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RESEARCH ARTICLE

Fault Diagnosis of High-Speed Train Motors Based on a Multidimensional Belief Rule Base

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ABSTRACT The safe operation of high-speed rail running gear is crucial, as fault diagnosis can effectively prevent potential risks and ensure the smooth operation of the train. The Belief Rule Base (BRB) method has demonstrated excellent performance in complex system modeling. However, during the optimization process, BRB may lead to a "combinatorial explosion" of rules within the model, resulting in a loss of model interpretability and an increase in complexity. To address this, a Multidimensional Belief Rule Base (MBRB) fault diagnosis method is proposed. By optimizing the structure and parameters, the interpretability of the model is enhanced, and its complexity is reduced. Specifically, the model inputs are decomposed into multiple dimensions for analysis, and then the MBRB rules are updated using the Projection Covariance Matrix Adaption Evolution Strategy (P-CMA-ES), increasing the model's interpretability and accuracy. Finally, the effectiveness of this method is validated through an example of high-speed rail running gear.

INDEX TERMS Running gear, belief rule base, fault diagnosis.

I. INTRODUCTION

The rapid development of high-speed railway technology has greatly promoted the progress of modern transportation, providing passengers with faster and more convenient travel options. However, with the increasing speed of high-speed trains, their safety issues have attracted more and more attention from the public and industry experts. The safety of high-speed railways is not only fundamental to ensuring the safe operation of trains but also directly related to the safety and comfort of passengers, as well as the public's trust and acceptance of the entire railway system. Therefore, the maintenance of the performance and reliability of the high-speed train running gear is particularly critical, and the role of the running gear motor should not be overlooked.

The running gear motor is the power heart of the high-speed train, which is responsible for converting electrical energy into mechanical energy to drive the train forward. The stability of this component directly affects the efficiency and safety of train operation. Any small performance deviation or fault may lead to the unstable running speed of the train, and even cause safety accidents, such as derailment or brake failure, which may pose a direct threat to the safety of passengers. In addition, the motor failure of the running gear may also cause the train to stop operation, affecting the efficiency and reputation of railway transportation.

From a technical point of view, the running gear of a high-speed train is a complex system containing multiple highly interactive components. These components include motors, bogies, braking systems, suspension systems, etc., and the proper functioning of each component is essential to ensure the overall system's stability. In such complex systems, each component may exhibit varying degrees of

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performance fluctuations due to changes in the external environment, such as temperature changes, humidity, mechanical wear, etc., making the dynamic and nonlinear characteristics of the system more obvious. Therefore, for such systems, it is challenging to meet the requirements by only relying on traditional fault diagnosis methods, especially when faced with diverse and interrelated fault modes; one-dimensional fault diagnosis methods are even more incompetent.

Fault diagnosis methods are mainly divided into data-driven [1] and model-based [2] methods. Model-based fault diagnosis methods include state observer method [3], [4] and statistical residual analysis method [5], [6]. Data-driven fault diagnosis methods include statistical analysis methods [7], machine learning methods [8], and deep learning methods [9], [10]. Among them, the fault diagnosis technology based on deep learning has made significant progress in many industrial fields [11], [12], [13], but the method based on BRB [14], [15], [16] has also become an important research direction in the field of fault diagnosis. Deep learning methods have shown efficient fault detection and diagnosis performance when dealing with large-scale and complex data due to their powerful data processing and feature learning capabilities. At the same time, the BRB method shows unique value due to its advantages in dealing with uncertain and fuzzy information, especially in scenarios where expert experience and prior knowledge need to be integrated. The belief rule base is a flexible reasoning tool that combines the advantages of traditional expert systems with the capability to handle the uncertainty inherent in evidence theory. It is especially suitable for dealing with the fault diagnosis problems of complex systems with uncertainty and fuzziness.

Although the traditional BRB method has certain advantages in dealing with uncertainty and fuzzy information, its one-dimensional identification framework cannot effectively capture and analyze the complex fault information caused by the interaction of multiple factors when it is applied to the fault diagnosis of complex systems such as high-speed train running gear. In order to enhance the reliability of the fault diagnosis and decision-making process, Li et al. [17] proposed a fault diagnosis method based on trust rule base and attribute reliability, which solves the worrying problem of small sample size and data. The matching degree calculation method is improved by introducing attribute reliability, and the optimization algorithm is used to adjust the model parameters. Zhu et al. [18]proposed a new 2-D evidence theory to solve specific decision problems and improve the efficiency and accuracy of decision-making by reflecting the information obtained from evidence sources. Traditional evidence theory is based on a single-dimensional evidence recognition framework, which can only reflect the reliability of the information provided by the evidence source and may not show the characteristics of the evidence source itself or the necessary information in the reliability judgment process. This affects decision-making processes such as evidence processing and synthesis to some extent. Feng et al. [19] proposed a fault diagnosis method based on a belief rule-based expert system with multi-source uncertainty information (BRB-MU). The modeling process of BRB-Mu is interpretable and transparent, which ensures a trustworthy fault diagnosis method. On the other hand, based on the transparency of BRB-MU, we quantitatively analyze the impact of uncertain information. Moreover, the aerospace relay is taken as the experimental object. However, inertial navigation systems, servo-mechanisms, etc., are more critical than relays in the vehicle system. Their failure mechanism is different from that of relays. These issues need to be further investigated. These methods often cannot be applied to complex systems such as the running section of high-speed trains to provide them with high diagnostic accuracy to meet the high standard requirements of high-speed railway safety. This approach often fails to provide sufficient diagnostic accuracy to meet the high standards required for high-speed railway safety.

In order to solve these problems, this paper proposes an MBRB framework, which can greatly improve the breadth and depth of information processing by introducing multidimensional input and output into fault diagnosis. Additionally, it addresses the issue of rule explosion inherent in traditional BRB models due to the large number of rules. In this study, the traditional BRB has $L = 4^4 = 256$ rules. The multidimensional belief rules base, however, comprises a total of 32 rules. This significantly mitigates the rule explosion problem and enhances interpretability, ensuring that each belief rule is endowed with expert knowledge. The core of the MBRB framework lies in its ability to comprehensively consider the data from different sensors, and through the comprehensive analysis of these data, the complex fault modes of critical components, such as the running gear motor, can be more accurately described and diagnosed. For example, by simultaneously monitoring multiple parameters of the motor, such as current, temperature, and vibration, MBRB is able to identify possible complex correlations among these parameters to accurately predict and diagnose potential faults.

In practice, the fault diagnosis of the running gear motor using MBRB not only improves the accuracy of the diagnosis but also significantly enhances the reliability and safety of the system. This method enables the maintenance team to detect and solve problems in time, reduces unnecessary maintenance costs and time, and ensures the efficient operation of high-speed trains. In addition, MBRB has also played an important role in enhancing the transparency and credibility of the railway system, which has promoted public trust and satisfaction with the high-speed railway system.

This paper thoroughly analyzes the shortcomings of single-dimensional recognition frameworks in high-demand engineering applications, highlighting the importance of multifactor comprehensive analysis in enhancing the accuracy and reliability of fault diagnosis. The proposed MBRB method addresses the interactive effects of multiple signals, preventing misdiagnosis and missed diagnosis. By optimizing the structure and parameters, the method enhances the interpretability of the model, reduces its complexity, and thereby improves the accuracy of fault diagnosis.

In summary, the introduction of the MBRB framework marks a big step forward in fault diagnosis techniques for high-speed railways. The efficient and accurate diagnosis of the key components, such as the motor of the running gear, not only ensures the safe and stable operation of the high-speed train but also provides solid technical support for the long-term sustainable development of the railway system. This innovative technological advancement ensures that high-speed railways can provide fast and convenient services and, at the same time, serve passengers more safely and reliably.

II. PROBLEM DESCRIPTION

In the process of fault diagnosis for the running gear of high-speed trains, motor data was selected as the experimental data due to its high compatibility with the proposed MBRB fault diagnosis method for the motors of high-speed train running gear. This study experimentally validated the applicability of motor data in MBRB fault diagnosis. Additionally, motor data is easy to collect and monitor. Modern high-speed trains are typically equipped with advanced sensors and monitoring devices capable of real-time collection of various motor operating parameters, such as current, voltage, power, speed, and temperature. These parameters provide comprehensive information for fault diagnosis. The selection of motor data ensures accurate and real-time diagnostic information, offering advantages such as ease of operation, non-invasive techniques, and cost-effectiveness. At the same time, the train running department, as one of the core systems of the train operation, includes critical components such as wheelset, bearing, braking system, bogie, and suspension system, which work together to ensure the smooth and safe operation of the train. However, during operation, the running gear is continuously subjected to high loads and harsh environments, and its components, such as bearings and wheelsets, are prone to failure. In addition, the complexity of the running gear significantly increases the difficulty of fault diagnosis.

Although the traditional BRB system has shown advantages in dealing with uncertain information, when it is applied to the fault diagnosis of the train running gear, its one-dimensional identification framework shows obvious limitations in the fault diagnosis and multi-attribute decision analysis of complex systems. This is mainly reflected in the following aspects:

1) Limitations of the identification framework: The current BRB identification framework only considers one dimension, and it is unable to describe more complex fault information in detail. It is difficult to capture and describe multiple attributes or multiple fault modes in complex systems, which affects the accuracy and reliability of fault diagnosis and decision-making. For example, abnormal changes in parameters such as vibration data, temperature, current, and sound of small motors in train running gear usually indicate potential faults. However, if the identification framework can only deal with data in one dimension, vibration data, it may miss fault signals caused by temperature changes or current anomalies. Suppose that the small motor in the running gear of the train is overheated during operation, but its vibration data is still within the normal range. Since the identification framework only focuses on the vibration data, it may ignore this fault signal, resulting in the overheating problem not being detected and handled in time. Prolonged overheating may damage small motors and other critical components, leading to more serious mechanical failures or even downtime.
2) Limitations of engineering applications: In engineering fields that require high accuracy and reliability judgments, the single-dimensional identification framework ignores the multi-factor causes in fault diagnosis. For example, the correlation between vibration and temperature may indicate different fault types, such as insufficient lubrication or motor overload. Relying on single-dimensional data, such as considering only vibration intensity, may lead to misjudging faults caused by temperature anomalies as normal conditions or failing to accurately judge the severity and specific type of faults. In addition, this method may ignore the potential correlation between faults, such as the abnormal rise of current affecting both temperature and vibration, but it is difficult to identify such composite fault modes if only a single indicator is focused. This will not only lead to misdiagnosis or missed diagnosis but also limit the ability to predict the fault development trend, which affects the formulation of maintenance strategies and the implementation of fault prevention measures.

In order to overcome these limitations, this paper proposes the belief rule base of a multidimensional identification framework to achieve more comprehensive and accurate fault diagnosis and analysis so as to provide more precise and reliable support for fault diagnosis, condition assessment, and maintenance decision-making. Extending it to a multidimensional identification framework can effectively overcome the problems faced by the traditional BRB and provide a more powerful framework for dealing with the fault diagnosis of complex systems.

III. METHODOLOGY

Human intuition and professional judgment play an irreplaceable role in the evaluation and decision-making process, especially when faced with complex problems containing incomplete or imprecise information. Therefore, it is particularly important to model and analyze the above problems by combining quantitative information with subjective judgments (semi-quantitative information) of experts.

Traditional methods mainly rely on complete historical data to make decisions, and these methods generally cannot effectively solve the above problems. BRB, a modeling

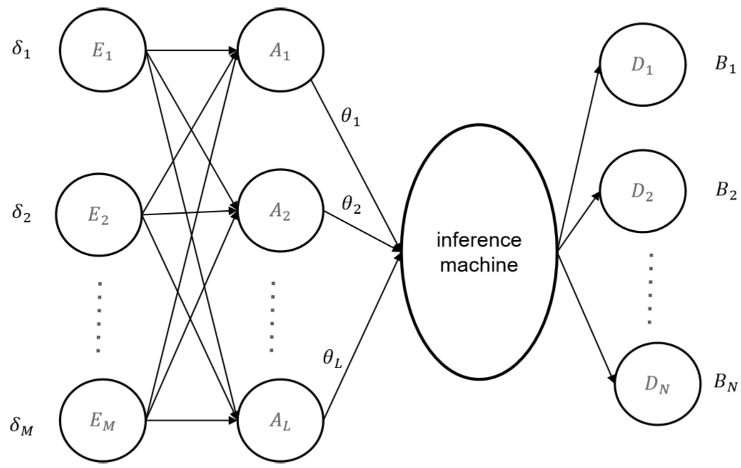

FIGURE 1. Basic structure of BRB.

method proposed in 2006 by Yang et al. [20] at the University of Manchester, UK, and further enriched and developed by Zhou et al. [21], [22], [23], [24], [25], was born to solve such challenges. BRB combines the clarity of traditional IF-THEN rules with the flexibility of confidence and takes into account the weight of each feature and rule so that it can effectively deal with nonlinear data with fuzzy or probabilistic uncertainty [26], so as to realize the effective modeling of complex decision problems. As a kind of "grey-box" model, BRB can not only accurately utilize quantitative and semi-quantitative information but also describe and deal with a variety of uncertain knowledge to effectively explain the model results. By integrating a series of simple IF-THEN rules with confidence, BRB has become a cutting-edge technology in the field of complex system modeling. It marks the in-depth research and application development of the basic theory of BRB and provides a powerful tool for dealing with uncertain information.

The BRB is mathematically described as follows [27].

$$\begin{aligned}
&R_k\ \{\\
&\text{IF } \left(E_1 \text{ is } A_1^k\right) \text{ AND } (E_2 \text{ is } A_2^k) \text{ AND } \ldots \text{ AND } (E_M \text{ is } A_M^k)\\
&\text{THEN } \left\{\left(D_1, \beta_{1,k}\right), \left(D_2, \beta_{2,k}\right), \cdots, \left(D_N, \beta_{N,k}\right)\right\}\\
&\left(\beta_{j,k} \geq 0, \sum_{j=1}^{N} \beta_{j,k} \leq 1\right)\\
&\text{with a rule weight } \theta_k (k = 1, 2, \cdots, L)\\
&\text{and attribute weights } \delta_1, \delta_2, \cdots, \delta_M
\end{aligned} \tag{1}$$

where R_k refers to the K-TH rule; $A_i^k (i = 1, 2, \ldots, M)$ refers to the reference value of the i-th premise attribute in the K-TH rule; M is the total number of premise attributes in the K-TH rule; $(E_1, E_2, \ldots, E_M)$ is the feature, while D_j and $\beta_{j,k} (j = 1, 2, \ldots, N)$ represent the J-TH evaluation result of the K-TH rule and its initial confidence, respectively. When $\sum_{j=1}^{N} \beta_{j,k} \neq 1$ holds, rule k is treated as incomplete. The K-TH rule is said to be complete when $\sum_{j=1}^{N} \beta_{j,k} = 1$ holds; $\theta_k (k = 1, 2, \ldots, L)$ can be interpreted as mapping the importance of the K-TH rule by its rule weight with respect to the other rules in the BRB; $\delta_i (i = 1, 2, \ldots, M)$ denotes the weight of the i-th premise attribute.

A. REASONING ABOUT BELIEF RULE BASES

In the rule inference process of BRB, the output of the model is completed by using the fused ER algorithm, which integrates the belief rule theory for reasoning, as shown in Fig. 1. This process is called the belief rule-base inference methodology using the evidential reasoning approach(RIMER).

The reasoning process mainly includes three steps:

Step 1: Calculate the matching of the premise attribute, which is the consistent degree of the characteristics. This matching degree reflects how well the premise attribute conforms to the rule.

In the first k rule premise attribute matching degree calculation as shown in (2):

$$a_k^i = \begin{cases} \dfrac{A_i^{l+1} - x_i}{A_i^{l+1} - A_i^l} & k = l \quad (A_i \leq x_i \leq A_{i+1}) \\ 1 - a_i^k & k = l + 1 \\ 0 & k = 1, \ldots, N \quad (k \neq l, l + 1). \end{cases} \tag{2}$$

Here, a_i^k represents the conformity degree of the i-th premise attribute in the K-TH rule, and A_i^l and A_i^{l+1} represent the reference value of the i-th premise attribute in the two neighboring rules, respectively.

Step 2: Calculate the activation weight, which is the activation weight of the model feature input to the rule. In the BRB model, the premise attributes in the input data activate the rules in the BRB, and the activation degree of its different rules varies according to their matching degree.

The activation weights for the K-TH rule are calculated as shown in (3):

$$\omega_k = \frac{\theta_k \prod_{i=1}^{N} \left(a_i^k\right)^{\bar{\delta}_i}}{\sum_{l=1}^{L} \theta_l \prod_{i=1}^{N} \left(a_i^l\right)^{\bar{\delta}_i}}. \tag{3}$$

where ω_k represents the activation weight of the K-TH rule; θ_k denotes the rule weight of the K-TH rule; $\bar{\delta}_i$ denotes attribute weights; a_i^k represents the matching degree of the attribute input with respect to the i-th attribute in the K-TH rule.

Step 3: Rule inference is performed using the evidential reasoning algorithm.

In the decision stage of the BRB model, the evidential reasoning algorithm is used to analytically reason and combine the rules in the model, and the final output of the BRB is obtained as shown in (4):

$$S(x) = \left\{ \left(D_j, \hat{\beta}_j \right), j = 1, 2, \cdots, N \right\}. \tag{4}$$

where $\hat{\beta}_j$ represents the confidence of evaluation result D_j, as shown in (5):

$$\widehat{\beta_j} = \frac{\mu \times \left[\prod_{k=1}^{L} \left(\omega_k \beta_{j,k} + 1 - \omega_k \sum_{i=1}^{N} \beta_{i,k} \right) - \prod_{k=1}^{L} \left(1 - \omega_k \sum_{i=1}^{N} \beta_{i,k} \right) \right]}{1 - \mu \times \left[\prod_{k=1}^{L} (1 - \omega_k) \right]}. \tag{5}$$

$$\mu = \left[\sum_{j=1}^{N} \prod_{k=1}^{L} \left(\omega_k \beta_{j,k} + 1 - \omega_k \sum_{i=1}^{N} \beta_{i,k} \right) - (M-1) \prod_{k=1}^{L} \left(1 - \omega_k \sum_{i=1}^{N} \beta_{i,k} \right) \right]^{-1}. \tag{6}$$

Here, $\hat{\beta}_j$ represents the function of rule weight θ_k, attribute weight $\bar{\delta}_i$ and confidence $\beta_{i,k}$. N stands for the number of evaluation results. The activation weight ω_k is shown in (3).

Assuming that the utility of evaluation result D_j is $\mu(D_j)$, the expected utility of $S(X)$ is shown in (7).

$$\mu(S(X)) = \sum_{j=1}^{M} \mu(D_j) \beta_j. \tag{7}$$

Here, β_j represents the confidence of the output with respect to D_j. Therefore, the output of the BRB-based fault diagnosis model is $\hat{y}$, as shown in (8):

$$\hat{y} = \mu(S(X)). \tag{8}$$

B. MULTIDIMENSIONAL BELIEF RULE BASE

Aiming at the limitations of the traditional BRB identification framework, especially the problem that the one-dimensional identification framework cannot describe the complex fault information objectively and in detail, an MBRB is proposed in this chapter. The multidimensional identification framework aims to improve the accuracy and reliability of fault diagnosis by comprehensively considering multiple dimensions of information so as to capture and analyze fault information more comprehensively.

C. DESCRIPTION OF MULTIDIMENSIONAL BELIEF RULE BASE

Traditional BRB relies on single-dimensional data processing, which limits its application effect in complex fault analysis. For example, the train group running gear only uses motor sensor temperature data to diagnose the fault of the train running gear, ignoring other key indicators such as vibration data and current, which cannot fully reflect the real situation of the fault. By integrating data from multiple dimensions, MBRB can analyze and describe fault information more comprehensively.

The proposed MBRB did not have an objective and detailed description of the fault information. By comprehensively considering the information of multiple related dimensions, the type, degree, and cause of the fault can be more accurately identified, and the effective diagnosis of complex fault patterns can be realized.

All in all, introducing MBRB effectively solves the traditional one-dimensional recognition framework limitations, which meet in the complex fault diagnosis for fault diagnosis and decision provides a more objective, comprehensive, and accurate method. In practical applications, the train running gear motor is a key component of many mechanical equipment and transportation systems, and its health status directly affects the reliability and safety of the whole system. Therefore, it is particularly important to apply MBRB to the sensor data of the running gear motor for fault diagnosis.

MBRB represented as:

$$\begin{aligned}
&\text{IF } (X_1 \text{ is } A_1^k) \text{ And } (X_2 \text{ is } A_2^k) \ \cdots \ \text{And } (X_M \text{ is } A_M^k) \\
&\text{THEN} \begin{bmatrix} Y_{11} & \cdots & Y_{1n} \\ \vdots & \ddots & \vdots \\ Y_{n1} & \cdots & Y_{nn} \end{bmatrix}, Y_{ij} = (FD_{ij}, FB_{ij}) \\
&(1 \le i \le n, \ 1 \le j \le n) \\
&\text{With a rule weight } \theta_k \ (k = 1, 2, \cdots, L) \\
&\text{And attribute weights } \delta_1, \delta_2, \cdots, \delta_M.
\end{aligned} \tag{9}$$

Here, $X_i (i = 1, 2, \cdots, M)$ is the MBRB input, A_i^k represents the reference value of the i-th premise attribute; M denotes the number of premise attributes in the K-TH rule; Y_i^n denotes n dimensions, FD_{ij} is the i-th rule of the j-th dimension and FB_{ij} represents the confidence of the MBRB. θ_k represents the weight of the K-TH rule and δ_i represents the weight of the i-th premise attribute.

After obtaining the confidence levels of the output of each dimension, these confidence levels are synthetically processed using expert systems or decision logic to form the final fault type or decision result. This process may involve operations such as weighting and aggregation of confidence measures.

IV. FAULT DIAGNOSIS PROCESS

The MBRB process involves extending the traditional BRB to multiple dimensions to support more complex fault diagnosis and decision making processes. Using MBRB for fault diagnosis of the whole process can be subdivided into the following steps:

A. DATA COLLECTION

According to the problem definition, multidimensional data related to fault diagnosis are collected. These data may come from sensors' temperature, vibration, etc.

B. DATA PREPROCESSING AND FEATURE EXTRACTION AND DATA CLEANING

Data cleaning: Removing outliers, missing values, and duplicate data to ensure data accuracy and consistency. Feature extraction: Features related to fault diagnosis are extracted from the raw data, which should be able to reflect the state or trend when the fault occurs. Data standardization: The extracted features are standardized to eliminate the dimensional differences between different features and facilitate subsequent analysis and calculation.

C. IDENTIFICATION OF MULTIDIMENSIONAL FRAMEWORK DETERMINE DIMENSIONS

Determine dimensions: Based on the problem definition and data characteristics, determine the dimensions that need to be incorporated into the identification framework, such as temperature, pressure, vibration, etc. Divide the state space: Divide the state space in each dimension; that is, define the range of possible states or values in each dimension.

Formation of multidimensional identification framework: The state Spaces of all dimensions are combined to form a multidimensional identification framework for subsequent rule matching and fault diagnosis. The multidimensional identification framework is usually expressed as follows.

$$\Theta = \{\Theta 1, \Theta 2, \cdots \Theta m\} . \tag{10}$$

Here, Θ represents the whole identification frame, and Θi represents the identification frame of the i-th dimension, including all possible values or states under this dimension.

D. RULE BASE CONSTRUCTION AND UPDATE

Rule formulation: Based on expert knowledge, historical data, and experience, a series of confidence rules are formulated. These rules describe the probability and confidence of a fault occurrence in different dimensional states. Rule base initialization: rules into MBRB form the initial rule base. Rule base update: As new data collection and analysis, the rule base can be updated dynamically and optimized in order to improve the accuracy of fault diagnosis.

E. FAULT DIAGNOSIS

Rule matching: The preprocessed data is input into the multidimensional identification framework and matched with the rules in the rule base. Find the set of rules that satisfy the condition. Confidence calculation: Based on the matched rules, we compute the confidence for each rule. This can be obtained by confidence values defined in the rules or by methods based on data statistics. Decision fusion: The confidence of multiple rules is fused, and the final fault diagnosis result can be obtained by using weighted average, voting, or other fusion strategies.

F. RESULT OUTPUT

Result output: The fault diagnosis result is output in an easy to understand way, including fault type, location, etc. MBRB is an identification framework that introduces multiple dimensions based on the traditional BRB. Each dimension represents a different feature or parameter for a more comprehensive description of the problem and diagnosis scenario.

V. P-CMA-ES OPTIMIZATION ALGORITHM

In the motor fault diagnosis model of train running gear based on MBRB, the initial parameters in the model are determined by experts, which has a certain degree of subjectivity, which leads to the inaccuracy of the model. The paper chooses P-CMA-ES for parameter optimization in MBRB due to its ability to handle high-dimensional data, thus enhancing MBRB's capacity to manage uncertainty and fuzzy information. It improves model accuracy by adaptively adjusting the covariance matrix, leading to better parameter optimization, inference accuracy, and decision quality in complex systems. P-CMA-ES also avoids local optima by performing a global search, thereby increasing the reliability of optimization results. Additionally, it accelerates the optimization process by speeding up convergence and reducing computing time and resource consumption while simplifying optimization complexity, making the parameter optimization process more feasible and efficient. Therefore, the P-CMA-ES optimization algorithm is used to find the optimal parameters of the model [28], [29], [30].

The fault diagnosis results of MBRB are calculated by (11), and the following Mean Square Error (MSE) objective function is constructed.

$$\psi(V) = \frac{1}{T}\sum_{n=1}^{T}\left(y_n - \hat{y}_n\right)^2. \tag{11}$$

where $V = \left[\theta_k, \delta_i, \beta_{j,k}, \mu\left(D_j\right)\right]^T$ represents the set of BRB parameters; T is the number of monitoring data; The physical meanings of θ_k, δ_i, $\beta_{j,k}$ and D_j are shown in Equation (1). In order to fit as well as possible, we construct the following objective function:

$$\min_{V} \{\psi\ (V)\} . \tag{12}$$

The constraints of the above objective function are as follows.

$$\begin{aligned} & 0 \le \theta_k \le 1, \quad k = 1, 2, \ldots, L \\ & 0 \le \beta_{j,k} \le 1, \quad j = 1, 2, \ldots, M, \quad k = 1, 2, \ldots, L \\ & \sum_{j=1}^{N} \beta_{j,k} \le 1, \quad k = 1, 2, \ldots, L \\ & 0 \le \overline{\delta_i} \le 1, \quad i = 1, 2, \ldots, N. \end{aligned} \tag{13}$$

where, min {} represents the minimum value of $\psi\ (V)$ and $\overline{\delta_i}$ is the attribute weight.

In order to solve the objective function shown in (13), the P-CMA-ES algorithm is selected in this paper. The optimization method is based on a multi-objective optimization

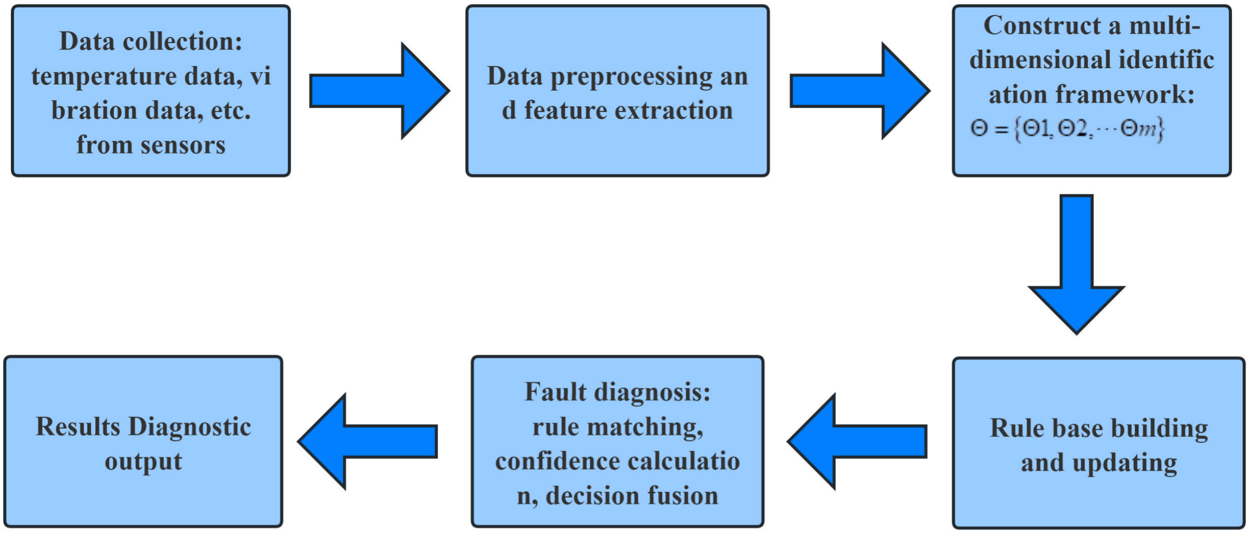

FIGURE 2. Fault diagnosis process.

method to solve constraints, and each constraint of the algorithm can be converted into a set of unconstrained objective functions, which makes it more suitable for the optimization of models with many parameters. In the optimization process, P-CMA-ES realizes the effective control of the population evolution direction by adjusting the covariance matrix and achieves the global optimum based on the fast convergence of small populations. There are four main steps.

Step 1: Perform the sampling operation. A solution is used as the expectation, and a normal distribution of the population is generated. As in (14), the expectation is the vector of the initial parameters in the BRB.

$$V_q^{g+1} \sim mean^g + \eta^g \mathbb{N}(0, \mathbf{C}^g)\,(q = 1, \cdots, \lambda). \tag{14}$$

where g and g_{th} are the generation parameters, *mean* is the central expectation, η is the step size, and $\mathbf{C}$ represents the covariance matrix.

Step 2: Perform multi-objective constraints. The corresponding constraint equation $\sum_{j=1}^{N} \beta_{j,k} = 1$ is transformed into the objective constraint function, as shown in (15):

$$H_k\left(\beta_{j,k}\right) = \left|\sum_{j=1}^{N} \beta_{j,k} - 1\right|. \tag{15}$$

where $H_k\left(\beta_{j,k}\right)$ is the constrained objective function of the BRB rule.

Step 3: Perform selection and reorganization. In this step, the central expectation is shifted to optimize the optimal solution. Update the state of the population evolution. Update the mean of the population by an optimal solution ε, as follows:

$$mean^{g+1} = \sum_{i=1}^{\varepsilon} \gamma_i V_{i:\lambda}^{g+1}. \tag{16}$$

where λ is the number of individuals, γ is the weight of the individual, the sum of all weights is equal to 1, and $V_{i:\lambda}^{g+1}$ is the i-th solution selected from the individuals of g+1 generations.

Step 4: Update the covariance matrix. As shown in (17)–(20):

$$\begin{aligned} \mathbf{C}^{g+1} &= (1 - a_1 - a_\varepsilon)\,\mathbf{C}^g \\ &\quad + a_1 b^{g+1}\left(b^{g+1}\right)^T \\ &\quad + a_\varepsilon \sum_{i=1}^{\varepsilon} \gamma_i \left(\frac{\left(V_{i:\lambda}^{g+1} - \mathrm{mean}^g\right)}{\eta^g}\right) \\ &\quad \left(\frac{\left(V_{i:\lambda}^{g+1} - \mathrm{mean}^g\right)}{\eta^g}\right)^T \end{aligned} \tag{17}$$

where a_1 and a_ε learn the factors, and b is the path of evolution. The initial value of the evolutionary path is 0, as shown in the following equation:

$$b^{g+1} = \left(1 - a_p\right) b^g + \sqrt{a_b\left(2 - a_b\right)\left(\sum_{i=1}^{\varepsilon} \gamma_i^2\right)^{-1}}\, \frac{mean^{g+1} - mean^g}{\eta^g}. \tag{18}$$

where η is the step size and $a_b \leq 1$ is the parameter of the evolutionary path, which is calculated by the following equation:

$$\eta^{g+1} = \eta^g \exp\left(\frac{a_\eta}{d_\eta}\left(\frac{\left\|b_\eta^{g+1}\right\|}{\mathbb{E}\left\|\mathbb{N}\left(0, \mathbf{I}\right)\right\|} - 1\right)\right). \tag{19}$$

where, $\mathbf{I}$ is the identity matrix, $\mathbb{E}\left\|\mathbb{N}\left(0, \mathbf{I}\right)\right\|$ is the expectation of $\left\|\mathbb{N}\left(0, \mathbf{I}\right)\right\|$, d_η is the damping coefficient, the parameter of

b_η, a_η is the path, b_η is calculated by (20):

$$b_\eta^{g+1} = (1 - a_\eta) b_\eta^g + \sqrt{a_\eta (2 - a_\eta) \left(\sum_{i=1}^{\varepsilon} \gamma_i^2 \right)^{-1}} \mathbf{C}^{(g)-\frac{1}{2}} \frac{m^{g+1} - m^g}{\eta^g}. \tag{20}$$

The above operation is repeated until the error requirement is satisfied and the final optimal parameter V_{best} is obtained.

The core of MBRB is that it can decompose a complex problem into multiple dimensions for independent analysis and processing, and each dimension is accurately processed by the corresponding BRB. The introduction of this dimensional processing strategy greatly improves the flexibility and accuracy of problem processing. The other is the comprehensive evaluation mechanism of the expert system, which not only provides a mechanism to solve the possible rule conflicts but also provides a scientific methodology for the generation of final decision or diagnosis results. In addition, the design idea of MBRB further improves the interpretability of the decision-making and diagnosis process and more intuitively understands the decision-making process and results.

MBRB realizes efficient and accurate judgment of complex problems through dimensional processing of each independent input and comprehensive evaluation of the expert system. At the same time, it solves the rule conflict problem encountered in traditional BRB by multidimensional processing. This method not only enhances the interpretability of the system but also improves the accuracy of decision-making and diagnosis.

TABLE 1. Running gear the health reference point.

reference value	H0	H1	H2	H3
reference value	0	1	2	3

VI. SIMULATION EXPERIMENT AND ANALYSIS

A. SIMULATION EXPERIMENT

1) FAULT DEGREE

In order to verify the utility of the MBRB model in practical applications and the applicability of the MBRB model to the reliability evaluation of the high-speed train running gear system, the running gear system of the high-speed train is taken as the verification object in this section. The system is composed of an axle box bearing, gearbox motor, and other key parts. If these components fail, it is bound to pose a serious threat to the stability and safety of the running gear and affect the operation efficiency of the whole train and the safety of passengers.

Therefore, this section extracts relevant data from the fault log provided by a company on July 27, 2017. Taking the temperature fault data of the small motor in the running gear as an example, the frequency, cause and influence range of the temperature fault of the motor during this period of time are compared and analyzed. The accuracy and effectiveness of the MBRB model in predicting and preventing such failures can be further verified.

TABLE 2. Previous attribute reference value.

	Reference Value			
Attribute	**L**	**M**	**H**	**VH**
Mean Value	20	56	75	110
Kurtosis	0.9	5	10	20

TABLE 3. The initial 1D BRB confidence.

Number of rules	Rule weight	Premise attribute		Rule confidence
		mean value	kurtosis	(H0,H1,H2,H3) = {3,2,1,0}
1	1	L	L	(0, 0, 0.8, 0.2)
1	1	L	L	(0, 0, 0.8, 0.2)
2	1	L	M	(0.1, 0, 0, 0.9)
3	1	L	VH	(0, 0, 0.9, 0.1)
4	1	L	H	(0, 0.5, 0.5, 0)
5	1	M	L	(0.5, 0, 0.5, 0)
6	1	M	M	(0, 0, 0.8, 0.2)
7	1	M	VH	(0.7, 0, 0.3, 0)
8	1	M	H	(0, 0, 1, 0)
9	1	VH	L	(0.9, 0, 0.1, 0)
10	1	VH	M	(0, 0.5, 0.5, 0)
11	1	VH	VH	(0.5, 0, 0, 0.5)
12	1	VH	H	(0, 1, 0, 0)
13	1	H	L	(0.1, 0, 0.9, 0)
14	1	H	M	(0.5, 0.5, 0, 0)
15	1	H	VH	(0, 1, 0, 0)
16	1	H	H	(0.8, 0.2, 0, 0)

The kurtosis and mean of temperature were used as the feature input of MBRB, 9480 data points were taken, and every 20 data points were taken as a group of samples to calculate their kurtosis and mean. There were 474 samples in total; 142 samples were taken as the test set, and the health reference points and reference values of walking parts were set, H0 (good), H1 (medium), H2 (general) and H3 (low), as shown in Table 1 and Table 2.

The expert gave the initial parameters of BRB, as shown in the Table 3. In order to reflect that without any prior knowledge, the weights of the 16 rules are equal in the initial stage; that is, the contribution of each rule to the inference result is equally important, so the initial belief rule weight is usually set to 1. This paper sets the initial rule weight to 1 for three reasons. First, the principle of fairness ensures that all rules are equally important at the beginning when there is insufficient historical data or expert knowledge. Second, it simplifies the initial setting process, reducing complexity and uncertainty. Third, it allows for gradual adjustment during the training and optimization process, providing a uniform starting point for weight updates. Lastly, it avoids initial bias, ensuring the model can converge to the optimal state without early-stage bias towards specific rules. In P-CMA-ES, the number of iterations is 200, and the MSE is 0.0401. In order to further verify the feasibility of the proposed method, four analogue signals with disturbance noise are designed in this section, and vibration signals are generated by simulating the real temperature. At the same time, in order to be more in line with the actual working conditions, random noise processing is added to

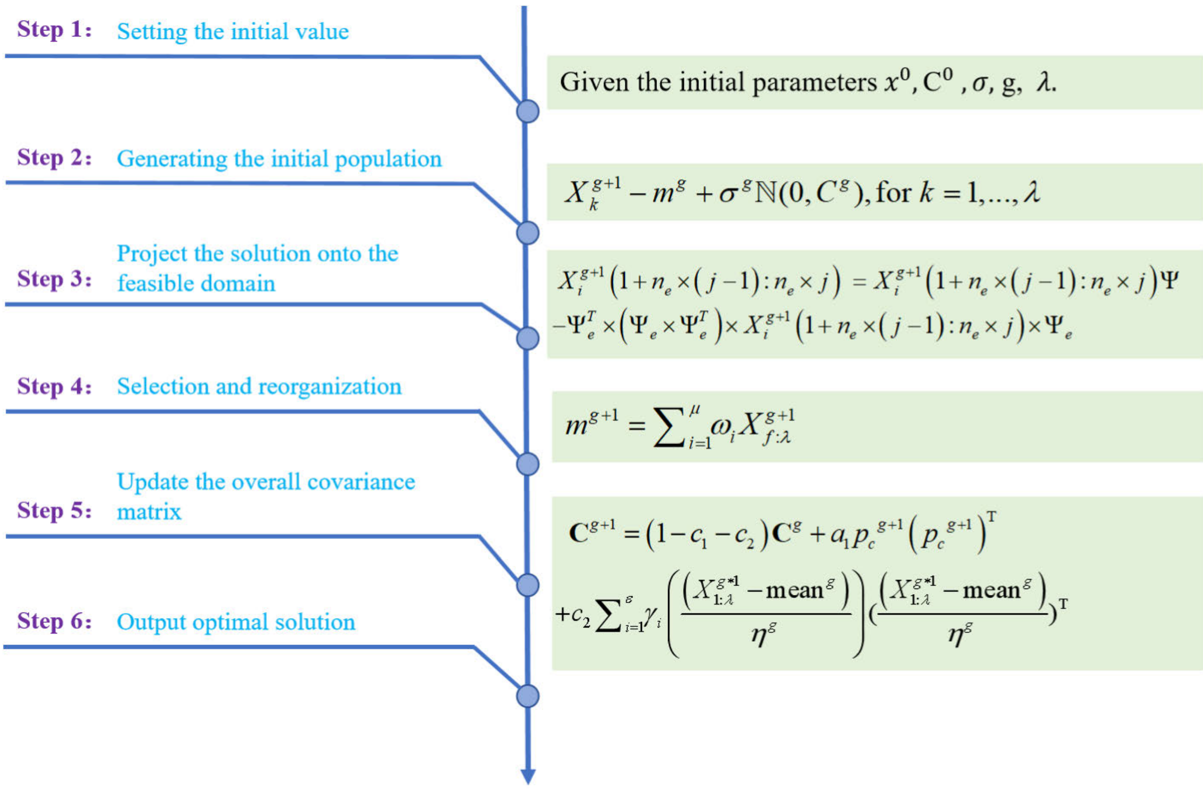

FIGURE 3. P-CMA-ES optimization algorithm steps.

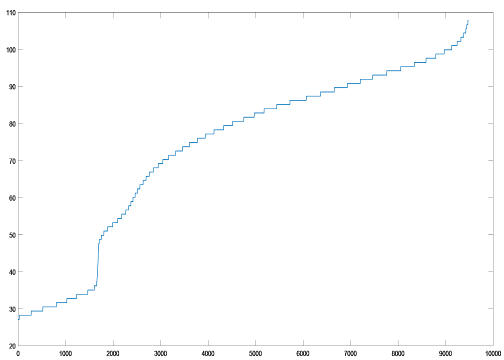

FIGURE 4. Raw data.

the simulation process. The above signals are mixed by different amplitude modulation and frequency modulation. Each signal has a fixed frequency and carrier centre, which is used to simulate the natural frequency of the equipment corresponding to different faults in the system. The formula is as follows:

The simulation signal $x(t)$ consists of harmonic signal $x_1(t)$ and random white noise w,

$$\begin{cases} x_1(t) = 5cos(2\pi t) + 10cos(4\pi t) + 15cos(60\pi t) \\ +20cos(80\pi t) \\ w = 20 * randn(1, n) \\ x(t) = x_1(t) + w \end{cases} \tag{21}$$

The simulation signal $y(t)$ consists of harmonic signal $y_1(t)$ and random white noise w,

$$\begin{cases} y_1(t) \\ = (1 + cos4\pi t) * cos(20\pi t) + 5cos(4\pi t) * cos(40\pi t) \\ +10 * (1 + cos(4\pi t)) * cos(60\pi t) \\ +20 * (1 + cos4\pi t) * cos(80\pi t) \\ y(t) = y_1(t) + w \end{cases} \tag{22}$$

The simulation signal $g(t)$ is composed of AM signal $g_1(t)$, FM signal $g_2(t)$ and random white noise w.

$$\begin{cases} g_1(t) = 1 + cos(4\pi t) + 5 * (1 + cos(4\pi t)) * cos(60\pi t) \\ +10 * (1 + cos(4\pi t)) * cos(80\pi t) \\ g_2(t) = 10 * cos\left(4\pi t^2\right) \\ g(t) = g_1(t) + g_2(t) + w \end{cases} \tag{23}$$

The simulation signal $h(t)$ is composed of AM signal $h_1(t)$, FM signal $h_2(t)$ and random white noise w.

$$\begin{cases} h_1(t) = 15 * sin(50\pi t) * sin(6\pi t) \\ h_2(t) = 20 * sin(20\pi t) * sin(10\pi t) \\ h(t) = h_1(t) + h_2(t) + w. \end{cases} \tag{24}$$

The above four signals are discretized and sampled once every 0.1s with a sampling time of 200s. The time-domain

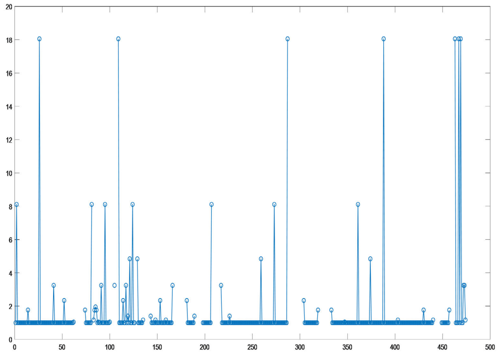

FIGURE 5. Kurtosis.

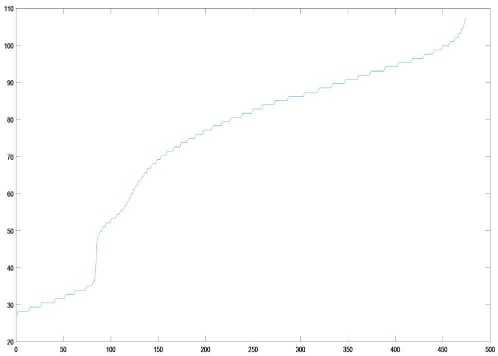

FIGURE 6. Mean value.

waveform is shown in Fig. 8, where x(t), y(t), g(t) and h(t) represent four different fault signals, respectively. In this section, five time domain indicators are selected from every 200 points in the fault signal (mean: reflects the center of the signal; Root mean square: reflects the change of signal energy; Variance: reflects the degree of dispersion of the signal; Skewness: it reflects the deviation between the actual curve and the ideal curve. Kurtosis: This reflects the convexity of the signal.) As input features. So that there are 40 samples in each signal, a total of 200 samples.

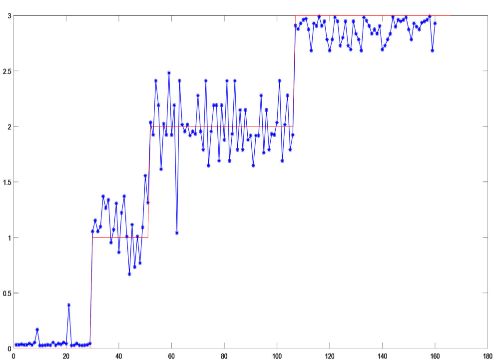

FIGURE 7. 1D BRB.

Randomly select data as training samples, then the remaining samples as testing samples. In order to simplify the experiment, mean and kurtosis are selected as the attributes of BRB. Four reference values are selected for mean: L, M, H, VH, and four reference values for kurtosis: L, M, H, VH, which are given by experts respectively. One simulation signal has three fault modes and one normal mode, which are F1, F2 and F3, corresponding to fault labels 1, 2 and 3, and the reference values are shown in Table 5.

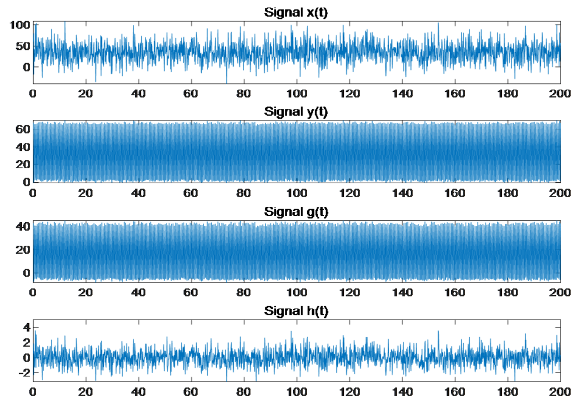

FIGURE 8. Raw signal data.

TABLE 4. Updated 1D BRB confidence.

Number of rules	Rule weight	Premise attribute		Rule confidence
		mean value	kurtosis	(H0,H1,H2,H3) = {3,2,1,0}
1	0.4678	L	L	(0.9970, 0, -0.0010, 0.0038)
2	0	L	M	(0.4005, 0.3544, 0.0206, 0.2244)
3	0.5003	L	VH	(0, 0, -0.0163, 0.9946)
4	1	L	H	(0.0028, 0.2591, 0.5289, 0.2092)
5	0.9634	M	M	(0.6528, 0.2705, 0.0694, 0.0074)
6	0.3573	M	M	(0.3741, 0.2405, 0.2772, 0.1081)
7	1	M	VH	(0.0084, 0.0085, 0.2060, 0.7771)
8	0.8531	M	H	(0.0040, 0.0042, 0, 0.9919)
9	1	VH	L	(0.3531, 0.2349, 0.2527, 0.1594)
10	1	VH	M	(0.4595, 0.3620, 0.0342, 0.1443)
11	1	VH	VH	(0.1686, 0.1039, 0.5286, 0.1988)
12	0.4528	VH	H	(0.0536, 0.3270, 0.2705, 0.3489)
13	0.5950	VH	L	(0.2220, 0.2653, 0.1702, 0.3425)
14	0	M	M	(0.1663, 0.5880, 0.2404, 0.0053)
15	1	H	VH	(0.2279, 0.1572, 0.1716, 0.4434)
16	0.4877	H	H	(0, 0, -0.0359, 0.9714)

TABLE 5. Previous attribute reference value.

	reference value			
attribute	L	M	H	VH
mean value	-13	10	30	60
kurtosis	1.0	3	5	6.5

In this section, the fault degree and fault type are taken as input by MBRB, and then the fault diagnosis of high-speed rail running gear is done through the fault degree and fault type. In addition, through 200 iterations of P-CMA-ES

TABLE 6. The initial 2D BRB confidence.

Number of rules	Rule weight	Premise attribute		Rule confidence
		mean value	kurtosis	(H0,H1,H2,H3) = {3,2,1,0}
1	1	L	L	(0, 0, 0, 1)
2	1	L	M	(0, 0.1, 0.9, 0)
3	1	L	VH	(0.5, 0.4, 0, 0.1)
4	1	L	H	(0.5, 0, 0.5, 0)
5	1	M	L	(0, 0, 0, 1)
6	1	M	M	(0, 0.5, 0, 0.5)
7	1	M	VH	(0.6, 0.4, 0, 0)
8	1	M	H	(0.1, 0.2, 0.2, 0.5)
9	1	VH	L	(0, 0, 0, 1)
10	1	VH	M	(0.2, 0.3, 0.3, 0.2)
11	1	VH	VH	(0.7, 0, 0.1, 0.2)
12	1	VH	H	(0.7, 0.2, 0.1, 0)
13	1	H	L	(0.5, 0, 0, 0.5)
14	1	H	M	(0.7, 0.3, 0, 0)
15	1	H	VH	(0.4, 0, 0.6, 0)
16	1	H	H	(1, 0, 0, 0)

TABLE 7. The updated 2D BRB confidence.

Number of rules	Rule weight	Premise attribute		Rule confidence
		mean value	kurtosis	(H0,H1,H2,H3) = {3,2,1,0}
1	0.0558	L	L	(0.9795, 0.0128, 0.0038, 0.0038)
2	0.0282	L	M	(0.0679, 0.0650, 0.6266, 0.2405)
3	0	L	VH	(0.0488, 0.1640, 0.4472, 0.3400)
4	0.5406	L	H	(0.0272, 0.7043, 0.0348, 0.2337)
5	0.9244	M	L	(0.05520, 0.0704, 0.1053, 0.2723)
6	0.1515	M	M	(0.2364, 0.3822, 0.0986, 0.2828)
7	0.1664	M	VH	(0.5606, 0.2814, 0.1479, 0.0101)
8	0.6484	M	H	(0.0025, 0.0025, 0.0025, 0.9924)
9	0.2553	VH	L	(0.9993, 0, 0.0021, 0)
10	0.6484	VH	M	(0.1007, 0.1057, 0.1224, 0.6711)
11	0.0565	VH	VH	(0.4393, 0.1944, 0.2547, 0.1116)
12	0.1242	VH	H	(0, 0.0211, 0.0080, 0.9722)
13	0.4703	H	L	(0.3736, 0.1197, 0.0506, 0.4561)
14	0.6749	H	M	(0.3755, 0.6870, 0.0318, 0.0057)
15	0.6749	H	VH	(0.2203, 0.4082, 0.0234, 0.3480)
16	0.0565	H	H	(0.0904, 0.2407, 0.0746, 0.5943)

algorithm optimization, the model MSE reaches 0.0153, which improves the accuracy of the model. It further proves the effectiveness of the proposed method. MBRB can improve the efficiency of diagnosis. This paper demonstrates the MBRB system's potential in fault diagnosis of complex systems and provides valuable methods and insights for future research in similar areas. Combining multidimensional fault data provides an efficient and practical tool for fault diagnosis of high-speed train running gear and other complex systems.

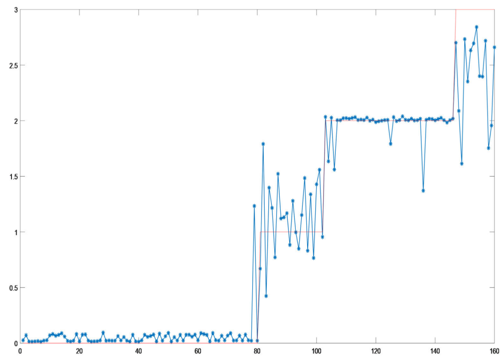

FIGURE 9. 2D BRB utility output.

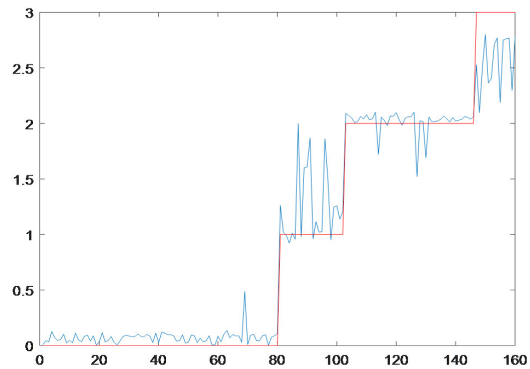

FIGURE 10. The utility output of the conventional BRB.

B. CONTRASTIVE ANALYSIS

In order to further demonstrate the superiority of the MBRB model proposed in this chapter, this section introduces four comparative methods: Traditional BRB, Support Vector Machine(SVM), Convolutional Neural Networks(CNN), and Particle Swarm Optimization-Back Propagation(PSO-BP). The aforementioned data are used as attributes for the Traditional BRB method. There are 4 attributes and 4 reference values of the premise attributes, and $L = 4^4 = 256$. According to Figures 10 and 11, the fitting degree indicates that although the Traditional BRB can describe the state of change, its fitting accuracy is not high. The PSO-BP method shows a better fit with the real data, especially in the regions labelled 0. The CNN method exhibits significant deviations from the real data in some areas, with its curve showing considerable fluctuations. The SVM method's curve follows the real data well in the regions labelled as 1; however, in certain areas, the SVM's fitting performance is inferior to that of the PSO-BP method.

According to the MSE results presented in Table 8, the MBRB model exhibits the best fitting performance with an MSE value of 0.0153, indicating the smallest error. Following this, the Traditional BRB method also shows a good fitting performance with an MSE value of 0.0556. The PSO-BP method ranks third with an MSE value of 0.1192. In contrast, the CNN and SVM methods have relatively larger errors, with MSE values of 0.7091 and 0.6017, respectively. These results suggest that both the MBRB and Traditional BRB models offer higher accuracy and better fitting capabilities

TABLE 8. MSE of different models.

Model	MSE
MBRB	0.0153
Traditional BRB	0.0556
PSO-BP	0.1192
CNN	0.7091
SVM	0.6017

for this dataset. The MBRB model, in particular, outperforms the Traditional BRB, PSO-BP, CNN, and SVM methods. The MBRB model proposed in this paper demonstrates the smallest prediction error and the best fitting capability.

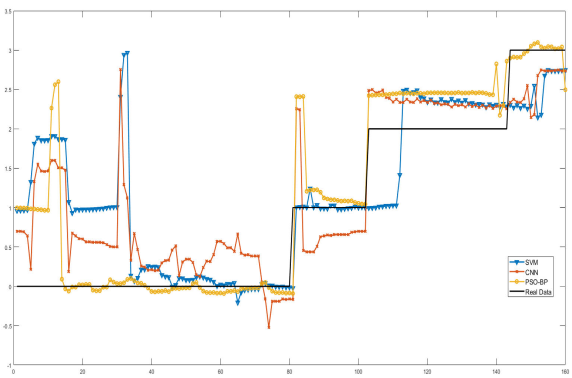

FIGURE 11. Comparison of utility outputs of different methods.

VII. CONCLUSION

In this chapter, the methodology of MBRB is introduced and discussed in detail, as well as its application example in the fault diagnosis of motor bearings in the running gear of high-speed trains. First, the rationale of the MBRB approach is illustrated, that is, how a decision or diagnosis problem can be subdivided into multiple independent dimensions, each handled by a specific BRB, to enable a comprehensive analysis and solution of the problem. Then, this chapter verifies the effectiveness and practicality of the MBRB method through an empirical study, namely the fault diagnosis of EMU motor bearings. Through this experiment, we show how MBRB can accurately identify the cause and extent of faults and which problems traditional BRB systems encounter in complex fault diagnosis processes, such as rule conflicts, are solved.

In addition, the research in this chapter not only strengthens the interpretability of the MBRB model and ensures the transparency and credibility of the decision-making process and results but also significantly improves the accuracy and efficiency of fault diagnosis through the multidimensional analysis of complex problems. It has important practical significance for reducing error diagnosis, ensuring the stable operation of critical systems, and reducing economic losses.

Finally, the successful practice of the MBRB method opens a new path for future state assessment and maintenance decisions of complex systems. The multidimensional analysis ability based on MBRB and the subsequent research combined with advanced data processing and machine learning technology will further improve the efficiency and accuracy of fault diagnosis. In addition, exploring the application potential of MBRB in broader areas such as condition assessment and maintenance decision making will provide stronger technical support and theoretical foundation to ensure the safe operation of critical systems such as high-speed trains. The research results and methodology in this chapter have laid a solid foundation for the health status assessment work in the next chapter and opened up a new way for the intelligent management and maintenance of complex systems in the future.

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