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Health Assessment for a Sensor Network With Data Loss Based on Belief Rule Base

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ABSTRACT As the complexity of a system increases, the use of sensor networks becomes more frequent and the network health management becomes more and more important. When sensor networks are applied to complex environments, they are influenced by the disturbance factors in engineering practice and observation data may be lost. This will decrease the accuracy of the health state assessment. Moreover, due to the disturbance factors and complexity of the system, observation data and system information cannot be adequately gathered. To deal with the above problems, a new health assessment model is developed based on belief rule base (BRB). The BRB model is one of the expert systems in which the quantitative data and qualitative knowledge can be aggregated simultaneously. In the new health assessment model for a sensor network, a new missing data compensation model based on BRB is constructed first, in which the historical data of the monitoring indicators are used. In addition, the expert knowledge for the historical working state of the sensor network is also applied in the constructed missing data compensation model. Then, based on the compensated data and the observation data of the sensor network, the health state can be estimated by the developed health assessment model based on BRB. Given the uncertainty of expert knowledge, the initial health assessment model cannot assess the health state of the sensor network in an actual working environment. Thus, in this paper, an optimization model is constructed based on the projection covariance matrix adaption evolution strategy (P-CMA-ES). To illustrate the effectiveness of the new proposed model, a practical case study of a sensor network in a laboratory environment is conducted.

INDEX TERMS Health assessment, expert system, belief rule base (BRB), sensor network.

I. INTRODUCTION

A sensor network is a kind of computer network composed of many automatic devices. These devices use sensors to gather complex system information (such as temperature, humidity, sound, vibration, pressure, motion or pollutants). They are applied to obtain the system state and to ensure the reliability and safety of the system [1]. Since these nodes are usually deployed in inaccessible areas or unattended environments to record data or sense the occurrence of certain events, it can be hard to maintain fault nodes in a timely manner. Once there is a node failure such as a hardware fault, software fault, energy fault, communication fault or an intrusion from attackers, it will lead to a decrease in the validity of the sensor network and even produce network failure. Therefore, it is necessary to take some measures to improve the reliability and safety of the sensor network [2], [3].

Health assessment has been widely used in the health management of complex systems, where the observation information is aggregated to assess the health state [4]–[6]. The current studies on the health assessment of sensor networks can be divided into three categories: the data-based health assessment method, the knowledge-based health assessment method and the semiquantitative (quantitative data and

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qualitative knowledge) based health assessment method. Many excellent studies have been conducted in recent years. For example, Mudziwepasi *et al.* introduced the sensor network to cattle healthcare and emphasized the importance of wireless sensor network reliability [7]; Tae *et al.* developed security management for a wireless healthcare sensor network in healthcare systems [8]; Hu *et al.* proposed a hidden behaviour prediction model for network safety assessment based on belief rule base (BRB) [9]. In these studies, three challenges need to be solved. First, due to the disturbance factors in engineering practice and the limitation of data transmission technology, it is difficult to obtain a large amount of available monitoring data, especially failure data [10], [11]. The data-based health assessment model is constructed based on a large amount of observation data, and a small sample cannot provide enough information to build an accurate health assessment model. Second, multiple factors exist in a practical system that simultaneously affect the health state of the sensor network. In addition, the sensors influence each other, and there may be information transmission between them [12], [13]. Thus, experts alone cannot establish an accurate mathematical model, and it is difficult to directly apply the ambiguity and uncertainty in natural language. Moreover, the sensor information transmission is carried out by wireless or wired methods that are sensitive to environmental interference. Once it is affected by the latter, the observation information may be lost, which increases the difficulty of health assessment [14], [15]. In engineering practice, the commonly used method is to calculate the lost data by the mean value of the two data before and after the lost data. However, the mean value cannot accurately reflect the change trend of the working state for the network. For example, when the observation data are 2.2 and 3.8 at time t and $t+2$ respectively, the missing data at time $t+1$ is 3 calculated in a practical system while the missing data may fluctuate around 3 influenced by disturbance factors in the environment. Thus, the missing data compensation method should consider both the historical data and the working environment. Based on the above analysis of challenges in the health assessment for a sensor network, the lack of monitoring information, complex system influencing factors, and data loss could not be solved simultaneously in previous studies. Therefore, to improve health assessment accuracy, a new model for the health assessment of a sensor network is developed in this paper.

BRB is one of the expert systems that has been developed based on the IF-THEN rule, fuzzy inference and D-S evidence theory [16]–[18]. In the BRB model, the quantitative data and qualitative knowledge can both be applied to improve the modelling ability for complex systems with samples containing both small and large numbers of values. In addition, the structure of the BRB model is determined by experts according to the system mechanism and it has interpretability. Therefore, the BRB model can be used to handle the lack of monitoring information and complex system influencing factors. However, in previous studies of health assessments based on BRB, data loss has not been considered and the observation data are assumed to be complete. This decreases the estimation accuracy of sensor networks with environmental interference. Thus, to improve the estimation accuracy of the health state of a sensor network, a new health assessment model based on BRB is developed, with a composite structure containing two constructed BRB models. In the new health assessment model, first, a missing data compensation model based on BRB is proposed, which is used to estimate the missing data based on the historical data and expert knowledge. The developed missing data compensation model can aggregate the historical data and expert knowledge simultaneously, thus dealing with the influence of the disturbance factors in an actual working environment that may cause irregular fluctuation of the observation data. Then, based on the compensated data and the observation data, the health state of the sensor network can be assessed by the constructed health assessment model. Moreover, the initial health assessment model constructed by BRB is determined by experts. Due to the uncertainty and ignorance of the expert knowledge, the initial assessment model cannot estimate the health state accurately in practical systems. Therefore, an optimization model for model parameters is developed based on the projection covariance matrix adaption evolution strategy (P-CMA-ES) algorithm [2], [3], [14].

The following parts of this paper are organized as follows: In Section 2, the notions are defined and the problem of health assessment for a sensor network is formulated. Section 3 presents the inference of the BRB-based health assessment for a sensor network. In Section 4, a case study for the health assessment of a sensor network is reported to illustrate the effectiveness of the proposed model. Section 5 concludes the paper.

II. PROBLEM FORMULATION

In this section, the problems in health assessment for a sensor network in engineering practice are summarized (2.1) and the construction of the new health assessment model based on BRB for a sensor network is presented (2.2).

A. PROBLEM FORMULATION FOR THE HEALTH ASSESSMENT OF A SENSOR NETWORK

To improve the estimation accuracy of the health state of a sensor network in a practical system, three challenges must be solved. These can be summarized as follows:

Problem 1: In engineering practice, influenced by environmental interference and limited by the sensor technology, a large amount of invalid data exist in the observation data and less data is available [2]. On the other hand, because of the high reliability of sensor design, there are few failures, which causes less failure data. Thus, how to integrate other network information in the health assessment is the first problem that needs to be addressed.

Problem 2: The health state of the sensor network is influenced by many factors in practical systems. Due to the limited knowledge of experts, they may not provide accurate network information. In addition, the knowledge provided by experts is presented in the form of natural language. The uncertainty and ambiguity increase the difficulty of using expert knowledge [11], [14]. Therefore, the second problem is how to aggregate the expert knowledge to increase the amount of information in the health assessment model.

Problem 3: When the sensor network is applied in engineering practice, disturbance factors will influence the data transformation and there may be an uncontrollable loss of observation data. In addition, influenced by the disturbance factors in an actual working environment, the observation data fluctuates and cannot be calculated by the mean values of historical data in a practical system. The incomplete observation data can degrade the accuracy of the health assessment. Thus, in view of the above two problems, the following health assessment model should be constructed:

$$H(t) = \Psi(x_1(t), x_2(t), \ldots, x_N(t), \Xi(x(1), x(2), \ldots, x(t-1)), R) \quad (1)$$

where $H(t)$ is the health state of a sensor network at time t, $x_i(t)$ denotes the ith network characteristic, and N is the number of network characteristics. $\Psi(\cdot)$ denotes a nonlinear function that is used to model the relationship between network characteristics and the health state, and $\Xi(\cdot)$ denotes the nonlinear function used to address the lost data with the consideration of the historical observation data. R represents the expert knowledge aggregated into the health assessment model, which can comprehensively consider the interference during the whole working process of the sensor network.

B. BRB-BASED HEALTH ASSESSMENT MODEL FOR A SENSOR NETWORK

The new constructed health assessment model consists of a missing data compensation model and a health state assessment model.

In the BRB-based missing data compensation model, multiple belief rules exist and the kth belief rule can be expressed as

$$\begin{aligned} B_k :\ & \text{If } x_i(1) \text{ is } A_1^k \wedge x_i(2) \text{ is } A_2^k \cdots \wedge x_i(t-1) \text{ is } A_{t-1}^k, \\ & \text{Then } x_i(t) \text{ is } \left\{(D_1, \beta_{1,k}), \ldots, (D_N, \beta_{N,k})\right\} \\ & \text{With rule weight } \theta_k, \text{ characteristic weight} \\ & \times \delta_1, \delta_2, \ldots, \delta_{t-1} \end{aligned} \quad (2)$$

where x_i is the network characteristic and the input characteristics of the missing data compensation model are the historical data of the ith characteristic. A_i^k ($i = 1, \ldots, t-1$, $k = 1, \ldots, L$) is the reference value of the ith network characteristic in the kth rule. $\beta_{j,k}$ ($j = 1, \ldots, N$, $k = 1, \ldots, L$) is the belief degree of the jth grade D_j. $\delta_1, \delta_2, \ldots, \delta_{t-1}$ are the weights of the characteristics used in the kth rule. θ_k denotes the rule weight of the kth belief rule. It should be noted that in the belief rule of the constructed model, the input characteristics can be the historical data at any point in time. For example, $x_i(t-2)$ and $x_i(t-1)$ can be used as the inputs to the missing data compensation model [19], [20].

After the missing data are compensated, the health state of the sensor network can be assessed. The health assessment model then is developed based on BRB, and the jth belief rule can be indicated as

$$\begin{aligned} E_k :\ & \text{If } x_1(t) \text{ is } C_1^k \wedge x_2(t) \text{ is } C_2^k \cdots \wedge x_M(t) \text{ is } C_M^k, \\ & \text{Then } H(t) \text{ is } \left\{(H_1, \varsigma_{1,k}), \ldots, (H_F, \varsigma_{F,k})\right\} \\ & \text{With rule weight } \vartheta_k, \text{ characteristic weight} \\ & \times \nu_1, \nu_2, \ldots, \nu_M \end{aligned} \quad (3)$$

where $H(t)$ is the estimated health state of the sensor network at time t. $x_1(t), x_2(t), \ldots, x_M(t)$ represent the M characteristics of the sensor network, and $\nu_1, \nu_2, \ldots, \nu_M$ are the corresponding weights. $C_1^k, C_2^k, \ldots, C_M^k$ are the reference values of the characteristics in the kth rule. $H_1, \ldots, H_F$ denote the health degrees and $\varsigma_{1,k}, \ldots, \varsigma_{F,k}$ are their corresponding belief degrees in the kth rule. ϑ_k is the rule weight.

The structure of the developed health assessment model is shown in Fig. 1.

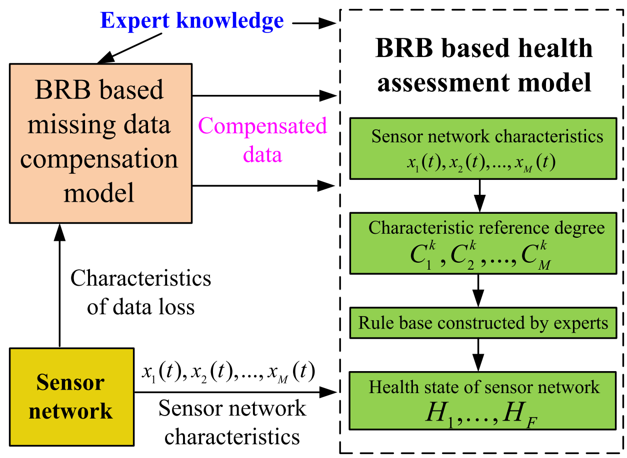

FIGURE 1. The BRB-based health state assessment model.

III. INFERENCE OF THE HEALTH ASSESSMENT MODEL FOR A SENSOR NETWORK

To accurately estimate the health state of a sensor network, a health assessment model using a BRB is constructed with a missing data compensation model and a health assessment model. In Subsection 3.1, the BRB-based missing data compensation model is constructed first, followed by the health state assessment model in 3.2. In Subsection 3.3, an optimization model based on the P-CMA-ES algorithm is proposed to address the influence of the uncertainty and ambiguity of expert knowledge. The modelling process of the new health assessment model is presented in Subsection 3.4.

A. BRB-BASED MISSING DATA COMPENSATION MODEL

This subsection introduces the construction of the BRB-based missing data compensation model, which is to ensure the completeness of the characteristics.

In the model, multiple belief rules exist and the kth rule can be expressed with Eq. (2). The model aims to estimate the lost data using historical information. The modelling process includes the following steps.

Step 1: Unify the formats of the historical data.

Once the historical data are available, they can be transformed into the matching degree by using the formula:

$$m_j^i = \begin{cases} \dfrac{A_{i(k+1)} - x_i^*}{A_{i(k+1)} - A_{ik}}, & j = k \text{ if } A_{ik} \leq x_i^* \leq A_{i(k+1)} \\ \dfrac{x_i^* - A_{ik}}{A_{i(k+1)} - A_{ik}}, & j = k+1 \\ 0, & j = 1, 2, \ldots |x_i|, j \neq k, k+1 \end{cases} \tag{4}$$

where m_j^i is the matching degree to the jth rule at time i. A_{ik} and $A_{i(k+1)}$ are the reference points in the kth rule and the $(k+1)$th rule, respectively. x_i^* represents the input to the missing data compensation model and $|x_i|$ is the number of the rules consisting of the characteristic data at time i [21].

Then, the matching degree of the input characteristic to the belief rule can be calculated by using the formula:

$$\bar{\delta}_i = \frac{\delta_i}{\max\limits_{i=1,\ldots,T_k} \{\delta_i\}}, \quad 0 \leq \bar{\delta}_i \leq 1 \tag{5}$$

$$m_k = \prod_{i=1}^{T_k} (m_k^i)^{\bar{\delta}_i} \tag{6}$$

where m_k is the matching degree of the input characteristics to the kth rule. $\bar{\delta}_i$ represents the relative weight of the historical data at time instant i. T_k denotes the number of input characteristics in the kth rule [22], [23].

Step 2: Obtain the activation weight of the belief rule.

With the historical data available, the belief rules will be active in different degrees and the activation weight can be calculated using the formula:

$$w_k = \frac{\theta_k m_k}{\sum_{l=1}^{L} \theta_l m_l}, \quad k = 1, \ldots, L \tag{7}$$

where w_k is the activation weight of the kth rule. θ_k denotes the rule weight of the kth rule. L is the number of the belief rule in the constructed model.

Step 3: Aggregate the activated belief rule and generate final output.

The output of a belief rule represents the belief degree of the estimated output in different degrees. The output of different belief rules cannot be aggregated directly due to the different activation weights of the belief rules The final output can be generated by the evidence reasoning (ER) algorithm shown as follows [24], [25]:

$$\beta_n = \frac{\mu[\prod\limits_{k=1}^{L} (w_k \beta_{n,k} + 1 - w_k \sum\limits_{j=1}^{N} \beta_{j,k}) - \prod\limits_{k=1}^{L} (1 - w_k \sum\limits_{j=1}^{N} \beta_{j,k})]}{1 - \mu[\prod\limits_{k=1}^{L} (1 - w_k)]} \tag{8}$$

$$\mu = [\sum_{n=1}^{N} \prod_{k=1}^{L} (w_k \beta_{n,k} + 1 - w_k \sum_{j=1}^{N} \beta_{j,k}) - (N-1) \times \prod_{k=1}^{L} (1 - w_k \sum_{j=1}^{N} \beta_{j,k})]^{-1} \tag{9}$$

where β_n is the final belief degree of the nth reference grade D_n. It should be noted that the output belief degree should satisfy the constraint $\sum\limits_{n=1}^{N} \beta_n \leq 1$.

Then, the estimated missing data of the ith characteristic at time instant t can be obtained using the following equation:

$$u(x_i(t)) = \sum_{n=1}^{N} u(D_n) \beta_n \tag{10}$$

where $u(x_i(t))$ is the estimated missing data. $u(D_n)$ is the utility of the nth reference grade D_n. Note that in the missing data compensation model, the utility of the reference grade and reference degree of the characteristics are all provided by experts.

Remark 1: In the modelling process of the BRB-based missing data compensation model, the value and number of the reference points of characteristics for the sensor network, the initial model structure and the parameters are all determined by experts. This is a process of expert knowledge fusion. The greatest advantage of experts is that they can consider the whole working process of the sensor network comprehensively and thus can address the data fluctuation caused by environmental interference.

B. BRB-BASED HEALTH ASSEMENT MODEL FOR A SENSOR NETWORK

After the missing data are compensated for, the health state of the sensor network can be assessed by the developed model based on BRB.

In the BRB-based health assessment model, as shown in Eq. (3), its input is the observation data and compensated data of the characteristics, and its output is the health state of the sensor network. The inference process of the health assessment model is similar to that of the missing data compensation model, and it can be summarized in following three steps.

Step 1: Calculate the matching degree of the observation data to the belief rule.

When the observation data of network characteristics are all available, their matching degree to the reference degree can be calculated using

$$\varpi_j^l = \begin{cases} \dfrac{C_{l(k+1)} - x_l^*}{C_{l(k+1)} - C_{lk}}, & j = k \text{ if } C_{lk} \leq x_l^* \leq C_{l(k+1)} \\ \dfrac{x_l^* - C_{lk}}{C_{l(k+1)} - A_{lk}}, & j = k+1 \\ 0, & j = 1, 2, \ldots |x_l|, j \neq k, k+1 \end{cases} \tag{11}$$

where ϖ_j^l is the matching degree of the jth rule to the lth network characteristic. C_{lk} and $C_{l(k+1)}$ are the reference points of the lth network characteristic in the kth rule and the $(k+1)$th rule respectively. $|x_l|$ is the number of the belief rule that contains the lth network characteristic.

Then, the matching degree of the input network characteristics with the belief rule can be obtained by the following formula:

$$\overline{\nu}_i = \frac{\nu_i}{\max\limits_{i=1,\ldots,M}\{\nu_i\}}, \quad 0 \leq \overline{\nu}_i \leq 1 \tag{12}$$

$$\varpi_k = \prod_{i=1}^{M}(\varpi_k^i)^{\bar{\nu}_i} \tag{13}$$

where ϖ_k is the matching degree of the input network characteristics with the kth rule. $\overline{\nu}_i$ is the relative weight of the ith input network characteristic.

Step 2: Obtain the activation weight of the belief rule.

After the matching degree of each belief rule is calculated, the effectiveness of the input network characteristics of the belief rule can be represented by the activation weight calculated by using the formula:

$$\psi_k = \frac{\vartheta_k \varpi_k}{\sum_{l=1}^{L}\vartheta_l \varpi_l}, \quad k = 1, \ldots, L_H \tag{14}$$

where ψ_k is the activation weight of the kth belief rule. ϑ_k represents the weight of the kth belief rule.

Step 3: Aggregate the active belief rules by the ER algorithm.

Based on the activation weight of the belief rules, the estimated health state of the sensor network can be calculated by using the formula [11], [14]:

$$\varsigma_f = \frac{\mu[\prod\limits_{k=1}^{L_H}(\psi_k\varsigma_{f,k}+1-\psi_k\sum\limits_{j=1}^{F}\varsigma_{j,k})-\prod\limits_{k=1}^{L_H}(1-\psi_k\sum\limits_{j=1}^{F}\varsigma_{j,k})]}{1-\xi[\prod\limits_{k=1}^{L_H}(1-\psi_k)]} \tag{15}$$

$$\xi = [\sum_{f=1}^{F}\prod_{k=1}^{L_H}(\psi_k\varsigma_{f,k}+1-\psi_k\sum_{j=1}^{F}\varsigma_{j,k})-(F-1) \times \prod_{k=1}^{L_H}(1-\psi_k\sum_{j=1}^{F}\varsigma_{j,k})]^{-1} \tag{16}$$

where ς_f is the final belief degree of the fth health state grade. L_H denotes the number of the belief rule in the health assessment model.

Then, the final estimated health state can be calculated by the following formula:

$$H(t) = \sum_{f=1}^{F}u(H_f)\varsigma_f \tag{17}$$

where $H(t)$ is the health state of the sensor network generated by the constructed model. $u(H_f)$ represents the utility of the fth health state grade.

Remark 2: The modelling processes of the missing data compensation model and the health assessment model are similar. The difference between the two models is the physical meaning of the parameters. This is because of the interpretability of the BRB model. In the modelling process, different parameters are given different physical meaning and their constraints are different.

Remark 3: It should be noted that the BRB-based missing data compensation model is used to estimate the missing data and the BRB health assessment model is applied to assess the health state of the sensor network. That is, the BRB-based compensation model solves the problem of data loss while the BRB-based health assessment model solves the problems of the lack of a sample containing a great number of values and a complex system. Thus, the new proposed can solve the problems concluded in Subsection II-A.

C. OPTIMIZATION MODEL FOR THE HEALTH ASSESSENT MODEL

The BRB model is one of the expert systems whose initial structure and parameters are given by experts. In this paper, the missing data compensation model and the health assessment model are both built on BRB. Due to the uncertainty and ambiguity of the expert knowledge, the initial missing data compensation model cannot estimate the lost data accurately and the initial health assessment model cannot assess the health state of the sensor network. Therefore, an optimization model is developed based on P-CMA-ES.

The mean square error (MSE) is an important way of representing the accuracy of the model and is calculated using the error between the estimated model output and actual model output. The MSE can be calculated by using the following formula:

$$MSE = \frac{1}{T}\sum_{t=1}^{T}(output_{estimated} - output_{actual})^2 \tag{18}$$

where T is the number of observation data. $output_{estimated}$ and $output_{actual}$ represent the model output and actual model output, respectively.

First, to ensure the interpretability of the missing data compensation model, some constraints should be given as follows.

$$0 \leq \theta_k \leq 1, \quad k = 1, 2, \ldots L \tag{19}$$

$$0 \leq \delta_i \leq 1, \quad i = 1, \ldots, t-1 \tag{20}$$

$$0 \leq \beta_{n,k} \leq 1, \quad n = 1, .., N, \quad k = 1, 2, \ldots L \tag{21}$$

$$\sum_{n=1}^{N}\beta_{n,k} \leq 1, \quad k = 1, 2, \ldots, L \tag{22}$$

The optimization model of the missing data compensation model can be represented as

$$\begin{aligned} &\min MSE(\theta_k, \beta_{n,k}, \delta_i) \\ &\text{s.t.} \\ &\quad \text{Eqs. } (19) - (22) \end{aligned} \tag{23}$$

It should be noted that the estimated output of the missing data compensation model is calculated by using Eq. (10).

Then, similar to that of the missing data compensation model, the optimization goal of the optimization model of the health assessment model is to minimize the error between the estimated health state of sensor network and that of the actual network. The optimization model of the health assessment model for the sensor network is as follows [2], [3].

$$\min MSE(\vartheta_k, \varsigma_{f,k}, \nu_i) \tag{24}$$

$$\text{s.t.} \quad 0 \leq \vartheta_k \leq 1, \quad k = 1, 2, \ldots L_H \tag{25}$$

$$0 \leq \nu_i \leq 1, \quad i = 1, \ldots, M \tag{26}$$

$$0 \leq \nu_{f,k} \leq 1, \quad f = 1, .., F, \ k = 1, 2, \ldots L_H \tag{27}$$

$$\sum_{f=1}^{F} \nu_{f,k} \leq 1, \quad k = 1, 2, \ldots, L_H \tag{28}$$

where the estimated output of the health assessment model is generated by using Eq. (17).

In the optimization models of the missing data compensation model and health assessment model, the P-CMA-ES algorithm is selected as the optimization algorithm, where the optimization parameters are the output belief degree of the belief rule, characteristic weight and rule weight. The iteration in the optimization algorithm is determined by experts according to the amount of observation data and the optimization parameters.

D. MODELLING PROCESS OF THE DEVELOPED HEALTH ASSESSMENT MODEL

In this subsection, the modelling process of the developed health assessment model is presented. It comprises the missing data compensation and health state assessment. The detailed inference process can be summarized as follows.

Step 1: Select the key characteristics of the sensor network. In the BRB-based health assessment model, the input sensor characteristics determine the model structure and initial parameters. In addition, the model complexity and accuracy have direct correlations with the input sensor characteristics. Thus, the key characteristics should be selected by experts first.

Step 2: Estimate the missing data of the network characteristics. Based on the analysis of the sensor network, the correct amount of the historical data can be selected by experts and the missing data compensation model can be constructed by using Eq. (2).

Step 3: Train the missing data compensation model and the health assessment model. Based on the historical data of the sensor network, the two constructed models can be trained by the proposed optimization models. The actual output of the missing data compensation model is generated by the truncation of complete historical data sets, and the actual output of the health assessment model is determined by experts according to the network principles.

Step 4: Test the developed health assessment model. After the training of the constructed models, the optimized models can be tested by using the historical data sets. It should be noted that the missing data compensation model is the foundation of the health assessment model, which is applied to ensure the integrity of the observation data.

IV. CASE STUDY

To illustrate the effectiveness of the health assessment model for sensor network, a case study is conducted and reported in this section.

A. PROBLEM FORMULATION FOR THE HEALTH ASSESSMENT OF A SENSOR NETWORK

A sensor network is used to monitor the system information of a complex system. The basis of the system reliability is to ensure the reliability of the sensor network. Therefore, it is important to assess the health state of the sensor network. In this paper, the sensor network is applied to monitor the working state of the liquefied natural gas (LNG) storage tank built in Hainan province, China.

The LNG storage tank is located near the South China Sea. Due to the disturbance factors of the seaside, the observation data gathered by the sensor network is influenced and less observation data is available. In addition, the sensor network is connected wirelessly, which may cause data loss. Moreover, multiple factors influence the health state of the sensor network, which increases the difficulty for experts to provide accurate information. Therefore, to solve these problems and improve the estimation accuracy of the sensor network, a BRB-based missing data compensation model and a BRB-based health assessment model are developed.

B. CONSTRUCTION OF THE MISSING DATA COMPENSATION MODEL

In the case study, the two characteristics of available range (AR) and failure rate (FR) are selected as the key characteristics of the sensor network. For these two characteristics, influenced by the disturbance factors in engineering practice, some observation data have been lost, for which a BRB-based missing data compensation model is constructed.

Multiple belief rules exist in the compensation model and the kth rule can be expressed as

$$\begin{aligned} B_k : &\text{ If } x_i(t-2) \text{ is } A_1^k \wedge x_i(t-1) \text{ is } A_2^k, \\ &\text{Then } x_i(t) \text{ is } \left\{ \left(D_1, \beta_{1,k}\right), \ldots, \left(D_{N_i}, \beta_{N,k}\right) \right\} \\ &\text{With rule weight } \theta_k, \text{ characteristic weight} \\ &\times \delta_1, \delta_2, i = 1, 2 \end{aligned} \tag{29}$$

In the above model, with the consideration of both model complexity and accuracy, the historical data at time $t-1$ and $t-2$ are selected as two input attributes of the BRB. As to the reference point of two characteristics, four reference points and five reference points are selected for AR and FR, respectively. In addition, four output degrees and five output degrees are given in the missing data compensation model for AR and FR respectively. That is, $N_1 = 4$ and $N_2 = 5$. It should be noted that the reference points and the output degree are the same in AR and FR.

TABLE 1. The reference points and values for *AR*.

Reference point	L	M	SH	H
Reference value	3.12	9.38	31.24	65.63

TABLE 2. The reference points and values for *FR*.

Reference point	L	SL	M	SH	H
Reference value	0.003	0.03	0.045	0.06	0.0944

TABLE 3. Initial missing data compensation model for *AR*.

No.	Rule weight	Attributes		Output distribution
		$t-2$	$t-1$	$\{L, M, SH, H\}$
1	1	L	L	(1 0 0 0)
2	1	L	M	(0.7 0.3 0 0)
3	1	L	SH	(0.6 0.4 0 0)
4	1	L	H	(0.5 0.5 0 0)
5	1	M	L	(0.65 0.35 0 0)
6	1	M	M	(0.3 0.7 0 0)
7	1	M	SH	(0.2 0.8 0 0)
8	1	M	H	(0.1 0.9 0 0)
9	1	SH	L	(0 0.7 0.3 0)
10	1	SH	M	(0 0.5 0.5 0)
11	1	SH	SH	(0 0.2 0.8 0)
12	1	SH	H	(0 0 1 0)
13	1	H	L	(0 0.3 0.7 0)
14	1	H	M	(0 0 0.3 0.7)
15	1	H	SH	(0 0 0.1 0.9)
16	1	H	H	(0 0 0 1)

The reference points and output values of AR and FR are given by experts as shown in Table 1 and Table 2 respectively. Then, according to Eq. (2), the initial missing data compensation model for AR and FR can be constructed as shown in Table 3 and Table 4. In Table 1 and Table 2, L, SL, M, SH and H represent low, slightly low, medium, slightly high, and high, respectively.

C. CONSTRUCTION OF THE HEALTH ASSESSMENT MODEL FOR THE SENSOR NETWORK

With the compensated data, the health state of the sensor network can be estimated using the health assessment model.

The reference points of the two characteristics of the sensor network can be determined by experts. In this section, the reference points of two characteristics are the same as those in the missing data compensation model. The output degrees of the health state of the sensor network are given by experts, the three degrees being low (L), medium (M) and high (H). Their reference points are shown in Table 5. The belief rules in the health assessment model can be expressed as

$$\begin{aligned} E_k &: \text{If } AR(t) \text{ is } C_1^k \wedge FR(t) \text{ is } C_2^k, \\ &\quad \text{Then } H(t) \text{ is } \left\{\left(H_1, \varsigma_{1,k}\right), \left(H_2, \varsigma_{2,k}\right), \left(H_3, \varsigma_{3,k}\right)\right\} \\ &\quad \text{With rule weight } \vartheta_k, \text{characteristic weight } \nu_1, \nu_2 \end{aligned} \tag{30}$$

TABLE 4. Initial missing data compensation model for *FR*.

No.	Rule weight	Characteristic		Output distribution
		$t-2$	$t-1$	$\{L, SL, M, SH, H\}$
1	1	L	L	(1 0 0 0 0)
2	1	L	SL	(0.7 0.3 0 0 0)
3	1	L	M	(0.6 0.4 0 0 0)
4	1	L	SH	(0.5 0.5 0 0 0)
5	1	L	H	(0.65 0.35 0 0 0)
6	1	SL	L	(0.3 0.7 0 0 0)
7	1	SL	SL	(0.2 0.8 0 0 0)
8	1	SL	M	(0.1 0.9 0 0 0)
9	1	SL	SH	(0 0.7 0.3 0 0)
10	1	SL	H	(0 0.5 0.5 0 0)
11	1	M	L	(0 0.2 0.8 0 0)
12	1	M	SL	(0 0 1 0 0)
13	1	M	M	(0 0 0.3 0.7 0)
14	1	M	SH	(0 0 0.2 0.8 0)
15	1	M	H	(0 0 0 1 0)
16	1	H	L	(0 0 0 0.8 0.2)
17	1	H	SL	(0 0 0 1 0)
18	1	H	M	(0 0 0 0.8 0.2)
19	1	H	SH	(0 0 0 0.9 0.1)
20	1	H	H	(0 0 0 1 0)
21	1	L	L	(0 0 0 0.8 0.2)
22	1	L	SL	(0 0 0 0.6 0.4)
23	1	L	M	(0 0 0 0.4 0.6)
24	1	L	SH	(0 0 0 0.2 0.8)
25	1	L	H	(0 0 0 0 1)

TABLE 5. Reference point of output degree.

Reference point	L	M	H
Reference value	0	0.5	1

In addition, according to Table 1 and Table 2, there are 20 belief rules. The parameters can be determined by experts with Eq. (3). The initial health state assessment model is shown in Table 6.

D. TRAINING AND TESTING PART OF THE DEVELOPED MODEL

In the experiment, 515 observation data are gathered, and 250 observation data are randomly selected to be applied as training data for the missing data compensation model for AR and FR. In the P-CMA-ES algorithm, the output belief degree, rule weight and characteristic weight are used as training parameters. In the missing data compensation model for AR and FR, 82 and 152 optimization parameters exist respectively; in the health assessment model for sensor network, there are 82 optimization parameters. In the optimized missing data compensation model for AR and FR, and the health assessment model, the generation numbers are set to 200, 200 and 300 respectively.

TABLE 6. Initial health assessment model for sensor network.

No.	Rule weight	Characteristic		Output distribution
		AR	*FR*	{*L*, *M*, *H*}
1	1	*L*	*L*	(1 0 0)
2	1	*L*	*SL*	(0.7 0.3 0)
3	1	*L*	*M*	(0.6 0.4 0)
4	1	*L*	*SH*	(0.5 0.5 0)
5	1	*L*	*H*	(0.65 0.35 0)
6	1	*M*	*L*	(0.3 0.7 0)
7	1	*M*	*SL*	(0.2 0.8 0)
8	1	*M*	*M*	(0.1 0.9 0)
9	1	*M*	*SH*	(0 0.7 0.3)
10	1	*M*	*H*	(0 0.5 0.5)
11	1	*SH*	*L*	(0.2 0.8 0)
12	1	*SH*	*SL*	(0 1 0)
13	1	*SH*	*M*	(0 0.8 0.2)
14	1	*SH*	*SH*	(0 1 0)
15	1	*SH*	*H*	(0 0.8 0.2)
16	1	*L*	*L*	(0 0.9 0.1)
17	1	*L*	*SL*	(0 1 0)
18	1	*L*	*M*	(0 0.8 0.2)
19	1	*L*	*SH*	(0 0.6 0.4)
20	1	*L*	*H*	(0 0.4 0.6)

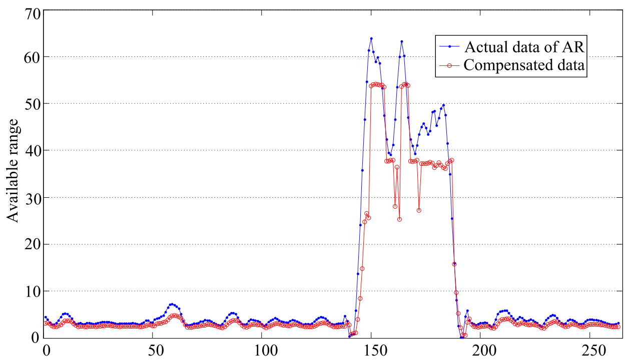

FIGURE 2. Compensated observation data of *AR*.

In the training parts of the missing data compensation models for *AR* and *FR*, the complete data are selected as the training data and there is no lost data. Missing data exist and they are compensated by the optimized missing data compensation model. The estimated outputs of *AR* and *FR* are shown in Fig. 2 and Fig. 3 respectively. As shown in Fig. 2 and Fig. 3, the constructed models can estimate the missing data of *AR* and *FR* accurately. Compared with the missing compensation model for *FR*, the estimation accuracy of that for *AR* is lower, especially if the state of the network is changing a lot. This is due to more factors affecting the characteristic *AR*. In addition, the optimized missing data compensation model for *AR* and *FR* are shown in

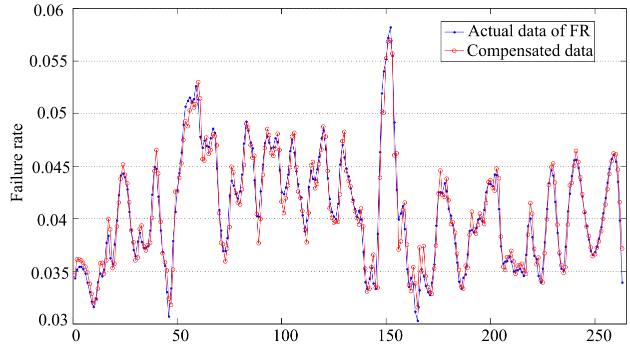

FIGURE 3. Compensated observation data of *FR*.

TABLE 7. Optimized missing data compensation model for *AR*.

No.	Rule weight	Attributes		Output distribution
		$t-2$	$t-1$	{*L*, *M*, *SH*, *H*}
1	0.8316	*L*	*L*	(0.9978 0.0000 0.0031 0.0000)
2	0.0072	*L*	*M*	(0.0235 0.2545 0.4207 0.3013)
3	0.2674	*L*	*SH*	(0.2133 0.6108 0.1127 0.0633)
4	0.4298	*L*	*H*	(0.2655 0.3356 0.1351 0.2639)
5	0.5638	*M*	*L*	(0.1399 0.3479 0.3140 0.1982)
6	0.6562	*M*	*M*	(0.6748 0.1443 0.0999 0.0809)
7	0.9976	*M*	*SH*	(0.3610 0.4185 0.1795 0.0409)
8	0.1617	*M*	*H*	(0.0639 0.0797 0.4170 0.4395)
9	0.2354	*SH*	*L*	(0.2093 0.1954 0.1991 0.3961)
10	0.4863	*SH*	*M*	(0.3706 0.3099 0.1158 0.2037)
11	0.0041	*SH*	*SH*	(0.2349 0.0932 0.4675 0.2044)
12	0.9458	*SH*	*H*	(0.3053 0.3954 0.1969 0.1024)
13	0.3434	*H*	*L*	(0.2634 0.0960 0.3611 0.2795)
14	0.5037	*H*	*M*	(0.2245 0.4765 0.1807 0.1182)
15	0.1384	*H*	*SH*	(0.0930 0.5255 0.2749 0.1066)
16	0.6671	*H*	*H*	(0.2848 0.2335 0.3066 0.1751)

Table 7 and Table 8 respectively. Therefore, based on the constructed missing data compensation model for *AR* and *FR*, the missing data can be accurately compensated.

Based on the compensated data of *AR* and *FR*, the health assessment model for the sensor network can be optimized and tested. In the health assessment model, 250 observation data are applied. A total of 125 observation data points are selected as the training data and the rest of the observation data are used as the testing data. According to the compensated data, the optimized health assessment model is shown in Table 9, and the estimated health state of the optimized health assessment model is shown in Fig. 4. It can be seen that the optimized health assessment model can accurately estimate the health state of the sensor network. The MSE of the optimized health assessment model is 0.0142. Fifty runs of the experiment are conducted. The mean of the MSEs is 0.0919 and the variance of the MSEs is 0.0138.

TABLE 8. Optimized missing data compensation model for *FR*.

No.	Rule weight	Characteristic $t-2$	Characteristic $t-1$	Output distribution $\{L, SL, M, SH, H\}$
1	0.5331	*L*	*L*	(0.0363 0.1536 0.1381 0.5365 0.1355)
2	0.2843	*L*	*SL*	(0.3700 0.0385 0.3933 0.0634 0.1347)
3	0.5501	*L*	*M*	(0.0586 0.1340 0.2630 0.3871 0.1573)
4	0.4842	*L*	*SH*	(0.0652 0.0463 0.2886 0.2370 0.3630)
5	0.9050	*L*	*H*	(0.0483 0.2931 0.1456 0.3692 0.1439)
6	0.3855	*SL*	*L*	(0.3732 0.0161 0.2500 0.2627 0.0980)
7	0.9668	*SL*	*SL*	(0.8223 0.0310 0.0696 0.0566 0.0204)
8	0.2927	*SL*	*M*	(0.2280 0.4650 0.2471 0.0000 0.0614)
9	0.6600	*SL*	*SH*	(0.1155 0.1970 0.3293 0.0207 0.3375)
10	0.2488	*SL*	*H*	(0.0533 0.1435 0.4641 0.1068 0.2323)
11	0.4892	*M*	*L*	(0.2103 0.0401 0.1295 0.1108 0.5093)
12	0.9183	*M*	*SL*	(0.0400 0.1549 0.2945 0.0287 0.4819)
13	0.1793	*M*	*M*	(0.2746 0.0872 0.2736 0.1726 0.1921)
14	0.6095	*M*	*SH*	(0.0846 0.3596 0.0255 0.2550 0.2753)
15	0.6825	*M*	*H*	(0.4215 0.1921 0.1603 0.1281 0.0980)
16	0.8559	*SH*	*L*	(0.0275 0.1132 0.2075 0.1425 0.5093)
17	0.1421	*SH*	*SL*	(0.0649 0.3374 0.4697 0.0421 0.0859)
18	0.3396	*SH*	*M*	(0.2072 0.0140 0.2925 0.0899 0.3965)
19	0.6243	*SH*	*SH*	(0.0000 0.0117 0.0503 0.1396 0.8024)
20	0.6283	*SH*	*H*	(0.1428 0.0761 0.1293 0.4683 0.1835)
21	0.0239	*H*	*L*	(0.0786 0.3210 0.0696 0.4142 0.1165)
22	0.7028	*H*	*SL*	(0.1086 0.3939 0.2139 0.1127 0.1708)
23	0.1477	*H*	*M*	(0.1959 0.1079 0.0835 0.5508 0.0620)
24	0.0556	*H*	*SH*	(0.0715 0.3855 0.0831 0.1727 0.2873)
25	0.3583	*H*	*H*	(0.0685 0.0877 0.1274 0.5104 0.2061)

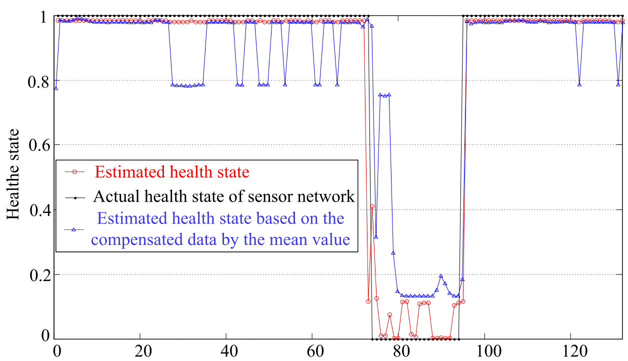

FIGURE 4. Estimated network health state with the developed model.

In this experiment, the input of the health assessment model is the compensated data. That is, wherever the observation data loss occurs, the sensor network can be evaluated based on its historical data. As shown in Fig.4, the blue line is the estimated health state based on the compensated data by the mean value method in engineering practice. It can be shown that the missing data generated by the mean value method cannot accurately assess the health state of the sensor network. The accuracy of the mean value method is greatly affected, especially when health state of the sensor network changes greatly. The reason is that the mean value method applied in current practical system estimates the missing data only based on the historical data. When the health state of the sensor network changes, the observation data of the sensor network changes irregularly. Thus, in the missing data compensation process, the expert knowledge should be applied to take into account the entire cycle of the sensor network. Moreover, due to the uncertainty and ambiguity of the expert knowledge, the observation data and the optimization model both should be applied to adjust the initial model constructed by experts.

TABLE 9. Optimized health assessment model for the sensor network.

No.	Rule weight	Characteristic *AR*	Characteristic *FR*	Output distribution $\{L, M, H\}$
1	0.1728	*L*	*L*	(0.0218 0.5859 0.3923)
2	0.9946	*L*	*SL*	(0.6016 0.3860 0.0124)
3	0.0412	*L*	*M*	(0.3810 0.3015 0.3175)
4	0.0313	*L*	*SH*	(0.6021 0.2254 0.1725)
5	0.7107	*L*	*H*	(0.2523 0.1534 0.5943)
6	0.2760	*M*	*L*	(0.3073 0.5902 0.1025)
7	0.0480	*M*	*SL*	(0.2619 0.4722 0.2659)
8	0.3215	*M*	*M*	(0.3463 0.6110 0.0427)
9	0.1318	*M*	*SH*	(0.1899 0.1590 0.6511)
10	0.8283	*M*	*H*	(0.0339 0.5602 0.4059)
11	0.0217	*SH*	*L*	(0.1108 0.8146 0.0746)
12	0.0000	*SH*	*SL*	(0.0106 0.8337 0.1557)
13	0.7394	*SH*	*M*	(0.0011 0.0000 0.9989)
14	0.0098	*SH*	*SH*	(0.7886 0.0317 0.1797)
15	0.2863	*SH*	*H*	(0.0046 0.8204 0.1750)
16	0.8640	*L*	*L*	(0.0000 0.1111 0.8889)
17	0.0270	*L*	*SL*	(0.1646 0.6099 0.2255)
18	0.0206	*L*	*M*	(0.5050 0.4108 0.0842)
19	0.8360	*L*	*SH*	(0.0034 0.0021 0.9945)
20	0.0574	*L*	*H*	(0.1341 0.6159 0.2500)

V. CONCLUSION

A sensor network is an important means of monitoring a complex system state, and its health state directly correlates with its accuracy. In the health assessment of a sensor network, the lack of observation data, the complexity of the system and the data loss all affect the assessment accuracy. In this paper, to solve these three problems and to estimate the health state accurately, a health assessment model for sensor network is constructed with two parts: the BRB-based missing data compensation model and the BRB-based health assessment model.

There are three innovations in this paper. First, due to the complexity of sensor networks and monitoring methods, observation data cannot be completely gathered, and thus, an accurate model cannot be constructed by experts. These two factors pose challenges for the health assessment model of the sensor network. Therefore, to deal with these problems, a BRB-based health assessment model is constructed in which the quantitative data and qualitative knowledge can both be aggregated. In addition, in the process of data transmission, the environment disturbance factors influence the data transmission efficiency. This further results in the loss of observation data characteristics and the observation data may fluctuate irregularly influenced by the disturbance factors in the environment. Thus, to handle data loss in the health assessment for a sensor network, a BRB-based missing data compensation model is developed in which the historical data and expert knowledge are applied as the inputs and the missing data is the model output. Finally, the BRB model is one of the expert systems and its initial parameters are determined by experts. Due to the uncertainty and ambiguity of expert knowledge, the initial health assessment model cannot accurately estimate the health state. Thus, in this paper, an optimization model based on P-CMA-ES is proposed, which consists of the missing data compensation optimization model and the health assessment compensation model.

In this paper, the health assessment model is constructed based on two parts. However, there is error transfer between the two models and it is not clear where the error comes from. Moreover, some attention should also be paid on the tabulations data to improve the persuasion of the proposed model. These problems leave room for future research.

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