IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received September 26, 2017, accepted November 28, 2017, date of publication December 8, 2017, date of current version February 14, 2018.

Digital Object Identifier 10.1109/ACCESS.2017.2781365

Fault Diagnosis Based on Belief Rule Base With Considering Attribute Correlation

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This work was supported in part by the Natural Science Foundation of China under Grant 61773388, Grant 61374138, Grant 61370031, and Grant 61702142, in part by the Postdoctoral Science Foundation of China under Grant 2015M570847, in part by the Natural Science Foundation of Shaanxi Province under Grant 2015JM6354, in part by the Assembly Research Foundation under Grant 9140A19030314JB47276, and in part by the National Natural Science Funds for Distinguished Young Scholar under Grant 61025014.

ABSTRACT With the growing demand for high safety in industrial system, fault diagnosis has attracted more and more attention. Currently, belief rule base (BRB) has shown an excellent performance in modeling complex system, where the expert knowledge is used effectively. Existing BRB models are assumed that the inputs of the attributes are independent and the attribute correlation is not taken into account. However, in some engineering system, there is an obvious correlation among these attributes. The correlated attributes may produce redundant information which limits the abilities of attributes to express the accurate information of system. In this paper, a new BRB model with considering attribute correlation (BRB-c) is proposed. Moreover, a decoupling matrix is introduced to eliminate the redundant information from the attributes. The initial parameters of the decoupling matrix are given according to the expert knowledge. And then, when the inputs of the attributes are available, the parameters in the decoupling matrix are trained by an optimization model. The projection covariance matrix adaption evolution strategy is chosen as an optimization algorithm. A practical case study about fault diagnosis of oil pipeline is conducted and the results show that the BRB-c model can diagnose the leak size and leak time of oil pipeline accurately, which can demonstrate that the proposed model can be widely applied in engineering for fault diagnosis.

INDEX TERMS Belief rule base (BRB), attribute correlation, decoupling matrix, fault diagnosis.

I. INTRODUCTION

For a complex engineering system, it becomes more and more important to diagnose the fault accurately in order to avoid damage and loss to the environment and companies [17], [18], [20]–[22]. However, it is difficult to gather a complete set of observation data in engineering practice [30], [31]. For example, the gyroscope is an equipment which has direct connection with the safety of rocket. In the fault diagnosis for the rocket control system, the state of the gyroscope is necessary to be obtained. However, due to the high price of the gyroscope, many experiments cannot be conducted and a large amount of observation data cannot be gathered. Therefore, the expert knowledge needs to be introduced into the modeling process. The belief rule base (BRB) model can integrate the expert knowledge and quantitative information adequately and its result has shown excellent performance in modeling engineering system [2]–[4], [24], [27]. It can be regarded as an expert system and has been widely applied in engineering practice, e.g., Zhao *et al.* [30] built a model for online failure prognosis based on belief rule base, Li *et al.* [12] developed a safety assessment model for complex system based on the belief rule base and Zhang *et al.* [29] used the fuzzy rule-based evidential reasoning approach in the navigational risk assessment. However, these models all assumed that the input attributes are independent.

In engineering practice, an attribute represents one of the aspects of system information which has physical significance, and the system information is represented by all the attributes corporately. So in an engineering system, there may contain correlation among these attributes. An attribute is regarded as containing redundant information if one or more other attributes are correlated with it [10], [14], [15], [23]. If we assume that the input attributes are independent and ignore the redundancy among them, it will affect the ability of the attributes in providing accurate information of system, e.g., in the fault diagnosis for oil pipeline [21], [32], [33], [37], the flow difference and pressure in oil pipeline are treated as two attributes in the BRB model. When the pipeline leaked, the flow and pressure in the pipeline decreased. It is obvious that the decreasing of flow may cause the decreasing of pressure and there is redundancy between them. If we assume that these two attributes are independent, it may overstate the information representing by these two attributes. Therefore, it is necessary to propose a new BRB model with considering the correlation between attributes, which is named as BRB-c.

In dealing with attribute correlation, there are three ways: building a correlation function, extracting a correlation coefficient from observation data and constructing a decoupling matrix. Firstly, the correlation represented by a function can reflect the mathematics connection among attributes. However, in engineering practice, their relationship may be complicated. Such as the height between parents and child, it is obvious that there is a correlation between them but it cannot be represented by a certain function. Another way to address the attribute correlation is to extract a correlation coefficient from observation data. Many methods are used to calculate the correlation coefficient, e.g., Pearson's correlation coefficient [14], mutual information estimators [5], maximum correlation coefficient [1], principle curve-based methods [6] and maximal information coefficient (MIC) [16], [19]. The correlation coefficient can be used in attributes selection which aims to decrease the attribute redundancy and improve the attribute ability in information representation [7], [10], [14], [28]. This method is mainly used in the situation that contains huge amounts of attributes. However, in engineering practice, the amount of the input attribute in the BRB model is limited and the attribute selection may lose some system information. The third method is that constructs a decoupling matrix which can eliminate the redundant information among nonlinear attributes. This method can also address the correlated attributes online by adjusting the parameters in the decoupling matrix. Therefore, in this paper, a decoupling matrix is proposed to handle the attribute correlation. To train the parameters in the BRB-c model, the projection covariance matrix adaption evolution strategy (P-CMA-ES) algorithm is chosen as the optimization algorithm [8], [9], [11].

The remainder of this paper is organized as follows: The problem of fault diagnosis with considering the correlation between attributes is formulated and defined in Section II. In Section III, the inference of the BRB model with attribute correlation is introduced. A case study of fault diagnosis for oil pipeline is proposed to illustrate the new BRB model in Section IV. The paper is concluded in Section V.

II. PROBLEM FORMULATION

In this section, the notations which will be used in this paper are introduced in subsection II-A. Then the problem formulation of fault diagnosis with considering correlation between attributes is presented. After that, in subsection II-C, a new BRB model with considering correlation between attributes, named BRB-c, is constructed.

A. NOTATIONS

The notations which will be used in this paper are listed as follows:

x_i	the ith antecedent attribute of BRB-c
x_i'	the ith antecedent attribute handled by the decoupling matrix
M	amount of the attribute in the BRB-c model
A_i^k	referential value of the ith antecedent attribute used in the kth rule
L	rule number of BRB-c
θ_k	rule weight of the kth rule
δ_i	weight of the ith attribute in BRB-c
$\bar{\delta}_i$	relative weight of the ith attribute
D_j	the jth consequent in BRB-c
N	consequent number of BRB-c
$\beta_{j,k}$	belief degree of the$j$th consequent $\theta_k$in the kth rule of BRB-c
β_n	total belief degree of the nth consequent $D_n$in the output of BRB-c
α_i^j	matching degree of the ith attribute in the jth rule
α_k	total matching degree of the kth rule
x_i^*	input data of the ith attribute
w_k	activation weight of the kth rule
κ_{ji}	weight coefficient between the ith attribute and the jth attribute in the decoupling matrix
κ_{ji}^u	upper bound of κ_{ij} in the decoupling matrix
κ_{ji}^l	lower bound of κ_{ij} in the decoupling matrix
$f(\cdot)$	nonlinear function modeled by BRB-c
K	decoupling matrix
$S(\cdot)$	nonlinear function modeled by BRB-c
T	size of the dataset

B. PROBLEM FORMULATION OF FAULT DIAGNOSIS WITH CONSIDERING ATTRIBUTE CORRELATION

In engineering practice, the attributes of BRB are used to represent the system information. When the attribute is correlated with other ones, their information has redundancy which may overstate the information represented by the attribute.

BRB can capture the vagueness, ignorance, and nonlinear causal relationships [24], [34]–[36]. These models are all assumed that the input attributes are independent, and cannot deal with the attributes containing redundant information. If the input attributes have correlation and contain redundant information, they may decrease the accuracy of the estimated output generated by the BRB model, e.g., in the fault

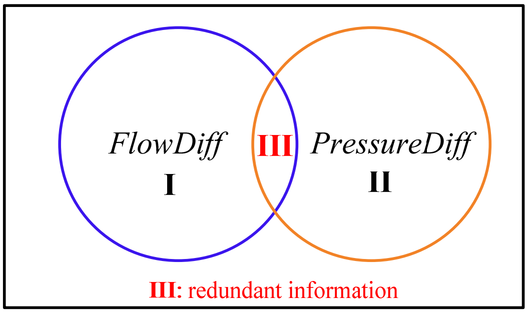

FIGURE 1. Relationship between two correlated attributes.

diagnosis of oil pipeline [21], [36], *FlowDiff* and *PressureDiff* are used as two attributes in BRB. In previous studies, they assumed that these two attributes are independent [33]. However, *FlowDiff* is used to represent the flow difference in the pipeline, and *PressureDiff* is used to denote the change of the pipeline pressure. It is obvious that there have correlation and redundant information among these two attributes. As shown in Fig. 1, if we assume that they are independent, it will overlook the redundant information containing in *FlowDiff* and *PressureDiff* simultaneously. This redundant information may aggravate the estimated error of the BRB output. Therefore, it is necessary to consider the correlation between attributes and propose a new BRB model to handle attribute correlation. On the basis of the above analysis, the relationship between the BRB-c output and the input attributes can be represented as follows:

$$\left\{\left(D_1, \beta_{1,k}\right), \ldots, \left(D_N, \beta_{N,k}\right)\right\} = f(K \cdot [x_1(t), \ldots, x_i(t), \ldots, x_M(t)]^{\mathrm{T}}) \quad (1)$$

where $\left\{\left(D_1, \beta_{1,k}\right), \ldots, \left(D_N, \beta_{N,k}\right)\right\}$ is the output of BRB at the time instant t and $\beta_{j,k}$ $(j = 1, \ldots, N, k = 1, \ldots, L)$ is the belief degree of D_j which represents the jth consequent. $x_i(t)$ represents the ith input attribute for the decoupling matrix at the time instant t, and the outputs of the decoupling matrix are used as the inputs of BRB which are regarded as the attributes without correlation. $f(\cdot)$ represents a nonlinear function which is built by the BRB-c model. K represents the decoupling matrix.

To improve the modeling ability of BRB, one challenge must be addressed, i.e., how to overcome the correlation among attributes in the modeling process of the BRB model. Thus, a BRB model with ability of recognizing the redundant information of the attributes should be proposed.

C. CONSTRUCTION OF THE BELIEF RULE BASE MODEL WITH ATTRIBUTE CORRLEATION

In this paper, a new belief rule base model with considering attribute correlation (BRB-c) is proposed which contains L belief rules and the kth rule is defined as follows:

$$\begin{aligned} R_k: \ & \text{If } x_1 \text{ is } A_1^k \wedge x_2 \text{ is } A_2^k \cdots \wedge x_M \text{ is } A_M^k, \\ & \text{Then } y \text{ is } \left\{\left(D_1, \beta_{1,k}\right), \ldots, \left(D_N, \beta_{N,k}\right)\right\} \\ & \text{With rule weight } \theta_k, \text{ attribute weight } \delta_1, \delta_2, \ldots, \delta_M \\ & \text{and the decoupling matrix } K \end{aligned} \quad (2)$$

where x_i is the input of the BRB-c model, A_i^k $\left(i = 1, \ldots, M, k = 1, \ldots, L\right)$ represents the referential value of the ith antecedent attribute in the kth rule. $\delta_1, \delta_2, \ldots, \delta_M$ are the weights of the antecedent attributes used in the kth rule and M is the amount of the antecedent attribute. θ_k is the rule weight of the kth rule. $\beta_{j,k}$ $(j = 1, \ldots, N, k = 1, \ldots, L)$ is the belief degree assessed to D_j which denotes the jth consequent. If $\sum_{j=1}^{N} \beta_{j,k} = 1$, the kth rule is said to be complete; otherwise, it is incomplete. K is a decoupling matrix used in the BRB-c model to address the correlated attributes. Note that "$\wedge$" is a logical connective to represent the "AND" relationship.

Remark 1: In engineering practice, the environment factors, such as the temperature, humidity and quake, may influence the correlation degree between the attributes. In this paper, we assume that the engineering environment cannot be changed in a certain period and the parameters κ_{ij} $(i, j = 1, \ldots, N)$ in the decoupling matrix are constants in this period. Moreover, suppose that the redundant information in attributes is linear.

Remark 2: In the BRB-c model, there are two parts: the decoupling matrix and the classical BRB model. The input attributes are handled by the decoupling matrix firstly, and then the output of the decoupling matrix is used as the input of the classical BRB model.

III. INFERENCE OF THE BRB MODEL WITH ATTRIBUTE CORRELATION

In this section, a decoupling matrix dealing with the correlated attribute is proposed. Then the inference of the BRB-c model is introduced in subsection III-B. In order to train the parameters in the BRB-c model, subsection III-C presents an optimization model and P-CMA-ES is used as the optimization algorithm. Complex system modeling method based on BRB-c is proposed in subsection III-D.

A. DECOUPLING MATRIX DEALING WITH THE CORRELATED ATTRIBUTE

In this subsection, a decoupling matrix is proposed to address the correlated attributes. For the ith input attribute x_i, it may has correlation with x_j, $j = 1, \ldots, M, j \neq i$. That is to say, when the ith attribute is available, it may contain the information about x_j, $j = 1, \ldots, M, j \neq i$ which is redundant for these attributes [10], [13]. Therefore, an output of decoupling matrix needs to integrate all the input attributes with different weights, and their relationship can be represented as

$$x_i' = \kappa_{1i}x_1 + \kappa_{2i}x_2 + \ldots + \kappa_{Mi}x_M = \sum_{j=1}^{M} \kappa_{ji}x_j \quad (3)$$

where x_i' represents the output of the decoupling matrix without redundant information, and it is used as the input

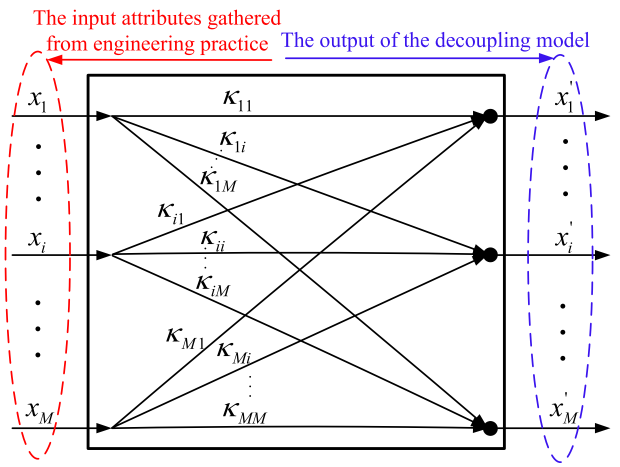

FIGURE 2. Decoupling matrix in the BRB-c model.

of the classical BRB model. κ_{ji} is the weight coefficient between the jth attribute and the ith attribute. Although the redundant information may exist in the ith attribute, most of the information in the ith attribute should be preserved to ensure that the outputs of the decoupling matrix have their original physical meanings. Thus, bounds should be set on the role that other attributes can play in the decoupling matrix. Note that $\kappa_{ji}^l \leq \kappa_{ji} \leq \kappa_{ji}^u$, where κ_{ji}^l and κ_{ji}^u are the lower and upper bound of the ith attribute determined by experts. That is to say, the decoupling matrix is only used to eliminate the redundant information from the ith attribute by κ_{ji}, and x_i' reserves the original physical meaning of x_i by the bound values. M is the amount of the attribute in the BRB-c model. Note also that if the information of the jth attribute is complete contained in the ith attribute, the jth attribute can be reduced from the BRB model. Thus, the decoupling matrix can also reduce the number of input attribute.

The decoupling matrix is written as

$$\begin{bmatrix} x_1' \\ \vdots \\ x_i' \\ \vdots \\ x_M' \end{bmatrix} = K \begin{bmatrix} x_1 \\ \vdots \\ x_i \\ \vdots \\ x_M \end{bmatrix} = \begin{bmatrix} \kappa_{11} & \cdots & \kappa_{M1} \\ \vdots & \ddots & \vdots \\ \kappa_{1M} & \cdots & \kappa_{MM} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_i \\ \vdots \\ x_M \end{bmatrix} \tag{4}$$

where K represents the decoupling matrix and its parameters can be trained by the optimization model. $[x_1 \cdots x_M]^{\mathrm{T}}$ $[x_1' \cdots x_M']^{\mathrm{T}}$ are the attribute matrixes with and without redundant information, respectively. The decoupling matrix can be shown in Fig. 2. For example, in the fault diagnosis of oil pipeline [21], there are two attributes, denoted by x_1 and x_2. These two attributes are used as the inputs of the decoupling matrix and the output matrix $[x_1' \ \ x_2']^{\mathrm{T}}$ can be obtained by

$$\begin{bmatrix} x_1' \\ x_1' \end{bmatrix} = \begin{bmatrix} \kappa_{11} & \kappa_{21} \\ \kappa_{12} & \kappa_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \tag{5}$$

Note that if there is no correlation between x_1 and x_2, $[x_1 \ \ x_2]^{\mathrm{T}} = [x_1' \ \ x_2']^{\mathrm{T}}$ and the decoupling matrix is represented as follows:

$$\begin{bmatrix} \kappa_{11} & \kappa_{21} \\ \kappa_{12} & \kappa_{22} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{6}$$

The decoupling matrix aims to obtain the optimal input attributes $[x_1' \cdots x_M']^{\mathrm{T}}$ which can be regarded as the ideal inputs of the classical BRB model. The decoupling weights κ_{ij} $(i, j = 1, \ldots, M)$ are trained by the optimization model. When the accuracy of BRB-c reaches the requirement determined by experts, the decoupling matrix K is obtained. Therefore, the decoupling matrix K is one part of the optimization model.

Remark 3: There are also other methods that can address the correlated attributes. For example, the correlation coefficient between two attributes can be used to denote the correlation degree between two attributes and it is gathered from observation data. In fault diagnosis of engineering system, the relationship between the input and output has the feature of nonlinear which may not be represented only by a correlation coefficient. So in this paper, a decoupling matrix is introduced to handle the correlated attributes.

B. INFERENCE OF THE BRB MODEL WITH ATTRIBUTE CORRELATION

After addressing by the decoupling matrix, the redundant information in the input attribute x_i, $i = 1, \ldots, M$ can be eliminated. Then the attributes can be used as the inputs of the BRB model.

Firstly, when the attribute x_i', $i = 1, \ldots, M$ is available, its matching degree for the ith attribute in the jth rule is calculated by

$$\alpha_j^i = \begin{cases} \dfrac{A_{i(k+1)} - x_i^*}{A_{i(k+1)} - A_{ik}} & j = k \text{ if } A_{ik} \leq x_i^* \leq A_{i(k+1)} \\ \dfrac{x_i^* - A_{ik}}{A_{i(k+1)} - A_{ik}} & j = k+1 \\ 0 & j = 1, 2, \ldots |x_i|, \ j \neq k, k+1 \end{cases} \tag{7}$$

where x_i^* represents the input data for the ith attribute. A_{ik} and $A_{i(k+1)}$ denote the referential values of the ith attribute in two adjacent activated rules, the kth rule and the $(k+1)$th rule, respectively. $|x_i|$ is the amount of the rule containing the ith attribute.

Secondly, the total matching degree containing the matching degree α_k^i and attribute weight δ_i can be calculated by

$$\bar{\delta}_i = \frac{\delta_i}{\max\limits_{i=1,\ldots,T_k} \{\delta_i\}}, \quad 0 \leq \bar{\delta}_i \leq 1 \tag{8}$$

$$\alpha_k = \prod_{i=1}^{T_k} (\alpha_k^i)^{\bar{\delta}_i} \tag{9}$$

where $\bar{\delta}_i$ is the relative weight of the ith attribute and T_k is the amount of the attributes in the kth rule. α_k is the total matching degree for the kth rule.

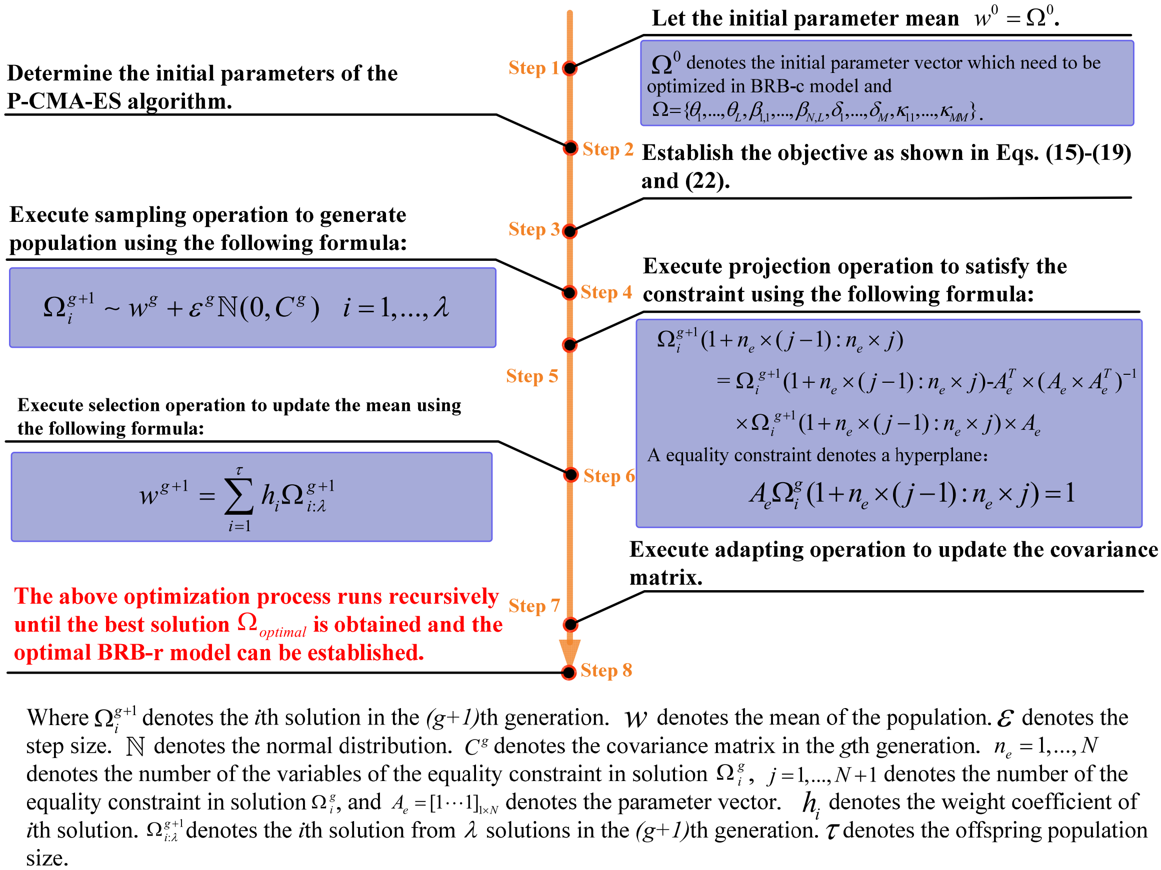

FIGURE 3. Process of P-CMA-ES optimization algorithm.

After the total matching degree has been obtained, the activation weight for the kth rule is calculated by

$$w_k = \frac{\theta_k \alpha_k}{\sum_{l=1}^{L} \theta_l \alpha_l}, \quad k = 1, \ldots, L \tag{10}$$

where θ_k is the weight of the kth rule. Note that $0 \le w_k \le 1$, and $\sum_{k=1}^{L} w_k = 1$. If the kth rule is not activated, $w_k = 0$.

When certain rules are activated by the input attributes, there are many output belief degrees $\beta_{j,k}$ which can be aggregated by the evidential reasoning (ER) algorithm and its analytic form is represented as follows [21]–[24], [30]–[37]:

$$\beta_n = \frac{\mu[\prod_{k=1}^{L}(w_k\beta_{n,k}+1-w_k\sum_{j=1}^{N}\beta_{j,k}) - \prod_{k=1}^{L}(1-w_k\sum_{j=1}^{N}\beta_{j,k})]}{1-\mu[\prod_{k=1}^{L}(1-w_k)]} \tag{11}$$

$$\mu = [\sum_{n=1}^{N}\prod_{k=1}^{L}(w_k\beta_{n,k}+1-w_k\sum_{j=1}^{N}\beta_{j,k}) - (N-1)\prod_{k=1}^{L}(1-w_k\sum_{j=1}^{N}\beta_{j,k})]^{-1} \tag{12}$$

where β_n represents the belief degree of the nth consequent D_n. Note that $0 \le \beta_n \le 1$ and $\sum_{n=1}^{N} \beta_n = 1$.

The final belief degrees generated by aggregating the L rules can be denoted as follows:

$$S(x^*) = \{(D_n, \beta_n); n = 1, 2, \ldots, N\} \tag{13}$$

where x_i^* represents the input of the ith attribute. $S(\cdot)$ denotes the nonlinear function modeled by BRB-c. The utility for the individual consequent D_n can be represented by $u(D_n)$, and the excepted utility for $S(x^*)$ is given as [24]–[27]

$$u(S(x^*)) = \sum_{n=1}^{N} u(D_n)\beta_n \tag{14}$$

where $u(S(x^*))$ is the final output of the BRB-c model.

C. OPTIMIZATION MODEL FOR BRB-C

The Initial parameters in BRB-c are given by experts. Due to the limitation of the expert knowledge, the parameters may not appropriate for the actual working environment and need to be trained. Therefore, in this subsection, an optimization model is introduced to optimize the parameters in the BRB-c model.

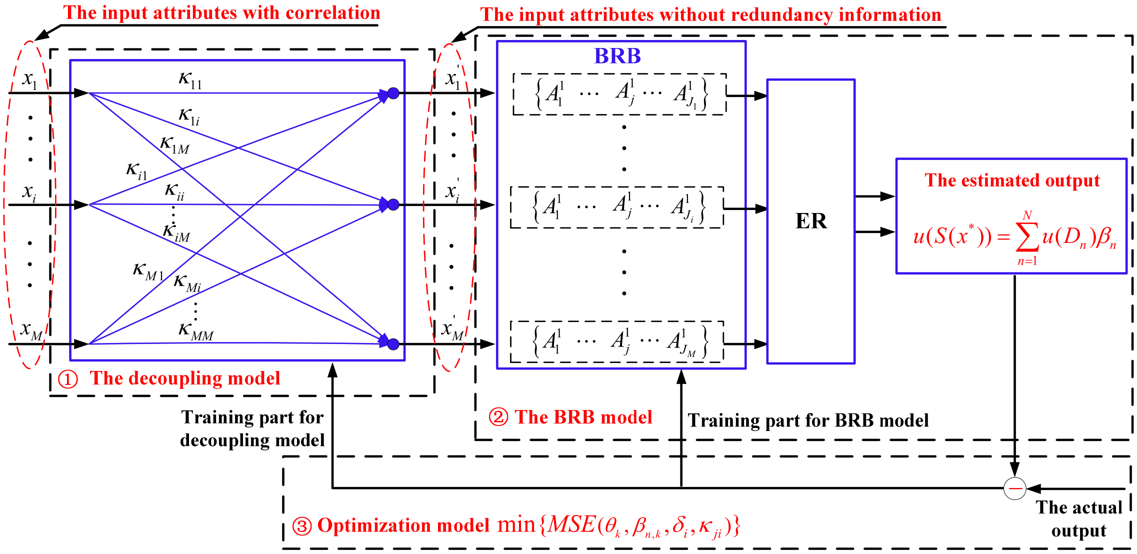

FIGURE 4. Modeling process of BRB-c.

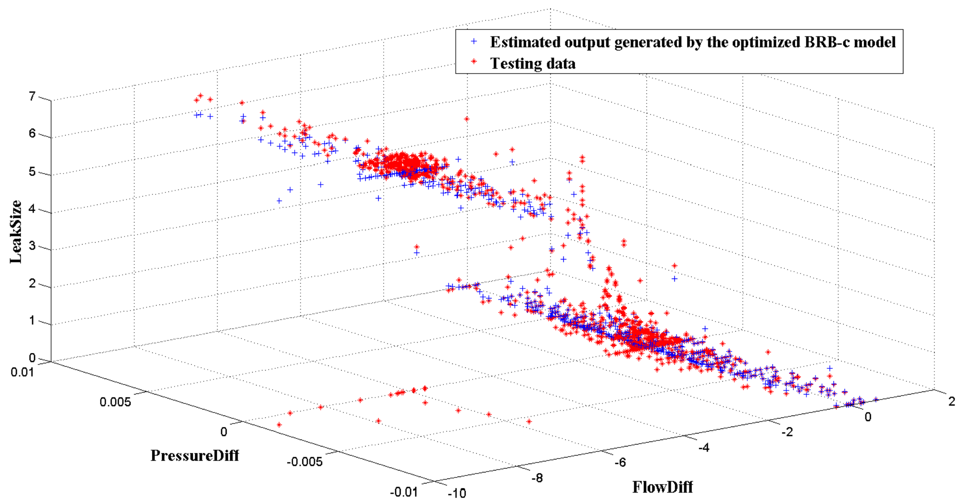

FIGURE 5. Estimated output generated by the optimized BRB-c model.

The decoupling weights, belief degrees in rules, attribute weights and rule weights are the parameters needed to be optimized which can be shown as follows:

(1) The decoupling weights. The decoupling weight among the ith attribute and the jth attribute κ_{ji} should satisfy the following restraint:

$$\kappa_{ji}^{l} \leq \kappa_{ji} \leq \kappa_{ji}^{u} \tag{15}$$

(2) The rule weights. A rule weight is normalized and between zero and one, i.e.:

$$0 \leq \theta_k \leq 1, \quad k = 1, 2, \ldots L \tag{16}$$

(3) The attribute weights. An attribute weight can reflect the relative importance of the attribute. It should satisfy the following restraint:

$$0 \leq \delta_i \leq 1, \quad i = 1, 2, \ldots M \tag{17}$$

(4) The belief degrees in the consequents for the rules. A belief degree should not be more than one or less than zero and it must satisfy the following restraint:

$$0 \leq \beta_{n,k} \leq 1, \quad n = 1, .., N, \ k = 1, 2, \ldots L \tag{18}$$

(5) If the kth rule is complete, the sum of the belief degrees in the consequent should equal to one; otherwise, its total degree should less than one, i.e.:

$$\sum_{n=1}^{N} \beta_{n,k} \leq 1, \quad k = 1, 2, \ldots, L \tag{19}$$

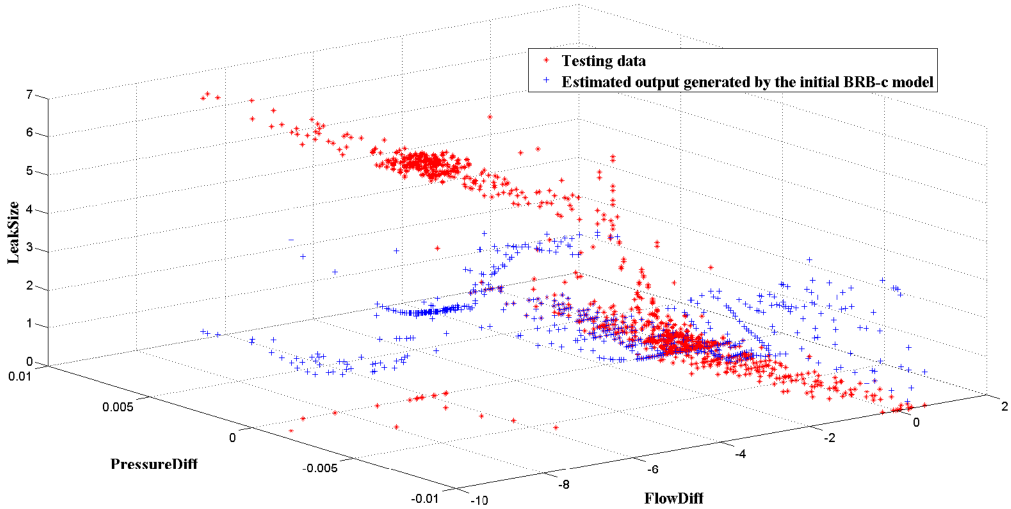

FIGURE 6. Estimated output generated by the initial BRB-c model.

The optimization objective for the optimization model is that the error between the estimated output of BRB-c and the actual output gathered from engineering practice can be as small as possible. The estimated output of BRB-c can be represented as

$$output_{estimated} = \sum_{n=1}^{N} u(D_n)\beta_n \tag{20}$$

where $u(D_n)$ denotes the utility of the nth consequent D_n. $\beta_n, n = 1, \ldots, N$ is calculated by Eqs. (11) and (12). The actual output is denoted by $output_{actual}$.

The mean square error (MSE) can be used to represent the accuracy of the BRB-c model [30]–[34]. It is calculated by

$$MSE(\theta_k, \beta_{n,k}, \delta_i, \kappa_{ji}) = \frac{1}{T}\sum_{t=1}^{T}(output_{estimated} - output_{actual})^2 \tag{21}$$

where T is the size of the dataset.

Finally, the optimization model is given as

$$\min\ MSE(\theta_k, \beta_{n,k}, \delta_i, \kappa_{ji}) \tag{22}$$

$$s.t.\ \kappa_{ji}^{l} \le \kappa_{ji} \le \kappa_{ji}^{u} \tag{15}$$

$$0 \le \theta_k \le 1 \tag{16}$$

$$0 \le \delta_i \le 1, \quad i = 1, \ldots, M \tag{17}$$

$$0 \le \beta_{n,k} \le 1, \quad n = 1, .., N, k = 1, \ldots, L \tag{18}$$

$$\sum_{n=1}^{N} \beta_{n,k} \le 1 \tag{19}$$

In this paper, the projection covariance matrix adaption evolution strategy (P-CMA-ES) is used as the optimization algorithm which is developed from the covariance matrix adaption evolution strategy (CMA-ES) algorithm [8], [11]. The procedure for P-CMA-ES can be presented as Fig. 3.

D. COMPLEX SYSTEM MODELING METHOD BASED ON BRB-C

In this subsection, the complex system modeling method for fault diagnosis based on BRB-c is proposed. On the basis of the above analysis, the BRB-c model contains two parts: the decoupling matrix and the classical BRB model. In the complex system modeling process of fault diagnosis, there are two parts, including the training part and the testing part. The detail functions can be introduced as follows:

Firstly, the training part includes two parts: the training part for the decoupling matrix and the training part for the classical BRB model. Their initial values are generated by the expert knowledge. The optimization model is used to train the parameters in these two parts as introduced in subsection III-C, where the training data are the input and the optimized BRB-c model is the output. In this process, the P-CMA-ES is used as the optimization algorithm as shown in Fig. 3.

Secondly, there is the testing part. The testing data and the optimized parameters for BRB-c, including the decoupling weights κ_{ji}, the rule weights θ_k, the belief degrees $\beta_{n,k}$ and the attribute weights δ_i are the inputs. The estimated outputs are obtained by BRB-c and the MSE can be calculated by Eq. (21) which is used to reflect the accuracy of the BRB-c model.

On the basis of the above discussion, the procedure of the BRB-c model for dealing with the correlation attributes can be summarized as follows:

Step 1: The observation data can be gathered from engineering practice and they are divided into the training data and testing data. The size of these two parts can be determined by experts according to the size of the total database.

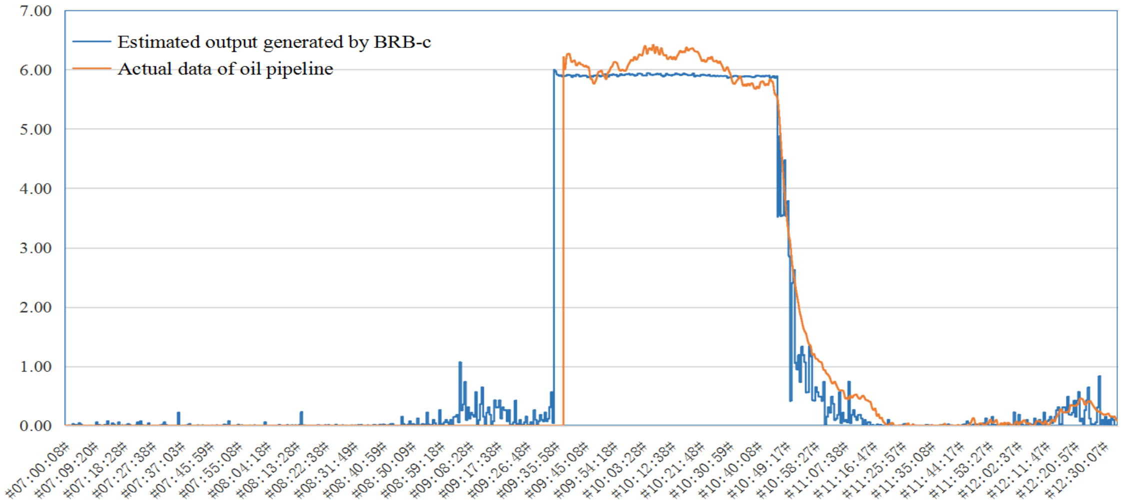

FIGURE 7. Actual data and the output of BRB-c on time scale.

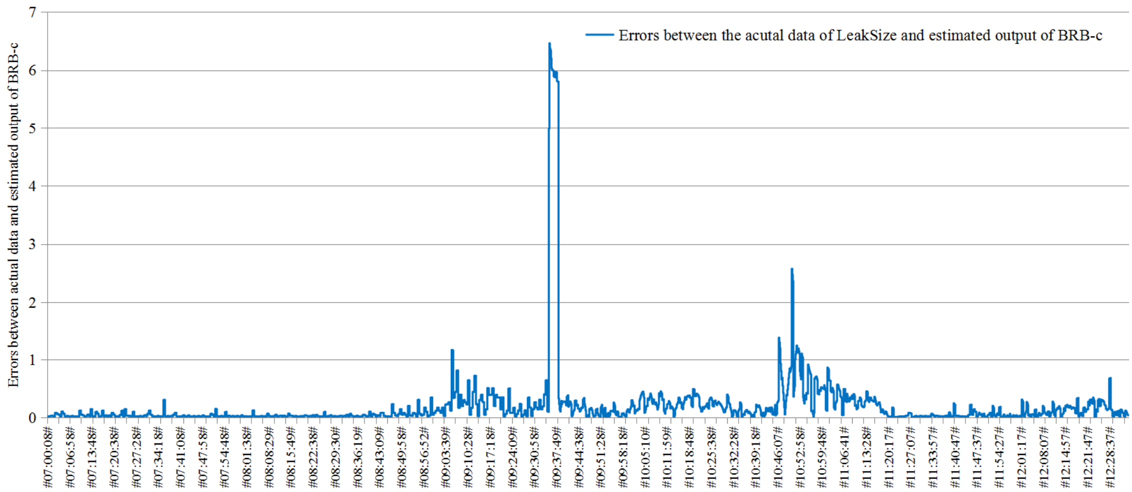

FIGURE 8. Errors between the actual data and the estimated output of BRB-c.

Step 2: The initial values of BRB-c and bound values of decoupling weights are given by experts, and the generation number for the P-CMA-ES algorithm can be set according to the engineering practice.

Step 3: After the training data and the initial values $\Omega = \{\theta_1, \ldots, \theta_L, \beta_{1,1}, \ldots, \beta_{L,N}, \delta_1, \ldots, \delta_M\}$ for BRB-c are available, the BRB-c model can be trained in the training part. According to the target of the optimization model, the decoupling weights $\kappa_{ji}(j, i = 1, 2, \ldots M)$, attribute weights δ_i, belief degrees $\beta_{n,k}$ and rule weights θ_k can be optimized by P-CMA-ES. Note that the belief degrees should satisfy the constraint $\sum_{n=1}^{N} \beta_{n,k} \leq 1, k = 1, \ldots, L$. The optimization procedure is introduced in Fig. 3, and it runs recursively until the best solution $\Omega_{optimal}$ is obtained.

Step 4: The optimized BRB-c model and the testing data are the inputs of the testing part. The estimated outputs are obtained and the accuracy of BRB-c can be represented by MSE.

Step 4.1: When the training data are available, the matching degree $\alpha_k, k = 1, \ldots, L$ and the activation weight $w_k, k = 1, \ldots, L$ are calculated by Eqs. (7)-(10).

Step 4.2: Once the belief rules in BRB-c are activated, they are aggregated by the ER algorithm, and then the final outputs of the BRB-c model are calculated by Eq. (14).

Step 4.3: The MSE of the BRB-c model is calculated by Eq. (21). Its value can be used to reflect the accuracy of BRB-c.

The whole modeling procedure of the BRB-c model can be introduced in Fig. 4.

IV. CASE STUDY

In this section, an engineering case of fault diagnosis for oil pipeline is examined in order to demonstrate that the BRB-c model can be widely applied in engineering practice.

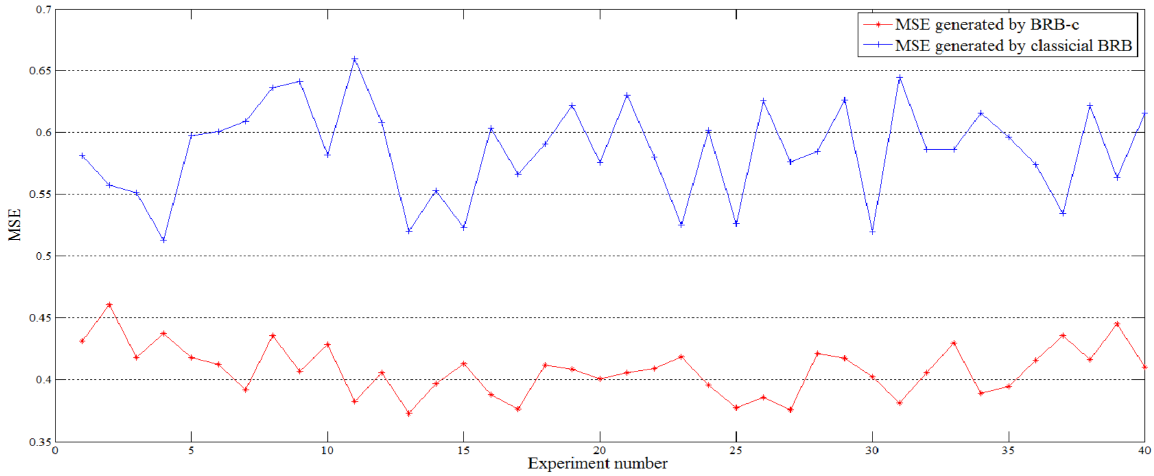

FIGURE 9. **MSEs generated by BRB-c and BRB.**

A. PROBLEM FORMULATION OF FAULT DIAGNOSIS FOR OIL PIPELINE

For the oil pipeline, it is important to diagnose its fault accurately to avoid serious damage to the environment and companies. Similar to [21], the experiment is conduct on a long distance oil pipeline in Great Britain. The actual leak size is denoted by *LeakSize* which is the actual output of BRB-c. The flow difference and the average pressure in oil pipeline, denoted by *FlowDiff* and *PressureDiff*, are chosen as two input attributes.

For these two attributes, they reflect the physical information of the oil pipeline. When the pipeline leaked, the difference between the inlet flow and outlet flow may decrease, and the flow rate of the oil decreases. In the meantime, the average pressure of the pipeline also decreases along with the decreasing of the flow rate of oil. The flow difference and average pressure are two independent aspects of the pipeline seemingly, but there is correlation between them. If we assume that these two attributes are independent, the correlation between the *FlowDiff* and *PressureDiff* will be overlooked, and the fault information represented by the attributes will be overstate which may increase the error of the estimated output of BRB. Therefore, the correlation between these two attributes needs to be considered in modeling procedure.

On the basis of the above analysis, a BRB model with considering attribute correlation is constructed for fault diagnosis of oil pipeline.

B. CONSTRUCTION FOR THE FAULT DIAGNOSIS MODEL OF OIL PIPELINE

In this paper, similar to [21] and [33], we use eight referential points for *FlowDiff* and seven referential points are selected for *PressureDiff*. Their referential points and values are given by experts as shown in Table 1 and Table 2. Five referential points and values are selected for *LeakSize* and their referential values are given in Table 3.

TABLE 1. **The referential points and values for FlowDiff.**

Referential point	NL	NM	NS	NVS	Z	PS	PM	PL
Referential value	-9.6	-6	-5.5	-1	0	0.5	0.8	1.2

TABLE 2. **The referential points and values for PressureDiff.**

Referential point	NL	NM	NS	Z	PS	PM	PL
Referential value	-0.01	-0.004	-0.002	0	0.002	0.004	0.01

TABLE 3. **The referential points and values for LeakSize.**

Referential point	Z	VS	M	H	VH
Referential value	0	2	4	6	8

In the BRB-c model of fault diagnosis for oil pipeline, the kth rule can be represented as

$$\begin{aligned} R_k :\ & \text{If FlowDiffis } A_1^k \wedge \text{PressureDiff is } A_2^k, \\ & \text{Then LeakSize is } \{(Z, \beta_{1,k}), (VS, \beta_{2,k}), (M, \beta_{3,k}), \\ & \qquad (H, \beta_{4,k}), (VH, \beta_{5,k})\} \\ & \text{With rule weight } \theta_k, \text{ attribute weights } \delta_1, \delta_2 \text{ and} \\ & \text{decoupling matrix } K \end{aligned} \tag{23}$$

where A_1^k and A_2^k are two referential values as presented in Table 1 and Table 2. θ_k denotes the weight of the kth rule and its initial value is set to one. δ_1 and δ_2 are weights of two attributes and their initial values are given to one. There are 56 combinations for two attributes which leads to 56 rules in BRB-c. The initial parameters of the BRB-c model are determined by experts as shown in Table 4 of Appendix, and the initial decoupling matrix is given to a unit matrix.

TABLE 4. Initial belief degrees of fault diagnosis for oil pipeline.

No.	Rule weight	Attributes x_1	Attributes x_2	*LeakSize* distribution $\{D_1, D_2, D_3, D_4, D_5\}$ $=\{0,2,4,6,8\}$	No.	Rule weight	Attributes x_1	Attributes x_2	*LeakSize* distribution $\{D_1, D_2, D_3, D_4, D_5\}$ $=\{0,2,4,6,8\}$
1	1	NL	NL	(0 0 0 0 1)	29	1	Z	NL	(1 0 0 0 0)
2	1	NL	NM	(0 0 0 0.3 0.7)	30	1	Z	NM	(1 0 0 0 0)
3	1	NL	NS	(0 0 0.2 0.8 0)	31	1	Z	NS	(1 0 0 0 0)
4	1	NL	Z	(0 0 0.8 0.2 0)	32	1	Z	Z	(1 0 0 0 0)
5	1	NL	PS	(0.65 0.35 0 0 0)	33	1	Z	PS	(1 0 0 0 0)
6	1	NL	PM	(0.85 0.15 0 0 0)	34	1	Z	PM	(1 0 0 0 0)
7	1	NL	PL	(0.95 0.05 0 0 0)	35	1	Z	PL	(1 0 0 0 0)
8	1	NM	NL	(0 0 0.1 0.9 0)	36	1	PS	NL	(0.39 0.61 0 0 0)
9	1	NM	NM	(0 0 0.7 0.3 0)	37	1	PS	NM	(0.9 0.1 0 0 0)
10	1	NM	NS	(0 0.7 0.3 0 0)	38	1	PS	NS	(1 0 0 0 0)
11	1	NM	Z	(0 0.9 0.1 0 0)	39	1	PS	Z	(1 0 0 0 0)
12	1	NM	PS	(0.8 0.2 0 0 0)	40	1	PS	PS	(1 0 0 0 0)
13	1	NM	PM	(0.9 0.1 0 0 0)	41	1	PS	PM	(1 0 0 0 0)
14	1	NM	PL	(0.99 0.01 0 0 0)	42	1	PS	PL	(1 0 0 0 0)
15	1	NS	NL	(0 0 0.4 0.6 0)	43	1	PM	NL	(0.1 0.9 0 0 0)
16	1	NS	NM	(0 0 0.8 0.2 0)	44	1	PM	NM	(0.3 0.7 0 0 0)
17	1	NS	NS	(0 0.3 0.6 0.1 0)	45	1	PM	NS	(0.85 0.15 0 0 0)
18	1	NS	Z	(0.1 0.7 0.2 0 0)	46	1	PM	Z	(0.98 0.02 0 0 0)
19	1	NS	PS	(0.7 0.3 0 0 0)	47	1	PM	PS	(1 0 0 0 0)
20	1	NS	PM	(0.9 0.1 0 0 0)	48	1	PM	PM	(1 0 0 0 0)
21	1	NS	PL	(1 0 0 0 0)	49	1	PM	PL	(1 0 0 0 0)
22	1	NVS	NL	(0.02 0.11 0.39 0.48 0)	50	1	PL	NL	(0.9 0.1 0 0 0)
23	1	NVS	NM	(0.1 0.78 0.12 0 0)	51	1	PL	NM	(0.99 0.01 0 0 0)
24	1	NVS	NS	(0.36 0.64 0 0 0)	52	1	PL	NS	(1 0 0 0 0)
25	1	NVS	Z	(1 0 0 0 0)	53	1	PL	Z	(1 0 0 0 0)
26	1	NVS	PS	(1 0 0 0 0)	54	1	PL	PS	(1 0 0 0 0)
27	1	NVS	PM	(1 0 0 0 0)	55	1	PL	PM	(1 0 0 0 0)
28	1	NVS	PL	(1 0 0 0 0)	56	1	PL	PL	(1 0 0 0 0)

C. UPDATING AND TESTING FOR THE FAULT DIAGNOSIS MODEL OF OIL PIPELINE

In this paper, 1000 data are selected as the training data and the total 2007 data are taken as the testing data. In the training part, P-CMA-ES is applied as the optimization algorithm. Its population size is set to be 342 and the generation number is set to be 200. The upper bounds of decoupling weights are given by $\kappa_{11}^u = 1$, $\kappa_{21}^u = 0.5$, $\kappa_{12}^u = 0.5$ and $\kappa_{22}^u = 1$, and the lower bounds are set to be zero.

The process of the training part and testing part of BRB-c is conducted using MATLAB.

The optimized BRB-c model is presented in Table 5 of Appendix. The optimized weights of *FlowDiff* and *PressureDiff* are 0.7774 and 0.2586 respectively, and the optimized decoupling matrix is obtained as follows:

$$\begin{bmatrix} \kappa_{11} & \kappa_{21} \\ \kappa_{12} & \kappa_{22} \end{bmatrix} = \begin{bmatrix} 0.6123 & 0.2768 \\ 0 & 0.1175 \end{bmatrix} \tag{24}$$

It can be seen from Fig. 5, the *LeakSize* estimated by the optimized BRB-c model can match the actual data accurately, compared with the initial BRB-c model as shown in Fig. 6. Fig. 7 shows the actual leak size and the estimated *LeakSize* on the time scale. It can be seen that the BRB-c model can diagnose the fault time of the oil pipeline accurately which leaked at around 9:35 A.M. The errors between the actual leak size of oil pipeline and the estimated output of BRB-c are calculated as shown in Fig. 8. The errors presented in Fig. 8 close to zero and it can be used to demonstrate that the new BRB model with considering attribute correlation can diagnose the fault size of the oil pipeline accurately.

D. COMPARATIVE STUDY

In order to demonstrate the effectiveness of BRB-c, in this subsection, the comparative study is conducted.

The MSE can be regarded as a parameter to represent the accuracy of a model and it can be calculated by Eq. (21). The experiment is conducted with 40 times with the same training part and testing part and their MSEs can be shown in Fig. 9. The MSEs of BRB-c range from 0.3727 to 0.4603 with the mean value as 0.4039 and variance as 4.2722E-04. The MSEs of BRB range from 0.5128 to 0.6595, and its mean value is 0.5887 and variance is 7.0848E-04. Compared with the smallest MSE of BRB, the smallest MSE of BRB-c improves 27.32%. In addition, compared with Zhou *et al.* [32], the accuracy of BRB-c improves 52.70%.

TABLE 5. Optimized belief degrees of fault diagnosis for oil pipeline.

No.	Rule weight	Attributes x_1	Attributes x_2	*LeakSize* distribution $\{D_1, D_2, D_3, D_4, D_5\}$ ={0,2,4,6,8}	No.	Rule weight	Attributes x_1	Attributes x_2	*LeakSize* distribution $\{D_1, D_2, D_3, D_4, D_5\}$ ={0,2,4,6,8}
1	0.6408	NL	NL	(0.2912 0.1705 0.1928 0.1841 0.1614)	29	0.2997	Z	NL	(0.3182 0.0851 0.1396 0.1718 0.2854)
2	0.3276	NL	NM	(0.4943 0.0167 0.0496 0.2854 0.1539)	30	0.9008	Z	NM	(0.1053 0.0694 0.3961 0.1998 0.2294)
3	0.1195	NL	NS	(0.2570 0.3494 0.1155 0.1969 0.0813)	31	0.2000	Z	NS	(0.2331 0.3136 0.0481 0.2491 0.1562)
4	0.9560	NL	Z	(0.2923 0.2293 0.2564 0.0898 0.1322)	32	0.7450	Z	Z	(0.9939 0.0000 0.0061 0.0000 0.0000)
5	0.7242	NL	PS	(0.0504 0.2750 0.2119 0.2850 0.1777)	33	0.1853	Z	PS	(0.2022 0.2753 0.2130 0.2330 0.0765)
6	0.6971	NL	PM	(0.0407 0.1934 0.2416 0.1477 0.3766)	34	0.1236	Z	PM	(0.1957 0.1506 0.1104 0.2464 0.2968)
7	0.2037	NL	PL	(0.1099 0.1623 0.0377 0.5286 0.1615)	35	0.7927	Z	PL	(0.0314 0.0974 0.3380 0.3883 0.1448)
8	0.3440	NM	NL	(0.2364 0.0824 0.1230 0.1085 0.4497)	36	0.4137	PS	NL	(0.2621 0.2881 0.0513 0.1056 0.2930)
9	0.7989	NM	NM	(0.0783 0.2195 0.2761 0.3253 0.1009)	37	0.3582	PS	NM	(0.0635 0.0791 0.2395 0.2456 0.3723)
10	0.9258	NM	NS	(0.4786 0.2060 0.0803 0.1643 0.0709)	38	0.1816	PS	NS	(0.0701 0.3146 0.1055 0.3574 0.1524)
11	0.6821	NM	Z	(0.1874 0.1694 0.3476 0.1647 0.1309)	39	0.1336	PS	Z	(0.1919 0.5528 0.0856 0.0662 0.1036)
12	0.3483	NM	PS	(0.3464 0.1694 0.1024 0.2399 0.1420)	40	0.0092	PS	PS	(0.0640 0.1443 0.3754 0.3392 0.0771)
13	0.4884	NM	PM	(0.3548 0.0901 0.3158 0.1190 0.1204)	41	0.8300	PS	PM	(0.4115 0.1643 0.1142 0.0387 0.2712)
14	0.6319	NM	PL	(0.3130 0.1259 0.3230 0.1287 0.1093)	42	0.3905	PS	PL	(0.0746 0.2280 0.0000 0.4907 0.1419)
15	0.9191	NS	NL	(0.2796 0.0745 0.1609 0.0809 0.4041)	43	0.8985	PM	NL	(0.5396 0.1544 0.1209 0.1606 0.0245)
16	0.2916	NS	NM	(0.1429 0.2290 0.3407 0.1009 0.1865)	44	0.5784	PM	NM	(0.1470 0.1232 0.0722 0.5296 0.1279)
17	0.6856	NS	NS	(0.2010 0.2092 0.1220 0.2377 0.2301)	45	0.4405	PM	NS	(0.2084 0.2994 0.1062 0.2535 0.1326)
18	0.8878	NS	Z	(0.0009 0.2014 0.1076 0.1032 0.5869)	46	0.8209	PM	Z	(0.1727 0.1574 0.2192 0.0738 0.3769)
19	0.6259	NS	PS	(0.0586 0.2054 0.3935 0.1180 0.2245)	47	0.8734	PM	PS	(0.1477 0.1381 0.4859 0.1178 0.1106)
20	0.2961	NS	PM	(0.3206 0.1862 0.0461 0.2211 0.2260)	48	0.2806	PM	PM	(0.4016 0.2021 0.1988 0.0682 0.1294)
21	0.5101	NS	PL	(0.4455 0.2844 0.0465 0.0728 0.1508)	49	0.6947	PM	PL	(0.3863 0.0536 0.2460 0.2207 0.0935)
22	0.7228	NVS	NL	(0.0215 0.5360 0.0779 0.0787 0.2859)	50	0.0594	PL	NL	(0.3045 0.2261 0.1963 0.0942 0.1789)
23	0.8596	NVS	NM	(0.1797 0.2390 0.0868 0.1478 0.3467)	51	0.3185	PL	NM	(0.1764 0.1867 0.2975 0.2111 0.1283)
24	0.5151	NVS	NS	(0.1331 0.2091 0.1050 0.3131 0.2397)	52	0.4150	PL	NS	(0.1222 0.1911 0.0369 0.2773 0.3725)
25	0.3840	NVS	Z	(0.3108 0.2840 0.0985 0.1229 0.1837)	53	1.0000	PL	Z	(0.2874 0.1080 0.2371 0.0457 0.3217)
26	0.3042	NVS	PS	(0.2990 0.0926 0.1374 0.2367 0.2343)	54	0.8823	PL	PS	(0.5251 0.1504 0.0118 0.2263 0.0864)
27	0.0717	NVS	PM	(0.1809 0.1657 0.2137 0.2619 0.1778)	55	0.2770	PL	PM	(0.3992 0.1333 0.2847 0.0825 0.1002)
28	0.1632	NVS	PL	(0.0732 0.1001 0.3171 0.1039 0.4057)	56	0.7211	PL	PL	(0.0910 0.1443 0.2440 0.3005 0.2204)

V. CONCLUSIONS

In this paper, a new belief rule base model with considering attribute correlation (BRB-c) for fault diagnosis is constructed to deal with the situation where the input attributes contain correlated information. In engineering practice, the correlated attributes is said to be redundant which can affect the attribute ability to provide accurate information, and further influence the accuracy of the estimated output. Thus, a decoupling matrix is constructed to eliminate the redundant information from the input attributes to improve the accuracy for fault diagnosis. A case study of fault diagnosis for the oil pipeline is examined to demonstrate that the BRB-c model can be widely used in engineering practice.

There are three features in the BRB-c model. Firstly, the attribute correlation is considered in the BRB model for the first time. The correlated information between the attributes is redundancy which may affect the modeling accuracy of the BRB model. Secondly, a decoupling matrix is constructed to address the correlated attributes. If an attribute correlates with other ones, its information is determined by these attributes simultaneously. Therefore, a decoupling attribute can be obtained by weighting all the input attributes which are correlated with the attribute. Finally, in order to determine the parameters in the decoupling matrix, a new optimization model is proposed where the decoupling weights are optimized.

In this paper, we assume that the actual working environment cannot affect the correlation among attributes. However, in engineering practice, the correlation between attributes may be influenced by temperature, humidity or stress, etc. In order to improve the modeling ability of BRB-c for a dynamic system, the decoupling matrix needs to be trained online. However, when there are many input attributes, the calculation of BRB-c is very huge. Thus, it is necessary to develop an appropriate model to adjust the decoupling matrix online and can handle huge amounts of attributes. These requirements pose challenges for future work.

APPENDIX

See Tables 4 and 5.

REFERENCES

[1] L. Breiman and J. H. Friedman, "Estimating optimal transformations for multiple regression and correlation," *J. Amer. Statist. Assoc.*, vol. 80, no. 391, pp. 580–598, 1985.

[2] L. L. Chang, J. B. Sun, J. Jiang, and M. J. Li, "Parameter learning for the belief rule base system in the residual life probability prediction of metalized film capacitor," *Knowl.-Based Syst.*, vol. 73, pp. 69–80, Jan. 2015.

[3] L. L. Chang, Z. J. Zhou, Y. You, L. H. Yang, and Z. G. Zhou, "Belief rule based expert system for classification problems with new rule activation and weight calculation procedures," *Inf. Sci.*, vol. 336, pp. 75–91, Apr. 2016.

[4] Y. W. Chen, J. B. Yang, D. L. Xu, and S. L. Yang, "On the inference and approximation properties of belief rule based systems," *Inf. Sci.*, vol. 38, pp. 121–135, Jun. 2013.

[5] G. A. Darbellay and I. Vajda, "Estimation of the information by an adaptive partitioning of the observation space," *IEEE Trans. Inf. Theory*, vol. 45, no. 4, pp. 1315–1321, May 1999.

[6] P. Delicado and M. Smerkar, "Measuring non-linear dependence for two random variables distributed along a curve," *Statist. Comput.*, vol. 19, pp. 255–269, Sep. 2009.

[7] M. A. Hall, "Correlation-based feature selection for machine learning," Ph.D. dissertation, Dept. CST., Univ. Waikato, Hamilton, New Zealand, 1999.

[8] N. Hansen and A. Ostermeier, "Completely derandomized self-adaptation in evolution strategies," *Evol. Comput.*, vol. 9, no. 2, pp. 159–195, Jun. 2001.

[9] N. Hansen, "The CMA evolution strategy: A comparing review," in *Towards a New Evolutionary Computation*. Berlin, Germany: Springer, 2006, pp. 75–102.

[10] M. Held, A. Rabe, C. Senf, S. van der Linden, and P. Hostert, "Analyzing hyperspectral and hypertemporal data by decoupling feature redundancy and feature relevance," *IEEE Geosci. Remote Sens. Lett.*, vol. 12, no. 5, pp. 983–987, May 2015, doi: 10.1109/LGRS.2014.2371242.

[11] 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.

[12] G. L. Li, Z. J. Zhou, C. H. Hu, L. L. Chang, Z. G. Zhou, and F. J. 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.

[13] H. Li, "Design of multivariable fuzzy-neural network decoupling controller," *Control Decision*, vol. 21, no. 5, pp. 593–596, 2006.

[14] P. Maji and P. Garai, "On fuzzy-rough attribute selection: Criteria of max-dependency, max-relevance, min-redundancy, and max-significance," *Appl. Soft Comput.*, vol. 13, no. 9, pp. 3968–3980, 2013.

[15] K. Pearson, "Notes on the history of correlation," *Biometrika*, vol. 13, no. 1, pp. 25–45, 1920.

[16] D. N. Reshef *et al.*, "Detecting novel associations in large data sets," *Science*, vol. 334, no. 6062, pp. 1518–1524, 2011.

[17] C. Sankavaram, B. Pattipati, K. R. Pattipati, Y. Zhang, and M. Howell, "Fault diagnosis in hybrid electric vehicle regenerative braking system," *IEEE Access*, vol. 2, pp. 1225–1239, 2017, doi: 10.1109/ACCESS.2014.2362756.

[18] C. Sankavaram, A. Kodali, K. R. Pattipati, and S. Singh, "Incremental classifiers for data-driven fault diagnosis applied to automotive systems," *IEEE Access*, vol. 3, pp. 407–419, 2017, doi : 10.1109/ACCESS.2015.2422833.

[19] T. Speed, "A correlation for the 21st Century," *Science*, vol. 334, no. 6062, pp. 1502–1503, 2011.

[20] Q. Tong *et al.*, "A fault diagnosis approach for rolling element bearings based on RSGWPT-LCD bilayer screening and extreme learning machine," *IEEE Access*, vol. 5, pp. 5515–5530, doi: 10.1109/ACCESS.2017.2675940.

[21] D.-L. Xu *et al.*, "Inference and learning methodology of belief-rule-based expert system for pipeline leak detection," *Expert Syst. Appl.*, vol. 32, no. 1, pp. 103–113, 2007.

[22] X. B. Xu, J. Zheng, D. L. Xu, and J. B. Yang, "Information fusion method for fault diagnosis based on evidential reasoning rule," *J. Control Theory Appl.*, vol. 32, pp. 1170–1182, Sep. 2015.

[23] X. Xu, X. He, Q. Ai, and R. C. Qiu, "A correlation analysis method for power systems based on random matrix theory," *IEEE Trans. Smart Grid*, vol. 8, no. 4, pp. 1811–1820, Jul. 2017, doi: 10.1109/TSG.2015.2508506.

[24] 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.

[25] J. B. Yang, J. Liu, D. L. Xu, J. Wang, and H. Wang, "Optimization Models for Training Belief-Rule-Based Systems," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 37, no. 4, pp. 569–585, Jul. 2007.

[26] J.-B. Yang and G. Singh Madan, "An evidential reasoning approach for multiple-attribute decision making with uncertainty," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 24, no. 1, pp. 1–18, Jan. 1994.

[27] J.-B. Yang and D.-L. Xu, "Evidential Reasoning rule for evidence combination," *Artif. Intell.* , vol. 205, pp. 1–29, Dec. 2013.

[28] L. Yu and H. Liu, "Efficient feature selection via analysis of relevance and redundancy," *J. Mach. Learn. Res.*, vol. 5, no. 10, pp. 1205–1224, 2004.

[29] D. Zhang, X. P. Yan, J. F. Zhang, Z. L. Yang, and J. Wang, "Use of fuzzy rule-based evidential reasoning approach in the navigational risk assessment of inland waterway transportation systems," *Safety Sci.*, vol. 82, pp. 352–360, Feb. 2016.

[30] 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.*, vol. 99, pp. 1–13, 2016.

[31] Z. J. Zhou, C. H. Hu, and J. B. Yang, "A model for real-time failure prognosis based on hidden Markov model and belief rule base," *Eur. J. Oper. Res.*, vol. 207, no. 1, pp. 269–283, 2010.

[32] 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, pp. 1790–1799, Mar. 2010.

[33] Z. J. Zhou, C. H. Hu, J. B. Yang, D. L. Xu, and D. H. Zhou, "Online updating belief-rule-base using the RIMER approach," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 41, no. 6, pp. 1225–1243, Nov. 2011.

[34] 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.

[35] Z.-J. Zhou, C.-H. Hu, G.-Y. Hu, X.-X. Han, B.-C. Zhang, and Y.-W. Chen, "Hidden behavior prediction of complex systems under testing influence based on semiquantitative information and belief rule base," *IEEE Trans. Fuzzy Syst.*, vol. 23, no. 6, pp. 2371–2386, Dec. 2015.

[36] Z.-J. Zhou, C.-H. Hu, and Y. M. Chen, "An improved fuzzy Kalman filter for state estimation of nonlinear systems," *Int. J. Syst. Sci.*, vol. 41, no. 5, pp. 537–546, 2010.

[37] Z.-J. Zhou, C.-H. Hu, D.-L. Xu, J.-B. Yang, and D.-H. Zhou, "Bayesian reasoning approach based recursive algorithm for online updating belief rule based expert system of pipeline leak detection," *Expert Syst. Appl.*, vol. 38, pp. 3937–3943, Apr. 2011.

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