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RESEARCH ARTICLE

A New Fault Diagnosis Method Based on Belief Rule Base With Attribute Reliability Considering Multi-Fault Features

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ABSTRACT Fault diagnosis plays a critical role in system health management. However, practical fault diagnosis encounters several challenges such as limited observational information, system complexity, and environmental disturbances. Belief rule base with attribute reliability (BRB-r) provides a valuable solution to these problems. In BRB-r, the reliability of the input information directly affects the reliability of the observed metrics and subsequently the accuracy of the output belief degree. To strike a balance between the reliability and accuracy of fault diagnosis models, a new fault diagnosis method for BRB-r considering multi-fault features (BRB-mr) is introduced. In the BRB-mr model, the reliability calculation method for attributes considering multi-fault features is proposed. The obtained attribute reliability is then introduced into the calculation of the matching degree, which ultimately reduces the interference of unreliable information to obtain more accurate and reliable diagnostic results. In addition, an optimization model is used to mitigate the effect of uncertainty in expert knowledge. The effectiveness of the method is validated by a case study of diesel engine fault diagnosis.

INDEX TERMS Fault diagnosis, belief rule base, attribute reliability, multi-fault features.

I. INTRODUCTION

Critical equipment holds an important position in the running of complicated systems, and any failure or malfunction of these components can have significant consequences [1], [2]. Timely fault diagnosis is essential to prevent potential financial losses and ensure smooth system operation [3]. Fault diagnosis is the process of identifying and determining abnormal operating conditions or faults in equipment. By employing fault diagnosis techniques, operators and maintenance personnel can quickly determine the fault status of equipment so that it can be repaired or replaced promptly. This proactive approach helps prevent further damage and optimizes system performance.

In the current research, fault diagnosis methods can be classified into three categories: physical methods, data-driven methods, and knowledge-based methods.

Physical methods rely on the understanding of the underlying physics and principles of the device to diagnose faults [4]. These approaches typically involve building mathematical models based on physical equations and system dynamics. They take into account factors such as structural integrity, material properties, and operating conditions to identify potential failures. Sarikhani et al. proposed an open-loop physics-based inverse electric potential estimator for inter-turn short-circuit fault detection in the permanent magnet synchronous motor [5]. Nguyen et al. constructed a

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physics-based model to monitor the performance of system components. Two real-time events were considered, representing pump failure and component performance degradation scenarios [6].

Data-driven methods rely on the analysis of large amounts of data collected from the plant to detect and diagnose faults [7]. These methods use techniques such as machine learning, pattern recognition, and statistical analysis to identify patterns and anomalies in the data that indicate the presence of faults. Based on previous research combining fuzzy theory and neural networks, Xu et al. proposed a new combined approach to develop a fuzzy neural network model suitable for fault diagnosis [8]. Wu et al. developed a convolutional neural network (CNN) that learns features directly from the original vibration signal and then diagnoses the fault [9]. Chen et al. proposed a fault diagnosis method based on cyclic spectral coherence and CNN two-dimensional map representation to improve the identification performance of rolling element-bearing faults [10]. Yao et al. proposed a support vector machine based intelligent fault diagnosis method for lithium-ion batteries, which can identify the fault state and fault level [11]. Hu et al. proposed an efficient fault diagnosis method based on a multi-scale dimensionless index and random forest [12]. The method developed by Kouadri et al. takes advantage of the Hidden Markov Model (HMM) and Principal Component Analysis (PCA) models. PCA technique is used to efficiently extract and select the features to be fed to the HMM [13].

The knowledge-based fault diagnosis methods use domain expertise and reasoning to identify and explain anomalies in complex systems [14]. It relies on a knowledge base containing information on normal behavior, failure modes, and symptom-fault relationships to enable fault diagnosis of equipment. Expert systems, fuzzy inference, and qualitative trend analysis are commonly used in knowledge-based modeling approaches. Lin et al. used fuzzy temporal-based Petri nets for fault diagnosis in power systems. An automatic model-building algorithm was also developed to improve the applicability of the method [15]. Moradi et al. proposed a novel mathematical architecture for operational state assessment and risk monitoring. In this architecture, Bayesian networks are used to model the system, the relationships of subsystems, and the scenarios leading to undesirable events [16]. Gang et al. developed a knowledge-based expert system for complex systems assessment based on the combination of object-oriented knowledge, which provides higher accuracy than the traditional manual analysis [17].

However, each method has its advantages and limitations when used in isolation [4], [7], [18]. Physical methods provide insight into devices and capture complex interactions, but they require precise and detailed models. Data-driven methods can handle large and complex data sets, but they can lack interpretability and rely heavily on data availability and quality. Limitations of knowledge-based fault diagnosis are the reliance on expert knowledge, the challenge of acquiring and maintaining a comprehensive knowledge base, and the difficulty of dealing with complex and dynamic systems.

The purpose of the research is dedicated to addressing the limitations of existing methods, contributing to the advancement of fault diagnosis methods, and improving the accuracy, interpretability, and reliability of models in complex systems.

Belief rule base (BRB) has advantages in dealing with both small sample problems and interpretability [19], [20]. In small-sample problems, BRB can effectively handle data scarcity by incorporating expert knowledge and using belief degrees to represent uncertainty. It allows more reliable inferences to be made even with limited data. In addition, BRB provides interpretability by using IF-THEN rules that are easily understood and validated by domain experts. Such transparency allows users to gain insight into the inference process and build trust in the diagnostic results.

However, the quality of the input data will directly influence the accuracy of the fault diagnosis model [21], [22]. Therefore, it is important to consider all uncertainties that affect the diagnosis results. The main aspects include the following: 1) influenced by the uncertainty of the degradation of the sensor's performance. 2) influenced by the uncertainty under the noise of the environment in which the equipment is located. 3) influenced by the uncertainty of the expert in constructing the rule base.

Considering various uncertainty factors is the foundation of reliable fault diagnosis methods. Based on the above analysis, the aim is to develop a fault diagnosis method for BRB that can take full advantage of the available information, including equipment monitoring data and domain knowledge, and has high accuracy, interpretability, and reliability. However, in engineering practice, different fault features may manifest themselves in widely different data fluctuation intervals. When analyzing the observed data of each index, the difference of each fault feature must be considered. This involves integrating and analyzing the data of various fault features to obtain a comprehensive understanding of the system behavior and to ensure a robust assessment of the attribute reliability.

Therefore, this work proposes a new method named BRB with attribute reliability considering multi-fault features (BRB-mr). In this work, the uncertainty of the data is transformed into attribute reliability combined with BRB. Secondly, the limitations of the literature [21] are overcome and the multi-fault feature states are considered for the first time to determine the reliability of attributes. In addition, a new matching degree calculation method is proposed to be introduced into the inference of BRB-mr.

The remainder of this paper is organized as follows. In Section II, the problems are formulated and the fault diagnosis method based on BRB-mr is developed. In Section III, the inference process with the attribute reliability is presented. An optimization method is presented in Section IV. The modeling process based on BRB-mr is introduced in

Section V. A case study is conducted in Section VI. This paper is concluded in Section VII.

II. PROBLEM FORMULATION AND CONSTRUCTION OF THE BRB-MR MODEL

The problems in the fault diagnosis process based on the BRB model are described in this section. Based on this, a fault diagnosis model based on BRB-mr is constructed.

A. PROBLEM FORMULATION

In engineering practice, there are several problems in fault diagnosis which can be summarized as:

Problem 1: Limited by the rarity of failure occurrences and the resource-consuming nature of conducting failure experiments, it becomes challenging to collect large amounts of high-value observations [23]. In addition, although experts have valuable knowledge, it is difficult for them to construct accurate physical models directly [24]. Therefore, the main challenge in performing fault diagnosis is to maximize the use of the limited multi-source information collected. This requires the development of an innovative fault diagnosis model that can efficiently integrate and utilize diverse information to facilitate accurate and reliable fault diagnosis.

$$D_n = \Phi\left(x_1(n), x_2(n), \ldots, x_M(n), E_k, P\right) \tag{1}$$

where D_n represents the diagnostic result. $x_1(n), x_2(n), \ldots, x_M(n)$ represents the input attribute. E_k represents expert knowledge. P represents the model parameter vector. $\Phi(\bullet)$ represents the constructed fault diagnosis model.

Problem 2: In engineering practice, the reliability of the collected information may be compromised by the presence of complex environmental disturbances [25]. For example, the performance of the sensors degrades over time and therefore the quality of the information collected decreases. In addition, the presence of noise in the actual operating environment may further exacerbate fluctuations in observed data. These factors introduce uncertainty and variability that can impede the accuracy of the fault diagnosis models. It is critical to recognize and address this challenge to ensure that the fault diagnosis models developed remain robust.

$$r_m = \Xi\left(x_m\right) \tag{2}$$

where r_m represents the reliability of the mth attribute x_m. $\Xi(\bullet)$ represents the statistical method used.

Problem 3: It is critical to acknowledge that experts may not always have accurate information to construct the models. In addition, there are extraneous uncertainty influences on the experts [26]. As a result, accurate diagnostic models may be difficult to initially construct. The challenge, therefore, is to design effective mechanisms to tune and train the model parameters. By carefully fine-tuning and optimizing these parameters, the fault diagnosis model can be refined and calibrated to more closely match the specific characteristics of the actual system.

$$\Theta_{best} = O\left(\Theta, Q\right) \tag{3}$$

where Θ is the parameters set involved in the optimization. Θ_{best} is the optimal parameters set sought by the optimization algorithm. Q represents the set of parameters required for optimization. $O(\bullet)$ represents the optimization process.

B. CONSTRUCTION OF THE BRB-MR MODEL

BRB was developed by Yang et al. based on Dempster-Shafer's theory of evidence [27]. BRB is constructed based on the IF-THEN causal structure, where each rule consists of antecedent (IF) and consequent (THEN) statements. The rules in BRB are designed to link input and output variables, allowing inference based on the given inputs. By defining and refining these rules, BRB can provide a systematic and interpretable framework for making informed decisions based on available information.

Based on the RIMER approach in the literature [27], the kth rule of the BRB-mr model is constructed as follows:

$$\begin{aligned}
&R_k : \text{IF} \left(x_1 is A_1^k\right) \wedge \left(x_2 is A_2^k\right) \wedge \cdots \wedge \left(x_M is A_M^k\right), \\
&\text{THEN} \left\{\left(F_1, \beta_1^k\right), \left(F_2, \beta_2^k\right), \ldots, \left(F_N, \beta_N^k\right)\right\}, \\
&\quad \times \left(\sum_{i=1}^{N} \beta_i^k \leq 1\right) \\
&\text{with rule weight } \theta_k, \\
&\text{attribute weight } \delta_m \ (m = 1, 2, \ldots, M), \\
&\text{and attribute reliability } r_m \ (m = 1, 2, \ldots, M), \\
&k = 1, 2, \ldots, L
\end{aligned} \tag{4}$$

where $x_m\ (m = 1, 2, \ldots, M)$ are the M attributes. $A_i^k\ (i = 1, 2, \ldots, M)$ denote the referential value of the ith attribute. $\beta_i^k\ (i = 1, 2, \ldots, N)$ represent the belief degree of the fault feature F. θ_k is the kth rule weight. δ_m represents the mth attribute weight. r_m represents the mth attribute reliability. M is the attribute number, and L is the rule number.

III. INFERENCE OF THE BRB-MR

The attribute reliability calculation method considering multi-fault features is presented in Section III-A. The inference process of the BRB-mr fault diagnosis model is presented in Section III-B.

A. CALCULATION METHOD OF THE ATTRIBUTE RELIABILITY CONSIDERING MULTI-FAULT FEATURES

In the context of BRB-mr, the reliability of attribute is an important measure reflecting the influence of confounding factors on observed data. It indicates the reliability of the observed data in accurately capturing the real system features [28].

In this paper, the disturbance environment is assumed to remain stable over a certain period. Under this assumption, the attribute reliability is considered to be constant over that particular period. To determine attribute reliability, statistical methods are used to analyze the observed data and to quantify the extent of fluctuations and errors caused by the disturbance factors.

Statistical methods are chosen for the calculation of attribute reliability because of their ability to capture the variability and errors in the observed data [21]. By analyzing the statistical properties of the data, such as mean, variance, and distribution, attribute reliability can be estimated. If the observed data exceeds a certain fluctuation threshold caused by disturbing factors, it indicates that the data is no longer reliable and does not accurately represent the true system properties.

By employing statistical techniques to calculate the reliability of attributes, this paper aims to provide a quantitative measure of the reliability of the observed data and ensure that the quality of the collected data is considered in the BRB-mr model. This helps to improve the model's accuracy in capturing and representing real system behavior, despite the presence of confounding factors in the observed data.

It is noted that in engineering practice, the various observed indicators revealed by each fault feature are differentiated, and the observed data for each indicator should be considered for the distinction of each fault feature. Finally, the attribute reliability considering multiple fault features affected by various uncertainties is statistically calculated.

First, assume that $x_{m,j}(m = 1, 2, \ldots, M;\ j = 1, 2, \ldots, J)$ is the observed data, where m is the mth observed indicator and j is the jth fault feature. The fluctuation range of the data can be expressed as:

$$[\bar{x}_{m,j} - \tau \cdot \sigma_{m,j}, \bar{x}_{m,j} + \tau \cdot \sigma_{m,j}] \tag{5}$$

where $\bar{x}_{m,j}$ and $\sigma_{m,j}$ are the mean and variance of $x_{m,j}$. τ is the control coefficient of the fluctuation range, which is given by the expert.

If the observed data are within this range, they are considered reliable and the number of reliable data of the jth feature is $y_{m,j} = y_{m,j}+1$. If the observations are outside this range, then $y_{m,j} = y_{m,j}+0$. Finally, the attribute reliability of the mth observation indicator is calculated as:

$$r_m = \frac{y_m}{N_m}, \tag{6}$$

where

$$y_m = \sum_{j=1}^{J} y_{m,j}, \tag{7}$$

and N_m represents the data number collected for that observation. y_m represents the number of reliable data of the J features.

B. INFERENCE PROCESS

The matching degree calculation method that considers both attribute reliability and attribute weight is proposed to integrate attribute reliability into the BRB-mr model. The ER algorithm is used to implement evidence fusion, and the model inference steps are as follows [29], [30]:

1) The input data is transformed into the form of a belief distribution based on the reference values of the attributes. The calculation formula is as follows:

$$\chi_i^h = \begin{cases} \dfrac{B_i^{j+1} - x_i}{B_i^{j+1} - B_i^j}, h = j, B_i^j \le x_i \le B_i^{j+1} \\ \\ 1 - \chi_i^j, h = j+1 \\ 0, h = 1, 2, \ldots, J, h \ne j, j+1 \end{cases} \tag{8}$$

where χ_i^h denotes the matching degree. B_i^j and B_i^{j+1} denote the two reference values of the ith attribute, respectively. x_i is the input value.

2) The attribute weights and attribute reliability are fused and represented by the parameter C_m.

$$\bar{C}_m = \frac{C_m}{\max\limits_{i=1,2,\ldots,M}\{C_i\}}, \tag{9}$$

where

$$C_m = \frac{\delta_m}{\delta_m + 1 - r_m}. \tag{10}$$

Then, the matching degree of the kth rule can be calculated by:

$$a_k = \prod_{m=1}^{M} (\chi_k^m)^{\bar{C}_m} \tag{11}$$

3) The activation weights of the rules are calculated according to the following formula:

$$w_k = \frac{\theta_k a_k}{\sum_{i=1}^{L} \theta_i a_i} \tag{12}$$

4) Using the calculated activation weights, rule synthesis is performed:

$$\beta_n = \frac{\left[\prod\limits_{k=1}^{L}\left(w_k\beta_n^k + \gamma_{n,i}^k\right) - \prod\limits_{k=1}^{L}\left(\gamma_{n,i}^k\right)\right]}{\sum\limits_{n=1}^{N}\prod\limits_{k=1}^{L}\left(w_k\beta_n^k + \gamma_{n,i}^k\right) - (N-1)\prod\limits_{k=1}^{L}\left(\gamma_{n,i}^k\right) - \prod\limits_{k=1}^{L}(1 - w_k)}, \tag{13}$$

$$\gamma_{n,i}^k = 1 - w_k \sum_{i=1}^{N} \beta_i^k \tag{14}$$

where $\gamma_{n,i}^k$ is an intermediate variable.

5) The final expected utility value is calculated by:

$$y = \sum_{n=1}^{N} u(F_n)\beta_n \tag{15}$$

where $u(F_n)$ denotes the utility of F_n and y represents the final utility value.

IV. OPTIMIZATION METHOD OF THE MODEL PARAMETERS

In this paper, a projection covariance matrix adaptive evolution strategy (P-CMA-ES) is used to implement the optimization of the model. The purpose of the optimization process is to improve the performance of BRB by finding the optimal model parameters [31], [32]. The optimization process of the algorithm is shown in Figure 1.

First, the objective function of BRB-mr is constructed as follows:

$$\psi(\theta,\delta,\beta)=\psi(\theta_1,\theta_2,\ldots,\theta_L,\delta_1,\delta_2,\ldots,\delta_M,\beta_1^1,\beta_2^1,\ldots,\beta_N^L)$$
$$s.t.\ 0\leq\theta_k(or\delta_m)\leq 1,$$
$$0\leq\beta_i^k\leq 1,\sum_{i=1}^{N}\beta_i^k\leq 1,$$
$$(k=1,\ldots,L,i=1,\ldots,N,m=1,\ldots,M) \tag{16}$$

where $\psi(\theta,\delta,\beta)$ denotes the mean squared error (MSE).

1) Initial optimization parameter setting operation

Initial step size ε, initial covariance matrix C, population number λ, subpopulation number τ.

2) Sampling operation

Ω^0 is the evolutionary center to generate the initial population, as shown below:

$$\Omega_i^{u+1}\tilde{w}^u+\varepsilon^u Q(0,C^u)\ i=1,2,\ldots,\lambda \tag{17}$$

where Ω_i^{u+1} denotes the ith population in the $u+1$th generation. $\Omega_i^{u+1}\tilde{w}^u$ denotes the mean of the solution. Q denotes the normal distribution.

3) Projection operation

The operation is to project the projection parameters onto the feasible region hyperplane, subject to the given constraints:

$$\begin{aligned}&\Omega_i^{u+1}(1+a_i\times(\lambda_k-1):a_i\times\lambda_k)\\&=\Omega_i^{u+1}(1+a_i\times(\lambda_k-1):a_i\times\lambda_k)-A_e^T\times(A_e\times A_e^T)^{-1}\\&\quad\times\Omega_i^{u+1}(1+a_i\times(\lambda_k-1):a_i\times\lambda_k)\times A_e\end{aligned} \tag{18}$$

where a_i denotes the variable number of equation constraints. λ_k is the equation constraints number. A_e is the vector of parameters in the equation.

The hyperplane representing the feasible region of the equation constraint is as follows:

$$A_e\Omega_i^{u+1}(1+a_i\times(\lambda_k-1):a_i\times\lambda_k)=1 \tag{19}$$

4) Selection and recombination operation

Select subpopulations and update expectations:

$$\vartheta^{u+1}=\sum_{i=1}^{\tau}r_i\eta_i^{u+1} \tag{20}$$

where r_i is the weight coefficient, η_j^{u+1} denotes the selected subpopulation, and τ denotes the number of subpopulations.

5) Update operation

The covariance matrix is updated:

$$\begin{aligned}C^{u+1}&=(1-c_1-c_2)C^u+c_1p_c^{u+1}(p_c^{u+1})^T\\&\quad+c_2\sum_{i=1}^{s}r_i\left(\frac{\Omega_j^{u+1}-\psi^u}{\varepsilon^u}\right)\left(\frac{\Omega_j^{u+1}-\psi^u}{\varepsilon^u}\right)^T\end{aligned} \tag{21}$$

where c_1 and c_2 are the learning rates, p is the evolutionary path of covariance, and the initial evolutionary path is 0.

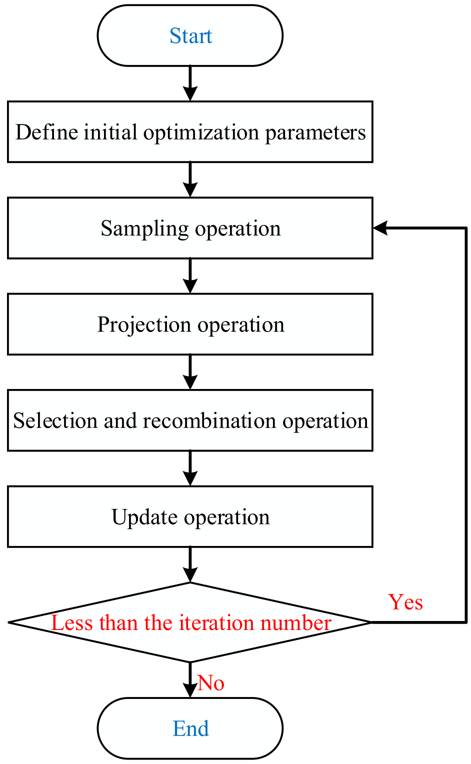

FIGURE 1. P-CMA-ES algorithm optimization process.

V. MODELING PROCESS BASED ON BRB-MR FAULT DIAGNOSIS METHOD

The modeling process is introduced in this section, including the attribute reliability calculation process, model training process, and model testing process. It is shown in Figure 2.

The specific modeling steps are as follows:

Step 1: Collect sensor measurement data, which are subject to environmental interference with sensor quality.

Step 2: Calculate attribute reliability based on multi-fault features.

Step 3: Construct the initial model based on the collected data and expert knowledge.

Step 4: The ER algorithm is used as an inference engine in which attribute reliability is introduced to calculate the matching degree.

Step 5: The optimization algorithm is used to train and adjust the model parameters.

Step 6: The obtained optimal parameters are used to infer the optimal diagnostic results. The obtained results will have high accuracy and reliability.

VI. CASE STUDY

The fault diagnosis of the WD615 diesel engine is used as a case study to demonstrate the effectiveness of the developed BRB-mr fault diagnosis model in this section.

A. PROBLEM FORMULATION

Diesel engines play an important role as power equipment in a variety of engineering applications. The fault diagnosis

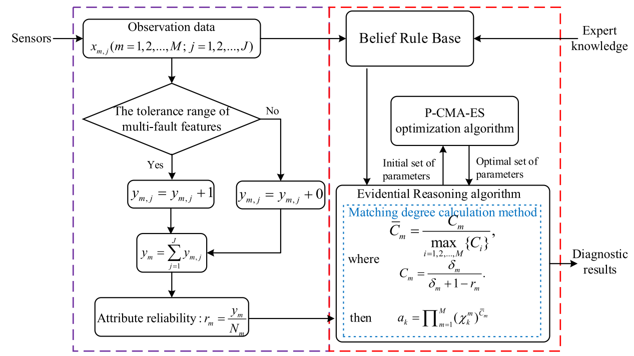

FIGURE 2. Modeling process based on BRB-mr fault diagnosis method.

in diesel engines is important to ensure reliable and efficient operation [33].

Due to the rarity of fault occurrence and the resource-intensive nature of fault experiments, it is difficult to obtain large amounts of high-quality fault data. In addition, it should be noted that in a real working environment, the observed data may be affected by various disturbing factors, leading to potential unreliability. Second, in real systems, experts may not be capable of directly constructing accurate physical models, which limitation poses a challenge to accurately diagnose the fault states of diesel engines.

To address the above-mentioned challenges, a fault diagnosis method based on BRB-mr was developed. By constructing the BRB-mr model, a reliable and effective framework is provided for fault diagnosis, ensuring optimal performance and minimizing potential risks.

B. CONSTRUCTION OF THE FAULT DIAGNOSIS MODEL

The fault features in the experiment were set to three cases, namely, normal state (N), medium fault (M), and severe fault (S). The vibration signals were collected under different fault features, and then similar to the time-domain feature extraction method proposed by literature [34], the mean value and kurtosis value were finally selected as the observation indicators for this experiment. In the time-domain analysis of signals, the mean and kurtosis are important statistical indicators that provide insight into the physical characteristics and behavior of the signals. The following is a brief explanation of the physical significance of mean and kurtosis in time-domain features:

(1) Mean: The mean represents the average value of the signal over a specific period. In its physical sense, the mean reflects the baseline or average level of the signal. It provides information about the overall amplitude or energy of the signal.

$$Mean = mean[x(n)] \tag{22}$$

(2) Kurtosis: The kurtosis is the measure of the peak or flatness of the probability distribution of the signal. It quantifies the distribution of the signal amplitude around the mean value. Kurtosis can indicate the presence of outliers or the concentration degree of signal values.

$$Kurtosis = mean[(x(n) - \bar{x})^4/\sigma^4] \tag{23}$$

In this paper, based on the collected vibration signals, features are extracted at every 15 data, and 300 sets of experimental data are extracted, of which 1:100 sets are severe fault data, 101:200 sets are medium fault data, and 201:300 sets are normal state data, as shown in Figure 3.

Attribute weight and semantic values of mean and kurtosis are shown in Table 1 and Table 2. The reference values of three fault features are shown in Table 3. Therefore, according to the Cartesian product calculation method, the number of rules for the combination is 3∗2=6. The initial parameters of the rule base are shown in Table 4.

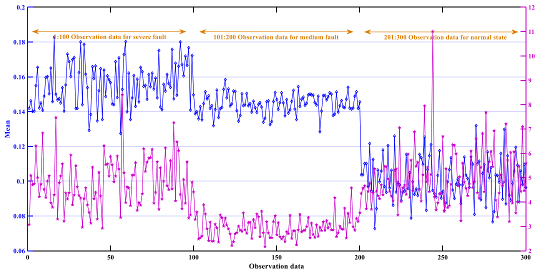

FIGURE 3. Two observation indicators for WD615 diesel engines.

TABLE 1. The initial weight and reference values of *mean*.

Attribute weight	Referential values		
δ_1	Low state (L)	Medium state (M)	High state (H)
1	0.072	0.112	0.183

TABLE 2. The initial weight and reference values of *kurtosis*.

Attribute weight	Referential values	
δ_2	Low state (L)	High state (H)
1	2.174	11.125

TABLE 3. The reference values of three fault features.

Safety states	S	M	N
Referential value	0	0.5	1

TABLE 4. The initial rule base.

Mean ∧ Kurtosis	Rule weights	The initial belief distribution
	θ_k	$\{\beta_1^k, \beta_2^k, \beta_3^k\}$
L ∧ L	1	{ 0.9, 0.1, 0 }
L ∧ H	1	{ 0, 0.2, 0.8 }
M ∧ L	1	{ 0.9, 0.1, 0 }
M ∧ H	1	{ 0.8, 0.2, 0 }
H ∧ L	1	{ 0, 0, 1 }
H ∧ H	1	{ 0, 0, 1 }

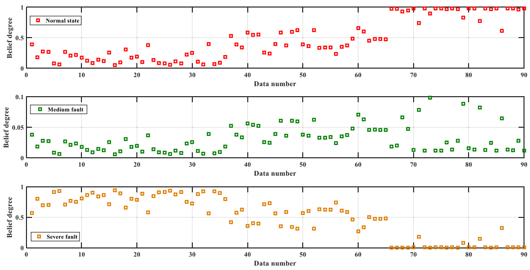

FIGURE 4. Belief distribution of the diagnostic results obtained based on BRB-mr.

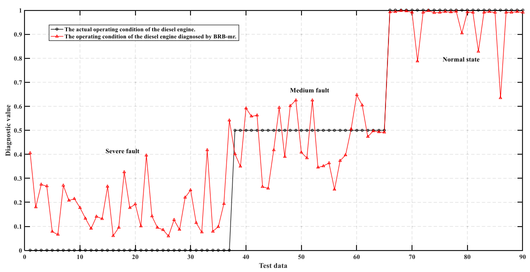

FIGURE 5. The diagnostic results obtained based on BRB-mr.

TABLE 5. The optimized rule base.

Mean ∧ Kurtosis	Rule weights θ_k	The belief distribution $\{\beta_1^k, \beta_2^k, \beta_3^k\}$
L ∧ L	0.6299	{ 0.9843, 0.0114, 0.0043 }
L ∧ H	0.4824	{ 0.647, 0.353, 0 }
M ∧ L	0.4	{ 0.748, 0.231, 0.021 }
M ∧ H	0.4	{ 0.9985, 0, 0.0015 }
H ∧ L	0.4	{ 0.5276, 0.2457, 0.2267 }
H ∧ H	1	{ 0, 0, 1 }

C. TRAINING AND TESTING OF THE BRB-MR

In this paper, 70% of the data is randomly selected for the training part and the remaining 30% for the testing part. $[\bar{x}_{m,j} - 1.2 \cdot \sigma_{m,j}, \bar{x}_{m,j} + 1.2 \cdot \sigma_{m,j}]$ is chosen as the tolerance range. In P-CMA-ES, the population size is set to 19, the subpopulation size is 9, the step size is 0.2, and the number of iterations is 200.

The reliability of mean and kurtosis were calculated as 0.7762 and 0.8143, respectively. After the training of the optimized model, the optimized weights of the two attributes were 0.7299 and 0.6338, respectively. The optimized rule base is shown in Table 5.

The calculated MSE value is 0.0268. The generated fault diagnosis results in the form of belief distribution are shown in Figure 4. It can be seen that the BRB-mr can give a clear semantic description of the results. As shown in Figure 5, the optimized BRB-mr model can accurately diagnose the fault state. After that, 20 identical experiments were conducted, and the average MSE value was 0.0287, and the standard deviation of MSE was 0.0025, indicating that the BRB-mr model has strong robustness.

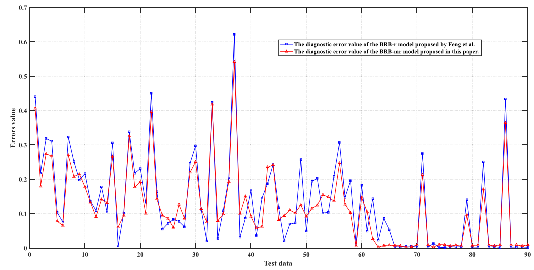

FIGURE 6. Error values of the diagnostic results from the BRB-mr compared to the BRB-r.

TABLE 6. Comparative experiments of the different models.

MSE	BRB-mr	BP neural network	random forest	Fuzzy inference
Max MSE	0.0331	0.0476	0.0472	*
Min MSE	0.0267	0.0278	0.0278	*
Average MSE	**0.0287**	0.0335	0.035	0.104

D. COMPARATIVE STUDIES

To demonstrate the effectiveness of the newly proposed fault diagnosis model, this section is divided into two parts for comparative study.

In the first part of the comparative experiments, the evaluation errors of the actual fault diagnosis for diesel engines based on the BRB-r model proposed by Feng et al. and the model based on the BRB-mr proposed in this paper are shown in Figure 6, which are indicated by the blue and red lines, respectively. From the figure, it can be seen that the fault diagnosis model constructed based on BRB-mr can diagnose the fault of the diesel engine more accurately. The accuracy of the BRB-mr is relatively improved by 16.08%.

In the second part, the BRB-mr proposed in this paper is compared with the BP neural network, random forest, and fuzzy inference algorithms. The comparison study from Table 6 shows that the developed model can diagnose the fault features of diesel engines more accurately.

E. EXPERIMENTAL SUMMARY

The proposed BRB-mr has several advantages in fault diagnosis methods.

1) BRB-mr can perform effective inference and decision-making even when limited samples or instances are available for training. Unlike other machine learning methods that require large amounts of data to obtain reliable results, BRB-mr can produce accurate results with a relatively small sample size. This advantage is particularly useful in situations where collecting large amounts of labeled data is challenging or costly.

2) BRB-mr provides a transparent and understandable framework for capturing and incorporating expert knowledge into the decision-making process. The rules in BRB-mr are designed based on the expertise and domain knowledge of human experts, allowing explicit representation of causal

relationships and inference mechanisms. This interpretability allows users to understand and trust the generated results, making it easier to validate and refine the model.

3) Attribute reliability in BRB-mr allows the reliability of each attribute to be quantified in the presence of data uncertainty. This robustness to unreliable or noisy data helps mitigate the effects of misleading observations and provides more reliable and accurate results.

VII. CONCLUSION

A fault diagnosis method based on BRB-mr is proposed for the problem of small samples of fault data and the complexity of the actual system with the interference problem of the environment in engineering practice. The model takes into account various uncertainty effects of data, and attribute reliability is introduced. Meanwhile, an optimization algorithm is used to balance the uncertainty of expert knowledge. The effectiveness of the model is illustrated by taking the fault diagnosis of the WD615 diesel engine as an example.

There are three innovative points in this paper. First, a new fault diagnosis model based on BRB-mr is developed to address the uncertain effects of various input data. Second, to estimate the influence of unreliable observation data on the diagnosis model, the attribute reliability calculation method with multi-fault features is considered. In addition, a new matching degree calculation method is proposed to introduce attribute reliability into the model inference, thus reducing the influence of unreliable data on accuracy. Finally, the model parameters are fine-tuned using the optimization algorithm.

In the case study, the assumption of a stable external disturbance environment may not always hold in practical applications. These factors may change dynamically over time, leading to fluctuations in the attribute reliability. To address this limitation, further research is needed to develop an online updated attribute reliability calculation method. Such a method would allow real-time adjustment of attribute reliability to meet changing external conditions. By incorporating the ability to adapt to changing disturbance environments, the fault diagnosis model can improve its accuracy and effectiveness in capturing the true state of the system. In addition, the BRB-mr fault diagnosis model can be used as a general approach. In some specific areas, the BRB-mr fault diagnosis model may need further customized to suit its specific needs. It would make sense for future work to focus on addressing these challenges.

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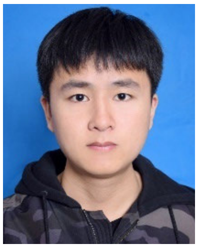

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