Journal of Process Control 113 (2022) 68–79

Contents lists available at ScienceDirect

Journal of Process Control

journal homepage: www.elsevier.com/locate/jprocont

Evidence fusion-based alarm system design considering coarse and fine changes of process variable

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ARTICLE INFO

Article history:
Received 23 September 2021
Received in revised form 18 February 2022
Accepted 18 March 2022
Available online xxxx

Keywords:
Dempster–Shafer theory of evidence
Industrial alarm system
Evidence fusion
Data segmentation

ABSTRACT

In view of the coarse and fine changes of process variable in industrial systems, this paper introduces a univariate alarm design method based on dynamic evidence fusion. Firstly, in order to describe the coarse statistical characteristics of historical sample data, the multi-transition data segmentation based on memory and forgetting strategies and the referential evidential matrix (REM) construction are presented. Secondly, the real-time sample of process variable is transformed into alarm evidence by matching with REM, and then such multiple pieces of alarm evidence continuously acquired in time are fused by evidence reasoning (ER) rule with the interval-valued fusion weights and reliabilities of alarm evidence, so as to accurately adapt the fine change of process variable. Finally, numerical experiment and motor rotor alarm experiment are implemented to validate that the proposed method has better performances than traditional alarm design methods.

1. Introduction

Industrial alarm systems monitor process variables in real time to ensure safe, efficient and continuous operation of industrial equipment [1,2]. The common univariate alarm methods include direct threshold method, deadband, filtering and time delay [3]. Among them, the direct threshold method is to compare sample values of process variable with alarm threshold, once the sample value exceeds the threshold, an alarm will be issued, otherwise no alarm will be issued [4]; The deadband uses high and low alarm thresholds, when the sample value is higher than the high threshold, an alarm is issued, and when the sample value is lower than the low threshold, the alarm is cleared [5]; The time delay only issues an alarm when the sample value exceeds alarm threshold for several consecutive times [6]; Filtering uses moving average or moving variance strategy to process sample values, and then compares the filtered value with threshold [7]. With the increasing complexity of equipment, the influence of interference in operating conditions, and the design constraints of the parameters such as alarm threshold, the performance of these traditional alarm methods are inadequate.

The performance of alarm methods need to be evaluated by corresponding indicators. [8] proposed to use average alarm delay (AAD), false alarm rate (FAR) and missed alarm rate (MAR) as vital evaluation indicators, which have been widely used in alarm methods. Among them, AAD evaluates the punctuality of alarm method when abnormal states occur, while FAR and MAR reflect the accuracy of alarm method in identifying normal/abnormal states. Too high AAD means too little time for on-site disposal, too high FAR and MAR indicate that the performances of alarm method are unsatisfactory.

In order to fully improve the performances of univariate alarm, it is necessary to focus on the coarse and fine changes of process variable, which respectively correspond to two main processes in alarm design: one is data preprocessing of historical sample data at the macroscopic level, and the other is dynamic parameter adjustment at the microscopic level [9,10]. The former is a typical data segmentation problem, and its purpose is to divide historical data into normal/abnormal data segments as the training set via the detected change points (namely the switching points between different normal and abnormal states of process variable), and then to train the parameters such as alarm threshold. In addition to the alarm design scenario, data segmentation is also applicable to process monitoring, fault detection and diagnosis, and other industrial scenarios. The latter is to appropriately adjust the design

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https://doi.org/10.1016/j.jprocont.2022.03.007

parameters with the dynamic change of process variable. In short, the purpose of the former is to mine the coarse statistical characteristics of historical data of process variable, while the latter is to accurately capture the fine change of real-time sample of process variable, and gives necessary response through dynamic parameter adjustment. Further, the main difference between the coarse and fine description of process variable is the usage of temporal information, the coarse description uses the data information of the historical moment, and on this basis, the fine description uses the data information of the current moment.

For the historical data segmentation, hypothesis testing and statistical model are two commonly used methods [11]. The hypothesis testing method requires the data conform to probability distributions, then the data are segmented via statistic strategies [12]. The statistical model method assumes that the data satisfy mathematical statistical laws, then divides the data by statistical indicators [13]. Obviously, these two methods need to give the initial distribution or model structure of process variable in advance, but it is often difficult to accurately obtain this prior information in practice. In addition, these methods are usually good at handling the sample sequence with only one transition between normal and abnormal state, but in practice there are often multiple transitions between normal and abnormal states, where the multiple transitions include one normal state changing to multiple abnormal states, and multiple normal states changing to multiple abnormal states. Therefore, it is necessary to provide methods to solve this complex multi-transition data segmentation problem.

For the dynamic parameter adjustment, deadband, filtering, and time delay methods need to adjust many parameters such as dead zone interval, filter order, delay step and alarm threshold [14]. These traditional methods usually need to get probability density function (PDF) model by fitting of historical data, then the optimal parameters are obtained by offline optimization. On the one hand, PDF hardly describe the dynamic change of data information. On the other hand, after the pivotal parameters are determined offline, it is difficult to make timely adjustments according to the fine change of real-time sample. It probably makes these traditional alarm methods ineffective in practical application.

In fact, the historical data segmentation and dynamic parameter adjustment can be attributed to the analysis and processing of the uncertainty of process variable under the coarse and fine changes essentially. The Dempster–Shafer (DS) theory of evidence originated from Bayesian theory [15], defines the set of normal and abnormal states as a frame of discernment (FoD), and constructs evidence on the power set of FoD. Moreover, it also provides optional evidence combination rules to effectively reduce the uncertainty of process variable through evidence fusion process [16–18]. In addition, the newly developed evidence reasoning (ER) rule clearly recognizes the difference between the fusion weight of evidence and reliability of evidence during fusion process, and more effectively focus the probability (belief degree) on real states, so as to reduce the uncertainty in making decision [19]. [20] uses the Jeffery-like evidence linear updating rule to design univariate alarm. Wherein, the process variable is transformed into alarm evidence by fuzzy membership function, then the historical and current alarm evidence are fused based on the linear updating rule, and finally the alarm-decision is made via the fused alarm evidence. However, due to the information loss in generating evidence, and the limited response of linear fusion mechanism to dynamic fine change of process variable, there is still room for improvement in alarm evidence fusion strategy.

Therefore, considering the coarse and fine changes of process variable, this paper proposes a novel univariate alarm design method based on dynamic evidence fusion, which mainly includes: (1) The coarse description of process variable. Firstly, the initial Mann–Kendall (MK) method is improved via the memory and forgetting strategies to divide historical sample data. It is suitable for the detection of several transitions, and can obtain multiple change points and diverse data segments without any prior knowledge. Then, the referential evidential matrix (REM) is established to realize the transformation of process variable to referential alarm evidence. Such data preprocessing and REM construction fully abstract the coarse statistical characteristics of historical data. (2) The fine description of process variable. First, the real-time sample activates REM to get the current alarm evidence. Then a newly dynamic ER rule considering interval-valued fusion weight is proposed, which can dynamically fuse current and historical alarm evidence to get current global alarm evidence. Among them, in order to accurately adapt the fine change of process variable, unlike the initial ER rule that the reliability and fusion weight are fixed, the new ER rule calculates the reliability online via the forgetting strategy, and describes the interval-valued fusion weight by random variable. Thus, the dynamic parameter adjustment can adapt the fine change of real-time data information, and realize efficient integration of historical and current alarm information. Finally, the precise alarm-decision is made based on the current global alarm evidence.

This paper is organized as follows: Section 2 introduces the basic concept of DS theory and alarm performance indicators; Section 3 presents the alarm design method based on dynamic evidence fusion; In Section 4, a numerical experiment and a motor rotor alarm experiment are given to illustrate the effectiveness of the proposed method; Finally, this study is concluded in Section 5.

2. Theoretical basis

2.1. Evidence reasoning rule in DS theory

In DS theory, there is a collectively exhaustive and mutually exclusive set of propositions, denoted by $\Theta = \{H_1, H_2, \ldots, H_n\}$, called a frame of discernment (FoD), and $P(\Theta) = 2^{\Theta} = \{\varnothing, H_1, \ldots, H_n, H_1, H_2, \ldots, \Theta\}$ consists of Θ and all its subsets are called a power set of Θ. A basic belief assignment function (also called BBA or evidence) on Θ is a function $m{:}P(\Theta) \to [0, 1]$, which satisfies $m(\varnothing) = 0$ and $\sum_{\theta \subseteq P(\Theta)} m(\theta) = 1$, wherein the belief degree of supporting the proposition θ is $m(\theta)$ [21].

In ER rule, a piece of evidence e is profiled by the following belief distribution form [22]

$$e = \{(\theta, m(\theta))|\forall\theta \subseteq \Theta, \sum_{\theta\subseteq\Theta} m(\theta) = 1\} \tag{1}$$

intuitively, e is the "number pairs" form of m. Each piece of evidence is associated with reliability r and fusion weight w respectively, $r, w \in [0, 1]$. Then the evidence e with reliability and fusion weight can be profiled by

$$\tilde{e} = \{(\theta, \tilde{m}(\theta))|\forall\theta \subseteq \Theta; (P(\Theta), \tilde{m}(P(\Theta)))\} \tag{2}$$

$$\tilde{m}(\theta) = \begin{cases} 0 & \theta = \varnothing \\ c_{rw} m(\theta) & \theta \subseteq \Theta, \theta \neq \varnothing \\ c_{rw}(1-r) & \theta = P(\Theta) \end{cases} \tag{3}$$

where c_{rw} is a normalization factor of reliability and fusion weight as follows

$$c_{rw} = \frac{w}{1 + w - r} \tag{4}$$

When two pieces of independent evidence e_1 and e_2 with reliabilities (r_1, r_2) and fusion weights (w_1, w_2) respectively are fused, the joint evidence to support the proposition θ can also be obtained by

$$m(\theta)^{e(2)} = [m_1 \oplus m_2](\theta) = \begin{cases} 0, & \theta = \varnothing \\ \dfrac{\hat{m}(\theta)^{e(2)}}{\sum_{D\subseteq\Theta} \hat{m}(D)^{e(2)}}, & \theta \subseteq \Theta, \theta \neq \varnothing \end{cases} \tag{5}$$
$$\hat{m}(\theta)^{e(2)} = [(1-r_2)w_1 m(\theta)_1 + (1-r_1)w_2 m(\theta)_2] + \sum_{B\cap C=\theta} w_1 m(B)_1 w_2 m(C)_2, \quad \forall\theta \subseteq \Theta$$

In addition, the evidence distance between two pieces of evidence m_1 and m_2 can be measured as [23]

$$d_J(m_1, m_2) = \sqrt{\frac{1}{2}(m_1 - m_2)^T \underline{\underline{D}}(m_1 - m_2)} \tag{6}$$

where the Jaccard coefficient $\underline{\underline{D}}$ is a $n\times n$ matrix, its elements satisfy: $\forall A, B \in 2^\Theta$, $\underline{\underline{D}}(A, B) = |A \cap B|/|A \cup B|$. In the univariate alarm system context, the $\underline{\underline{D}}$ is a 3×3 matrix, that is

$$\underline{\underline{D}} = \begin{bmatrix} 1 & 0 & 1/2 \\ 0 & 1 & 1/2 \\ 1/2 & 1/2 & 1 \end{bmatrix} \tag{7}$$

$d_J(m_1, m_2)$ takes 0 means these two evidence are exactly same, and takes 1, otherwise. The similarity measure between m_1 and m_2 is

$$Sim(m_1, m_2) = 1 - d_J(m_1, m_2) \tag{8}$$

obviously, $Sim(m_1, m_2) \in [0, 1]$

For the design of univariate alarm systems, the FoD $\Theta = \{A(\text{Alarm}), NA(\text{Non-Alarm})\}$, so the alarm evidence is $m = (m(A), m(NA), m(\Theta))$. Among them, the belief degree of supporting the propositions "Alarm" and "Non-Alarm" are $m(A)$ and $m(NA)$ respectively, and $m(\Theta)$ represents the complete unknown for these two propositions. Obviously, if the sum of $m(A)$ and $m(NA)$ is 1, $m(\Theta) = 0$.

2.2. Performance indicators in industrial alarm

The $x(t)$ is discrete sample signal of process variable x, the sample period is h, and x_{tp} is alarm threshold for safe operation of equipment. There are alarm generation mechanisms: when $x(t) \geq x_{tp}$, alarm; when $x(t) < x_{tp}$, no alarm. Obviously, the random change of $x(t)$ and the improper selection of x_{tp} will lead to false alarm and missed alarm: when process variable $x(t)$ is in normal state, the alarm given by alarm system is false alarm; when $x(t)$ is in abnormal state, the alarm not issued by alarm system is missed alarm. Therefore, the two performance indicators of the alarm system are derived: false alarm rate (FAR) and missed alarm rate (MAR) [24]:

$$\text{FAR} = (FA/(FA + TN)) \times 100\% \tag{9}$$

$$\text{MAR} = (MA/(MA + TA)) \times 100\% \tag{10}$$

among them, TN and FA are respectively the number of non-alarms and the number of false alarms when $x(t)$ is in normal state; MA and TA are respectively the number of missed alarms and the number of alarms when $x(t)$ is in abnormal state.

The time when $x(t)$ is in the abnormal state is t_0, and the alarm system will give an alarm at t_a, then the alarm delay T_d is defined as [25]

$$T_d = t_a - t_0 \tag{11}$$

if $x(t)$ has multiple transitions from normal state to abnormal state, the average alarm delay (AAD) is defined as the average value of T_d, namely

$$AAD = \text{Mean}(T_d) \tag{12}$$

3. Alarm design method based on dynamic evidence fusion

3.1. Framework

To describe and adapt the coarse and fine changes of process variable, and further improve the performance of the univariate alarm system, the following six-step framework is proposed. To describe the coarse change of process variable, Section 3.2 first introduces the data preprocessing based on multi-transition data segmentation (step 1) and the construction of REM (step 2). To adapt the fine change of process variable, Section 3.3 exhibits the alarm design method based on dynamic evidence fusion, which includes the last four steps: acquire current alarm evidence $m_t = (m_t(A), m_t(NA), m_t(\Theta))$ (step 3); calculate reliability and interval-valued fusion weight of alarm evidence (step 4); obtain current global alarm evidence $m_{1:t} = (m_{1:t}(A), m_{1:t}(NA), m_{1:t}(\Theta))$ by dynamic fusion of historical global alarm evidence $m_{1:t-1} = (m_{1:t-1}(A), m_{1:t-1}(NA), m_{1:t-1}(\Theta))$ and m_t (step 5); and make alarm-decision based on $m_{1:t}$ (step 6). The whole process of the designed univariate alarm method is shown in Fig. 1.

Step 1 (Multi-transition data segmentation): Establish the memory and forgetting strategies to improve the initial MK method for multi-transition data segmentation. Namely the detected first change point and its subsequent sample points are selectively memorized, and the sample points before the first change point are intentionally forgotten, so as to continuously obtain multiple change points and diverse data segments in historical sample data, and the corresponding label is added to each sample point to form sample pair. More details are presented in Section 3.2.1.

Step 2 (The construction of REM): Based on the divided historical sample data obtained in step 1, the referential evidential matrix (REM) is constructed by calculating the similarity distribution of each sample pair in historical sample data, which is used for the transformation of process variable to referential alarm evidence, and realizes the accurate description of the coarse statistical characteristics of historical sample data. More details can be found in Section 3.2.2.

Step 3 (Acquisition of current alarm evidence): The real-time sample of process variable $x(t)$ activates the REM to obtain the current alarm evidence m_t. More details are presented in Section 3.3.1.

Step 4 (Calculation of reliability and interval-valued fusion weight of alarm evidence): Before using dynamic ER rule to fuse the current alarm evidence m_t and the historical global alarm evidence $m_{1:t-1}$, the first thing to be solved is how to adjust the reliability and fusion weight of the corresponding alarm evidence. Therefore, a new dynamic ER rule considering interval-valued fusion weight is proposed. Wherein, the reliability is calculated online according to the forgetting strategy, the interval-valued fusion weight is described by random variable with certain probability distribution characteristics, so as to fully adapt to the dynamic fine change of real-time sample. More details can be found in Section 3.3.2.

Step 5 (Dynamic fusion of current and historical alarm evidence): On the basis of the real-time online calculation of reliability and the timely adjustment of interval-valued fusion weight, this step extends the initial ER rule with fixed fusion weight and reliability to the new dynamic ER rule, which is used for dynamic fusion of current alarm evidence $m_t = (m_t(A), m_t(NA), m_t(\Theta))$ and historical global alarm evidence $m_{1:t-1} = (m_{1:t-1}(A), m_{1:t-1}(NA), m_{1:t-1}(\Theta))$ to obtain current global alarm evidence $m_{1:t} = (m_{1:t}(A), m_{1:t}(NA), m_{1:t}(\Theta))$. More details are presented in Section 3.3.3.

Step 6 (Alarm-decision making based on current global alarm evidence): Based on the given alarm-decision criteria, the accurate alarm-decision is made according to current global alarm evidence $m_{1:t}$. More details can be found in Section 3.3.4.

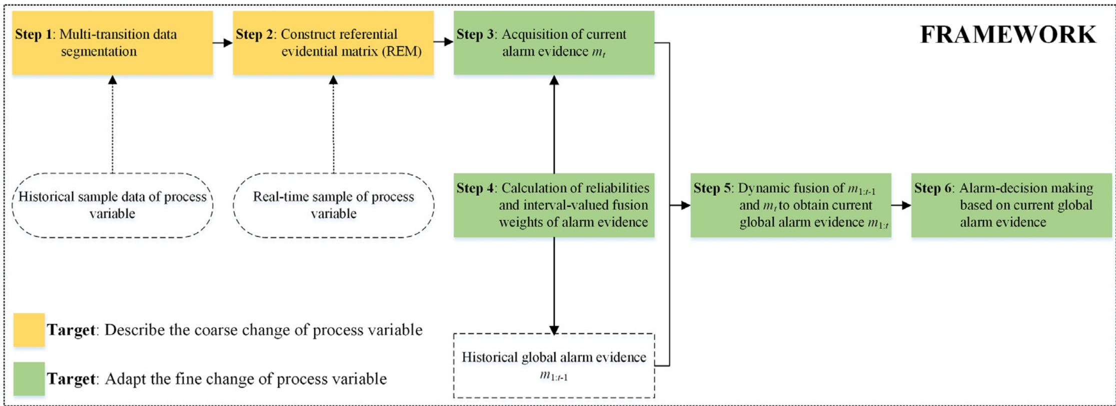

Fig. 1. The flowchart of the designed univariate alarm method.

3.2. The coarse description of process variable via data segmentation and REM

3.2.1. Multi-transition data segmentation

Step 1.1: The $x(t)_{t=1}^{T}$ is divided into T segments with lengths 1, 2, …, T, and the first sample point of each segment is $x(1)$. Then the nth segment can be expressed as $F_n = [x(1), x(2), \ldots, x(n)]$, $1 \leq n \leq T$. For the segment F_n, the rank sequence s_k can be defined as

$$s_k = \sum_{i=1}^{k} z_i,\ k = 2, 3, \ldots, n \tag{13}$$

among them

$$z_i = \begin{cases} 1, & x(i) > x(j) \\ 0, & x(i) \leq x(j) \end{cases} \quad j = 1, 2, \ldots, i \tag{14}$$

obviously, the rank sequence s_k is the cumulative number that $x(i)$ at the ith time is greater than $x(j)$ at the jth time.

Step 1.2: The forward statistics of standard normal distribution UF_k is defined as follows

$$UF_k = \frac{[s_k - \mathrm{Mean}(s_k)]}{\sqrt{\mathrm{Var}(s_k)}}, k = 1, 2, \ldots, n \tag{15}$$

where $UF_1 = 0$, the mean and variance of s_k are represented by Mean (s_k) and Var (s_k) respectively, as shown below

$$\begin{aligned} &\mathrm{Mean}(s_k) = n(n+1)/4, k = 2, 3, \ldots, n \\ &\mathrm{Var}(s_k) = n(n-1)(2n+5)/72, k = 2, 3, \ldots, n \end{aligned} \tag{16}$$

Step 1.3: Similarly, the above process is repeated according to the reverse order $x(T)$, $x(T-1)$, …, $x(1)$, and the reverse statistics of standard normal distribution UB_k is calculated by Eqs. (13)–(16). Obviously, $UB_k = -UF_k$, $UB_1 = 0$.

Step 1.4: $\pm U_{1-\alpha/2}$ is the $(1-\alpha/2)$ quantile, and α is the given significance level. According to the memory and forgetting strategies, segment F_n is extended as far as possible until the following two conditions are met, the data length of segment F_n stops increasing, and the intersection is marked as the first change point $x(t_1)$, $x(t_1) \in F_n$. Then, $x(t_1)$ is remembered as the new starting point of historical data, step 1.1∼step 1.3 are repeated in many times until all the change points are found, and all of them are represented as $x(t_q)$, $q = 1,2, \ldots, Q$, Q is the number of detected change points.

Condition 1. The reverse statistics of standard normal distribution UB_k enters the range of the critical line $\pm U_{1-\alpha/2}$ for the first time;

Condition 2. When Condition 1 is satisfied, the statistics of standard normal distribution UF_k and UB_k have an intersection between the critical line $\pm U_{1-\alpha/2}$.

Remark 1. Currently, there are some improved methods based on traditional data segmentation methods so as to apply to the multiple transitions situation. [8] revised traditional Pettitt method by adopting the idea of bisection method to find multiple change points. [26,27] sliced the data through a sliding window model, divided the complete data into sequential sub-windows, and then performed multiple detections to locate the change points. These improved methods introduce additional parameters such as trip point and window width, and these parameters restrict the effect of data segmentation to some extent.

The MK method suitable for single change point detection, which is based on the mean change between adjacent data segments to determine change points and divide data segments [28]. Obviously, the nonparametric MK method can effectively avoid the problems of the above parametric detection methods, such as the need to know initial distribution or signal model structure of process variable. But in practice, the sample sequence must have multiple change points, not just one change point, so the initial MK method is not applicable. In fact, for the first mean change of sample sequence, once the MK method detects the change time and its corresponding sample point, the sample point is regarded as the first change point. At this time, the statistical characteristics of all sample points before the first change point have been fully utilized. Briefly, in the sample sequence, the statistical characteristics of the sample points after the first change point play a direct role in the detection of the second change point, rather than the statistical characteristics of the sample points before the first change point. Hence, according to the memory and forgetting principle of cognitive science [29], the original MK method is improved to solve this complex multi-transition data segmentation problem.

Remark 2. The proposed multi-transition data segmentation algorithm needs to satisfy the following two assumptions: (1) the historical sample sequence of the process variable $x(t)$ has different mean values under normal and abnormal states; (2) different mean values corresponding to different states of the process variable $x(t)$ are known. Based on full understanding of industrial process, these two assumptions can be established through prior knowledge learning.

3.2.2. The construction of REM

Step 2.1: According to the change points obtained in step 1, the historical data is divided into normal and abnormal data

Table 1
Referential evidential matrix table.

$y(t)$	$x(t)$				
	e_1 R_1	e_2 R_2	e_3 R_3	$\cdots$ $\cdots$	$e_{\tilde{a}}$ $R_{\tilde{a}}$
Y_1	$\beta_{1,1}$	$\beta_{1,2}$	$\beta_{1,3}$	$\cdots$	$\beta_{1,\tilde{a}}$
Y_2	$\beta_{2,1}$	$\beta_{2,2}$	$\beta_{2,3}$	$\cdots$	$\beta_{2,\tilde{a}}$

segments, and the corresponding sample labels "Alarm (A)" and "Non-Alarm (NA)" are added respectively, which contains T sample pairs, denoted as $Z = [x(t), y(t)]$, $x(t)$ and $y(t)$ are the input and output of the designed alarm system respectively. The reference values set of input $x(t)$ is $R = \{R_{\tilde{a}} | \tilde{a} = 1, 2, \ldots, a\}$, a is the number of input reference values, and the specific values of $R_{\tilde{a}}$ are determined according to expert knowledge; the reference values set of output $y(t)$ is $Y = \{Y_{\tilde{b}} | \tilde{b} = 1, 2\}$, $Y_1 = 0$, $Y_2 = 1$, the output reference values 0 and 1 represent non-alarm action "NA" and alarm action "A" respectively. Thus, the relationship between $x(t)$ and $y(t)$ can be approximately represented by the relationship between input reference values and output reference values.

Step 2.2: The similarity distribution $V(x(t))$ of the input $x(t)$ about R can be calculated by information transformation methods:

$$\begin{aligned} &V(x(t)) = \{(R_{\tilde{a}}, \alpha_{\tilde{a}}) | \tilde{a} = 1, 2, \ldots, a\} \\ &\alpha_{\tilde{a}} = (R_{\tilde{a}+1} - x(t))/(R_{\tilde{a}+1} - R_{\tilde{a}}) \\ &\alpha_{\tilde{a}+1} = (x(t) - R_{\tilde{a}})/(R_{\tilde{a}+1} - R_{\tilde{a}}) \end{aligned} \tag{17}$$

where, $\alpha_{\tilde{a}}$ and $\alpha_{\tilde{a}+1}$ represent the similarity of $x(t)$ matching $R_{\tilde{a}}$ and $R_{\tilde{a}+1}$ respectively, obviously $R_{\tilde{a}} + R_{\tilde{a}+1} = 1$.

Step 2.3: Because $y(t)$ can only take the discrete value $Y_{\tilde{b}}$, the similarity distribution $V(y(t))$ of $y(t)$ about Y is

$$\begin{aligned} &V(y(t)) = \{(Y_{\tilde{b}}, \lambda_{\tilde{b}}) | \tilde{b} = 1, 2\} \\ &\lambda_{\tilde{b}} = 1,\ when\ y(t) = Y_{\tilde{b}},\ otherwise\ \lambda_{\tilde{b}} = 0 \end{aligned} \tag{18}$$

Therefore, each sample pair $(x(t), y(t))$ in Z can be converted into the form of comprehensive similarity distribution $(\alpha_{\tilde{a}}\lambda_{\tilde{b}}, \alpha_{\tilde{a}+1}\lambda_{\tilde{b}}, \alpha_{\tilde{a}}\lambda_{\tilde{b}+1}, \alpha_{\tilde{a}+1}\lambda_{\tilde{b}+1})$, $\alpha_{\tilde{a},\tilde{b}}$ is the comprehensive similarity of $x(t)$ matching $R_{\tilde{a}}$ and $y(t)$ matching $Y_{\tilde{b}}$. $\delta_{\tilde{a},\tilde{b}}$ is the sum of all $\alpha_{\tilde{a},\tilde{b}}$ in Z, $\psi_{\tilde{b}} = \sum_{\tilde{a}=1}^{a} \delta_{\tilde{a},\tilde{b}}$ is the sum of comprehensive similarity of all $y(t)$ matching $Y_{\tilde{b}}$ in Z, $\eta_{\tilde{a}} = \sum_{\tilde{b}=1}^{2} \delta_{\tilde{a},\tilde{b}}$ is the sum of comprehensive similarity of all $x(t)$ matching $R_{\tilde{a}}$ in Z, and $\sum_{\tilde{b}=1}^{2} \psi_{\tilde{b}} = \sum_{\tilde{a}=1}^{a} \eta_{\tilde{a}} = T$.

Step 2.4: When the input $x(t)$ is the reference value $R_{\tilde{a}}$, the belief degree that the output $y(t)$ is the reference value $Y_{\tilde{b}}$ is

$$\beta_{\tilde{a},\tilde{b}} = (\delta_{\tilde{a},\tilde{b}}/\psi_{\tilde{b}}) / \sum_{\tilde{b}=1}^{2} \left(\delta_{\tilde{a},\tilde{b}}/\psi_{\tilde{b}}\right) \tag{19}$$

and the referential alarm evidence $e_{\tilde{a}}$ is obtained

$$e_{\tilde{a}} = \{(NA, \beta_{\tilde{a},1}), (A, \beta_{\tilde{a},2})\} \tag{20}$$

The REM as shown in Table 1 is established to describe the relationship between input $x(t)$ and output $y(t)$.

3.3. The fine description of process variable based on dynamic evidence fusion

In engineering practice, whether the industrial equipment is in normal state or abnormal state, the operation state of the equipment before and after has certain correlation. That is to say, the correct decision of "Alarm (A)" and "Non-Alarm (NA)" are often made by integrating the historical and current process variable information, rather than only based on the current state change of process variable, because the latter is likely to be caused by the measurement error in sensor or environmental interference. The evidence reasoning (ER) rule is widely used in the fusion of multi-source evidence with its strict probabilistic reasoning process and rigorous logical reasoning mechanism. Hence, the ER rule can be used to fuse the historical global alarm evidence $m_{1:t-1}$ and the current alarm evidence m_t to get the current global alarm evidence $m_{1:t}$, which is the best judgment of the current state of the equipment and greatly eliminates the influence of various uncertainty.

3.3.1. Acquisition of current alarm evidence

Step 3: The real-time sample of process variable $x(t)$ must be in interval $[R_{\tilde{a}}, R_{\tilde{a}+1}]$, then the current alarm evidence m_t corresponding to $x(t)$ can be obtained by the weighted sum of the activated referential alarm evidence $e_{\tilde{a}}$ and $e_{\tilde{a}+1}$

$$\begin{aligned} &m_t = (m_t(NA), m_t(A), m_t(\Theta)) \\ &m_t(NA) = \alpha_{\tilde{a}}\beta_{1,\tilde{a}} + \alpha_{\tilde{a}+1}\beta_{1,\tilde{a}+1} \\ &m_t(A) = \alpha_{\tilde{a}}\beta_{2,\tilde{a}} + \alpha_{\tilde{a}+1}\beta_{2,\tilde{a}+1} \end{aligned} \tag{21}$$

among them, $m_t(A)$ and $m_t(NA)$ are the belief degree of supporting propositions "Alarm (A)" and "Non-Alarm (NA)" respectively, and $m_t(A) + m_t(NA) = 1$. The common alarm design methods are based on whether $x(t)$ exceeds the alarm threshold x_{tp} to absolutely assigns probability 1 to "A" or "NA". Compared with them, the proposed alarm evidence generating mechanism can be regarded as the lossless transformation process from process variable information to alarm evidence. Note that since the sum of $m_t(A)$ and $m_t(NA)$ is 1, there is no situation where the propositions "A" and "NA" are completely unknown, so $m_t(\Theta) = 0$.

3.3.2. Calculation of reliability and interval-valued fusion weight of alarm evidence

Step 4.1: According to similarity measure between the corresponding alarm evidence, the forgetting strategy is established to adjust the reliability of current and historical alarm evidence. The reliability $r_{1:t-1}$ of historical global alarm evidence $m_{1:t-1}$, and the reliability r_t of current alarm evidence m_t are

$$\begin{aligned} &r_{1:t-1} = \sum_{t=t-l}^{t-1} r_t \Big/ l \\ &r_t = r_{1:t-1} + r_0 * \tau * \phi \\ &s.t.\ 0 \le r_{1:t-1}, r_t \le 1 \end{aligned} \tag{22}$$

$$\phi = (Sim(m_t, e_B))/(Sim(m_{1:t-1}, e_B) + Sim(m_t, e_B)) \tag{23}$$

among them, the reliability $r_{1:t-1}$ of $m_{1:t-1}$ is given by the average value of the reliabilities at the previous l moments, and l depends on the sample size; r_0 is initial reliability, generally $r_0 = 0.5$; τ is reward and punishment function, when both $m_{1:t-1}$ and m_t support propositions "A" or "NA" at the same time, $\tau = 1$, otherwise $\tau = -1$; e_B is standardized alarm evidence, when $m_{1:t-1}$ or m_t supports proposition "A", $e_B = (0, 1, 0)$, and when $m_{1:t-1}$ or m_t supports proposition "NA", $e_B = (1, 0, 0)$; ϕ is forgetting enhancement factor, which can be given according to the similarity measure between e_B and m_t, and the similarity measure between e_B and $m_{1:t-1}$ comprehensively.

Step 4.2: The interval-valued fusion weight of corresponding alarm evidence is characterized by continuous random variable with uniform distribution. The interval-valued fusion weight $W_{1:t-1}$ of $m_{1:t-1}$, and interval-valued fusion weight W_t of m_t are

$$\begin{aligned} &W_t \sim U(w_t^-, w_t^+) \\ &W_{1:t-1} \sim U(w_{1:t-1}^-, w_{1:t-1}^+) \\ &s.t. 0 \le W_{1:t-1}, W_t \le 1 \end{aligned} \tag{24}$$

$$\begin{aligned} &w_t^- = w_{c\_tp} - \tilde{d}, w_t^+ = w_{c\_tp} + \tilde{d} \\ &w_{1:t-1}^- = w_{h\_tp} - \tilde{d}, w_{1:t-1}^+ = w_{h\_tp} + \tilde{d} \end{aligned} \tag{25}$$

among them, the historical sample data is used as the training set, and the initial ER rule with fixed fusion weights is used to fuse current and historical alarm evidence, w_{c_tp} and w_{h_tp} are the optimal fusion weights of the current and historical alarm evidence obtained based on training set respectively. This process can be realized in Matlab toolbox by classical optimization algorithms. $\tilde{d}$ is the evidence distance between $m_{1:t-1}$ and m_t through Eq. (6). Note that w_{c_tp} and w_{h_tp} represents the contribution of historical data to interval-valued fusion weight, while $\tilde{d}$ reflects the dynamic fine adjustment of current process variable information to interval-valued fusion weight. So the W_t and $W_{1:t-1}$ accurately reflect the relationship between historical and current process variable information.

Remark 3. When the initial static ER rule is used for the fusion of current and historical alarm evidence, the reliability and fusion weight of corresponding alarm evidence are determined, and not change in each fusion on this condition. However, process variable information change dynamically, and the relationship between current and historical alarm evidence will also change. In this case, continuing to use fixed reliability and fusion weight for reasoning will reduce the trust of fusion result. Therefore, it is necessary to design dynamic ER rule, whose reliability and fusion weight can be real-timely adjusted according to the relationship between corresponding alarm evidence, so as to ensure the correct reasoning, accurately adapt the fine change of the process variable, and improve the efficiency of alarm evidence fusion.

Tracing back to the origin of ER rule, the reliability r objectively represents the accurate judgment ability of information source for a given problem, which is the inherent nature of evidence itself and will not be affected by other evidence. The fusion weight w subjectively represents the importance of current evidence relative to other evidence. Due to the subjective nature of the fusion weight, it may fluctuate irregularly over time, and has no obvious statistical characteristics. It is impossible to obtain accurate values through function modeling and calculation, so the fusion weight can only be obtained in the interval form. In contrast, the reliability may also change over time, but for a fixed information source, a more reasonable and accurate reliability can be obtained on the basis of fully considering the fine change of process variable and combining with the statistical characteristics in a certain period. Hence, based on the above analysis of the difference between reliability and fusion weight, the thought of intentional forgetting and the interval form are adopted in each fusion.

Remark 4. Based on the above analysis that the fusion weight is described as interval form, it can be seen that the original intention of the interval-valued fusion weight is evenly to set the fusion weight with equal possibilities in the specified interval, in order to reflect its fluctuations characteristics in a certain range over time. The interval-valued fusion weight cannot be interpreted as taking values in a specific part of interval or absolutely taking fixed values in the interval. Therefore, compared with the probability distribution of continuous random variables such as exponential distribution and normal distribution, the uniform distribution is more suitable for characterizing interval-valued fusion weight due to its good probability characteristics.

3.3.3. Dynamic fusion of current and historical alarm evidence

Step 5.1: The ER rule (Eq. (5)) in Section 2.1 is extended to the alarm design as Eq. (5) in Box I.

Among them, reliabilities $\{r_t, r_{1:t-1}\}$ and interval-valued fusion weights $\{W_t, W_{1:t-1}\}$ of $m_{1:t-1}$ and m_t can be obtained by step 4 respectively, $m(\theta)_{1:t}^{e(2)}$ is the fusion result of $m_{1:t-1}$ and m_t by using the proposed dynamic ER rule. Obviously, $m(\theta)_{1:t}^{e(2)}$ is an interval value, the optimization model is as follows:

$$\begin{aligned} &\max / \min m(\theta)_{1:t}^{e(2)} \\ &st: W_t \sim U(w_t^-, w_t^+), W_{1:t-1} \sim U(w_{1:t-1}^-, w_{1:t-1}^+) \end{aligned} \tag{27}$$

where $m(\theta)_{1:t}^{e(2)}$ is calculated in Eq. (26), and some simple optimization methods can be used to calculate the extreme value of $m(\theta)_{1:t}^{e(2)}$.

Step 5.2: In order to facilitate the formulation of the final alarm-decision, based on mathematical principles, the $m_{1:t}$ is obtained by calculating the mathematical expectation of the interval-valued fusion result $m(\theta)_{1:t}^{e(2)}$

$$m_{1:t} = E(m(\theta)_{1:t}^{e(2)}), \theta \subseteq \Theta, \theta \neq 0 \tag{28}$$

$$E(m(\theta)_{1:t}^{e(2)}) = \iint_{\Xi} m(\theta)_{1:t}^{e(2)} \frac{1}{w_{1:t-1}^+ - w_{1:t-1}^-} \times \frac{1}{w_t^+ - w_t^-} dW_{1:t-1} dW_t \tag{29}$$

where, $E(\bullet)$ represents the mathematical expectation of $\bullet$, and Ξ is the rectangular area determined by $W_{1:t-1}$ and W_t.

3.3.4. Alarm-decision making based on current global alarm evidence

Step 6: After the iterative fusion in step 5, the current global alarm evidence $m_{1:t} = (m_{1:t}(A), m_{1:t}(NA), m_{1:t-}(\Theta))$ is obtained, and the following alarm-decision criteria are given

$$\begin{aligned} &\text{if } m_{1:t}(NA) \geq m_{1:t}(A), \text{ then output } y(t) = 0, \text{ no alarm}; \\ &\text{if } m_{1:t}(NA) < m_{1:t}(A), \text{ then output } y(t) = 1, \text{ alarm}. \end{aligned} \tag{30}$$

4. Comparative analysis of experiments

This section demonstrates the design process of univariate alarm method based on dynamic evidence fusion through a numerical simulation experiment (Experiment 1) and a motor rotor alarm experiment (Experiment 2), and verifies the effectiveness of the designed alarm method. In Experiment 1, a piecewise white Gaussian random process with both average and variance varying in intervals is used to generate process variable $x(t)$; Experiment 2 implements an alarm experiment on the multifunctional motor rotor experimental platform, and uses the vibration acceleration signal of the experimental platform as the process variable $x(t)$ in the designed alarm.

In these two experiments, the data preprocessing is implemented first, and then multiple change points and diverse data segments in historical sample data are obtained as training set. Based on the training set, the REM of the proposed alarm design method, the optimal alarm threshold in [20], the optimal alarm thresholds of the moving average filter method under different filter orders, and the optimal alarm thresholds of the time delay method under different delay steps are obtained respectively. Then, the proposed univariate alarm design method based on dynamic evidence fusion (DF) is compared with the moving average filter method with different filter orders under optimal alarm thresholds (AF), the combined on and off-time delay method with different delay steps under optimal alarm thresholds (TD), and the alarm evidence linear updating method (LU) in [20]. The experimental results illustrate that the proposed DF method has better effectiveness than traditional AF/TD/LU methods in improving the accuracy and sensitivity, and achieving the trade-off between accuracy and sensitivity.

$$m(\theta)^{e(2)}_{1:t} = \frac{(1-r_t)W_{1:t-1}m_{1:t-1}(\theta) + (1-r_{1:t-1})W_t m_t(\theta) + W_{1:t-1}W_t m_{1:t-1}(\theta)m_t(\theta)}{(1-r_t)W_{1:t-1} + (1-r_{1:t-1})W_t + W_{1:t-1}W_t \sum_{\Upsilon \in \theta} m_{1:t-1}(\Upsilon)m_t(\Upsilon)}, \ \theta \subseteq \Theta, \theta \neq 0 \tag{26}$$

Box I.

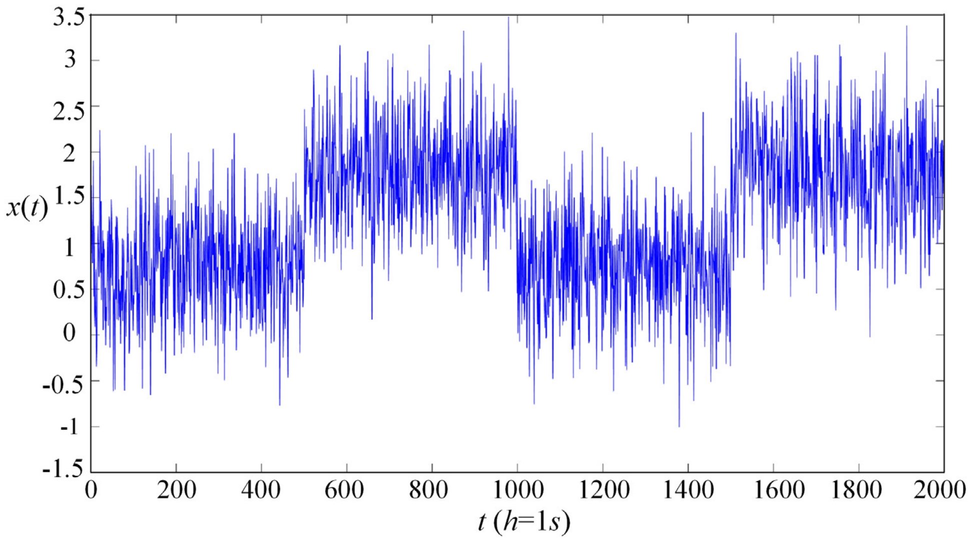

Fig. 2. The sample sequence of process variable $x(t)$.

4.1. Experiment 1

The following piecewise white Gaussian random process with both average and variance varying in intervals is used to generate the sample sequence of process variable $x(t)$. Obviously, the interval-valued average and variance reflect that the statistical properties of $x(t)$ are inaccurate and partly unknown (namely, the coarse change of process variable). The segmentations corresponding to $t < 500$ and $1000 \le t < 1500$ are normal data segments, and the segmentations corresponding to $500 \le t < 1000$ and $1500 \le t < 2000$ are abnormal data segments, and the change points in the sample sequence of the process variable $x(t)$ are 500, 1000, and 1500 respectively, as shown in Fig. 2.

$$\begin{cases} x(t) \sim N([0.2, 0.3], [0.5, 0.6]^2) & t < 500 \\ x(t) \sim N([1.2, 1.5], [0.5, 0.6]^2) & 500 \le t < 1000 \\ x(t) \sim N([0.2, 0.3], [0.5, 0.6]^2) & 1000 \le t < 1500 \\ x(t) \sim N([1.2, 1.5], [0.5, 0.6]^2) & 1500 \le t < 2000 \end{cases} \tag{31}$$

Firstly, the preprocessing of the alarm design is carried out. According to step 1, the sample sequence of process variable $x(t)$ is divided into 2000 segments: $F_1 = \{x(1)\}$, $F_2 = \{x(1), x(2)\}$, …, $F_{2000} = \{x(1), x(2), \ldots, x(2000)\}$. Then, started from the segment F_1, calculate the forward statistics of standard normal distribution UF_k and the reverse statistics of standard normal distribution UB_k in each segment according to Eqs. (13)∼(16). Take the significance level $\alpha = 0.05$, consult the normal distribution chart to get $|U_{1-\alpha/2}| = 1.96$. When segment F_{523} is calculated, UF_{523} and UB_{523} satisfy Conditions 1 and 2, and at $t = 502$, UF_{523} and UB_{523} intersect in the range of critical line ± 1.96, so $x(502)$ is the first change point in the sample sequence of $x(t)$, as shown in Fig. 3. Record $x(502)$ as the new starting point in the sample sequence of $x(t)$, and repeat the above steps until two other change points $x(1001)$ and $x(1499)$ in the sample sequence are found. Thus, the sample sequence is divided into normal data segments $\{x(1, 501), x(1001, 1498)\}$ and abnormal data segments $\{x(502, 1000), x(1499, 2000)\}$ by combining the detected change points, and the corresponding sample labels "Alarm (A)" and "Non-Alarm (NA)" are added respectively, as shown in Table 2. Take these 2000 sample pairs with sample labels as training set, combined with expert knowledge, set the reference values set of input $x(t)$ as $\{-1.5, -1, -0.5, 0, 0.5, 1, 1.5, 2, 2.5, 3, 3.5\}$, and the reference values set of output $y(t)$ as $\{0, 1\}$. According to the information transformation methods in step 2, use Eqs. (17)∼(20) to establish the REM shown in Table 3. At the same time, based on the above training set, traverse the sample sequence of $x(t)$ and combined with the ROC curve, the optimal alarm threshold $x_{otp} = 0.86$ in [20], the optimal alarm thresholds of the moving average filter under different filter orders, and the optimal alarm thresholds of the time delay under different delay steps as shown in Table 4 are obtained respectively.

Table 2
Classification of sample sequence into normal and abnormal data.

Normal data	Abnormal data
$x(1, 501)$	$x(502, 1000)$
$x(1001, 1498)$	$x(1499, 2000)$

Table 3
Referential evidential matrix table.

$y(t)$	$x(t)$										
	−1.5	−1	−0.5	0	0.5	1	1.5	2	2.5	3	3.5
Y_1	1	1	0.9884	0.9263	0.7325	0.326	0.0831	0.0252	0	0	0
Y_2	0	0	0.0116	0.0737	0.2675	0.674	0.9169	0.9768	1	1	1

Next, the alarm system based on dynamic evidence fusion is designed. Follow the distribution law of Eq. (31) to randomly generate 2000 samples as test set. Combine the REM, use Eq. (21) to transform the real-time sample of process variable $x(t)$ into the corresponding current alarm evidence m_t. Then take m_1 as the current global alarm evidence $m_{1:1}$ at $t = 1$, started from $t = 2$,

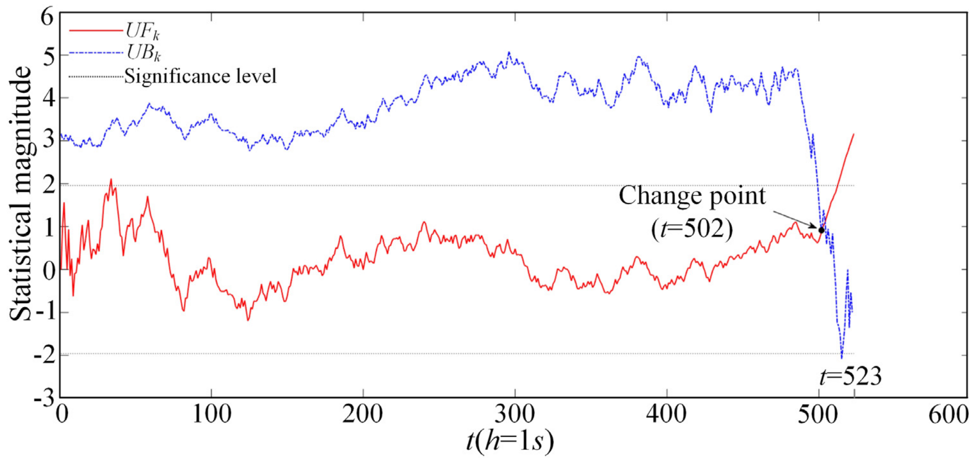

Fig. 3. Mann–Kendall statistical curve of process variable $x(t)$.

Table 4
The optimal alarm thresholds in moving average filter and time delay.

	Filter orders/delay Steps								
	3	4	5	6	7	8	9	10	11
Moving average filter	0.77	0.79	0.83	0.75	0.81	0.81	0.77	0.79	0.72
Time delay	0.82	0.73	0.74	0.60	0.48	0.57	0.33	0.31	0.30

use Eqs. (26)∼(29) to fuse the current alarm evidence m_t with historical global alarm evidence $m_{1:t-1}$ to get the current global alarm evidence $m_{1:t}$. Among them, according to step 4, $l = 7$, and the initial values of reliabilities and interval-valued fusion weights are both set to 1; Combine the optimal fusion weights $w_{c\_tp} = 0.58$ and $w_{h\_tp} = 0.66$ of the current and historical alarm evidence under the training set, using Eqs. (22)∼(25) to determine the reliabilities r_t and interval-valued fusion weights w_t of current alarm evidence m_t, the reliabilities $r_{1:t-1}$ and interval-valued fusion weights $W_{1:t-1}$ of historical global alarm evidence. Finally, make alarm-decision according to the criterion of Eq. (30), and MAR = 0.7%, FAR = 0.2% and AAD = 2.5 respectively. In addition, here another alarm system is designed based on the initial static ER rule with fixed parameters as a comparative experiment. Repeat the above experimental steps, when use Eq. (28) to fuse m_t and $m_{1:t-1}$, the optimal fusion weights $\{w_{c\_tp} = 0.58, w_{h\_tp} = 0.66\}$ and optimal reliabilities $\{r_{c\_tp} = 0.45, r_{h\_tp} = 0.57\}$ of current and historical alarm evidence are obtained according to the training set, and the alarm results are MAR = 4.5%, FAR = 4.8% and AAD = 4 respectively.

Table 5 shows the partial reliabilities and interval-valued fusion weights under dynamic ER rule. It can be seen from Table 5 that in each fusion, the reliabilities and interval-valued fusion weights dynamically change according to data information, obviously this is more in line with the fine change of real-time sample of process variable. Correspondingly, whether the optimal values of reliabilities and interval-valued fusion weights are obtained by training set, or them are set according to expert knowledge, the reliability and fusion weight of the initial static ER rule are fixed in each fusion, which restricts the performance of ER rule in designing alarm system. Further analysis, Table 5 also shows that the reliabilities and interval-valued fusion weights of historical alarm evidence are not always higher than that of current alarm evidence, there is a fluctuating and corresponding relationship between them, so as to reflect the real fine change law of process variable.

Fig. 4 shows a complete process in which $x(t)$ changes from normal state to abnormal state (namely $t = 1 \sim t = 1000$), the interval-valued fusion results $m(NA)^{e(2)}_{1:t}$ and $m(A)^{e(2)}_{1:t}$ corresponding to the change process calculated by Eq. (26), the upper and lower limits of $m(NA)^{e(2)}_{1:t}$ and $m(A)^{e(2)}_{1:t}$ are marked with red dotted line and cyan solid line respectively. The part of the red dotted line that exceeds the cyan solid line at each moment represents the adjustment effect of the interval-valued fusion weight in the fusion process. It is worth noting that the red dotted line at certain moments in Fig. 4 is much higher than the cyan solid line, this is because the range of interval-valued fusion weights at that moment are wider, resulting in larger range of interval-valued results obtained by dynamic fusion. Further analysis, from the comparison between Figs. 4(a) and 4(b), it can be seen that the upper and lower limits of $m(NA)^{e(2)}_{1:t}$ in normal state (namely $t = 1 \sim t = 500$) are higher than that of $m(A)^{e(2)}_{1:t}$; Similarly, it can be seen from the comparison of Figs. 4(c) and 4(d) that the upper and lower limits of $m(A)^{e(2)}_{1:t}$ under abnormal state (namely $t = 501 \sim t = 1000$) are both higher than $m(NA)^{e(2)}_{1:t}$. To sum up, regardless of whether process variable is in normal state or abnormal state, the interval-valued fusion results obtained by the dynamic fusion based on ER rule considering interval-valued fusion weight can accurately describe the true state of process variable. It is also not difficult to see that in order to facilitate the formulation of the final alarm-decision, the use of mathematical expectation to transform the interval-valued fusion results into the corresponding current global alarm evidence m_t does not change the essential characteristics of the dynamic ER rule.

In order to show the effectiveness of the proposed DF method, use the distribution law in Eq. (31) to randomly generate 300 test sets, and each test set includes 2000 samples. Repeat the above experimental steps and perform multiple test experiments. Calculate the average values of FAR, MAR and AAD for DF, AF, TD and LU respectively. Table 6 shows the statistical results of m(FAR), m(MAR) and AAD.

It can be seen from Table 6 that compared with the alarm evidence linear updating method (LU) in [20], the proposed DF method can greatly reduce AAD, and at the same time, FAR and MAR are also reduced. On the one hand, this is because LU method uses piecewise fuzzy membership function to transform process variable into alarm evidence, which leads to excessive information loss; The alarm evidence in the proposed DF method is obtained through the data-driven REM, which can be regarded as a lossless conversion from process variable to alarm evidence, and an accurate description of the coarse statistical characteristics of the historical sample data. On the other hand, the LU method overemphasizes the importance of historical alarm evidence in each fusion process, the corresponding fusion weights cannot be

Table 5
Partial reliabilities and interval-valued fusion weights under dynamic ER rule.

Parameter		t							
		499	500	501	502	···	1695	1696	1697
Reliability	r_t	0.7403	0.7258	0.7179	0.7021	···	0.6533	0.7513	0.7549
	$r_{1:t-1}$	0.7321	0.6834	0.7735	0.7469	···	0.7302	0.8038	0.7496
Interval weight	W_t	[0.55, 0.61]	[0.38, 0.78]	[0.21, 1]	[0.21, 1]	···	[0.53, 0.62]	[0.56, 0.59]	[0.46, 0.69]
	$W_{1:t-1}$	[0.62, 0.69]	[0.46, 0. 86]	[0.13, 1]	[0.11, 1]	···	[0.76, 0.85]	[0.79, 0.82]	[0.69, 0.92]

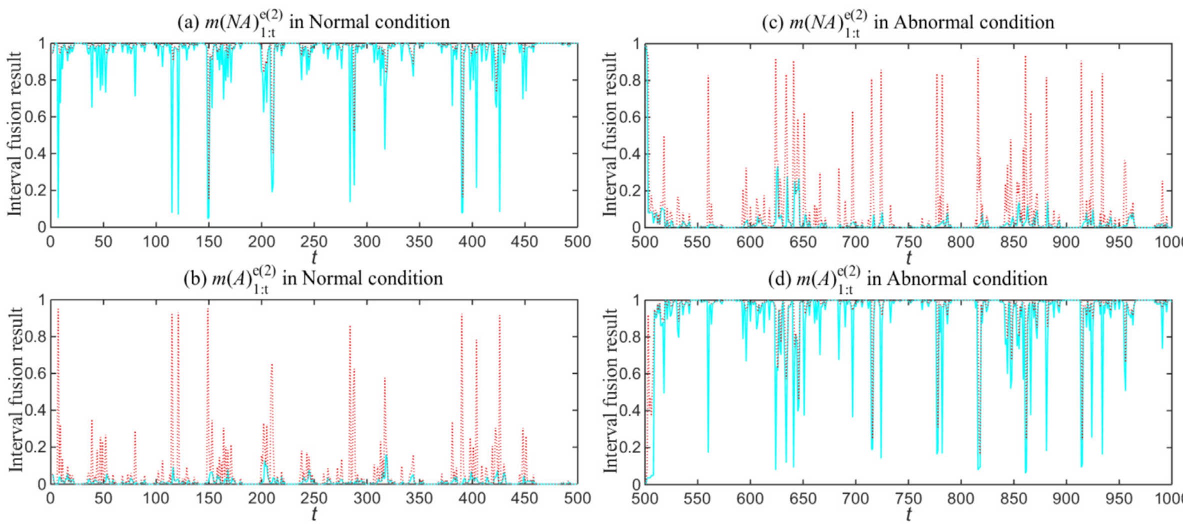

Fig. 4. Interval-valued fusion results $m(\theta)^{e(2)}_{1:t}$.

Table 6
Performance comparison of various methods.

	DF	LU	n-step TD						n-order AF			
			3	4	5	6	7	8	3	4	5	6
m(FAR) (%)	**0.18**	0.72	2.61	0.71	1.13	2.9	0.34	13.87	4.12	2.48	2.14	0.73
m(MAR) (%)	**0.75**	1.96	1.06	0.63	0.53	0.59	0.87	0.61	4.15	2.58	1.01	1.17
AAD	**2.9**	19.3	2.62	4.6	5.34	5.98	8.68	7.5	17.98	29.31	32.55	60.77

adjusted real-timely according to the fine change of the process variable during the transition from normal state to abnormal state, which ultimately makes the AAD too high; The DF method is based on dynamic ER rule to adjust the interval-valued fusion weights and reliabilities of the historical and current alarm evidence in a timely manner, and then can reduce AAD, and make precise alarm-decision during the transition stage.

In addition, the experimental results in Table 6 also show that since the alarm thresholds, delay steps and filter orders of the traditional TD and AF methods will not change after offline determination, the effectiveness of these two methods is certainly not as good as the proposed DF method. Compared with the TD method with different delay steps from $n = 3$ to $n = 8$, and the AF method with different filter orders from $n = 3$ to $n = 6$, the proposed DF method realizes the trade-off between the accuracy (FAR/MAR) and sensitivity (AAD), and to a certain extent achieves the synchronous improvement of the accuracy and sensitivity. Most notably, in the TD method, when delay steps n increase from 3 to 5, FAR decreases, and FAR starts to increase again when $n = 6$; when delay steps n increase from 3 to 6, MAR decreases, and MAR starts to increase again when $n = 7$; There is a similar situation in the AF method. All of these indicate that the introduction of the delay steps and filter orders will improve the performance at the beginning, but it is not an unlimited improvement. There is a basic trade-off between the performance indicators in the field of alarm design.

4.2. Experiment 2

This section implements alarm experiment on the ZHS-2 multifunctional motor rotor experimental platform as shown in Fig. 5. By installing vibration acceleration sensors on the base, the vibration acceleration signal of the rotor is recorded through the HG-8902 data acquisition box. Then the fast Fourier transform (FFT) method is used to convert the collected time-domain signal into frequency-domain signal as process variable. Two states of process variable are considered in the alarm experiment: the normal state, and the abnormal state caused by the unbalance of the rotor. Among them, the turntable is not equipped with any screws to simulate the normal state of the rotor, and the abnormal state is simulated by installing screws on the turntable. In the alarm experiment, the speed of the motor rotor is set at 1500 rpm, the sample frequency of the sensor is 1280 Hz, and the 1 times fundamental frequency is 25 Hz.

The abnormal vibration generated by the screw on the turntable will specifically cause the amplitude of the frequency component to change. Therefore, the amplitude of 1 times fundamental frequency signal is selected as process variable $x(t)$. According to the above experimental conditions, the normal state and abnormal state of the rotor are simulated for many times to carry out alarm experiment. Wherein the process variable data is collected continuously with sample interval of 4 s, and four groups of sample sequences are obtained under normal and abnormal states, each group includes 100 samples, which are

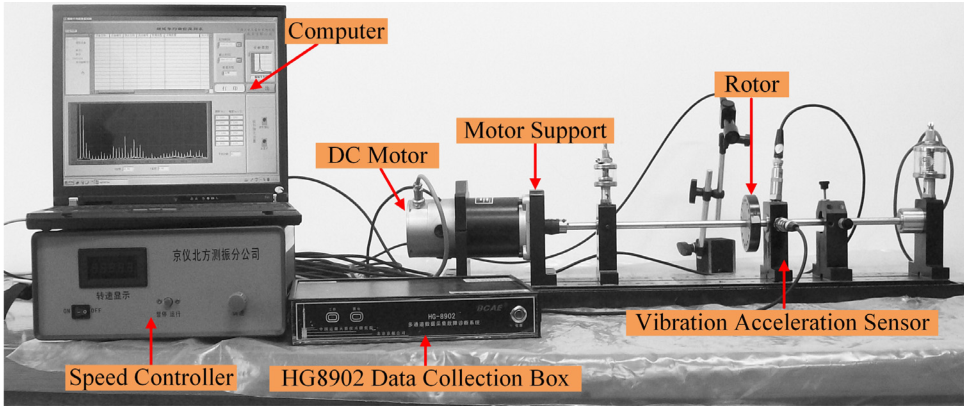

Fig. 5. ZHS-2 multifunctional motor rotor experimental platform.

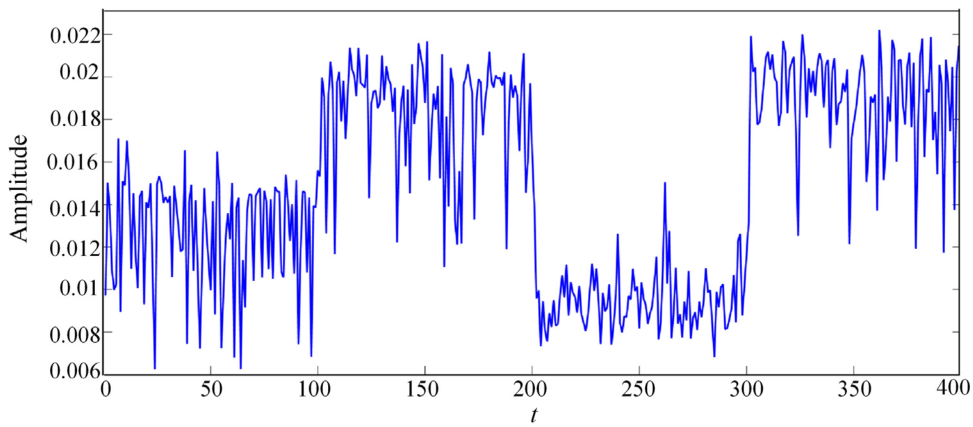

Fig. 6. The sample sequence of process variable $x(t)$.

Table 7
Referential evidential matrix table.

$y(t)$	$x(t)$									
	0.006	0.008	0.01	0.012	0.014	0.016	0.018	0.02	0.022	0.024
Y_1	1	1	0.9876	0.9494	0.7664	0.4003	0.1101	0.0075	0.0042	0
Y_2	0	0	0.0124	0.0506	0.2336	0.5997	0.8899	0.9925	0.9958	1

recorded as $x(t)_{t=1}^{400}$, as shown in Fig. 6 (Fig. 6 shows the sample sequence formed by splicing the data of the rotor in the normal state and the abnormal state).

Use $x(t)_{t=1}^{400}$ as training set, repeat the experimental process in Experiment 1. When segment F_{114} is calculated, UF_{114} and UB_{114} satisfy Conditions 1 and 2, and at $t = 102$, UF_{114} and UB_{114} intersect in the range of critical line ± 1.96, so $x(102)$ is the first change point in the sample sequence, as shown in Fig. 7. Then the two other change points $x(209)$ and $x(301)$ in the sample sequence are found. Based on these detected change points, the normal data segments $\{x(1, 102), x(209, 300)\}$ and abnormal data segments $\{x(103, 208), x(301, 400)\}$ are obtained. These 400 sample pairs are set as training set, the reference values set of input $x(t)$ is set as {0.006, 0.008, 0.01, 0.012, 0.014, 0.015, 0.016, 0.018, 0.02, 0.022, 0.024} by expert knowledge, and the reference values set of output $y(t)$ is set as {0, 1}. Then the REM is established as shown in Table 7. Similarly, the optimal alarm thresholds in moving average filter and time delay are obtained respectively as shown in Table 8. In addition, $w_{c\_tp} = 0.47$ and $w_{h\_tp} = 0.7$ are the optimal fusion weights of the current and historical alarm evidence obtained based on training set.

The alarm experiment is repeated 200 times on motor rotor experimental platform, and the average values of FAR, MAR and

Table 8
The optimal alarm thresholds in moving average filter and time delay.

	Filter orders/delay Steps					
	3	4	5	6	7	8
Average filter	0.0153	0.0155	0.0153	0.0152	0.0158	0.0153
Time delay	0.0151	0.0155	0.0149	0.0133	0.0132	0.0133

AAD are calculated respectively. Table 9 shows the statistical results of m(FAR), m(MAR) and AAD. It can be seen from Table 9 that the m(MAR) = 0.83% of the alarm evidence linear updating method (LU) is close to the m(MAR) = 0.51% of the proposed DF method, but the other two indicators m(FAR) = 1.17%, AAD = 5.2 are higher than m(FAR) = 0.17%, AAD = 2.3 of the proposed method. For the time delay method (TD), when the delay step $n = 4$ and $n = 5$, the corresponding m(FAR) are 0.28% and 0.25%, which are close to the m(FAR) of the proposed method; but the AAD of TD are 4.7 and 5.7, which are higher than the AAD of the proposed method. Similarly, for the moving average filter method (AF), when the filter order $n = 5$ and $n = 6$, the corresponding m(MAR) are 0.75% and 0.52% respectively, which is close to the m(MAR) of the proposed method, but the AAD of AF are 87.6 and 95.4 respectively, which are much higher than

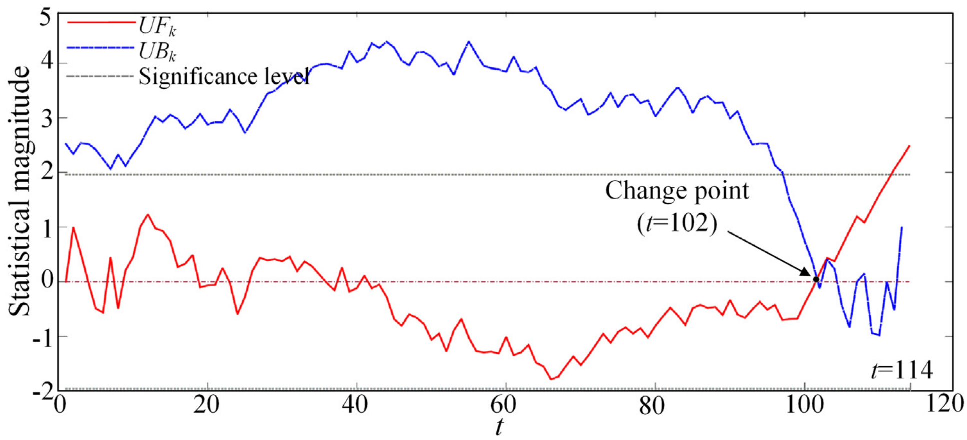

Fig. 7. Mann–Kendall statistical curve of process variable $x(t)$.

Table 9
Performance comparison of various methods.

	DF	LU	n-step TD						n-order AF			
			3	4	5	6	7	8	3	4	5	6
m(FAR) (%)	**0.17**	1.17	1.95	0.28	0.25	10.7	11.7	5.61	4.11	1.54	1.32	0.99
m(MAR) (%)	**0.51**	0.83	0.75	0.91	0.95	0.71	0.95	1.13	2.11	1.48	0.75	0.52
AAD	**2.3**	5.2	2.6	4.7	5.7	4.9	6.4	7.3	17.9	49.8	87.6	95.4

the AAD of the proposed method. Therefore, compared with LU, TD and AF, the proposed univariate alarm design method based on dynamic evidence fusion shows good performance in accuracy and sensitivity. The reason for these performance gaps have been explained detailedly in Experiment 1 and will not be repeated here.

5. Conclusion

In view of the coarse and fine changes of process variable, and the problems existing in the two important processes of data preprocessing and dynamic parameter adjustment, this paper proposes a univariate alarm design method based on dynamic evidence fusion under FoD of DS theory. The main contributions are as follows: (1) For the coarse change of process variable, the initial Mann–Kendall method is improved based on memory and forgetting strategies to divide the historical sample data into normal and abnormal data segments. Then, the REM is established to realize the transformation from process variable to alarm evidence. Both of them are used to reflect the coarse statistical characteristics of historical sample data. (2) For the fine change of process variable, a new dynamic ER rule considering interval-valued fusion weight is proposed. That is, the reliability of alarm evidence is calculated in real time according to the forgetting strategy, and the interval-valued fusion weight of alarm evidence is described by random variable with uniform distribution. All which are used for the dynamic fusion of historical and current alarm evidence, so as to adapt the fine change of real-time sample of process variable and make more accurate alarm-decision. Finally, two experiments are presented to validate the effectiveness of the proposed method than the traditional alarm design methods.

In essence, this paper considers the coarse and fine changes of process variable. For future work, other changes of process variable need to be considered. For instances, the process variable under different working conditions may change essentially with the increasing complexity of industrial equipment. How to make full use of process variable information under different working conditions to formulate accurate alarm may be more significant in practice.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors acknowledge financial support from the Zhejiang outstanding youth fund project (LR21F030001), the NSFC-Zhejiang Joint Fund for the Integration of Industrialization and Informatization (U1709215), the Zhejiang Province Key R&D projects (No. 2019C03104, 2021C03015, 2018C01031), Zhejiang Province Public Welfare Technology Application Research Project (No. LGF20H270004), Key project of Zhejiang Provincial Medical and health Science and Technology Plan (WKJ-ZJ-2038).

References

[1] EEMUA-191, Alarm Systems: A Guide to Design, Management and Procurement, Engineering Equipment and Materials Users' Association, London, 2013.
[2] W. Hu, T. Chen, S.L. Shah, Discovering association rules of mode-dependent alarms from alarm and event logs, IEEE Trans. Control Syst. Technol. 26 (3) (2018) 971–983.
[3] K. Parsa, M. Hassall, M. Naderpour, Process alarm modeling using graph theory: Alarm design review and rationalization, IEEE Syst. J. 15 (2) (2020) 2257–2268.
[4] T. Xie, Z. Li, T. Wang, Y. Wang, An integration fault detection method using stator voltage for marine current turbines, Ocean Eng. 226 (3) (2021) 108808.
[5] M.S. Afzal, T. Chen, A. Bandehkhoda, I. Izadi, Analysis and design of time-deadbands for univariate alarm systems, Control. Eng. Pract. 71 (2) (2018) 96–107.
[6] A. Tulsyan, F. Alrowaie, B. Gopaluni, Design and assessment of delay timer alarm systems for nonlinear chemical processes, AIChE J. 64 (1) (2018) 77–90.
[7] M.H. Roohi, T. Chen, Generalized moving variance filters for industrial alarm systems, J. Process Control 95 (2020) 75–85.
[8] J. Xu, J. Wang, I. Izadi, T. Chen, Performance assessment and design for univariate alarm systems based on FAR, MAR, and AAD, IEEE Trans. Autom. Sci. Eng. 9 (2) (2012) 296–307.

[9] C. Zhao, J. Chen, H. Jing, Condition-driven data analytics and monitoring for wide-range nonstationary and transient continuous processes, IEEE Trans. Autom. Sci. Eng. 18 (4) (2021) 1563–1574.
[10] C. Zhao, H. Sun, Dynamic distributed monitoring strategy for large-scale nonstationary processes subject to frequently varying conditions under closed-loop control, IEEE Trans. Ind. Electron. 66 (6) (2019) 4749–4758.
[11] S. Aminikhanghahi, D.J. Cook, A survey of methods for time series change point detection, Knowl. Inf. Syst. 51 (2) (2017) 339–367.
[12] X. Li, S. Ghosal, Bayesian change point detection for functional data, J. Statist. Plann. Inference 213 (2021) 193–205.
[13] H. Keshavarz, C. Scott, X.L. Nguyen, Optimal change point detection in Gaussian processes, J. Statist. Plann. Inference 193 (2018) 151–178.
[14] C. Yu, H. Wang, J. Yao, J. Zhao, Q. Sun, H. Zhu, A dynamic alarm threshold setting method for photovoltaic array and its application, Renew. Energy 158 (2020) 13–22.
[15] Y. Du, J. Zhong, Generalized combination rule for evidential reasoning approach and Dempster–Shafer theory of evidence, Inf. Sci. 547 (2021) 1201–1232.
[16] S. Frittella, K. Manoorkar, A. Palmigiano, A. Tzimoulis, N. Wijnberg, Toward a Dempster-Shafer theory of concepts, Internat. J. Approx. Reason. 125 (2020) 14–25.
[17] S. Mandal, B. Jayaram, Bandler-Kohout subproduct with Yager's classes of fuzzy implications, IEEE Trans. Fuzzy. Syst. 22 (3) (2014) 469–482.
[18] D. Han, Y. Yang, C. Han, Evidence updating based on novel Jeffrey-like conditioning rules, Int. J. Gen. Syst. 46 (6) (2017) 587–615.
[19] J. Yang, D. Xu, Evidential reasoning rule for evidence combination, Artificial Intelligence 205 (2013) 1–29.
[20] X. Xu, S. Li, X. Song, C. Wen, D. Xu, The optimal design of industrial alarm systems based on evidence theory, Control. Eng. Pract. 46 (2016) 142–156.
[21] Z. Luo, Y. Deng, A matrix method of basic belief assignment's negation in Dempster-Shafer theory, IEEE Trans. Fuzzy. Syst. 28 (9) (2020) 2270–2276.
[22] M. Zhou, X. Liu, J. Yang, Y. Chen, J. Wu, Evidential reasoning approach with multiple kinds of attributes and entropy-based weight assignment, Knowl.-Based Syst. 163 (2019) 358–375.
[23] A.L. Jousselme, P. Maupin, Distances in evidence theory: Comprehensive survey and generalizations, Internat. J. Approx. Reason. 53 (2) (2012) 118–145.
[24] Y. Yan, J. Wang, Alarm monitoring for multivariate processes based on a convex-hull normal operating zone, IEEE Trans. Control Syst. Technol. 28 (6) (2020) 2649–2656.
[25] I. Izadi, S.L. Shah, D.S. Shook, S.R. Kondaveeti, T. Chen, A framework for optimal design of alarm systems, IFAC Proc. Vol. 42 (8) (2009) 651–656.
[26] S.K. Tanbeer, C.F. Ahmed, B.S. Jeong, Y.K. Lee, Sliding window-based frequent pattern mining over data streams, Inf. Sci. 179 (22) (2009) 3843–3865.
[27] N. Fatemeh, D. Mahmood, H.S. Mohamad, A sliding window based algorithm for frequent closed itemset mining over data streams, J. Syst. Softw. 86 (3) (2013) 615–623.
[28] E. Boissard, T.L. Gouic, J.M. Loubes, Distribution's template estimate with Wasserstein metrics, Bernoulli 21 (2) (2015) 740–759.
[29] A. Yan, W. Wang, C. Zhang, H. Zhao, A fault prediction method that uses improved case-based reasoning to continuously predict the status of a shaft furnace, Inf. Sci. 259 (2014) 269–281.