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Fault Prediction Method for Wireless Sensor Network Based on Evidential Reasoning and Belief-Rule-Base

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ABSTRACT Wireless sensor network (WSN) is a distributed intelligent network, which can independently achieve the information collection task of monitoring targets. However, the WSN is susceptible to faults due to various factors, such as sensor resources, network bandwidth, and work environment. The WSN fault prediction technology can estimate the fault trend of the WSN, which can provide the basis for the formulation and implementation of emergency strategies. In this paper, a new WSN fault prediction method is proposed based on evidential reasoning (ER) and belief rule base (BRB). First, the process of the WSN fault prediction is described, which mainly includes the fault assessment of the current WSN and the fault prediction of future WSN. Second, the WSN fault prediction model is constructed, including the ER-based fault assessment model and BRB-based fault prediction model. The projection covariance matrix adaptation evolutionary strategies (P-CMA-ESs) are used to optimize model parameters. Finally, a case study is constructed to verify the validity of the WSN fault prediction model. The experimental results show that the model can adequately estimate the fault state of the current WSN and then predict the fault status of future WSN.

INDEX TERMS Fault prediction, belief rule base (BRB), fault assessment, evidential reasoning (ER) wireless sensor network (WSN).

I. INTRODUCTION

WSN is a data-centric system [1]. The WSN collects the information of monitoring objects, and the valuable information is provided to users through data fusion and data analysis. As an essential part of the Internet of Things, WSN is widely used in environmental monitoring, disaster warning, medical health, space exploration, and intelligent agriculture [2]. However, a large number of abnormal data are generated by WSN faults, which seriously affects the validity of the WSN data fusion [3].

WSN is an unreliable network. Many factors can cause WSN faults, which can be described as follows [4]:

1) There are a lot of sensors in WSN, and the sensor resources are limited due to the sensors are inexpensive. WSN faults are natural to occur when the sensors are working for a long time.

2) Batteries are used as energy sources by sensors, which limits the energy supply of the sensors. As the energy of the sensors is continuously consumed, the accuracy of the data collected continues to decrease.

3) WSN usually works in harsh environments. Many factors cause sensors to be destroyed, such as natural environments, weather changes, and wildlife.

4) The self-organizing wireless communication mode is adopted by WSN, and the communication bandwidth of the sensors is limited. When the WSN is subjected to electromagnetic interference or carry out a large amount of data communication, it will cause the distortion and loss of sensor data.

Through the above analysis, with the increase of the running time, the fault probability of WSN increases gradually,

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which leads to the decrease of the reliability of WSN. Therefore, early detection of faults in WSN is of great value to the stability of the WSN. WSN fault prediction is a new sensing technology of WSN fault status, which can analyze the fault status of current WSN so that the fault status of future WSN is predicted. On the one hand, WSN fault prediction can ensure that the WSN has sufficient fault-free time to complete the assigned tasks. On the other hand, WSN fault prediction is significant for WSN management and maintenance.

In recent years, fault prediction has gradually attracted the attention of many scholars. Many different methods of fault prediction have been proposed. Cozar *et al.* [5] proposed a state monitoring and fault prediction method based on a dynamic Bayesian network in a sensor system. Similarly, Lakehal and Tachi [6] offered a Bayesian network for fault prediction of power transformers. Zhou *et al.* [7] suggested a multi-fault prediction method based on time series extended finite-state machine. To reduce the errors caused by task scheduling, Ji and Wang [8] designed a fault prediction method for workshop scheduling by big large data analysis. Ding and Fang [9] proposed a fault estimation algorithm based on a particle filter, through the study of the fault prediction of nonlinear stochastic systems with initial faults. Yue *et al.* [10] proposed a fault prediction method based on kernel function, which is used to evaluate the network performance of Ribbon WSN. Zhang *et al.* [11] established a back propagation (BP) neural network prediction model of industrial equipment based on a dynamic cuckoo search optimization algorithm. Mahdi and Genc [12] proposed a post-fault prediction method of transient instability based on stacked sparse autoencoder. Considering the changes in the working environment and the problem of data imbalance, Di *et al.* [13] presented a fault prediction method for power converters in power conversion systems. To quantitatively monitor the state of complex systems, Wang *et al.* [14] proposed a data-driven fault prediction method. To ensure the safety, reliability and continuous operation of vehicular networks, Geng *et al.* [15] proposed a fault prediction algorithm based on BP neural network and rough set. Hu *et al.* [16] designed a fault prediction method of track circuit based on expert system and grey theory. To ensure the performance and security of complex systems, Li *et al.* [17] proposed a fault diagnosis and prediction method for complex systems based on a hidden Markov model.

According to the information used in modeling, fault prediction can be divided into three categories, which can be described as:

1) Fault prediction method based on qualitative knowledge. The operating principle and fault characteristics of the system are analyzed. The fault prediction model is established through expert knowledge, such as an expert system [16], Petri net, and fault tree. These methods are not affected by the observation information. However, when the system structure is complex, uncertainty and incompleteness of expert knowledge can lead to the decline of model accuracy.

2) Fault prediction method based on quantitative information. The observational data of the system state is analyzed. Combined with the system identification and optimization theory, the fault prediction model is established, such as Bayesian [5], [6], neural network [11], particle filter [9], time series [7], and deep learning [12]. The methods do not need to understand the internal mechanisms of the system before modeling, and the accuracy of the model is improved by training samples. When the number of samples is lacking, or the number of samples is not equal, it is difficult to establish an accurate fault prediction model. At the same time, the model belongs to the black-box model, and the process of modeling is not interpretable.

3) Fault prediction method based on semi-quantitative information. Combined with qualitative knowledge and quantitative information, a fault prediction model is established, such as Markov [17], fuzzy neural network [18]. These methods can solve the problems of incomplete samples and inaccurate knowledge to build a fault prediction model, but it is difficult to build and train the model.

In WSN, many factors affect the accuracy of fault prediction [19]. Firstly, System status information contains different types of data from multiple data sources, which are described qualitatively and quantitatively. Secondly, under the influence of environmental changes and electromagnetic interference, there are fuzzy uncertainties and probability uncertainties in the system status information. Thirdly, there are many characteristics in WSN fault, such as uncertainty, nonlinearity, and concurrency, which lead to the fault status of the WSN cannot be accurately described. Therefore, the fault prediction method based on semi-quantitative information is more suitable for the WSN.

To effectively use of semi-quantitative information, Yang et al. proposed a BRB expert system based on ER method [20]. It can effectively integrate qualitative knowledge and quantitative information, which can effectively deal with the fuzzy uncertainty, probability uncertainty and incompleteness of input information [21]. The method is a white-box method, which can provide adequate access for decision makers. The system includes knowledge representation and knowledge reasoning. Knowledge representation is implemented by the BRB. Knowledge reasoning is realized by the ER method. Complex system modeling based on ER and BRB is widely used in many fields such as financial risk assessment, fault diagnosis [22], optimal maintenance [23], and medical decision [24]. Therefore, by analyzing the working characteristics and fault characteristics of WSN, we propose a fault prediction method of WSN based on ER and BRB. This paper mainly contains two innovations, which are described as:

1) For the first time, an ER-based fault assessment method for WSN is proposed. Multiple fault indicators are effectively fused by the ER method to ensure the validity and interpretability of the assessment results.

2) For the first time, a BRB-based fault prediction method for WSN is proposed. Expert knowledge and training samples

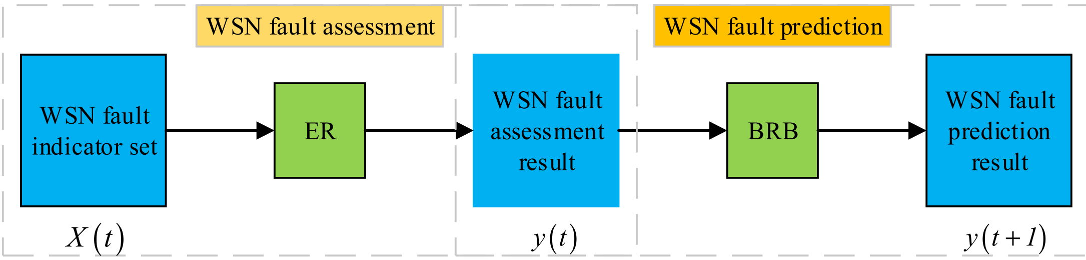

FIGURE 1. The structure of WSN fault prediction.

are used by BRB. The antecedent attributes and initial parameters of the BRB are defined by the expert knowledge. The parameter values of the BRB are optimized by the training samples to obtain more accurate prediction results.

The structure of this paper is described as follows. In Section II, the problem formulation of WSN fault prediction is analyzed and described. In Section III, WSN fault prediction model is constructed based on ER and BRB. In Section IV, a case study is designed to verify the validity of the WSN fault prediction model. In Section V, the future research plans are developed on WSN fault prediction.

II. PROBLEM FORMULATION

WSN fault prediction is defined which includes fault assessment and prediction of WSN as shown in Fig.1.

Different methods are used in fault assessment and fault prediction, which are described as:

1) In the fault assessment, the fault status of WSN is evaluated by analyzing the fault indicator set of WSN. There are many characteristics in the fault indicators, such as a large number, different types, and uncertainties. ER-based fault assessment model is implemented, which can successfully solve the fusion problem of many uncertain indicators and improve the science of WSN fault assessment.

2) In the fault prediction, by analyzing the results of WSN fault assessment, the fault status of WSN is predicted. BRB-based fault prediction model is proposed, which can effectively use expert knowledge and system data to improve the accuracy of WSN fault prediction.

A. NOTATIONS

All notations are defined as shown in Table 1.

B. WSN FAULT ASSESSMENT

Two assumptions are defined to describe the problem of WSN fault assessment.

1) $y(t)$ is defined as the results of fault assessment.

2) $X(t)$ is defined as the set of fault indicators, which can be described as:

$$X(t) = \begin{bmatrix} x_1^1(t) \cdots x_n^1(t) \\ \vdots \quad \ddots \quad \vdots \\ x_1^m(t) \cdots x_n^m(t) \end{bmatrix}, \quad n = 1 \cdots N, \ m = 1 \cdots M \tag{1}$$

where $x_n^m(t)$ denotes the n values of the mth indicator at time t. M is the number of fault indicators. N is the number of values contained in each fault indicator.

The process of the fault assessment can be described as follow:

$$y(t) = ER(X(t), \alpha) \tag{2}$$

where $ER(\cdot)$ denotes the nonlinear transformation based on ER. α denotes the set of ER parameters.

C. WSN FAULT PREDICTION

To describe the problem of WSN fault prediction, let $y(t+1)$ denotes the results of fault prediction. The process of the fault prediction can be described as follow:

$$y(t+1) = BRB(y(t), \varepsilon) \tag{3}$$

where $BRB(\cdot)$ denotes the nonlinear transformation based on BRB. ε denotes the set of BRB parameters.

In this paper, the problem of WSN fault prediction can be defined as the solution of $ER(\cdot)$ and $BRB(\cdot)$, and the solution of parameters α and parameters ε.

Remark1: In this paper, the one-step prediction mechanism is adopted for the WSN fault prediction. The WSN fault status is analyzed at time t, so that the WSN fault status is predicted at time $t+1$.

III. A MODEL OF ER AND BRB FOR WSN FAULT PREDICTION

WSN fault prediction model is established based on ER and BRB. Firstly, the implementation process of fault prediction is described. Secondly, ER-based fault assessment model is constructed. Thirdly, BRB-based fault prediction model is constructed. Finally, a parameter optimization algorithm for BRB model is proposed.

A. IMPLEMENTATION PROCESS OF WSN FAULT PREDICTION

The implementation process of WSN fault prediction model is designed is shown in Fig.2.

There are three components in the fault prediction model, which can be described as:

1) The ER-based fault assessment model is constructed. In WSN running phase, the fault status indicators are extracted by analyzing WSN fault characteristics. ER method

TABLE 1. Dictionary of notations.

Notation	Meaning
t	time
$y(t)$	results of fault assessment
$X(t)$	set of fault indicators at time t
$x_n^m(t)$	the nth value of the mth fault indicator at time t
M	number of fault indicators
N	number of values contained in each fault indicator
$ER(\bullet)$	nonlinear transformation from set of fault indicators to results of fault assessment based on ER
α	set of ER parameters
$y(t+1)$	results of fault prediction
$BRB(\bullet)$	nonlinear transformation from results of fault assessment to results of fault prediction based on BRB
ε	set of BRB parameters
e_m	the mth fault indicator
A	set of fault assessment levels
A_r	the rth fault assessment level
$\rho_{r,m}$	belief degree of the rth fault assessment level in the mth fault indicator
R	number of fault assessment levels
Θ	global ignorance
$\rho_{\Theta,m}$	unassigned belief degree in the mth fault indicator
$mass_{r,m}$	basic probability mass of the rth fault assessment level in the mth fault indicator.
ω_m	weight of the mth fault indicator
$mass_{A,m}$	basic probability mass not assigned to set of fault assessment levels
$m\bar{a}ss_{A,m}$	unimportance degree of the mth fault indicator
$m\tilde{a}ss_{A,m}$	incomplete degree of the mth fault indicator
$mass_{r,I(m)}$	basic probability mass of the rth fault assessment level after m fault indicators are fused
ρ_r	belief degree of the rth fault assessment level
$U(\bullet)$	utility formula
$Rule_k$	the kth belief rule
K	number of belief rules
$\beta_{i,k}$	belief degree of the ith fault prediction level in the kth belief rule
θ_k	rule weight of the kth belief rule
δ	attribute weight
η_k	the kth rule matching degree
ψ_k	the kth rule activation weight
β_r	belief degree of the rth fault prediction level
$MSE(\bullet)$	mean square error(MSE) function
Z	number of training samples
$\hat{y}(t+1)$	expected output of fault prediction at time $t+1$
$PNUM$	number of solutions in population
$DNUM$	number of solutions in optimal subgroup
$GMAX$	maximum number of evolutions
ε_i^g	the ith solution in the gth generation population
$mean^g$	mean of optimal subgroup solutions in the gth generation population
λ^g	the gth generation evolutionary step
$N(\bullet)$	normal distribution.
C^g	covariance matrix of the gth generation population
$vnum$	number of variables inequality constraints
$enum$	number of constraints in the solution.
V	parameter vector of the equation
μ_i	weight of the ith solution in optimal subgroup
$s_1, s_{DNUM}, s_p, s_\lambda$	learning rate
p_c^g	evolution path of covariance matrix in the gth generation.
p_λ^g	step-size of evolutionary in the gth generation.
κ_λ	damping coefficient
$E\|N(0,1)\|$	expectation of normal distribution $N(0,1)$
I	unit matrix
$rate_i$	fault rate of the ith fault status.
F_i	number of sensors in the ith fault status.
ALL	number of all sensors.

is used to realize the evidence fusion of qualitative and quantitative indicators with uncertainties so that the fault evaluation results of current WSN are calculated.

2) The BRB-based fault prediction model is constructed. The current WSN fault assessment results are taken as inputs, which are analyzed by ER algorithm. Furthermore, the fault prediction results of the future WSN are obtained.

3) To improve the prediction accuracy of the BRB model. The projection covariance matrix adaptation evolutionary strategies (P-CMA-ES) is used to optimize the model.

B. AN ER MODEL FOR WSN FAULT ASSESSMENT

WSN faults include network faults and sensor faults. Each fault is affected by multiple fault indicators. In this section, the indicators are fused based on ER iteration algorithm, and then the results of fault assessment are obtained. The results of fault assessment are quantified, which can be described as follow:

1) The results of fault assessment are quantified to the real number interval of [0, 1].

2) The results of fault assessment are positively correlated with the WSN fault threat. The higher the results of fault assessment, the more serious the WSN is threatened by the faults. The implementation process of WSN fault assessment is described in Fig.3.

The ER iteration algorithm is used for reasoning in fault assessment model, and the process can be described as:

Step 1: Initialization: the set $A$of fault assessment levels is set by experts. Belief degree of different fault assessment levels in each indicator is initialized based on expert knowledge. The mth fault indicator e_m is described as:

$$e_m = \left\{\left(A_r, \rho_{r,m}\right), r = 1 \cdots R, \left(\Theta, \rho_{\Theta,m}\right)\right\} \tag{4}$$

where A_r denotes the rth fault assessment level. $\rho_{r,m}$ is the belief degree of the rth fault assessment level in the mth fault indicator. R is the number of fault assessment levels. Θ is the

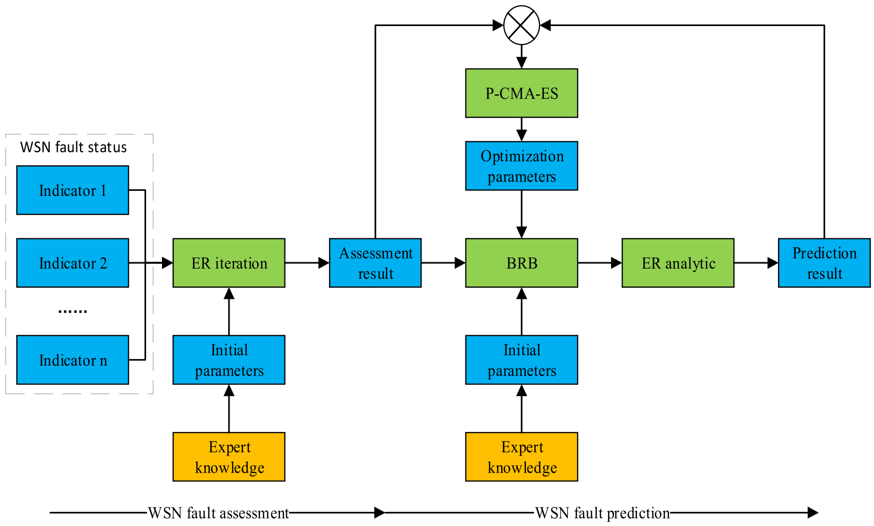

FIGURE 2. The implementation process of WSN fault prediction.

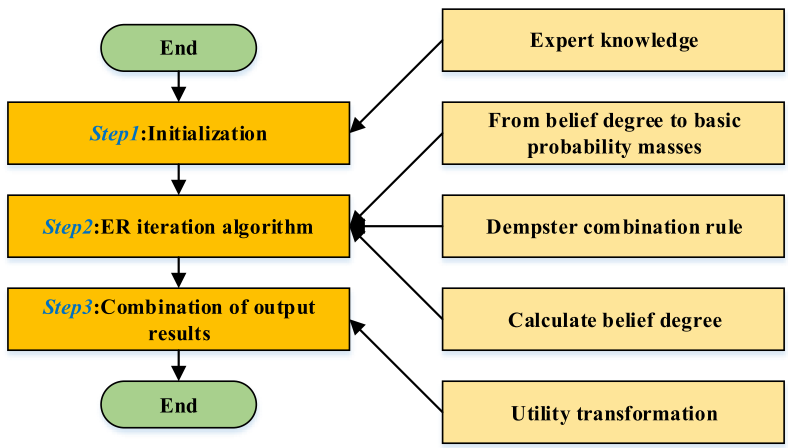

FIGURE 3. The implementation process of ER-based WSN fault assessment.

global ignorance. $\rho_{\Theta,m}$ is the unassigned belief degree in the *mth* fault indicator.

Step 2: ER iteration algorithm: fault indicators are fused, which can be described as follow:

Firstly, the basic probability masses are solved by the belief degree $\rho_{r,m}$. It can be described as:

$$\begin{aligned} mass_{r,m} &= \omega_m \rho_{r,m} \\ mass_{A,m} &= 1 - \omega_m \sum_{r=1}^{R} \rho_{r,m} \\ \bar{mass}_{A,m} &= 1 - \omega_m \\ \tilde{mass}_{A,m} &= \omega_m \left(1 - \sum_{r=1}^{R} \rho_{r,m}\right) \end{aligned} \tag{5}$$

where $mass_{r,m}$ denotes the basic probability mass of the *rth* fault assessment level in the *mth* fault indicator. ω_m denotes the weight of the *mth* fault indicator. $mass_{A,m}$ is the basic probability mass not assigned to set of fault assessment levels. $\bar{mass}_{A,m}$ is the unimportance degree of the *mth* fault indicator. $\tilde{mass}_{A,m}$ is the incomplete degree of the *mth* fault indicator.

Secondly, the fault indicators are fused by Dempster rule. It can be described as (6), shown at the bottom of the next page.

where $mass_{r,I(m)}, mass_{r,I(1)} = mass_{r,1}$ denotes the basic probability mass of the *rth* fault assessment level after *m* fault indicators are fused.

Thirdly, the belief degree of fault assessment level is calculated. It can be described as:

$$\rho_r = \frac{mass_{r,I(M)}}{1 - \bar{mass}_{A,I(M)}} \tag{7}$$

where ρ_r denotes the belief degree of the *rth* fault assessment level.

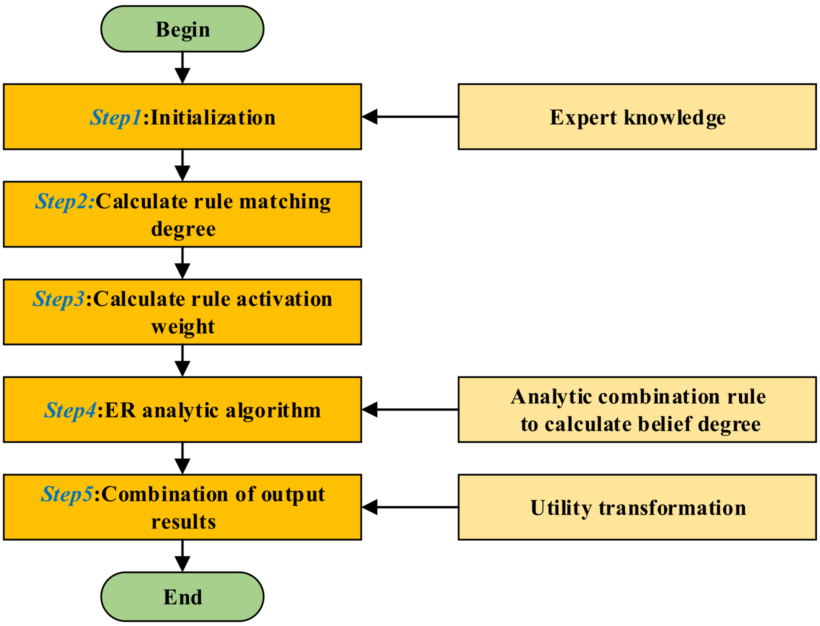

FIGURE 4. The implementation process of BRB-based WSN fault prediction.

Step 3: Combination of output results: the results of fault assessment are solved by the utility formula. It can be described as:

$$y(t) = \sum_{r=1}^{R} U(A_r)\rho_r \tag{8}$$

where $U(\cdot)$ denotes the utility formula.

C. A BRB MODEL FOR WSN FAULT PREDICTION

The results $y(t)$of fault assessment at time t are analyzed, and the results $y(t+1)$ of fault prediction at time $t+1$ are calculated. The BRB model can be described as:

$$\begin{aligned} &Rule_k : If\ y(t)\ is\ A_r,\ Then\ y(t+1)\ is \\ &\quad \left\{(A_1, \beta_{1,k}), \cdots, (A_R, \beta_{R,k})\right\} \\ &\quad With\ rule\ weight\ \theta_k\ and\ attribute\ weight\ \delta = 1 \end{aligned} \tag{9}$$

where $Rule_k, k = 1 \cdots K$ denotes the kth belief rule. K is the number of belief rules. Fault prediction and fault evaluation have the same set. $\beta_{i,k}$ is the belief degree of the ith fault prediction level in the kth belief rule. δ is the attribute weight. θ_k is the rule weight of the kth belief rule.

The implementation process of the WSN fault prediction is described in Fig.4.

The fault prediction model is reasoned by the ER analytic algorithm. The process can be described as:

Step 1: Initialization: the set $\varepsilon = \left\{\theta_1 \cdots \theta_K, \beta_{1,1} \cdots \beta_{R,K}\right\}$ of the BRB model is defined and the belief degree of rules is initialized by expert knowledge.

Step 2: Calculate the rule matching degree: The matching degree of the input sample to the kth rule can be described as:

$$\eta_k = \begin{cases} \dfrac{A_{j+1} - y(t)}{A_{j+1} - A_j} & k = j\ (A_j \le y(t) \le A_{j+1}) \\ \dfrac{y(t) - A_j}{A_{j+1} - A_j} & k = j+1 \\ 0 & k = 1 \cdots K\ (k \ne j\ and\ k \ne j+1) \end{cases} \tag{10}$$

where η_k denotes the kth rule matching degree.

$$\begin{aligned} mass_{r,I(m+1)} &= V_{I(m+1)}\left[mass_{r,I(m)}mass_{r,m+1} + mass_{r,I(m)}mass_{A,m+1} + mass_{A,I(m)}mass_{r,m+1}\right] \\ mass_{A,I(m)} &= \bar{m}ass_{A,I(m)} + \tilde{m}ass_{A,I(m)} \\ \tilde{m}ass_{A,I(m+1)} &= V_{I(m+1)}\left[\tilde{m}ass_{A,I(m)}\tilde{m}ass_{A,m+1} + \bar{m}ass_{A,I(m)}\tilde{m}ass_{A,m+1} + \tilde{m}ass_{A,I(m)}\bar{m}ass_{A,m+1}\right] \\ \bar{m}ass_{A,I(m+1)} &= V_{I(m+1)}\left[\bar{m}ass_{A,I(m)}\bar{m}ass_{A,m+1}\right] \\ V_{I(m+1)} &= \frac{1}{1 - \sum\limits_{r=1}^{R}\sum\limits_{\substack{s=1 \\ s \ne r}}^{R} mass_{r,I(m)}mass_{s,m+1}} \end{aligned} \tag{6}$$

Step 3: Calculate rule activation weight: The calculation process of the rule activation weight can be described as:

$$\psi_k = \frac{\theta_k \eta_k}{\sum_{j=1}^{K} \theta_j \eta_k} \tag{11}$$

where ψ_k denotes the *kth* rule activation weight.

Step 4: ER analytic algorithm: The belief degree of the sample $y(t)$ for different fault assessment levels are calculated based on ER analytic algorithm. It can be described as (12), shown at the bottom of this page, where β_r denotes the belief degree of the *rth* fault assessment level

Step 5: Combination of output results: the results of fault prediction are solved by the utility formula. It can be described as:

$$y(t+1) = \sum_{r=1}^{R} U(A_r)\beta_r \tag{13}$$

D. OPTIMIZE THE BRB MODEL

To improve the accuracy of BRB-based fault prediction model, the parameters of the model are optimized by labeled samples. The objective optimization function of the BRB model is described as:

$$\begin{aligned} &\min MSE(\varepsilon) \\ &s.t. \sum_{r=1}^{R} \beta_{r,k} = 1, \quad k = 1 \cdots K \\ &\quad 0 \le \beta_{r,k} \le 1 \\ &\quad 0 \le \theta_k \le 1 \end{aligned} \tag{14}$$

where $MSE(\cdot)$ denotes the mean square error(MSE) function, which can be described as follows:

$$MSE(\varepsilon) = \frac{1}{Z} \sum_{z=1}^{Z} \left(y(t+1) - \widehat{y}(t+1) \right)^2 \tag{15}$$

where Z is the number of training samples. $\widehat{y}(t+1)$ demotes the expected output of fault prediction at time $t+1$.

Through the above analysis, the optimization problem of the BRB model is a global optimization problem with constraint conditions. The P-CMA-ES algorithm is selected, which can deal with high-dimensional non-linear optimization problems [26]. The optimization process of BRB model is described in Fig.5.

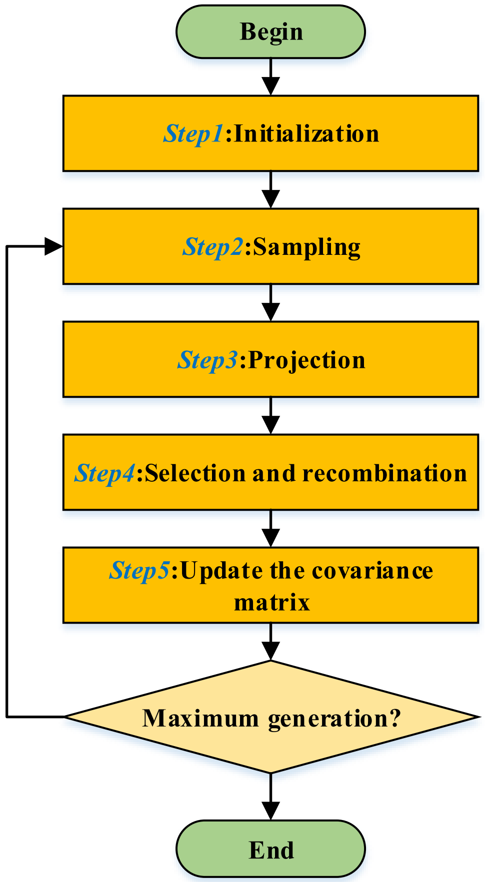

FIGURE 5. The optimization process of the BRB-based WSN fault prediction model.

The progress of P-CMA-ES algorithm is described as:

Step 1: Initialization: On the basis of the BRB parameters set ε^0, the initial parameters are defined. The number of solutions in population is defined as $PNUM$. The number of solutions in optimal subgroup is defined as $DNUM$. The maximum number of evolutions is defined as $GMAX$.

Step 2: Sampling: The expected value is defined, which is the mean of optimal subgroup solution. A population is generated based on a normal distribution, which can be described as:

$$\varepsilon_i^{g+1} = mean^g + \lambda^g N\left(0, C^g\right) \tag{16}$$

$$\begin{aligned} \beta_r &= \frac{\varphi \left[\prod_{k=1}^{K} \left(\psi_k \beta_{r,k} + 1 - \psi_k \sum_{j=1}^{R} \beta_{j,k} \right) - \prod_{k=1}^{K} \left(1 - \psi_k \sum_{j=1}^{R} \beta_{j,k} \right) \right]}{1 - \varphi \left[\prod_{k=1}^{K} 1 - \psi_k \right]} \\ \varphi &= \frac{1}{\left[\sum_{r=1}^{R} \prod_{k=1}^{K} \left(\psi_k \beta_{r,k} + 1 - \psi_k \sum_{j=1}^{R} \beta_{j,k} \right) - (R-1) \prod_{k=1}^{K} \left(1 - \psi_k \sum_{j=1}^{R} \beta_{j,k} \right) \right]} \end{aligned} \tag{12}$$

where ε_i^{g+1} is the ith $(i = 1 \cdots PNUM)$ solution in the $g+1th$ generation population. $mean^g$, $mean^0 = \varepsilon^0$ is the mean of the optimal subgroup solutions in the gth generation population. λ^g is the gth generation evolutionary step. $N(\cdot)$ is the normal distribution. C^g is the covariance matrix of the gth generation population.

Step 3: Projection: in Eq.(14), $R+1$ equality constraints are included. Rsolutions are included in each constraint. The projection operation is performed for each equality constraint, which can be described as:

$$\begin{aligned}&\varepsilon_i^{g+1}(1+vnum\times(enum-1):vnum\times enum)\\&\quad=\varepsilon_i^{g+1}(1+vnum\times(enum-1):vnum\times enum)\\&\qquad-V^T\times\left(V\times V^T\right)^{-1}\\&\qquad\times\varepsilon_i^{g+1}(1+vnum\times(enum-1):vnum\times enum)\times V\end{aligned}\tag{17}$$

where $vnum = (1 \cdots R)$ is the number of variables inequality constraints. $enum = (1 \cdots R+1)$ is the number of constraints in the solution. $V = [1 \cdots 1]_{1\times N}$ is the parameter vector of the equation.

Step 4: Selection and recombination: Eq.(15) is defined as a fitness function. The optimal subgroup containing $DNUM$ solutions is selected. The solutions are solved for the mean, which can be described as:

$$mean^{g+1} = \sum_{i=1}^{DNUM} \mu_i \varepsilon_i^{g+1}, \quad \sum_{i=1}^{DNUM} \mu_i = 1 \tag{18}$$

where μ_i, $i = 1 \cdots DNUM$ denotes the weight of the ith solution in optimal subgroup.

Step 5: Update the covariance matrix: The covariance matrix of the $g+1th$ generation population is calculated, and the range and direction of the population search are obtained. This process can be described as:

$$\begin{aligned}C^{g+1}&=(1-s_1-s_{DNUM})C^g+s_1p_c^{g+1}\left(p_c^{g+1}\right)^T\\&\quad+s_{DNUM}\sum_{i=1}^{DNUM}\mu_i\left(\frac{\varepsilon_i^{g+1}-mean^g}{\lambda^g}\right)\\&\quad\times\left(\frac{\varepsilon_i^{g+1}-mean^g}{\lambda^g}\right)^T\\p_c^{g+1}&=(1-s_c)p_c^g+\sqrt{s_c(2-s_c)\left(\sum_{i=1}^{DNUM}\mu_i^2\right)^{-1}}\\&\quad\times\frac{mean^{g+1}-mean^g}{\lambda^g}\\\lambda^{g+1}&=\lambda^g\exp\left(\frac{s_\lambda}{\kappa_\lambda}\left(\frac{\left\|p_\varsigma^{g+1}\right\|}{E\left\|N(0,I)\right\|}-1\right)\right)\\p_\lambda^{g+1}&=(1-s_\lambda)p_\lambda^g+\sqrt{s_\lambda(2-s_\lambda)\left(\sum_{i=1}^{DNUM}\mu_i^2\right)^{-1}}\\&\quad\times C^{g-\frac{1}{2}}\frac{mean^{g+1}-mean^g}{\lambda^g}\end{aligned}\tag{19}$$

where $s_1, s_{DNUM}, s_p, s_\lambda$ denotes the learning rate. $p_c^g, p_c^0 = 0$ denotes the evolution path of covariance matrix in the gth generation. $p_\lambda^g, p_\lambda^0 = 0$ denotes the step-size of evolutionary in the gth generation. κ_λ denotes the damping coefficient. $E\|N(0,I)\|$ is the expectation of the normal distribution $N(0,I)$. $I$is the unit matrix.

Finally, if the maximum evolution generation of the population reaches$GMAX$, the optimization is terminated. Otherwise, step 2 is continued.

Remark2: In the fault prediction model, the ER analytic algorithm and the ER iteration algorithm are used respectively. Evidence fusion is implemented by the ER iteration algorithm based on the Dempster rule. The reasoning result of the algorithm is more accurate but the algorithm is more complex. It is suitable for evidence reasoning in a non-training environment. ER analytic algorithm is simple and ideal for evidence reasoning in a trainable environment. Therefore, the model of fault assessment is reasoned by the ER iteration algorithm, and the model of fault prediction is reasoned by the ER analytic algorithm.

Remark3: In this paper, an ER-based fault assessment model and a BRB-based fault prediction model are constructed. ER can analyze a large amount of uncertain information, so as to obtain credible assessment results. BRB has more excellent modeling ability for complex systems. BRB is easy to add expert knowledge, and its interpretability is better than ER. However, when the BRB antecedent attribute is too much, the rule combination explosion problem is generated. Therefore, the ER-based fault assessment model is built to solve the complexity of fault indicators, and BRB-based fault prediction model is built to improve the prediction accuracy.

Remark4: CMA-ES is an excellent unconstrained global optimization algorithm with fast convergence and high accuracy. To solve the equality constraint problem in the BRB model, P-CMA-ES algorithm is proposed, which implements the transformation of equality constraints by projection operation.

IV. CASE STUDY

To verify the validity of the proposed method, the Intel Lab Data are used as primary experimental data. The data are modified according to different fault types, and then the fault status data of WSN are generated. The sensors distribution is shown in Fig.6. The necessary information of the Intel Lab Data is shown in Table 2.

A. PROBLEM FORMULATION

The problem of fault prediction is defined as solving $(ER(\cdot), \alpha)$ in fault assessment and $(BRB(\cdot), \varepsilon)$ in

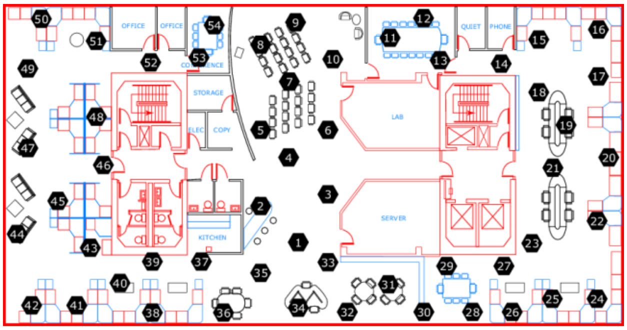

FIGURE 6. The sensors distribution diagram.

TABLE 2. The dataset information.

Parameter	information
Acquisition time	February 28, 2004 - April 5, 2004
Collection location	the Intel Berkeley Research lab
Sensor type	Mica2Dot sensors with weatherboards
Data acquisition system	TinyDB
Number of sensors	54
Acquisition interval	31 seconds
Collecting information	temperature, humidity, light, and voltage values
Data size	2.3 million

fault prediction. The fault status data of WSN are generated as follows:

1) In the Intel Lab Data, The temperature data collected by all sensors from March 1 to March 5 is selected to create WSN fault status data. The time interval of sampling is 1 hour. Each sensor contains 120 sets of experimental data.

2) In the initial state, the sensor 5 and sensor 15 have completely fault, and the other sensors are operating normally.

3) The generation rules of sensor fault are designed. Every hour, the fault probability of the sensor in normal operation is 1%.

4) The type of sensor fault is random, including complete fault, fixed bias fault, drift fault, and precision decline fault.

5) It is assumed that the kind of sensor fault will not change. The sensor is always running under the fault type.

Through the above rules, 120 sets of WSN fault status data are generated as the experimental dataset.

B. ESTABLISHMENT OF WSN FAULT PREDICTION MODEL BASED ON ER AND BRB

WSN fault prediction model including WSN fault assessment and WSN fault prediction. The dataset of fault indicators are analyzed, and the fault status of current WSN is evaluated. Based on the assessment results, the fault status of future WSN is predicted.

When the fault assessment model is established, different types of fault indicators are fused by the ER iterative algorithm, and then the fault assessment results are generated. In this experiment, the fault type and fault rate are selected as the primary indicators for fault assessment. The fault type is a qualitative indicator, including normal, complete fault, fixed bias fault, drift fault, and precision decline fault. The fault rate is a quantitative indicator that can be solved as follow:

$$rate_i = \frac{F_i}{ALL} \tag{20}$$

where $rate_i$ denotes the fault rate of the ith fault type. F_i is the number of sensors in the ith fault type. ALL is the number of all sensors.

The same indicator of weight is set. WSN fault assessment results are defined, including very high(VH), high(H), medium(M), low(L), and very low(VL). The results of fault assessment are shown in Fig.7. With the increase of sensor running time, the number of sensor faults will gradually increase.

By the above experiments, fault assessment results are generated, which can be used as the dataset for fault prediction. BRB-based fault prediction model can be formally described as:

$$\begin{aligned} &Rule_k : If\ \ y(t)\ \ is\ A_r, \quad Then\ y(t+1)\ \ is \\ &\quad \left\{(VL, \beta_{1,k}), (L, \beta_{2,k}), (M, \beta_{3,k}), (H, \beta_{4,k}), (VH, \beta_{5,k})\right\} \\ &\quad With\ rule\ weight\ \theta_k \end{aligned} \tag{21}$$

The fault assessment level A_r is defined as antecedent attributes and fault prediction results. The referential points A_r are determined and the quantified as shown in Table 3.

TABLE 3. The referential points and referential values of A_r.

Referential points	VL	L	M	H	VH
Referential values	0.25	0.47	0.58	0.69	0.8

Through Eq.(21), all belief rules for fault prediction are defined, and the initial belief degree is generated as shown in Table 4.

TABLE 4. The initial belief degree of BRB.

No.	θ_k	A_r	$\{(VL,\beta_{1,k}),(L,\beta_{2,k}),(M,\beta_{3,k}),(H,\beta_{4,k}),(VH,\beta_{5,k})\}$
1	1	VL	$\{(VL,1),(L,0),(M,0),(H,0),(VH,0)\}$
2	1	L	$\{(VL,0),(L,1),(M,0),(H,0),(VH,0)\}$
3	1	M	$\{(VL,0),(L,0),(M,1),(H,0),(VH,0)\}$
4	1	H	$\{(VL,0),(L,0),(M,0),(H,1),(VH,0)\}$
5	1	VH	$\{(VL,0),(L,0),(M,0),(H,0),(VH,1)\}$

The BRB model is established by the above process. ER analytic algorithm is used to implement the reasoning of the BRB model. P-CMA-ES algorithm is used to achieve parameter optimization of the BRB model.

C. COMPARATIVE ANALYSIS

In this experiment, a dataset consisting of 120 samples was used to test the BRB-based fault prediction model, which was established by the ER-based fault assessment model. There are ten rounds of tests have been completed. In each round of experiments, 60 samples were randomly selected for the

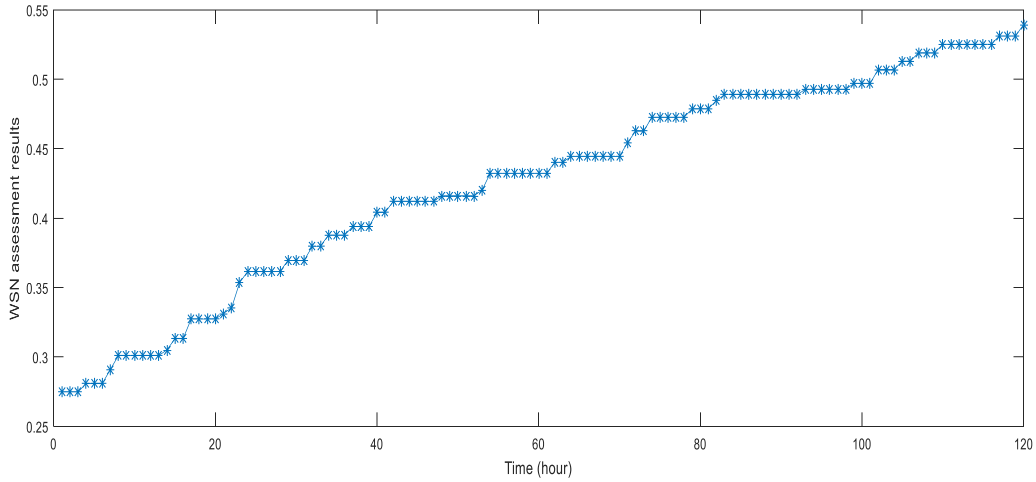

FIGURE 7. WSN assessment results.

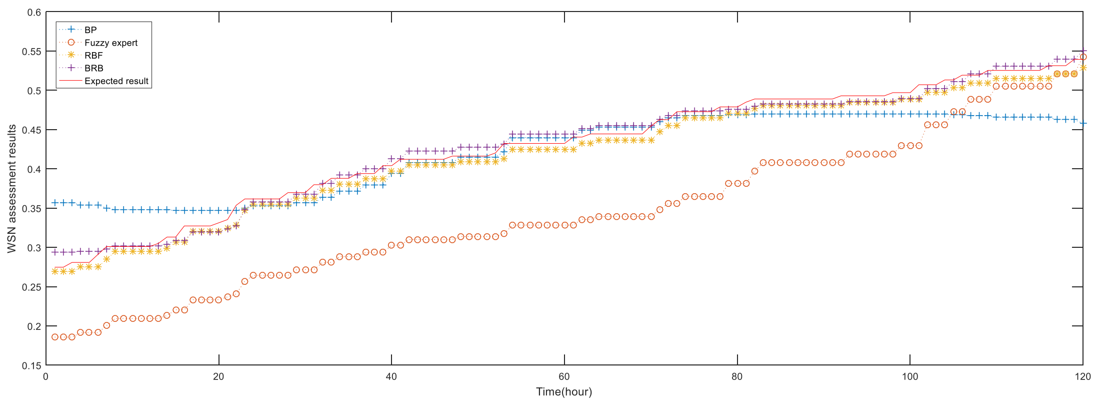

FIGURE 8. Comparison of the four methods and expected results.

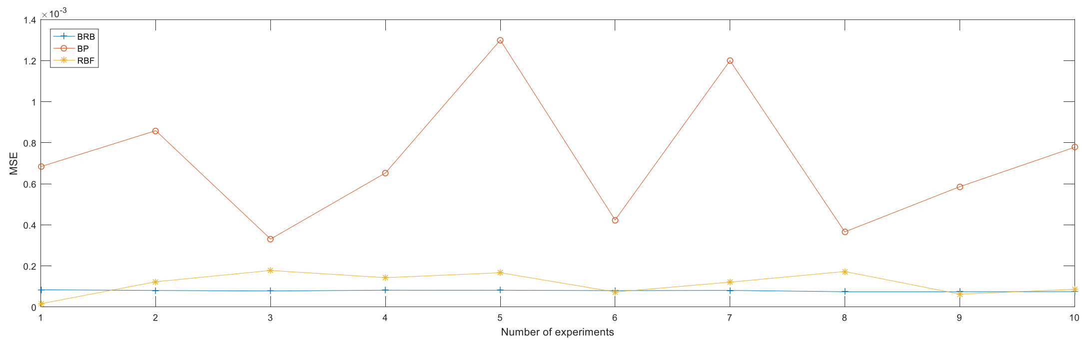

FIGURE 9. MSE comparison of BP, RBF, and BRB.

training model, and all 120 samples were selected for the test model.

Meanwhile, the BRB is compared with the fuzzy expert system, radial basis function (RBF) neural network and BP neural network. The fuzzy expert system is a method based on qualitative knowledge. RBF and BP are methods based on quantitative information. In the current research, all the above methods are important fault prediction methods.

The fitting results of the four methods with samples are shown in Fig. 8. The suitable effect of BRB is better than the other three methods.

The MSE results of ten rounds of tests are compared as shown in Fig. 9. The MSE mean is shown in Table 5. The prediction accuracy of BRB is better than the other three methods.

From the above results, the proposed WSN fault prediction model is reliable, which has higher prediction accuracy.

TABLE 5. The MSE mean.

	BRB	Fuzzy expert system	RBF	BP
MSE	7.92E-5	8.23E-3	1.14E-4	7.18E-4

At the same time, by the analysis of the experimental results, the conclusions can be described as:

1) In ten rounds of experiments, the MSE of the BRB was between 8.40E-05 and 7.45E-05. This shows that BRB can overcome the model training problem in the absence of samples.

2) Because modeling process of BRB has clear causality. BRB-based fault prediction method has better credibility than the fault prediction methods based on quantitative information.

3) Because BRB can be trained by samples, BRB-based fault prediction method has better accuracy than the fault prediction methods based on qualitative knowledge.

V. CONCLUSION

To make better use of semi-quantitative information and solve the impact of uncertain information on modeling. In this paper, An ER and BRB method is designed for WSN fault prediction. Experiments show that the way has better WSN fault prediction ability. Based on the above research, future work mainly includes the following aspect:

1) Through an in-depth analysis of WSN fault characteristics, a perfect multi-step prediction model will be constructed.

2) Joint optimization of structure and parameters are studied to improve the accuracy of WSN fault prediction model.

3) Deep ER model and deep BRB model are constructed to solve the rule-combination explosion problem of the BRB model, while exploring the construction of the interpretable deep learning model for WSN fault prediction.

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