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Fault-alarm-threshold optimization method based on interval evidence reasoning

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Dear editor,
Fault alarm threshold is an important parameter of a system used to monitor the condition of industrial equipment. Therefore, reasonably setting the fault alarm threshold and reducing both false negative and positive rate (FNPR) are vital for improving the efficiency of industrial operations and ensuring the safety and reliable operation of equipment.

Thresholds can be optimized using statistics-based, model-based, neural network-based, and fuzzy-based methods in corresponding fields. However, the industrial environment is complex and there may be problems associated with multiple interval uncertainties. A threshold optimization method based on expert knowledge is more effective compared with the methods mentioned above [1–4]; it can solve multi-attribute decision problems with multiple uncertainties. Wang et al. [5] studied the interval uncertainty caused by interval data and interval belief degrees and solved the multi-attribute decision-making problem under interval uncertainty by using a method based on interval evidence reasoning (IER).

A nonlinear optimization model for updating the threshold is constructed by integrating expert knowledge and training data. First, when the initial threshold interval is given, the data and threshold interval are transformed into a unified interval belief framework by using rule-based transformation techniques. Second, a nonlinear optimization model based on IER is proposed to update the threshold. Finally, an optimization objective for obtaining the optimal threshold interval is established through the minimum FNPR method and projection covariance matrix adaptation evolution strategy (P-CMA-ES) algorithm.

Optimization model and problem formulation. The threshold optimization model is shown in Figure 1(a), which consists of two parts. The first part is updating the threshold, which involves iteratively updating the interval threshold by combining the interval threshold and the training data with IER. The second part involves testing the threshold. First, the FNPR of the updated threshold is counted using the test data. Then, within the constraint condition of the initial threshold interval, the threshold interval is found when the FNPR is the lowest. Finally, the interval is output to optimize the threshold. The following three problems need to be resolved when optimizing the threshold based on the IER algorithm.

Problem 1. Because the threshold interval $[y_1, y_2]$ and the training data $x_1, x_2, \ldots, x_L$ are different types of indicators, they cannot be combined directly. According to the IER algorithm, both the threshold interval and training data need to be converted to an interval confidence structure before combining.

Problem 2. The overall interval belief degrees of the new threshold interval can be obtained by

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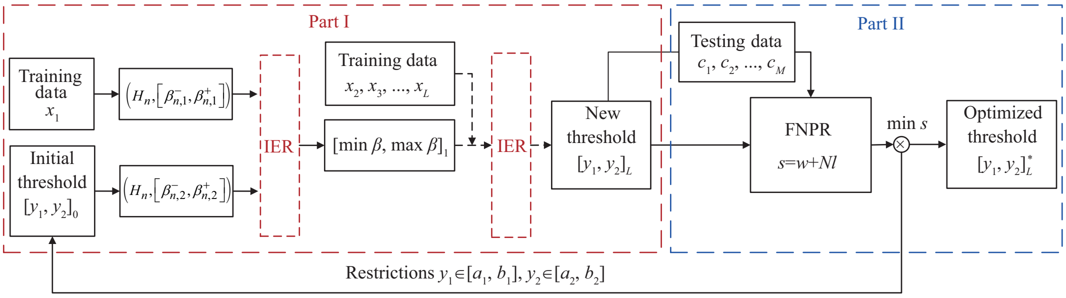

(a)

Method	w (%)	l (%)	s (%)
No optimization	1.5	10.5	12
3σ method	38	0	38
Neural network method	5	5.5	10.5
IER method	6	3	9

(b)

Figure 1 (Color online) (a) Structure of threshold optimization model based on IER; (b) comparison of threshold optimization methods.

solving the nonlinear optimization model

$$\text{Max/Min} \quad \beta_n = \frac{m_n}{1-\bar{m}_H}, \tag{1}$$

where β_n stands for the interval belief degrees of the new threshold relative to the evaluation grades H_n, and m_n, $\bar{m}_H$ denote interval probability masses.

Problem 3. The initial threshold interval $[y_1, y_2]_0$ is optimized to obtain the new threshold $[y_1, y_2]_L$, which has the minimum FNPR. The following threshold optimization model needs to be developed:

$$\min s = w + Nl, \tag{2}$$

where s denotes the FNPR, w denotes the false positive rate, which should not be reported. Conversely, l represents the false negative rate. The value of N depends on the impact of false negative rate on the system.

To solve the above three problems, the interval threshold and indicator data are converted to the interval belief structures of the relative evaluation grades initially, and then the nonlinear optimization model shown in Eq. (1) is built. The overall interval belief degrees are obtained by integrating the interval belief degrees and weight. After the interval belief degrees are converted to the interval threshold, the initial threshold is optimized, according to the optimization model of Eq. (2). Finally, based on the statistical result, the threshold interval with the lowest FNPR is obtained, and threshold optimization is completed. The procedure of the threshold optimization method based on IER can be summarized as follows.

Step 1. Give initial thresholds $[y_1, y_2]_0$ based on equipment specifications, structural characteristics, work environment, provide constraint ranges $y_1 \in [a_1, b_1]$ and $y_2 \in [a_2, b_2]$, and the false negative coefficient N.

Step 2. To use the IER method to update interval threshold, it is necessary to define a set of evaluation grades for the interval threshold and training data. There is a group of evaluation grades defined by experts $H = (H_1, H_2, \ldots, H_n)$. If $[\beta^-_{n,1}, \beta^+_{n,1}]$, $[\beta^-_{n,2}, \beta^+_{n,2}]$ denote the interval belief degrees of interval threshold v_1 and training data v_2 relative to evaluation grades H_n, then the interval belief structures can be expressed as follows:

$$\begin{cases} [y_1, y_2], \\ x_1, x_2, \ldots, x_L, \end{cases} \Leftrightarrow (H_n, [\beta^-_{n,i}, \beta^+_{n,i}]). \tag{3}$$

Step 3. According to Yang et al. [6] and Wang et al. [5], the IER fusion model is constructed as follows:

$$\text{Max/Min} \quad \beta_n = \frac{m_n}{1-\bar{m}_H} \tag{4}$$

$$\text{s.t.} \quad m_n = k\left[\begin{array}{c}\prod_{i=1}^{L}(m_{n,i} + \bar{m}_{H,i} + \tilde{m}_{H,i}) \\ -\prod_{i=1}^{L}(\bar{m}_{H,i} + \tilde{m}_{H,i})\end{array}\right], \tag{5}$$

$$\tilde{m}_H = k\left[\prod_{i=1}^{L}(\bar{m}_{H,i} + \tilde{m}_{H,i}) - \prod_{i=1}^{L}\bar{m}_{H,i}\right], \tag{6}$$

$$\bar{m}_H = k\left[\prod_{i=1}^{L}\bar{m}_{H,i}\right], \tag{7}$$

$$k = \left[\begin{array}{c}\sum_{n=1}^{N}\prod_{i=1}^{L}(m_{n,i} + \bar{m}_{H,i} + \tilde{m}_{H,i}) \\ -(N-1)\prod_{i=1}^{L}(\bar{m}_{H,i} + \tilde{m}_{H,i})\end{array}\right]^{-1}, \tag{8}$$

where $n = 1, 2, 3$ stands for the number of evaluation grades and $i = 1, 2$ stands for the indicators. The interval probability mass $m_{n,i} = [\omega_i\beta_{n,i}^-, \omega_i\beta_{n,i}^+]$, $\bar{m}_{H,i} = 1 - \omega_i$, $\tilde{m}_{H,i} = [\omega_i\beta_{H,i}^-, \omega_i\beta_{H,i}^+]$, satisfies $m_{n,i}^- \leqslant m_{n,i} \leqslant m_{n,i}^+$ and $\sum_{n=1}^{N} m_{n,i} + \bar{m}_{H,i} + \tilde{m}_{H,i} = 1$. Based on the IER algorithm, the training data x_1 and the initial threshold $[y_1, y_2]_0$ are firstly aggregated to obtain the interval belief degree $[\min(\beta_n), \max(\beta_n)]_1$. Then, the other training data $x_2, x_3, \ldots, x_L$ are used to train the last aggregation result $[\min(\beta_n)$, $\max(\beta_n)]_i$, respectively, and the overall interval belief degree $[\min(\beta_n)$, $\max(\beta_n)]_L$ is obtained, which can be equivalently converted to the updated threshold interval $[y_1, y_2]_L$.

Step 4. According to the testing data $c_1, c_2, \ldots, c_M$ and the updated threshold $[y_1, y_2]_L$, the false negative rate l and false positive rate w are calculated, and the value of $s = (w + Nl)$ is obtained.

Step 5. Based on the minimum FNPR model, when the initial threshold satisfies the constraint $y_1 \in [a_1, b_1]$, $y_2 \in [a_2, b_2]$, and the FNPR s caused by the new threshold $[y_1, y_2]_L^*$ is less than g (g is given according to industrial requirements), the new threshold is output, and finally, the interval threshold optimization is completed. For more details on optimization model, please refer to Appendixes A and B.

Experiments. The IER-based threshold optimization method proposed in this study was used to detect leaks in an oil pipeline to verify the effectiveness of the method. This example investigates the alarm threshold optimization of the flowdiff. A total of 300 sets of data are obtained during the critical leak state and normal state. Of these, 200 sets of leak data are selected as false negative test data [7]. According to expert knowledge, a set of evaluation levels: H_1 (normal), H_2 (leak), H_3 (severe leak) are defined. By performing the threshold optimization steps, the optimized alarm threshold interval is obtained.

The comparison of the FNPR obtained using the IER method and those obtained using other methods is shown in Figure 1(b). It can be seen that the threshold interval optimized by the IER method has the smallest value of s, and it is obviously superior to other methods. The effectiveness of the proposed method in solving the threshold optimization problems is verified.

Conclusion. This study aims at the alarm threshold optimization problem in industrial equipment or system condition monitoring. Based on the analysis of model-based, statistical-based, knowledge-based, and other common threshold setting methods, a threshold optimization method based on IER is proposed. This method first transforms the data and the threshold interval into a unified interval belief structure, and then updates the threshold interval by solving a pair of nonlinear optimization models. Finally, the threshold interval is optimized by solving the threshold optimization model, which is based on FNPR. The advantage of the IER method lies in the effective use of expert knowledge and better resolution of data missing, noise, and other interval uncertainties. The effectiveness of the proposed threshold optimization method is validated by using it to detect leaks in an oil pipeline.

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Supporting information Appendixes A and B. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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