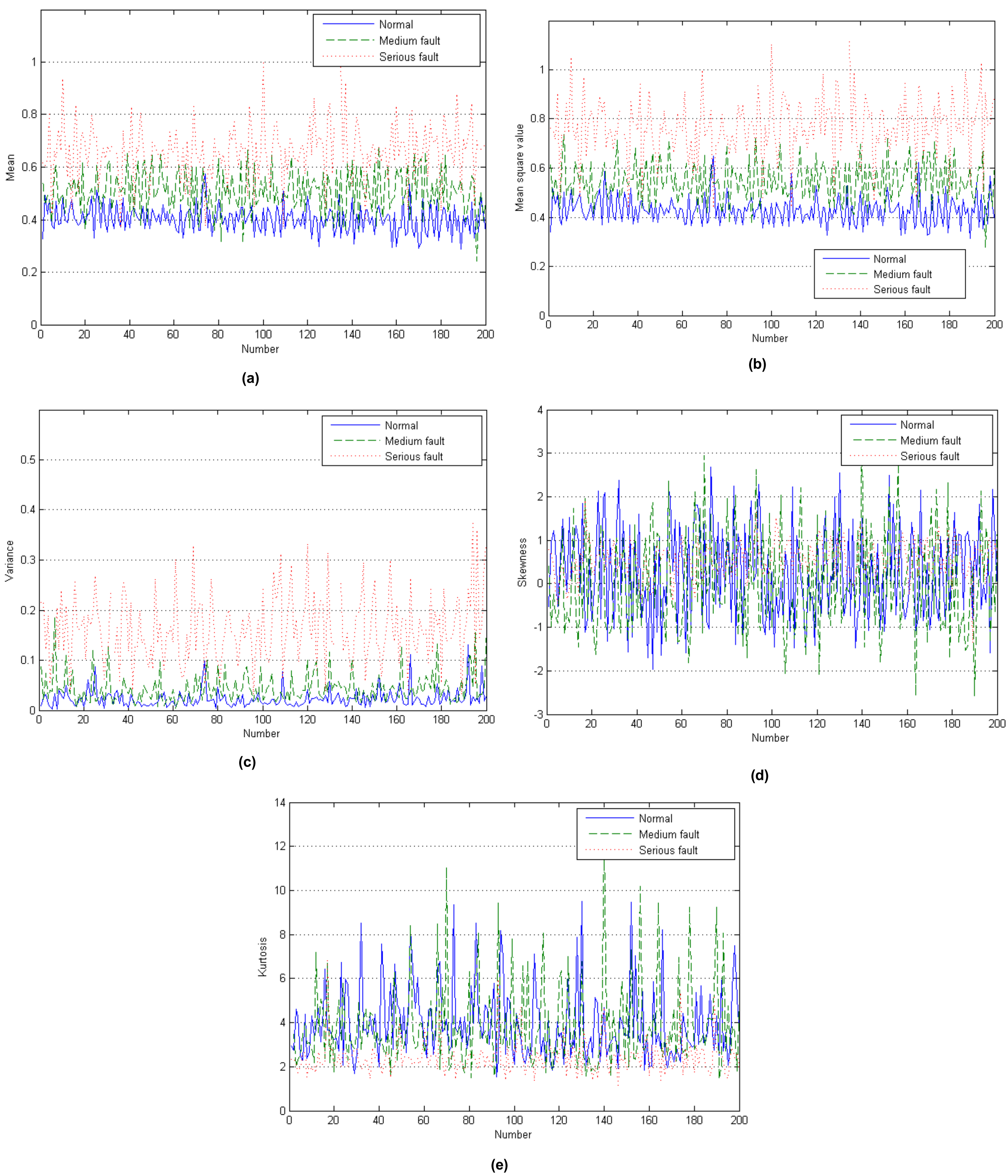
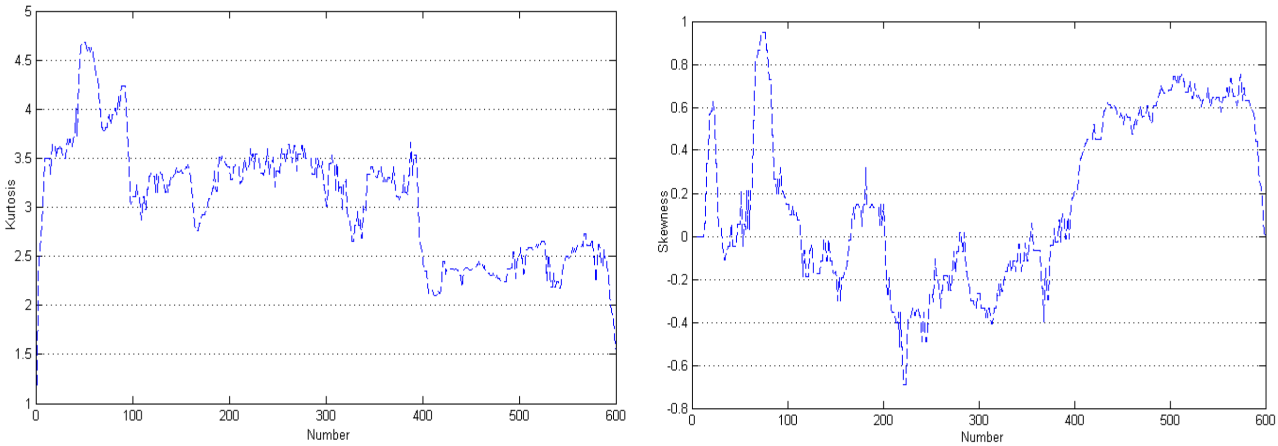


FIGURE 6. **The feature extraction results. (a) Mean. (b) Mean square value. (c) Variance. (d) Skewness. (e) Kurtosis.**

set to 500. After the training part, the optimized parameters in BRB1 and BRB2 are shown in Table 4 and Table 5. The optimized attribute weights for x_1 and x_2 are set to 0.6078 and 0.0219 in BRB1, and 0.8642 and 0.5632 in BRB2, respectively.

A total of 600 data points are used as the testing data, and the predictive outputs of *Kurtosis* and *Skewness* are shown in Fig. 8 and Fig. 9. From these figures, the prediction outcomes can flow the change of the testing data, and the prediction results of optimized BRBs have higher fitting degree than



(a) (b)

FIGURE 7. The features after data cleaning. (a) Kurtosis. (b) Skewness.

TABLE 2. The referential points and values of ***Skewness***.

Referential points	L	M	H	VH
Referential values	-0.6907	-0.1000	0.6000	0.9510

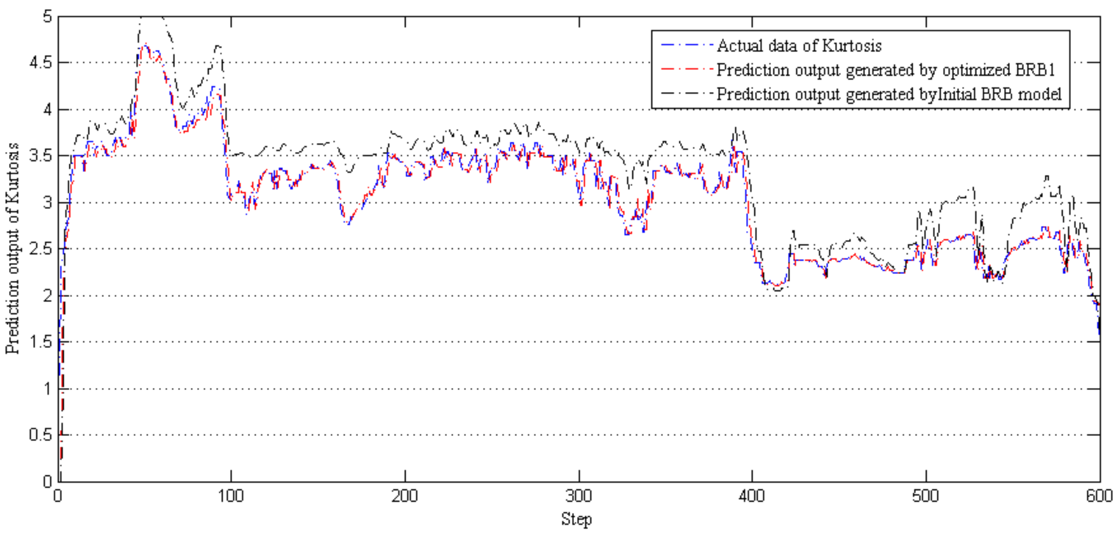


FIGURE 8. Prediction output of Kurtosis by BRB1.

the initial ones. The MSE of optimized BRB1 and BRB2 are set to 0.00387 and 0.0452, respectively. Thus, it can be seen that the two optimized BRB models can accurately predict the dynamic changes of *Kurtosis* and *Skewness*.

C. ESTABLISHING BRB_LAYER2 MODEL

According to the experiment, four-level referential points of the aero-engine health state are set, denoted by Serious, medium Serious and Normal. The referential points and values for the health states $(H_0, H_1, H_2) = (00.51)$. The aero-engine health predictive model named BRB3 is established as follows:

$$\begin{aligned}&\text{If } Kurtosis \text{ is } A_1^k \wedge Skewness \text{ is } A_2^k\\&\text{Then the health state is } \left\{\left(H_0, \beta_{1,k}\right), \left(H_1, \beta_{2,k}\right), \left(H_2, \beta_{3,k}\right)\right\}\\&\text{with a rule weight } \theta_k \text{ and attribute weight } \delta_1, \delta_2\end{aligned} \tag{16}$$

where A_1^k and A_2^k are the referential values of two input attributes, *Kurtosis* and *Skewness*. Similar to the BRB model built in subsection *B*, there are also 4 reference values for

TABLE 3. The initial parameters of BRB1 and BRB2.

No.	Rule weights	Attributes		Estimated output distribution
		$x(t)$	$x(t-1)$	$\{D_1, D_2, D_3, D_4\}$
1	1	L	L	(1 0 0 0)
2	1	L	M	(0.75 0.25 0 0)
3	1	L	H	(0 0.45 0.55 0)
4	1	L	VH	(0 0 0.35 0.65)
5	1	M	L	(0.75 0.25 0 0)
6	1	M	M	(0 1 0 0)
7	1	M	H	(0 0.5 0.5 0)
8	1	M	VH	(0 0.15 0.75 0.1)
9	1	H	L	(0 0.35 0.65 0)
10	1	H	M	(0 0.333 0.667 0)
11	1	H	H	(0 0 1 0)
12	1	H	VH	(0 0 0.65 0.35)
13	1	VH	L	(0 0 0.25 0.75)
14	1	VH	M	(0 0.1 0.3 0.6)
15	1	VH	H	(0 0 0.65 0.35)
16	1	VH	VH	(0 0 0 1)

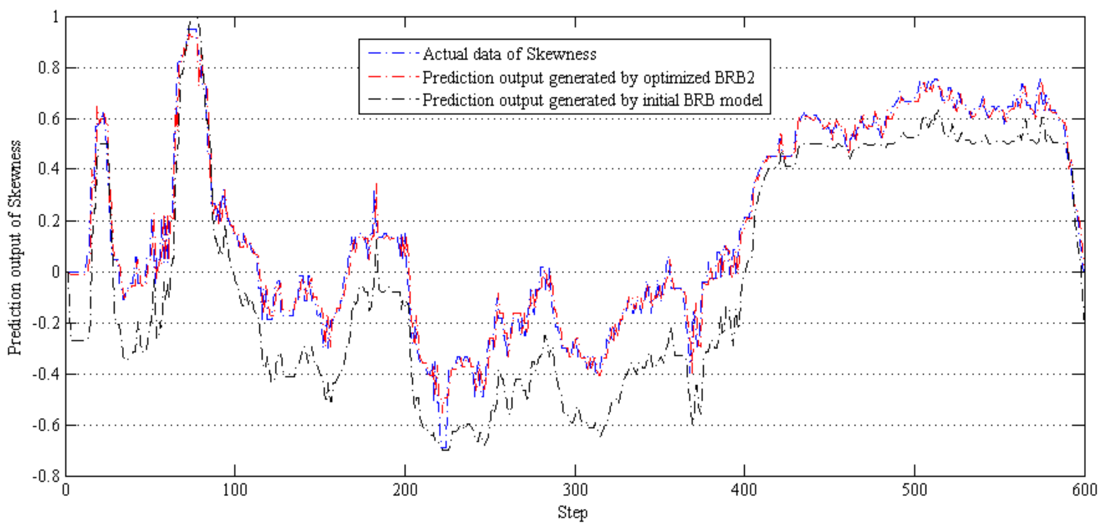


FIGURE 9. Prediction output of Skewness by BRB2.

two attributes. The initial parameters in BRB3 are shown in Table 6.

The health predictive model contains two parts: the training part and testing part. The functions of these two parts are training the BRB3 model with the training data and then testing the effectiveness of the BRB3 model with the testing data. In this paper, 599 sets of data of *Kurtosis* and *Skewness* are predicted by using the time series prediction model.

TABLE 4. The optimized parameters of BRB1.

No.	Rule weights	Attributes		Estimated output distribution
		$x_1(t)$	$x_1(t-1)$	$\{D_{11}, D_{12}, D_{13}, D_{14}\} = \{0\ 2\ 3.5\ 5\}$
1	0.0676	L	L	(0.4094 0.1650 0.3186 0.1070)
2	0.8114	L	M	(0.2208 0.6465 0.1090 0.0237)
3	0.4931	L	H	(0.6145 0.0984 0.0477 0.2395)
4	0.2898	L	VH	(0.3344 0.4005 0.1412 0.1239)
5	0.4086	M	L	(0.5429 0.1108 0.0467 0.2995)
6	0.8055	M	M	(0.2656 0.4157 0.2847 0.0340)
7	0.0023	M	H	(0.3157 0.1946 0.2295 0.2602)
8	0.4661	M	VH	(0.1693 0.3077 0.0660 0.4570)
9	0.6134	H	L	(0.1706 0.5829 0.0673 0.1792)
10	0.6214	H	M	(0.1316 0.1461 0.3239 0.3984)
11	0.5508	H	H	(0.0908 0.3004 0.6051 0.0037)
12	0.7559	H	VH	(0.1190 0.2669 0.4265 0.1875)
13	0.4491	VH	L	(0.4949 0.1515 0.0322 0.3214)
14	0.4425	VH	M	(0.1588 0.2022 0.2163 0.4227)
15	0.5541	VH	H	(0.0038 0.0629 0.2769 0.6563)
16	0.7401	VH	VH	(0.0055 0.0844 0.0147 0.8954)

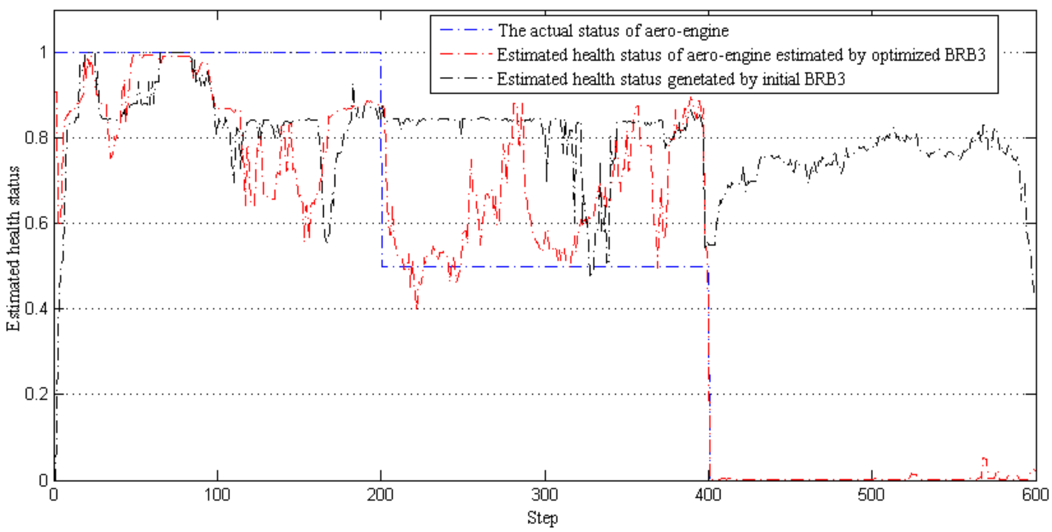


FIGURE 10. Estimated health state of aero-engine.

For each test condition, 100 sets of prediction data are selected as the training data of BRB3. P-CMA-ES is used as the optimization algorithm, and the population number is set to 66 and the generation number is set to 500.

After the part of training, the optimized parameters of BRB3 are obtained as shown in Table 7. The optimized attributes are obtained as 0.7300 and 0.4338 for *Kurtosis* and *Skewness*. Then, the total dataset of the optimized

TABLE 5. The optimized parameters of BRB2.

No.	Rule weights	Attributes		Estimated output distribution
		$x_2(t)$	$x_2(t-1)$	$\{D_{21}, D_{22}, D_{23}, D_{24}\} = \{-0.7\ 0\ 0.5\ 1\}$
1	0.8664	L	L	(0.8573 0.0098 0.0590 0.0739)
2	0.8613	L	M	(0.8628 0.0387 0.0903 0.0082)
3	0.1743	L	H	(0.1676 0.0000 0.8294 0.0022)
4	1.0000	L	VH	(0.3941 0.1262 0.0976 0.3821)
5	0.4367	M	L	(0.0759 0.0301 0.7935 0.1005)
6	0.8508	M	M	(0.5823 0.0116 0.1834 0.2248)
7	0.9470	M	H	(0.5041 0.0267 0.1141 0.3551)
8	0.6980	M	VH	(0.5011 0.4358 0.0170 0.0461)
9	0.8464	H	L	(0.4438 0.0417 0.4685 0.0460)
10	0.7844	H	M	(0.0000 0.0029 0.5234 0.4742)
11	0.5696	H	H	(0.0542 0.0401 0.5581 0.3476)
12	0.3510	H	VH	(0.1555 0.0296 0.0319 0.7831)
13	0.5189	VH	L	(0.4016 0.2403 0.0000 0.3580)
14	0.6891	VH	M	(0.0103 0.0666 0.1902 0.7329)
15	0.5237	VH	H	(0.0257 0.0175 0.0048 0.9520)
16	0.0276	VH	VH	(0.4448 0.3049 0.0264 0.2239)

BRB3 model are the inputs of the testing part. The predicted health state generated by the optimized BRB3 is shown in Fig. 10. It can be seen that the red line can follow the change of blue line, and the fitting degree is increasingly accurate with model updating, which reflects that the optimized BRB3 model can accurately predict the health state of the aero-engine. Therefore, we can conclude that when the health state of the aero-engine is lower than 0.4, it needs to be maintained.

From Fig. 10, it can be seen that the red line has a fluctuation in the normal state and medium fault of the aero-engine. When observation data are gathered from engineering practice, they may be affected by some unmeasured factors that can decrease the accuracy of the prediction model, e.g., temperature, humidity and vibration. If these factors are taken into consideration, the fluctuation in the normal state and medium fault can be well avoided.

D. COMPARATIVE STUDIES

In this section, to demonstrate the effectiveness of the new proposed model, a comparative study between the BP neural network and double-layer BRB model is conducted.

The training data are the same as the dataset used in subsections of B and C. The initial parameters of the BP neural network are as follows: net. trainParam. epochs = 10000, net. trainParam. epochs = 1e-004 and net. trainParam. lr = 0.01. The safety levels are also selected as 1, 0.5 and 0, denoted as normal, medium fault and serious fault, respectively.

Fig. 11 and Fig. 12 are the prediction results for the dynamic changes of *Kurtosis* and *Skewness* compared with the BP neural network. It can be seen that the BP neural network can predict the changes of the two attributes from the beginning. However, when the *Kurtosis* and *Skewness* change significantly, the BP neural network cannot follow the changes accurately and has a certain delay time. Compared with the predictive BRB models, which are represented by the red line in Figs. 11 and 12, the errors of the BP neural network are huge, and their MSEs are 0.6028 and 0.3343 for the prediction model of *Kurtosis* and *Skewness*, respectively. The MSEs generated by the predictive BRB models proposed in subsection B are 0.0123 and 0.0039 for *Kurtosis* and *Skewness*, respectively. On the basis of the above analysis, it can be seen that the accuracy of the prediction BRB model is improved compared with the BP neural network.

TABLE 6. The initial parameters of BRB3.

No.	Rule weights	Attributes		Estimated output distribution
		Kurtosis	*Skewness*	$\{H_0, H_1, H_2\} = \{0\ 0.5\ 1\}$
1	1	L	L	(1 0 0)
2	1	L	M	(0.75 0.25 0)
3	1	L	H	(0 0.45 0.55)
4	1	L	VH	(0 0.35 0.65)
5	1	M	L	(0.75 0.25 0)
6	1	M	M	(0 1 0)
7	1	M	H	(0 0.5 0.5)
8	1	M	VH	(0 0.25 0.75)
9	1	H	L	(0 0.35 0.65)
10	1	H	M	(0 0.3 0.7)
11	1	H	H	(0 0 1)
12	1	H	VH	(0 0.65 0.35)
13	1	VH	L	(0 0.25 0.75)
14	1	VH	M	(0.1 0.3 0.6)
15	1	VH	H	(0 0.65 0.35)
16	1	VH	VH	(0 0 1)

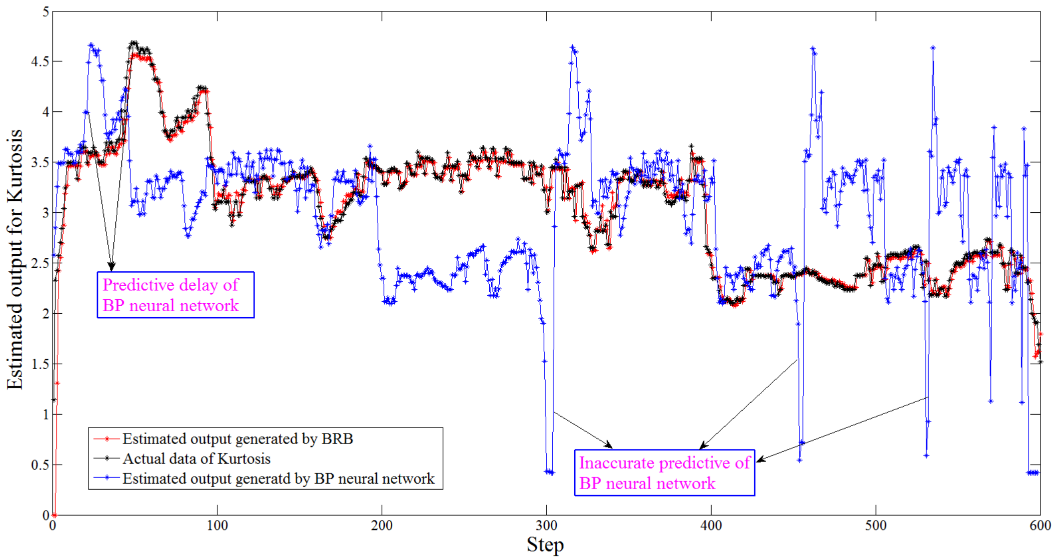


FIGURE 11. Comparison between BP neural network and BRB model for *Kurtosis*.

Comparing the BRB-based model with the BP neural network in the health state prognostics, its accuracy is also improved. As shown in Fig. 13, the red line, which represents the assessment of the health state by BRB, can follow the black line denoting the actual health state of the aero-engine accurately. However, the blue

TABLE 7. The optimized parameters of BRB3.

No.	Rule weights	Attributes		Estimated output distribution
		Kurtosis	*Skewness*	$\{H_0, H_1, H_2\} = \{0\ 0.5\ 1\}$
1	0.7888	L	L	(0.0610 0.6202 0.3188)
2	0.0074	L	M	(0.0024 0.2064 0.7911)
3	0.7872	L	H	(0.8593 0.1412 0.0000)
4	0.1234	L	VH	(0.4321 0.0241 0.5437)
5	0.5475	M	L	(0.5337 0.2487 0.2176)
6	0.1000	M	M	(0.0906 0.4545 0.4549)
7	0.4248	M	H	(0.9963 0.0020 0.0017)
8	0.2738	M	VH	(0.9665 0.0258 0.0078)
9	0.9805	H	L	(0.3412 0.4436 0.2152)
10	0.6456	H	M	(0.0226 0.2877 0.6897)
11	0.0038	H	H	(0.0494 0.1850 0.7556)
12	0.5048	H	VH	(0.0062 0.0211 0.9727)
13	0.9379	VH	L	(0.7562 0.2333 0.0104)
14	0.5938	VH	M	(0.0039 0.0000 0.9962)
15	0.7029	VH	H	(0.0000 0.0132 0.9868)
16	0.1695	VH	VH	(0.0962 0.1964 0.7075)

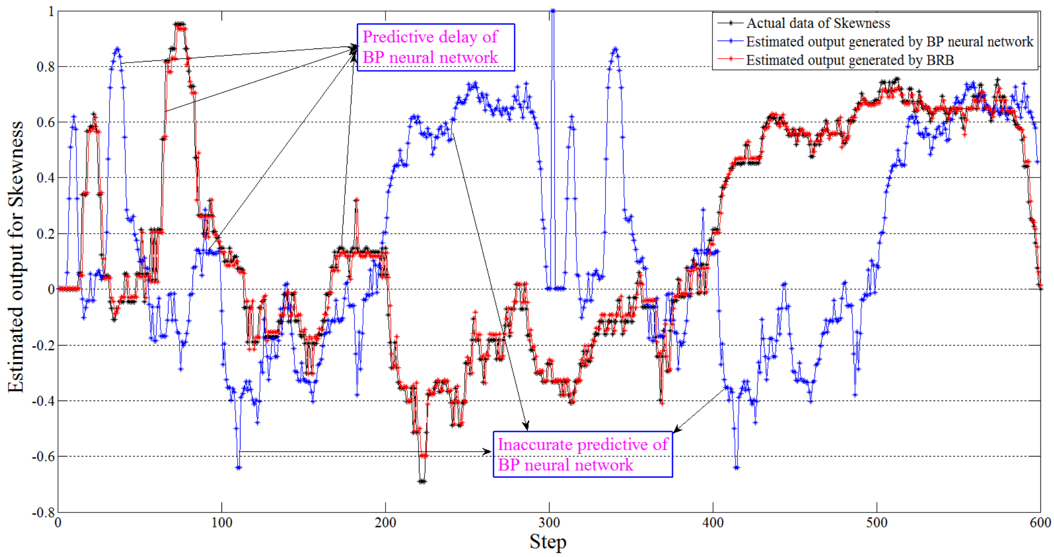


FIGURE 12. Comparison between BP neural network and BRB model for *Skewness*.

line, representing the assessment of the health state by the BP neural network, cannot reflect the actual status of the engine when under normal condition and medium fault.

From the above comparison, we conclude that compared with the BP neural network, the BRB-based prognostics model can predict the attributes and evaluate the engine health state accurately.

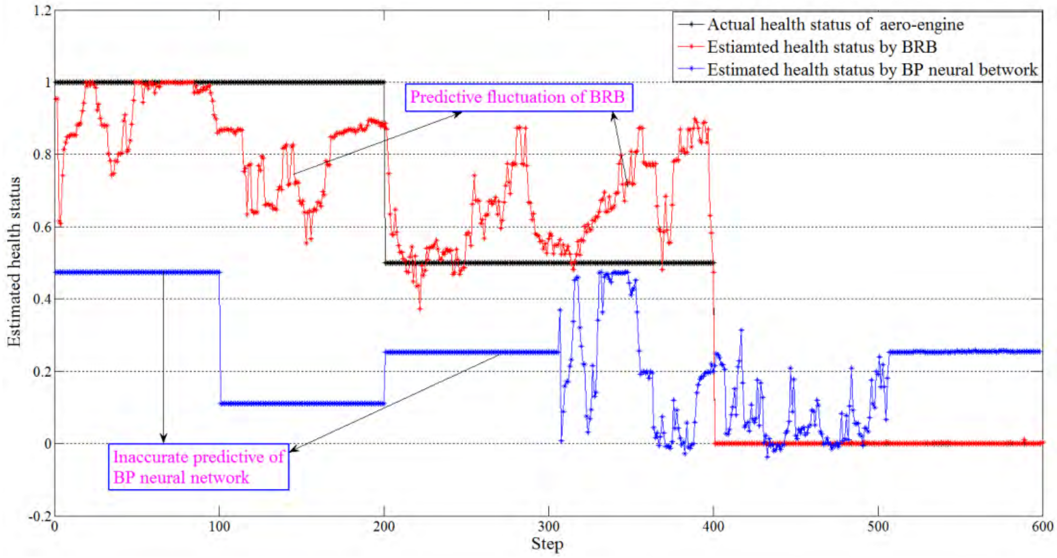


FIGURE 13. Comparison between BP neural network and BRB model in the estimation for the health state.

V. CONCLUSIONS

In this paper, a double-layer BRB model is proposed to dynamically predict the health state for a complex electromechanical system. Both qualitative knowledge and quantitative information are considered to build the model of health prognostics. In the process of health prognostics, an infinite irrelevance method and P-CMA-ES are selected as the features selection method and optimization model to optimize the size and accuracy. A type of aero-engine is taken as an example, and the case study demonstrates that the proposed method can predict the health state well.

The proposed model can take advantage of expert experience which improves the training accuracy compared with the traditional data-driven model. In addition, history and current data are used to predict future data, which can reflect the dynamic changes in a complex electromechanical system. Moreover, features are combined to determine the health state with different weights to ensure the accuracy of prediction.

In this paper, we assume that the data obtained are fully reliable. However, in the actual working environment, the quality of sensors may cause errors in the observation data. This could create doubts in the data that are collected by the sensors, thus reducing the reliability of the data. Therefore, a model of health prognostics considering data reliability should be further studied for a complex electromechanical system. Moreover, this future work may have a better engineering significance.

REFERENCES

[1] F. Camci and R. B. Chinnam, "Health-state estimation and prognostics in machining processes," *IEEE Trans. Autom. Sci. Eng.*, vol. 7, no. 3, pp. 581–597, Jul. 2010.

[2] L. Tao, C. Yang, Y. Cheng, C. Lu, and M. Ragulskis, "Machine component health prognostics with only truncated histories using geometrical metric approach," *Mech. Syst. Signal Process.*, to be published, doi: 10.1016/j.ymssp.2017.01.052.

[3] C. D. Dao and M. J. Zuo, "Optimal selective maintenance for multi-state systems in variable loading conditions," *Rel. Eng. Syst. Safety*, vol. 166, pp. 171–180, Oct. 2017.

[4] P. Lall, M. Hande, C. Bhat, and J. Lee, "Prognostics health monitoring (PHM) for prior damage assessment in electronics equipment under thermo-mechanical loads," *IEEE Trans. Compon., Packag., Manuf. Technol.*, vol. 1, no. 11, pp. 1774–1789, Nov. 2011.

[5] C. Lu, L. Tao, and H. Fan, "An intelligent approach to machine component health prognostics by utilizing only truncated histories," *Mech. Syst. Signal Process.*, vol. 42, no. 1, pp. 300–313, 2014.

[6] L. Lei, J. H. Yan, Y. Meng, "Dynamic genetic algorithm-based feature selection scheme for machine health prognostics," *Procedia CIRP*, vol. 56, pp. 316–320, Mar. 2016.

[7] J. B. Yu, "Machine health prognostics using the Bayesian-inference-based probabilistic indication and high-order particle filtering framework," *J. Sound Vibrat.*, vol. 358, pp. 97–110, Dec. 2015.

[8] P. Lall, R. Lowe, and K. Goebel, "Prognostics health management of electronic systems under mechanical shock and vibration using Kalman filter models and metrics," *IEEE Trans. Ind. Electron.*, vol. 59, no. 11, pp. 4301–4314, Nov. 2012.

[9] F. Lu, J. Q. Huang, and Y. Q. Lv, "Gas path health monitoring for a turbofan engine based on a nonlinear filtering approach," *Energies*, vol. 6, no. 1, pp. 492–513, 2013.

[10] F. Lu and J.-Q. Huang, "Contracted Kalman filter estimation for turbofan engine gas-path health," *Control Theory Appl.*, vol. 29, no. 12, pp. 1543–1550, 2012.

[11] Z. Xi, R. Jing, P. Wang, and C. Hu, "A copula-based sampling method for data-driven prognostics," *Rel. Eng. Syst. Safety*, vol. 132, pp. 72–82, Dec. 2014.

[12] Z. Tian and M. J. Zuo, "Health condition prognostics of gears using a recurrent neural network approach," in *Proc. Annu. Rel. Maintainability Symp.*, Jan. 2009, pp. 460–465.

[13] X. Xie, W. Sun, and K. C. Cheung, "An advanced PLS approach for key performance indicator-related prediction and diagnosis in case of outliers," *IEEE Trans. Ind. Electron.*, vol. 63, no. 4, pp. 2587–2594, Apr. 2016.

[14] S. Yin, X. Xie, and W. Sun, "A nonlinear process monitoring approach with locally weighted learning of available data," *IEEE Trans. Ind. Electron.*, vol. 64, no. 2, pp. 1507–1516, Feb. 2017.

[15] S. Yin, X. Xie, J. Lam, K. C. Cheung, and H. Gao, "An improved incremental learning approach for KPI prognosis of dynamic fuel cell system," *IEEE Trans. Cybern.*, vol. 46, no. 12, pp. 3135–3144, Dec. 2016.

[16] H. Jiang, R. Wang, J. Gao, Z. Gao, and X. Gao, "Evidence fusion-based framework for condition evaluation of complex electromechanical system in process industry," *Knowl.-Based Syst.*, vol. 124, pp. 176–187, May 2017.

[17] J.-B. Yang, J. Liu, J. Wang, H.-S. Sii, and H.-W. Wang, "Belief rule-base inference methodology using the evidential reasoning Approach-RIMER," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 36, no. 2, pp. 266–285, Mar. 2006.

[18] Z.-J. Zhou, C.-H. Hu, J.-B. Yang, D.-L. Xu, M.-Y. Chen, and D.-H. Zhou, "A sequential learning algorithm for online constructing belief-rule-based systems," *Expert Syst. Appl.*, vol. 37, no. 2, pp. 1790–1799, 2010.

[19] Z.-J. Zhou, L.-L. Chang, C.-H. Hu, X.-X. Han, and Z.-G. Zhou, "A new BRB-ER-based model for assessing the lives of products using both failure data and expert knowledge," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 46, no. 11, pp. 1529–1543, Nov. 2016.

[20] F.-J. Zhao, Z.-J. Zhou, C.-H. Hu, L.-L. Chang, Z.-G. Zhou, and G.-L. Li, "A new evidential reasoning-based method for online safety assessment of complex systems," *IEEE Trans. Syst., Man, Cybern., Syst.*, to be published, doi: 10.1109/TSMC.2016.2630800.

[21] G. Li, Z. Zhou, C. Hu, L. Chang, Z. Zhou, and F. Zhao, "A new safety assessment model for complex system based on the conditional generalized minimum variance and the belief rule base," *Safety Sci.*, vol. 93, pp. 108–120, Mar. 2017.

[22] Z.-J. Zhou, G.-Y. Hu, B.-C. Zhang, C.-H. Hu, Z.-G. Zhou, and P.-L. Qiao, "A model for hidden behavior prediction of complex systems based on belief rule base and power set," *IEEE Trans. Syst., Man, Cybern., Syst.*, to be published, doi: 10.1109/TSMC.2017.2665880.

[23] G. Y. Hu, "Study on network security situation awareness based on belief rule base," Ph.D. dissertation, Dept. CST, Harbin Univ. Sci. Technol., Harbin, China, 2016.

[24] J. Hu and L. Zhang, "Opportunistic maintenance strategy for complex oil and gas production equipment based on fault preventive defense," *J. Mech. Eng.*, vol. 49, no. 12, pp. 167–175, 2013.

[25] X. Wang, G. Li, and B. You, "Debris flow hazard assessment based on Monte Carlo simulation," in *Proc. Int. Conf. Multimedia Technol.*, 2011, pp. 3912–3915.

[26] Y. J. Liu, "Research on new method of condition monitoring and fault diagnosis for vehicle," Ph.D. dissertation, Dept. VE, Northeastern Univ., Shenyang, China, 2008.

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