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A new preferential decision mechanism for complex electromechanical equipment based on the belief rule base considering transportation impact

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A preferential decision mechanism for complex electromechanical equipment can effectively improve its reliability during operation. However, due to the high cost of high-precision complex electromechanical equipment and experiments, high-value samples such as those representing suboptimal health or fault conditions are scarce among the large number of samples collected. Expert experience or mechanistic knowledge is often incorporated to supplement modeling efforts. Nevertheless, uncertainties such as fuzziness, ignorance, and randomness exist in expert experience and mechanistic knowledge. The belief rule base (BRB) is a good choice to address the aforementioned issues, where the uncertain expert knowledge and high-value samples can be combined, simultaneously.

However, traditional BRB cannot consider the influence of high-precision complex electromechanical equipment under complex road conditions. Therefore, this study proposes complex road condition influence factors and, based on this, proposes a BRB model that considers the influence of complex road conditions, called belief rule base-transportation (BRB-t). Finally, the output results of the BRB-t model are ranked to provide a reference for decision-makers to make optimal decisions for different tasks.

Methodology validation. The modeling steps for the BRB-t model proposed in this study, which considers the impact of complex road conditions, are as follows:

$$\begin{aligned} R_k: & \text{ If } x_1(t) \text{ is } A_1^k \wedge x_2(t) \text{ is } A_2^k \wedge \cdots \wedge x_M(t) \text{ is } A_M^k, \\ & \text{then } T \text{ is } \{(D_1, \beta_{1,k}), (D_2, \beta_{2,k}), \cdots, (D_N, \beta_{N,k})\} \\ & \text{with rule weight } \theta_k, \text{ attribute weight } \delta_1, \cdots, \delta_M, \\ & \text{and road condition impact factor } y, \end{aligned} \tag{1}$$

where $x_1(t), \ldots, x_M(t)$ is the monitoring information obtained. $A_1^k, \ldots, A_M^k$ is the reference level corresponding to the indicator. $D_1, \ldots, D_N$ is a fault state. $\beta_{1,k}, \ldots, \beta_{N,k}$ is the fault state feature vector. θ_k is rule weight. $\delta_1, \ldots, \delta_M$ is attribute. y is the complex road condition impact factor.

Part 1. Calculate the complex terrain impact factor y based on the specific transportation conditions of the complex electromechanical equipment being transported. The vibration impact sources of transporting complex electromechanical equipment mainly come from railways and highways, and a standardized complex road condition impact factor y calculation formula is proposed as follows [1]:

$$y = \frac{a_2 - (\beta_1 \times r_1 + \beta_2 \times r_2)}{a_2 - a_1}, \tag{2}$$

where r_1 is road transport mileage and r_2 is railway transport mileage. β_1 is the coefficient corresponding to r_1 and β_2 is the coefficient corresponding to r_2. a_1 and a_2 are the minimum and maximum values of the converted value of the specified transport mileage, respectively.

Part 2. In order to convert multi-source indicators into a unified framework, the following matching conversion method based on indicator reference levels is used:

$$\alpha_j^i = \begin{cases} \frac{R_{i(k+1)} - x_i^*(t)}{R_{i(k+1)} - R_{ik}}, & j = k, \text{if } R_{ik} \leqslant x_i^*(t) \leqslant R_{i(k+1)}, \\ \frac{x_i^*(t) - R_{ik}}{R_{i(k+1)} - R_{ik}}, & j = k+1, \\ 0, & j = 1, 2, \ldots, L', j \neq k, k+1, \end{cases} \tag{3}$$

$$\alpha_k = \prod_{i=1}^{M} (y\alpha_k^i)^{\overline{\delta}_i}, \tag{4}$$

where R_{ik} and $R_{i(k+1)}$ represent the reference levels for the key feature indicators i in rules k and $k+1$, respectively. The reference levels must be determined based on the distribution and type of feature information. $x_i^*(t)$ is the input data. L' is the number of rules after adaptive adjustment of the model. α_j^i denotes the matching degree of the indicator in the jth rule after conversion. α_k is the match of all key feature indicators in the kth rule. $\overline{\delta}_i$ denotes the relative weight size of the indicator.

Part 3. Activate and fuse rule weights using the evidence reasoning (ER) algorithm to determine quality status. Different monitoring information has different utility for different rules, and the rule activation weight w_k can be obtained by

$$w_k = \frac{\hat{\theta}_k \alpha_k}{\sum_{l=1}^{L} \hat{\theta}_l \alpha_l}, \quad k = 1, \ldots, L', \tag{5}$$

where $\hat{\theta}_k$ denotes the weight of the rule in the dynamic adjustment process of the model.

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Then, the output $u(S(x^*))$ of the quality state of the complex electromechanical device is calculated by

$$u(S(x^*)) = \sum_{n=1}^{N} u(D_n)\beta_n \tag{6}$$

with

$$\beta_n = \frac{\mu[\prod_{k=1}^{L'}(w_k\beta_{j,k}+1-w_k\sum_{j=1}^{N}\beta_{j,k})-\prod_{k=1}^{L'}(1-w_k\sum_{j=1}^{N}\beta_{j,k})]}{1-\mu[\prod_{k=1}^{L'}(1-w_k)]}, \tag{7}$$

$$\begin{aligned}\mu = \Bigg[&\sum_{n=1}^{N}\prod_{k=1}^{L'}\left(w_k\beta_{n,k}+1-w_k\sum_{j=1}^{N}\beta_{j,k}\right)\\ &-(N-1)\prod_{k=1}^{L'}\left(1-w_k\sum_{j=1}^{N}\beta_{j,k}\right)\Bigg]^{-1},\end{aligned} \tag{8}$$

where β_n is the integrated belief degree of the nth quality state of the complex electromechanical device. N is the number of quality states. β_N denotes the residual belief degree generated by the uncertain expert knowledge. $u(S(x^*))$ is the preferential decision-making mechanisms output.

Part 4. Reasons for adding model optimization are as follows. The initial model of BRB-t is given by experts. However, due to the limitation of experts' cognitive ability, there are certain deviations in the parameters of the initial BRB-t model. This leads to its actual modeling effect not meeting the requirements. Therefore, it is essential to construct an optimization model. This model will optimize the BRB-t model parameters and achieve the integration of data and knowledge at the same time.

$$\text{minMSE}(\theta_k, \beta_{n,k}, \overline{\delta}_i) \tag{9}$$

with

$$0 \leqslant \theta_k \leqslant 1, \tag{10}$$

$$0 \leqslant \overline{\delta}_i \leqslant 1, \quad i = 1,2,...,M, \tag{11}$$

$$0 \leqslant \beta_{n,k} \leqslant 1, \quad n = 1,2,...,M,\ k = 1,2,...,L', \tag{12}$$

$$\sum_{n=1}^{M}\beta_{n,k} \leqslant 1, \quad k = 1,2,...,L', \tag{13}$$

where the mean square error (MSE) is applied as the modeling accuracy of BRB-t.

Part 5. Preferential decision-making based on the BRB-t model. After completing a quality assessment that considers the impact of complex road conditions for multiple complex electromechanical devices, the devices are ranked based on their quality. This ranking provides decision-makers with recommendations for preferential decision-making.

Sensitivity analysis aims to quantify the impact of different transport factors on performance. The transport factors with higher impact should be designed and improved. Sensitivity analysis is expressed as a partial derivative of β_n to y as follows:

$$\frac{\partial\beta_n}{\partial y} = \prod_{i=1}^{M}\bar{\delta}_i\left(y\alpha_k^i\right)^{\bar{\delta}_k^i-1}\alpha_k^i. \tag{14}$$

Table 1 Comparative studies with other mechanisms.

Method	MSE	Stability
BRB-t	0.0369	7.32e−4
PCA-BPNN [2]	0.0884	1.4022e−3
Hidden Markov model [3]	0.0836	1.2087e−3
Lian et al. [4]	0.0902	1e−3
FIS & PSO [5]	0.1005	1.09176e−3

Experiments. An inertial navigation system (INS) is used as the experimental object. Considering the complexity of the model and the size of the observed data, four reference points are selected for the three sensors in the experiment, i.e., large, good, fair and poor. INS has four quality states, which can be expressed as excellent, good, moderate and awful. The present invention collected 800 sets of data during the experiment and 400 sets were randomly selected from the dataset as training data.

The comparison of MSE and stability between BRB-t and other advanced methods is shown in Table 1. Compared with principal component analysis-back propagation neural network (PCA-BPNN), BRB-t has more advantages in terms of interpretability and transparency [2]. Compared with the hidden Markov model (HMM), BRB-t has advantages such as input data processing capabilities and explicit expression of output uncertainty [3]. Compared to Lian et al., BRB-t has more advantages in handling complex road conditions [4]. Compared with fuzzy inference system & particle swarm optimization (FIS&PSO), BRB-t has more advantages in terms of uncertainty handling, knowledge representation, and fusion [5]. It can be observed that BRB-t has achieved an MSE improvement of 58.26% compared to PCA-BPNN. Additionally, BRB-t outperforms the hidden Markov model by 55.86% in MSE. When compared to Lian et al., BRB-t exhibits an MSE improvement of 59.09%. Furthermore, BRB-t improves upon FIS & PSO by 63.28% in terms of MSE. Obviously, the BRB-t model possesses relatively significant advantages.

Conclusion. This work addresses the problems of transport impact, lack of fault data and uncertain expert knowledge of complex electromechanical equipment. The calculation method for the influencing factors of complex road conditions is proposed. Then, the BRB-t model considering the influencing factors of complex road conditions is developed. The application scenarios of this article are suitable for complex electromechanical equipment with high reliability and high value, such as rockets and satellites.

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References

1 Li M, Shi Y, Li M, et al. Solving the vehicle routing problem for a reverse logistics hybrid fleet considering real-time road conditions. Mathematics, 2023, 11: 1–19
2 Zhou S, Liu X, Tian Y, et al. Multi-fault diagnosis of district heating system based on PCA-BP neural network. Process Saf Environ Protection, 2024, 186: 301–317
3 Jia Y, Li Y, Xu M, et al. A fault diagnosis scheme for harmonic reducer under practical operating conditions. Measurement, 2024, 227: 114234
4 Lian Z, Zhou Z, Hu C, et al. A belief rule-based performance evaluation model for complex systems considering sensors disturbance. IEEE Trans Rel, 2024, 73: 1245–1257
5 Dieste-Velasco M I. Fault detection in analog electronic circuits using fuzzy inference systems and particle swarm optimization. Alexandria Eng J, 2024, 95: 376–393