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A new method to detect and quantify correlated alarms with occurrence delays☆

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ABSTRACT

This paper proposes a new method to detect correlated alarms and quantify the correlation level to improve the management of industrial alarm systems. The method is mainly composed of three parts. First, a so-called occurrence delay is defined as the main cause leading to erroneous conclusions from existing methods to detect correlated alarms. In order to tolerate the presence of occurrence delays, a mechanism is presented to generate continuous-valued pseudo alarm signals. Second, a novel approach is given to estimate the correlation delay between alarm signals, so that the correlation delay can be separated from occurrence delays to obtain real occurrence delays (ROD). Third, a statistical test based on the ROD is proposed to determine whether two alarm signals are correlated or not, and the Pearson's correlation coefficient is applied to quantify the correlation level. Numerical examples and industrial case studies are provided to support the proposed method.

1. Introduction

Modern industrial plants consist of many highly interconnected sensors, actuators and control loops. Due to system complexity, a single fault may happen in one component and propagate throughout plant devices to cause operational upsets or even catastrophic consequences. Alarm systems are critical assets of modern industrial plants to assist operators in managing plant upsets and hazardous situations. However, alarm systems often poorly function and suffer from some serious problems, such as nuisance alarms and alarm floods (Hollifield and Habibi, 2007). Consequently, operators might be confounded by these problems, and be less alert to meaningful alarms.

Industrial guidelines and standards such as ISA 18.02 (2009) and EEMUA-191 (2013) have been developed and well accepted for the management of industrial alarm systems. In particular, the ISA-18.2 standard (2009) draws a lifecycle covering many stages of alarm management; at the rationalization stage, alarm justification and prioritization should ensure that one alarm does not duplicate another alarm that is designed for the same abnormality. However, massive interacting components make redundancy almost inevitable. As a result, alarms could be either redundant or highly overlapping to indicate the presence of the same abnormality (Rothenberg, 2009). The monitoring burden of operators is increased due to redundant alarm annunciators; these redundant alarms should be detected and suppressed. Meanwhile, related alarms could be grouped and presented to operators as symptoms to detect abnormalities. Therefore, to improve the alarm management, it is necessary to identify correlated alarms, namely the alarms always occurring within a short time period to each other (Rothenberg, 2009).

Some techniques have been developed recently to detect correlated alarms from historical data. Yang et al. (2010) analyzed the difference between the cross correlation of process signals and that of alarm signals, and combined the results of cross correlation with process connectivity information to design alarm limits. Noda et al. (2011) proposed a scheme called event correlation analysis to quantify the relationship between alarms and operating actions, and to identify correlated alarms and unnecessary operating actions. Kondaveeti et al. (2012) grouped similar alarms together based on Jaccard similarity coefficients in an alarm similarity map. Yang et al. (2012) transformed binary alarm sequences to continuous-valued pseudo alarm sequences and clustered correlated alarms based on the

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cross correlation of pseudo alarm sequences. Yang et al. (2013) compared different similarity coefficients for binary-valued alarm signals, and detected correlated alarms based on the Sorgenfrei coefficient and the distribution of correlation delays.

This paper is a continuing study of our previous work (Yang et al., 2013), and is motivated by two drawbacks revealed in our industrial experience in the application of the method proposed in Yang et al. (2013) to detect correlated alarms: (i) the estimated Sorgenfrei coefficients (as well as Jaccard coefficients in Kondaveeti et al. (2012)) sometimes are quite small even for two alarm signals that have been known to be physically related; (ii) the distribution of correlation delays requires a large amount of data samples to get a sufficient number of alarm activations, which sometimes is a demanding requirement in practice. This paper analyzes the causes of the two drawbacks and proposes corresponding solutions. To be precise, the contributions of this paper is to propose a new method to detect correlated alarms and quantify their correlation level. The proposed method is composed of three parts. First, the so-called occurrence delay is defined and identified as the main cause of the first drawback mentioned above; in order to tolerate the presence of occurrence delays, a mechanism is proposed to generate pseudo alarm signals. Second, a novel approach is given to estimate the correlation delay in order to formulate real occurrence delays (ROD), and is shown to perform better than the counterparts based on maximizing Sorgenfrei and Jaccard coefficients. Third, a statistical test based on the ROD is proposed to determine whether two alarm signals are correlated or not; this test requires a much smaller number of alarm activations so that the second drawback discussed earlier is resolved.

The rest of the paper is organized as follows. Section 2 defines the occurrence delay and presents the mechanism to obtain pseudo alarm signals. Section 3 proposes an algorithm to estimate the correlation delay and a novel statistical test to detect correlated alarms. Industrial case studies are provided in Section 4 to validate the obtained results. Section 5 concludes the paper.

2. Occurrence delays

This section first introduces alarm signals, and defines the occurrence delays caused by random noises. Next, a mechanism to generate pseudo alarm signals is presented to alleviate the effects of occurrence delays on the detection of correlated alarms.

2.1. Alarm signals

Alarm signals can be represented in two forms. One formulation is that an alarm signal takes the value of 1 only at the time instant when its associated process signal goes into the abnormal state from the normal state. To be precise, if $x_p(t)$ is a discrete-time process signal, then the corresponding alarm signal $x_a(t)$ is generated as

$$x_a(t) = \begin{cases} 1, & \text{if } x_p(t) \notin \mathcal{T} \ \& \ x_p(t-1) \in \mathcal{T} \\ 0, & \text{otherwise} \end{cases}, \tag{1}$$

where $\mathcal{T}$ is the normal range of $x_p(t)$. Taking the generation of high alarms as an example, if a real-valued constant x_{tp} is the high-alarm trip point, then $\mathcal{T}$ stands for the normal range $(-\infty, x_{tp}]$. Another formulation of alarm signals is that an alarm signal takes the value of 1 throughout the time duration when the associated process signal is in the abnormal state, i.e.,

$$\tilde{x}_a(t) = \begin{cases} 1, & \text{if } x_p(t) \notin \mathcal{T} \\ 0, & \text{otherwise} \end{cases}. \tag{2}$$

Yang et al. (2013) (Section II-B therein) investigated the two formulations for the purpose of detecting correlated alarms, and recommended the usage of $x_a(t)$ in (1), which is adopted in this paper. Note that if the return to normal time instants in $\tilde{x}_a(t)$ need to be considered, the proposed algorithm is equally applicable after adding extra '1's to $x_a(t)$ in (1) at these time instants.

Chattering alarms are the most common nuisance alarms caused by measurement noises and disturbances (EEMUA-191, 2013). They make fast transitions between alarm and non-alarm states in a short span of time without operators' response. Removing chattering alarms is a prerequisite for alarm flood analysis (Cheng et al., 2013). In the detection of correlated alarms, chattering alarms play a role as 'noise', while the alarms activated by actual abnormal conditions serve as 'signal'. If chattering alarms are dominant, then the signal-to-noise level is too low to detect correlated alarms. Therefore, it is necessary to remove chattering alarms before detecting correlated alarms. The detection and removal of chattering alarms have been studied recently by Naghoosi et al. (2011), Wang and Chen (2013, 2014). In particular, an m-sample delay timer is an effective way to remove chattering alarms, and can be represented as

$$x'_a(t) = \begin{cases} 1, & \text{if } \tilde{x}_a(t-m+1:t) = 1 \text{ and } x'_a(t-1) = 0 \\ 0, & \text{if } \tilde{x}_a(t-m+1:t) = 0 \text{ and } x'_a(t-1) = 1 \\ x'_a(t-1), & \text{otherwise} \end{cases}, \tag{3}$$

where $\tilde{x}_a(t-m+1:t)$ is a short notation for the set $\left\{\tilde{x}_a(t-m+1), \ldots, \tilde{x}_a(t)\right\}$. In the sequel, we assume that chattering alarms have been effectively removed by using the delay timer with the designed m as proposed by Wang and Chen (2014).

2.2. Definition of occurrence delays

This subsection defines the occurrence delays that have significant effects on the detection of correlated alarms.

As revealed in (1), the occurrence of an alarm is associated with an event that the corresponding process signal runs into the abnormal state. Thus, the correlation between process signals is the essence leading to correlated alarms. In general, the relation between two correlated process signals $x_p(t)$ and $y_p(t)$ can be described as

$$y_p(t) = f\left(x_p(t-\tilde{\tau})\right) + \omega(t) \tag{4}$$

where the symbol $f(\cdot)$ stands for a functional linear/nonlinear relationship, the constant $\tilde{\tau}$ is the time delay, and the signal $\omega(t)$ is a disturbance additive to $y_p(t)$.

Suppose that the occurrence of an abnormality in $x_p(t)$ causes an alarm activation of $x_a(t)$, i.e., $x_a(t)$ changes from the non-alarm state 0 to the alarm state 1 at a particular time instant k. Because $x_p(t)$ and $y_p(t)$ are connected as that in (4), the abnormality in $x_p(t)$ may be propagated to $y_p(t)$, leading to an alarm activation in $y_a(t)$. Then, three terms are defined as follows:

Definition 1. If the disturbance $w(t)$ is absent, and an abnormality always causes the alarm signals $x_a(t)$ and $y_a(t)$, associated with two correlated process signals $x_p(t)$ and $y_p(t)$, changing from 0 to 1 at the time instants k and $k+\tau$ respectively for a positive integer k, then the time difference τ is defined as the correlation delay between $x_a(t)$ and $y_a(t)$. If $w(t)$ is present, then an abnormality may cause $x_a(t)$ and $y_a(t)$ respectively changing their values from 0 to 1 at the time instants k and $k+\lambda(k)$, where $\lambda(k)$ is a random variable. Here $\lambda(k)$ is referred to as the occurrence delay between $x_a(t)$ and $y_a(t)$. The sequence

$$\lambda_r(k) := \lambda(k) - \tau \tag{5}$$

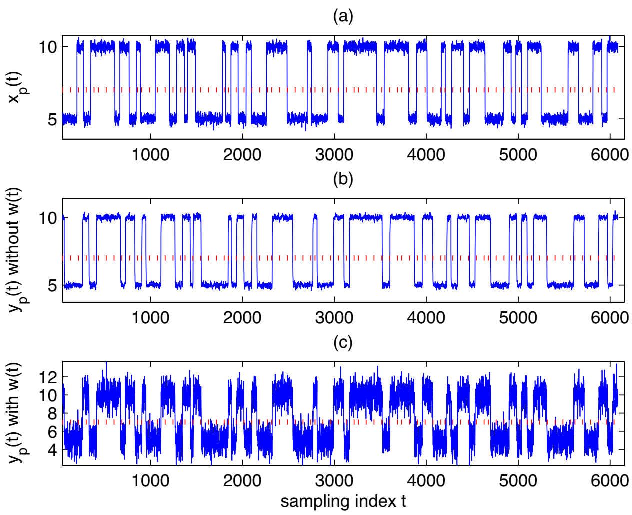

Fig. 1. Process signals in Example 1: (a) $x_p(t)$ (solid) with x_{tp} (dash), (b) $y_p(t)$ (solid) with y_{tp} (dash) for the case that $w(t)$ is absent, (c) $y_p(t)$ (solid) with y_{tp} (dash) for the case that $w(t)$ is present.

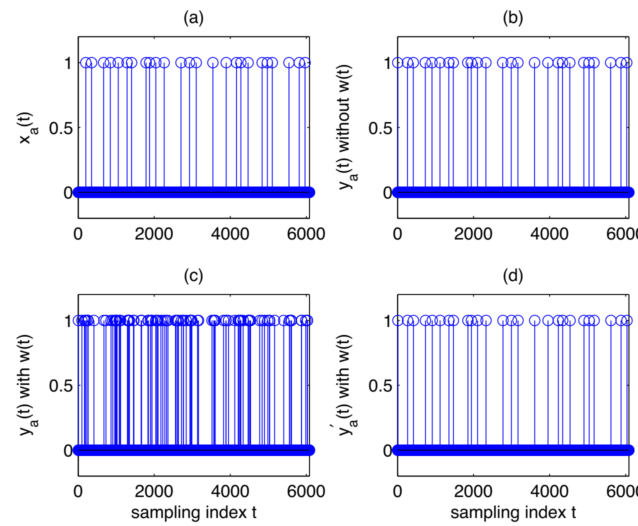

Fig. 2. Alarm signals in Example 1: (a) $x_a(t)$, (b) $y_a(t)$ for the case that $w(t)$ is absent, (c) $y_a(t)$ for the case that $w(t)$ is present, (d) $y'_a(t)$ for the case that $w(t)$ is present.

is defined as the real occurrence delay (ROD) between $x_a(t)$ and $y_a(t)$.

It is worthy to note that owing to the possible presence of nonlinearity in $f(\cdot)$, the correlation delay τ does not have to be the same as $\tilde{\tau}$ in (4).

Example 1. This example is used to illustrate the presence of occurrence delays. The process signal $x_p(t)$ is generated as

$$x_p(\tilde{l}_{m-1}+1:\tilde{l}_m)=\begin{cases}\mathcal{N}(\mu_1,\sigma_1), & \text{if } x_s(m)=0\\ \mathcal{N}(\mu_2,\sigma_2), & \text{if } x_s(m)=1\end{cases}. \tag{6}$$

Here $x_p(t)$ is composed by M segments, and the length of the mth segment for $m=1, 2, \ldots, M$ is a uniform random variable l_m in the range $[L_1, L_2]$ for two positive integers L_1 and L_2; thus, $x_p(\tilde{l}_{m-1}+1:\tilde{l}_m)$ represents the samples of $x_p(t)$ over a range $t\in[\tilde{l}_{m-1}+1:\tilde{l}_m]$ with $\tilde{l}_{m-1}:=\sum_{i=1}^{m-1}l_i$ and $\tilde{l}_m=\tilde{l}_{m-1}+l_m$. In the mth segment, $x_p(t)$ is in the normal or abnormal state, determined by a Bernoulli random variable $x_s(m)\sim\mathcal{B}(1,p)$, where p is the probability of abnormal state. The symbol $\mathcal{N}(\mu,\sigma)$ stands for the Gaussian distribution with mean μ and standard deviation σ. The disturbance $\omega(t)\sim\mathcal{N}(0,\sigma_\omega)$ is another Gaussian white noise being independent to $x_p(t)$. The process signal $y_p(t)$ is obtained from (4), where the process function $f(\cdot)$ is a first-order dynamic digital filter,

$$f(z)=\frac{0.5}{z-0.5}, \tag{7}$$

and the time lag between $x_p(t)$ and $y_p(t)$ is $\tilde{\tau}=60$. In this example, the parameters in (6) are selected as $M=100$, $L_1=30$, $L_2=90$, $\mu_1=5$, $\mu_2=10$, $\sigma_1=0.2$, $\sigma_2=0.2$, and $p=0.25$. Assume that the alarms $x_a(t)$ and $y_a(t)$ are generated from $x_p(t)$ and $y_p(t)$ as that in (1) by using high-alarm trip points $x_{tp}=7$ and $y_{tp}=7$.

If the noise $w(t)$ is absent, i.e., $\sigma_\omega=0$, then $x_p(t)$ and $y_p(t)$ are respectively presented in Fig. 1(a) and (b), while the alarm signals $x_a(t)$ and $y_a(t)$ are respectively given in Fig. 2(a) and (b). The distribution of occurrence delays is shown in Fig. 3(a). All the 25 occurrence delays are the same, namely, $\lambda(k)=61$ for $k=1, 2, \ldots, 25$.

If $w(t)$ is present with $\sigma_\omega=1$, then $y_p(t)$ becomes the one in Fig. 1(c), while $y_a(t)$ is shown in Fig. 2(c). There are many chattering alarms in $y_a(t)$; using the m-sample delay timer in (3) with $m=5$ can effectively remove all the chattering alarms, as shown by the resulting alarm signal $y'_a(t)$ in Fig. 2(d). The resulting 25 occurrence delays are not equal, as shown by the histogram of these occurrence delays in Fig. 3(b). Note that the usage of the delay timer introduces some extra time delay (about 5 samples) to the occurrence delays. □

The presence of occurrence delays has significant effects on the existing methods to detect correlated alarms, which are based on similarity measures of binary sequences such as Jaccard and Sorgenfrei coefficients (Kondaveeti et al., 2012; Yang et al., 2013). The definitions of Jaccard and Sorgenfrei coefficients are

$$S_{Jacc}=\frac{C}{N_x+N_y-C}, \tag{8}$$

$$S_{Sorg}=\frac{C^2}{N_xN_y}. \tag{9}$$

Here C is the number of 1's appeared simultaneously in $x_a(t)$ and $y_a(t)$, and N_x and N_y are the total numbers of 1's in $x_a(t)$ and $y_a(t)$, respectively. The effectiveness of these coefficients requires an alignment of the time instants that $x_a(t)$ and $y_a(t)$ are activated to take the value 1. However, if occurrence delays are present, as illustrated in Example 1, then there is no way to achieve an alignment

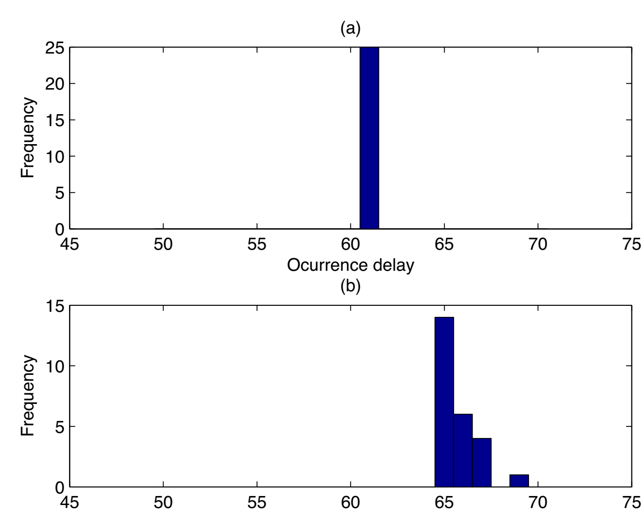

Fig. 3. The histograms of occurrence delays without (a) and with (b) the presence of $\omega(t)$.

without errors, so that the methods based on Jaccard and Sorgenfrei coefficients may lead to erroneous conclusions. In particular, the calculated Jaccard or Sorgenfrei coefficient could be very low even for the case that two alarm sequences are indeed correlated. This issue had been noticed previously and two solutions were proposed (Kondaveeti et al., 2012; Yang et al., 2012). One solution is to pad extra 1's at both sides of each 1 in $x_a(t)$ (Kondaveeti et al., 2012). That is, if $x_a(t)=1$, then extra 1's are padded to $x_a(t)$ to have $x_a(t-\delta:t+\delta)=1$ for a positive integer δ. This solution apparently introduces extra 1's and leads to biased estimates of Jaccard and Sorgenfrei coefficients; thus, it is not adopted here. Another solution is to transform the alarm signal $\tilde{x}_a(t)$ in (2) into the so-called pseudo alarm signals (Yang et al., 2012). We will adopt the similar idea for $x_a(t)$ in (1), with the details to be presented in the next subsection.

2.3. Mechanism to generate pseudo alarm signals

This subsection is on the mechanism to generate pseudo alarm signals in order to tolerate the presence of occurrence delays.

First, the generation of pseudo alarm signals is to deal with the RODs $\lambda_r(k)$ in (5) so that it should be independent to the correlation delay τ. Thus, $x_a(t)$ or $y_a(t)$ needs to be shifted by τ samples properly in order to set the correlation delay after shifting to be zero. Without loss of generality, we choose to shift $y_a(t)$, i.e.,

$$y_{a,s}(t) := y_a(t-\tau). \tag{10}$$

After the data shifting, the sequence of $y_{a,s}(t)$ needs to be padded with zeros to have the same length with that of $x_a(t)$. Thus, two alarm sequences are formulated $X_a := \{x_a(t)\}_{t=1}^N$ and $Y_{a,s} := \{y_{a,s}(t)\}_{t=1}^N$, respectively.

Second, we obtain pseudo alarm signals for the alarm sequences X_a and $Y_{a,s}$ as follows. A kernel density estimation method is used to convert the binary alarm signal $x_a(t)$ to a real-valued pseudo alarm signal denoted as $x_{a,p}(t)$. If the Gaussian kernel function is used (Silverman, 1998), then $x_{a,p}(t)$ is formulated as

$$x_{a,p}(t) = \sum_{i=1}^{N_x} e^{-\frac{(t-t_i)^2}{2h^2}}, \tag{11}$$

where the alarm quantity N_x is the total number of 1's in X_a, t_i is the time index that $x_a(t)$ takes the value 1, and h is the bandwidth of the Gaussian kernel function. Note that the difference between $x_{a,p}(t)$ and the pseudo alarm signals in Yang et al. (2012) is that $x_a(t)$ in (1) is used, instead of $\tilde{x}_a(t)$ in (2). As shown in Yang et al. (2013) (Section II-B therein), $x_a(t)$ is more suitable for the detection of correlated alarms than $\tilde{x}_a(t)$, so that generating pseudo alarm signals based on $x_a(t)$ is a more reasonable choice, too. Analogously to $x_{a,p}(t)$ in (11), the pseudo alarm signal for $y_{a,s}(t)$ in (10) is

$$y_{a,p}(t) = \sum_{j=1}^{N_y} e^{-\frac{(t-t_j)^2}{2h^2}}, \tag{12}$$

where N_y is the total number of 1's in $Y_{a,s}$, and t_j is the time index that $y_{a,s}(t)$ takes the value 1.

The bandwidth h in (11) and (12) is a critical parameter that affects the subsequent detection of correlated alarms. The selection of h should satisfy two conditions: (1) h should be large enough to cover the nonzero RODs between possibly correlated alarm signals; (2) h should not be too large so as to avoid the possible overlapping in $x_{a,p}(t)$ or $y_{a,p}(t)$ between adjacent 1's in $x_a(t)$ or $y_{a,s}(t)$. Thus, h is

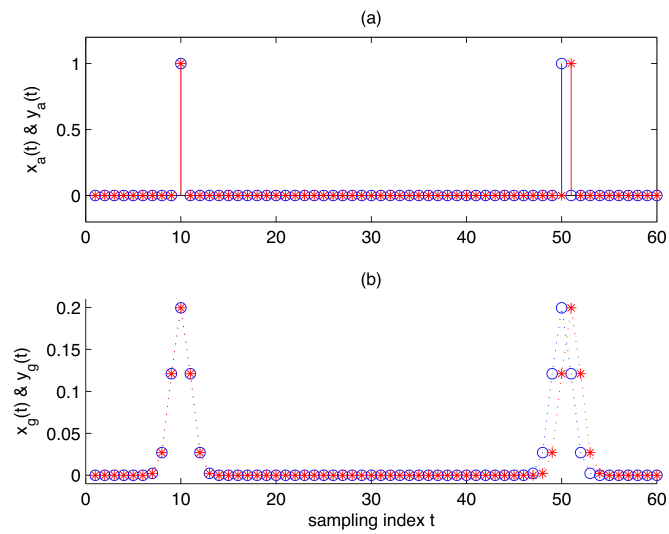

Fig. 4. Example 2a: (a) $x_a(t)$ and $y_a(t)$, (b) $x_g(t)$ and $y_g(t)$.

subject to such a tradeoff. An empirical choice of h is the sample mean of all nonzero RODs,

$$h = \frac{1}{L}\sum_{l=1}^{L}\tilde{\lambda}_r(l) \tag{13}$$

where $\tilde{\lambda}_r(l)$'s for $l=1, 2, \ldots, L$ are the nonzero RODs of $\lambda_r(k)$ in (5).

Now, it is ready to calculate Pearson's correlation coefficient that is a widely-used statistic to measure the correlation between two random variables (Johnson and Wichern, 2002). That is, Pearson's correlation coefficient between pseudo alarm sequences $X_{a,p} := \{x_{a,p}(t)\}_{t=1}^N$ and $Y_{a,p} := \{y_{a,p}(t)\}_{t=1}^N$ is

$$r_{xy} = \frac{1}{N-1}\sum_{t=1}^{N}\left(\frac{x_{a,p}(t)-\bar{x}_{a,p}}{S_x}\right)\left(\frac{y_{a,p}(t)-\bar{y}_{a,p}}{S_y}\right) \tag{14}$$

where $\bar{x}_{a,p}$ ($\bar{y}_{a,p}$) and S_x (S_y) are the sample mean and standard deviation of $x_{a,p}(t)$ ($y_{a,p}(t)$), respectively. The overlapped area between two pseudo sequences $X_{a,p}$ and $Y_{a,p}$ is able to alleviate the effects of occurrence delays, and thus to reflect the correlation between alarm signals more accurately than the similarity measures for binary alarm signals such as Jaccard and Sorgenfrei coefficients. Two numerical examples are presented here to support this statement.

Example 2a. This is an illustrative example with only two occurrences of alarms in $x_a(t)$ and $y_a(t)$ as shown in Fig. 4(a). The first pair of alarms occurs at the time instant $t=10$ for both $x_a(t)$ and $y_a(t)$, while the second pair of alarms occurs at $t=50$ for $x_a(t)$ and $t=51$ for $y_a(t)$, respectively. If the one-sample time difference between the second pair of alarms is a realization of RODs, then $x_a(t)$ and $y_a(t)$ are regarded to be completely correlated with a correlation measure about 1. However, Jaccard and Sorgenfrei coefficients are respectively calculated from (8) and (9) as $S_{Jacc}=1/(2+2-1)=0.3333$ and $S_{Sorg}=1/(2\cdot 2)=0.25$, which are far away from 1. If pseudo alarm signals are generated, as shown in Fig. 4(b), Pearson's correlation coefficient r_{xy} is equal to 0.8745. Thus, pseudo alarm signals can effectively alleviate the negative effects of RODs on the detection of correlated alarms.

Example 2b. The configuration is the same as Example 1, except that the original correlation delay $\tau=61$ (see Fig. 3(a)) has been removed. 1000 Monte Carlo simulations are implemented. In each simulation, the noise $\omega(t)$ is randomly generated with the standard deviation $\sigma_\omega=1.4$. To generate pseudo signals, the bandwidth h is

Table 1
Calculated correlation statistics for Example 2b.

Signal type	Statistic	Mean	Std
Pseudo alarm signals	Pearson's correlation coefficient	0.8532	0.0290
Binary alarm signals	Jaccard coefficient	0.4780	0.0569
	Sorgenfrei coefficient	0.4271	0.0487

calculated using (13). The value of h is changing with the mean 1.01 and standard deviation 0.04 as calculated from the simulations. Table 1 compares the sample means and standard deviations of Pearson's correlation coefficient based on pseudo alarm signals, and Jaccard and Sorgenfrei coefficients based on alarm signals. Considering the linear relationship between $x_p(t)$ and $y_p(t)$, the alarm signals $x_a(t)$ and $y_a(t)$ should be highly correlated to each other and the correlation statistics should be close to 1. It is obvious that Pearson's correlation coefficients are much higher than Jaccard and Sorgenfrei coefficients, and are consistent with the fact that $x_a(t)$ and $y_a(t)$ are indeed correlated. Hence, the utilization of pseudo alarm signals is effective in avoiding false detection in the presence of occurrence delays.

3. Detection of correlated alarms

This section presents a new approach to estimate the correlation delay, and a statistical test to determine whether two alarm signals are correlated or not. Next, the procedures of the proposed method to detect and quantify correlated alarms are summarized.

3.1. Estimation of the correlation delay

In Section 2.3, the correlation delay τ is set to zero by shifting data samples before generating pseudo alarm signals. This subsection provides a new approach to estimate τ.

Algorithm 1. Occurrence delay based estimation (ODE) algorithm.

```
Input Argument #1: Alarm sequences X_a := {x_a(t)}_{t=1}^N and Y_a := {y_a(t)}_{t=1}^N;
Input Argument #2: L the maximum value of the correlation delay;
for i = −L to L do
  if i < 0 then
    S_1 = Y_a(1 : N + i); S_2 = X_a(1 − i : N);
  else
    S_1 = X_a(1 : N − i); S_2 = Y_a(1 + i : N);
  end if
  a_1 = find (S_1 = =1); a_2 = find (S_2 = =1);
  q_1 = length (a_1); q_2 = length (a_2);
  if q_1 < q_2 then
    for k = 1 to q_1 do
      λ_r(k) = min (|a_1(k) − a_2|);
    end for
  else
    for k = 1 to q_2 do
      λ_r(k) = min (|a_2(k) − a_1|);
    end for
  end if
  λ̄_r(i) = mean (λ_r);
end for
τ̂ = arg_i min λ̄_r(i).
```

Based on the definition of the ROD $\tilde{\lambda}(k)$ in (5), it is obvious that $\tilde{\lambda}(k)$ should be close to zero for correlated alarms. This leads us to estimate the correlation delay τ as

$$\hat{\tau} = \arg\min_{\tau} \bar{\lambda}_r(\tau), \tag{15}$$

where

$$\bar{\lambda}_r(\tau) = \frac{1}{K}\sum_{k=1}^{K} |\lambda(k) - \tau|. \tag{16}$$

Here $\lambda(k)$'s for $k = 1, 2, \ldots, K$ are the occurrence delays between $x_a(t)$ and $y_a(t)$. Based on (15), a so-called occurrence delay based estimation (ODE) algorithm is proposed, with the computer pseudo codes listed as Algorithm 1. The ODE algorithm provides an estimate of the correlation delay τ. If τ is positive, it is said that $y_a(t)$ follows $x_a(t)$ by τ samples; otherwise, $y_a(t)$ proceeds $x_a(t)$ by $|\tau|$ samples.

Estimating the correlation delay τ is also a necessary step in the existing methods of detecting correlated alarms based on Jaccard and Sorgenfrei coefficients (Kondaveeti et al., 2012; Yang et al., 2013). For instance, the estimation of τ based on Sorgenfrei coefficient is (Yang et al., 2013),

$$\hat{\tau} = \arg\max_{\tau} S_{Sorg}(\tau), \tag{17}$$

where $S_{Sorg}(\tau)$ takes the value of Sorgenfrei coefficient in (9) between $x_a(t)$ and $y_a(t+\tau)$. Thus, $\hat{\tau}$ in (17) is based on the best alignment of 1's in alarm signals to have the largest value of Sorgenfrei coefficient, while $\hat{\tau}$ in (15) is to make the mean of RODs close to zero. Therefore, the proposed approach to estimate τ is very different from the existing approaches in Kondaveeti et al. (2012) and Yang et al. (2013).

Example 3. The configuration is the same as in Example 1. Parameters M, L_1, L_2, μ_1, μ_2, σ_1, σ_2, x_{tp} and y_{tp} are the same as in Example 1, while other parameters $\tilde{\tau}$, p, and σ_ω, are randomly determined in each simulation, in the ranges $\tilde{\tau} \in [-80, 80]$, $p \in [0.15, 0.5]$, and $\sigma_\omega \in [2, 5]$. 10,000 Monte Carlo simulations are implemented. The ODE algorithm and the approaches by maximizing Sorgenfrei and Jaccard coefficients, e.g., that in (17), are applied to estimate the correlation delay $\tau = 61$ between $x_a(t)$ and $y_a(t)$. Table 2 presents the mean absolute errors (MAE) and mean absolute percentage errors (MAPE) from the 10,000 Monte Carlo simulations. It is obvious that the ODE algorithm performs much better than the other two approaches. The difference arises from a fact that the presence of occurrence delays introduces errors in the alignment of alarm activations, and leads to the erroneous estimates of τ in the approaches based on Jaccard and Sorgenfrei coefficients; by contrast, such an alignment of alarm activations is not required in the ODE algorithm.

Table 2
Estimation of the correlation delay using different approaches for Example 3.

Approaches	MAE	MAPE %
The ODE algorithm	0.5752	2.4981
Estimation based on Jaccard coefficients	1.2385	7.6430
Estimation based on Sorgenfrei coefficients	1.1811	7.5249

3.2. Statistical test

This subsection provides a statistical test to tell whether two alarm signals are correlated or not.

The Pearson's correlation coefficient r_{xy} in (14) based on pseudo alarm signals $x_{a,p}(t)$ and $y_{a,p}(t)$ is able to quantify the level of correlation; however, r_{xy} is not suitable for determining whether the alarm signals $x_a(t)$ and $y_a(t)$ are correlated, because the distributions of $x_{a,p}(t)$ and $y_{a,p}(t)$ are unavailable so that a threshold for testing $r_{xy} \neq 0$ is rather difficult to be determined.

If alarm signals $x_a(t)$ and $y_a(t)$ are correlated, then the estimated correlation delays $\hat{\tau}$'s in (15) for different realizations of $x_a(t)$ and $y_a(t)$ should be concentrated to a small interval around the actual correlation delay τ; by contrast, if $x_a(t)$ and $y_a(t)$ are uncorrelated, then $\hat{\tau}$'s in (15) are distributed randomly. A similar observation has been presented in Yang et al. (2013), where a statistical test is proposed on whether the distribution of $\hat{\tau}$ in (17) is concentrated to a small interval. However, such a statistical test has a drawback for practical applications, namely, multiple estimates of $\hat{\tau}$ have to be obtained. A recommendation therein is to have at least 10 estimates of $\hat{\tau}$, each of which requires data samples of $x_a(t)$ and $y_a(t)$ having more than 30 alarm activations. As a result, the statistical test in Yang et al. (2013) requires the data samples containing more than 300 alarm activations, which sometimes is hard to meet in practice. Hence, it is desirable to design a statistical test that has less demanding requirements on the data samples of $x_a(t)$ and $y_a(t)$.

A significant test is presented in Bauer and Thornhill (2008) to determine whether two process signals $x_p(t)$ and $y_p(t)$ are linearly correlated, solely based on one single estimate of cross-correlation between $x_p(t)$ and $y_p(t)$. This significant test is certainly applicable to pseudo alarm signals $x_{a,p}(t)$ and $y_{a,p}(t)$ here. That is, if r_{xy} in (14) satisfies the following inequality (18), then $x_{a,p}(t)$ and $y_{a,p}(t)$ are claimed to be correlated,

$$r_{xy} \geq r_{th} := \mu_{r_{xy}} + 3\sigma_{r_{xy}}, \tag{18}$$

where $\mu_{r_{xy}}$ and $\sigma_{r_{xy}}$ are the sample mean and standard deviation of r_{xy}, respectively; an empirical estimate of the threshold r_{th} is

$$r_{th} = 1.85N^{-0.41} + 2.37N^{-0.53}, \tag{19}$$

where N is the data length of $x_{a,p}(t)$ and $y_{a,p}(t)$. It is obvious that r_{th} only relates to the data length N. However, the detected alarm correlation based on $x_{a,p}(t)$ and $y_{a,p}(t)$ is highly associated with the distribution of alarm points in $x_a(t)$ and $y_a(t)$. If the empirical estimate in (19) is directly applied, the significance threshold is always the same no matter how the alarm rate and alarm count of $x_a(t)$ and $y_a(t)$ change. Therefore, a more accurate estimate of the significance threshold should be specified by incorporating the distribution information of alarm data.

We adopt the similar idea of the significant test in (18) to design a statistical test for the ROD $\tilde{\lambda}(k)$ in (5) between $x_a(t)$ and $y_a(t)$. A critical observation is that for correlated alarms, realizations of $\tilde{\lambda}(k)$ are close to zero, while $\tilde{\lambda}(k)$ could be very large for uncorrelated alarms. To be consistent with the estimate $\hat{\tau}$ in (15), a lag factor is defined,

$$\varphi = \min_{\tau} \bar{\lambda}_r(\tau), \tag{20}$$

where $\bar{\lambda}_r(\tau)$ is given in (16). Since φ is always positive and is close to zero if $x_a(t)$ and $y_a(t)$ are correlated, a one-sided hypothesis test should be applied. Analogously to (18), $x_a(t)$ and $y_a(t)$ are claimed to be correlated if the following inequality holds,

$$\varphi < \varphi_{th} := \mu_\varphi - 3\sigma_\varphi \tag{21}$$

where μ_φ and σ_φ are respectively the mean and the standard deviation of φ. Under the null hypothesis that $x_a(t)$ and $y_a(t)$ are uncorrelated, we find that μ_φ and σ_φ can be modelled as functions of two factors, namely, the alarm probability rate denoted as p_r and the alarm quantity denoted as q_r,

$$\begin{aligned} \mu_\varphi &= a_\mu p_r^{b_\mu} q_r^{c_\mu} \\ \sigma_\varphi &= a_\sigma p_r^{b_\sigma} q_r^{c_\sigma} \end{aligned} \tag{22}$$

The two functions can be estimated empirically. For instance, Fig. 5 shows the histograms of φ in 1000 Monte Carlo simulations for uncorrelated alarms with a pair of p_r and q_r. To identify the parameters a_μ, b_μ, c_μ and a_σ, b_σ, c_σ, the values of p_r and q_r are changed in the ranges [0.0003, 0.02] and [20, 1000] with certain step sizes, respectively. For each pair of p_r and q_r, 1000 Monte Carlo simulations are implemented to estimate μ_φ and σ_φ. The estimated values of μ_φ and σ_φ are presented in Fig. 6 and 7, respectively. By the standard least-squares based curve-fitting method, the functions in (22) are estimated as

$$\begin{aligned} \mu_\varphi &= 0.4390 p_r^{-1.0010} q_r^{0.0163}, \\ \sigma_\varphi &= 0.7886 p_r^{-0.9900} q_r^{-0.4855}. \end{aligned} \tag{23}$$

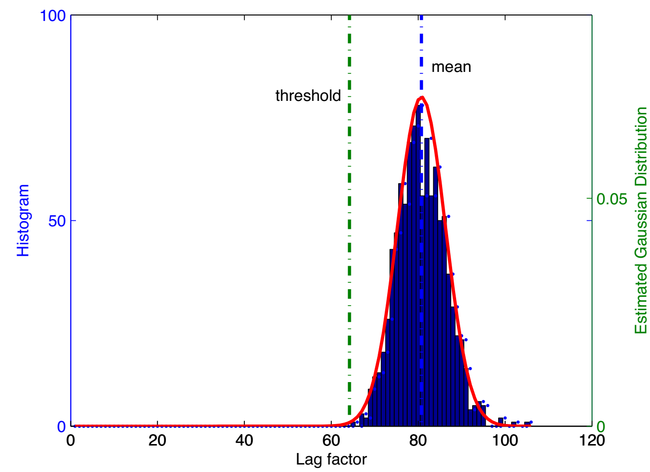

Fig. 5. Histogram of φ in 1000 Monte Carlo simulations for uncorrelated alarms with $p_r = 0.005$ and $q_r = 360$.

As shown in Figs. 6 and 7, the estimated functions in (23) fit the samples of (p_r, q_r, μ_φ) and $(p_r, q_r, \sigma_\varphi)$ very well. Therefore, the threshold φ_{th} in (21) can be calculated for one set of realizations of $x_a(t)$ and $y_a(t)$ from (23); the values of p_r and q_r can be obtained from $x_a(t)$ and $y_a(t)$ as

$$q_r = \min(N_x, N_y), \quad p_r = \frac{q_r}{N}, \tag{24}$$

where N_x and N_y are the alarm quantities in $x_a(t)$ and $y_a(t)$, respectively, and N is the data length of $x_a(t)$ and $y_a(t)$. If (21) is satisfied, then the RODs are claimed to be close to zero, and the alarm signals $x_a(t)$ and $y_a(t)$ are believed to be correlated. Then, the level of correlation can be measured by Pearson's correlation coefficient r_{xy} in (14) based on pseudo alarm signals $x_{a,p}(t)$ and $y_{a,p}(t)$.

The numbers of alarm quantities N_x in $x_a(t)$ and N_y in $y_a(t)$ cannot be too small, in order to make the statistical test in (21) reliable. The functions in (23) can be used to determine the least number of alarm quantities. In general, the threshold φ_{th} is positive; however, if the alarm quantity q_r is too small, φ_{th} could drop below zero. Based on (21) and (23), we can find the relation between q_r and p_r to achieve $\varphi_{th} = 0$ as

$$q_r = 28.6936 \quad p_r^{0.0219}. \tag{25}$$

The alarm probability rate p_r is a real value in the range [0, 1]. In practice, after removing chattering alarms, p_r should be less than 0.05, namely, 3 alarm activations per minute, which is a well-accepted benchmark for chattering alarms (ISA 18.02, 2009). Eq. (25) yields $q_r = 26.8715$ for $p_r = 0.05$. Hence, we choose $q_r = 27$ as a threshold of trusty, i.e., both of $x_a(t)$ and $y_a(t)$ should contain at least 27 alarm activations to ensure that the statistical test is reliable. By contrast, as mentioned earlier in this subsection, the statistical test in Yang et al. (2013) requires at least 300 alarm activations. Therefore, the proposed statistical test in (21) is much less demanding on the data samples of $x_a(t)$ and $y_a(t)$.

3.3. Detection procedure

The complete procedure of the proposed method to detect and quantify correlated alarms is composed by the following steps, and is depicted in Fig. 8.

1 Obtain two alarm sequences $X_a := \{x_a(t)\}_{t=1}^N$ and $Y_a := \{y_a(t)\}_{t=1}^N$ with at least 27 alarm activations in each sequence, and remove chattering alarms by the delay timer in (3) if necessary.

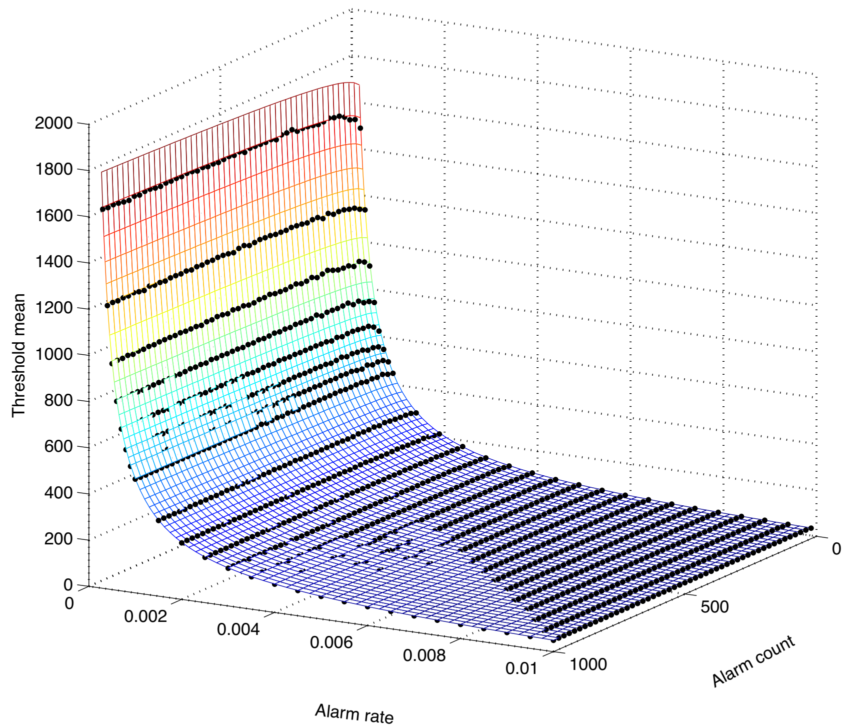

Fig. 6. μ_φ as a function of p_r and q_r.

2 Estimate the correlation delay τ between X_a and Y_a using the ODE algorithm in (15), and remove τ by shifting $y_a(t)$ to reach $y_{a,s}(t)$ in (10) to formulate $Y_{a,s} := \{y_{a,s}(t)\}_{t=1}^{N}$.
3 Perform the statistical test in (21) based on X_a and $Y_{a,s}$ to determine whether $x_a(t)$ and $y_a(t)$ are correlated, where the threshold φ_{th} is calculated using the empirical functions of μ_φ and σ_φ in (23) with the parameters p_r and q_r in (24). If (21) holds, then $x_a(t)$ and $y_a(t)$ are claimed to be correlated, and we proceed to Step 4 to quantify the correlation level; otherwise, $x_a(t)$ and $y_a(t)$ are regarded to be uncorrelated and the detection procedure is terminated.
4 Transform X_a and $Y_{a,s}$ respectively into the pseudo alarm sequences $X_{a,p} := \{x_{a,p}(t)\}_{t=1}^{N}$ and $Y_{a,p} := \{y_{a,p}(t)\}_{t=1}^{N}$ using the kernel bandwidth h in (13), and calculate Pearson's correlation coefficient r_{xy} in (14).

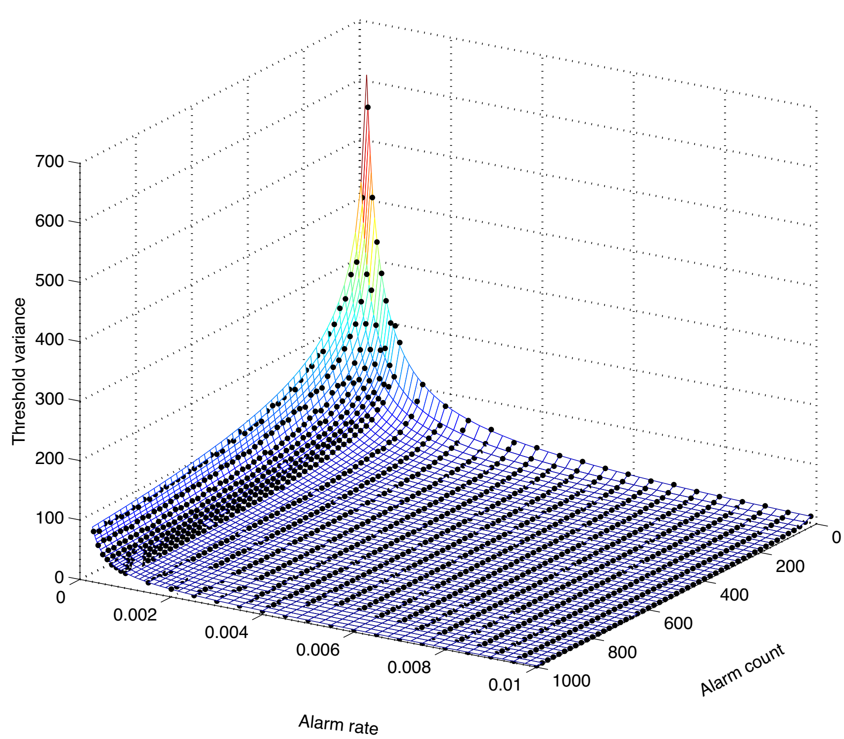

Fig. 7. σ_φ as a function of p_r and q_r.

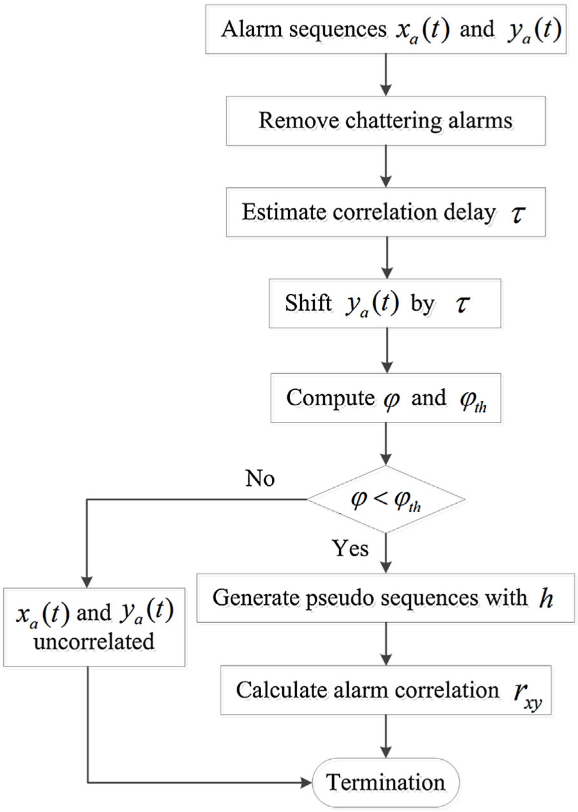

Fig. 8. Flowchart for detecting correlated alarms.

4. Industrial case studies

This section provides two industrial case studies as the representative examples of many successful applications of the proposed method. The case studies show that the proposed method performs well in detecting correlated or uncorrelated alarms.

4.1. Case I: Correlated alarms

Historical samples of two alarm signals $x_a(t)$ and $y_a(t)$ are obtained from an oil plant in Canada, as shown in Fig. 9. The data length is N = 241, 556 with the sampling interval 1 s (about 67 h). Alarm quantities of $x_a(t)$ and $y_a(t)$ are N_x = 653 and N_y = 242, respectively. The m-sample delay timer in (3) is exploited to remove chattering alarms in $x_a(t)$, where m = 20 is used as recommended in Wang and Chen (2013); the alarm quantity in $x_a(t)$ is reduced to N_x = 391. Using the ODE algorithm with the searching range $\tau \in [-100, 100]$ s, the correlation delay τ is estimated to be $\hat{\tau} = 28$. Fig. 10 shows the sequence of the ROD $\tilde{\lambda}_r(k)$ and the estimated distribution of ROD in the form of a histogram; in particular, the RODs are found to be mainly located between −30 and 30.

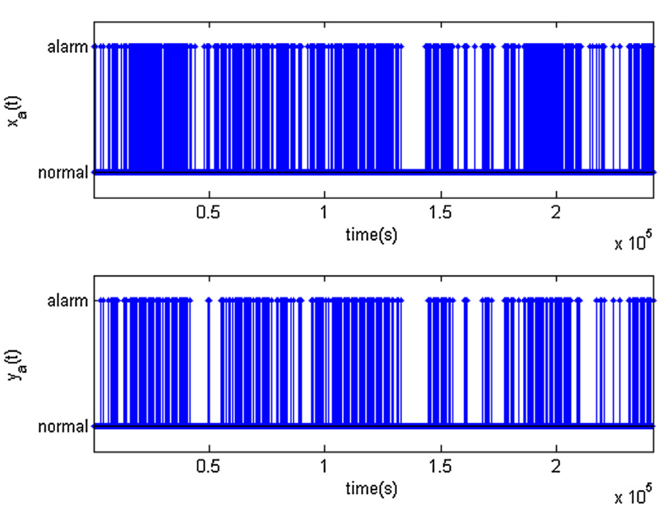

Fig. 9. Samples of $x_a(t)$ (top) and $y_a(t)$ (bottom) for Case I.

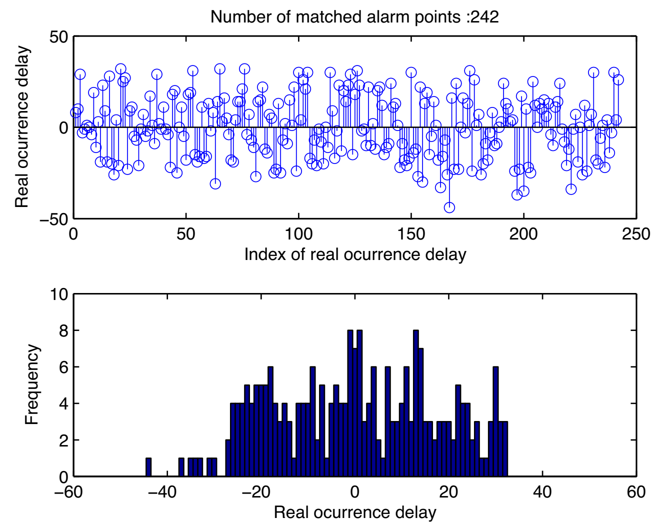

Fig. 10. The sequence of ROD (top) and the histogram of ROD (bottom) for Case I.

After shifting $y_a(t)$ backward by $\hat{\tau} = 28$ samples, the lag factor is calculated to be φ = 14.591. Since $y_a(t)$ contains fewer alarm points, the threshold φ_{th} = 329.121 is calculated by using μ_φ and σ_φ in (23) based on the alarm quantity of $y_a(t)$, i.e., $q_r = N_y = 242$ and $p_r = N_y/N = 0.001$. Because $\varphi < \varphi_{th}$, $x_a(t)$ and $y_a(t)$ are claimed to be correlated. Next, the pseudo alarm signals $x_{a,p}$ in (11) and $y_{a,p}(t)$ in (12) are generated, with the kernel bandwidth h in (13) equal to 15.026. Finally, Pearson's correlation coefficient is calculated to be r_{xy} = 0.571. As a comparison, the correlated alarm detection methods based on Jaccard coefficients S_{Jacd} in (8) and Sorgenfrei coefficients S_{Sorg} in (9) (Kondaveeti et al., 2012; Yang et al., 2013) are implemented based on $x_a(t)$ and $y_a(t)$. For instance, Sorgenfrei coefficients S_{Sorg} in (9) are calculated for different values of τ for $x_a(t)$ and $y_a(t+\tau)$, and the maximum value of the calculated Sorgenfrei coefficients is taken as the final estimate. The calculated Sorgenfrei and Jaccard coefficients are shown in Fig. 11. Their maximum values are S_{Sorg} = 0.000676 and S_{Jacd} = 0.0128. The thresholds of Sorgenfrei and Jaccard coefficients to separate independent and correlated alarm signals are respectively equal to 1/16 and 1/7 (Yang et al., 2013) (Proposition 1 therein); thus, the calculated Sorgenfrei and Jaccard coefficients are smaller than their thresholds, respectively, so that $x_a(t)$ and $y_a(t)$ are claimed to be uncorrelated. This erroneous results are caused by the presence of the occurrence delays, which introduce errors in the alignment of alarm activations causing such small values of Sorgenfrei and Jaccard coefficients. By contrast, the proposed method gives a relatively higher correlation coefficient. In fact, the process signals $x_p(t)$ and $y_p(t)$ associated with $x_a(t)$ and $y_a(t)$ are physically connected: $y_p(t)$ is the flow rate of the fuel gas in a burner which has two supplies from cell A and cell B; $x_p(t)$ is the flow rate of the feed fuel gas from cell B. Thus, $x_a(t)$ and $y_a(t)$ are expected to be correlated.

4.2. Case II: Uncorrelated alarms

To validate the performance of the proposed method for uncorrelated alarms, historical samples of two alarm signals $x_a(t)$ and

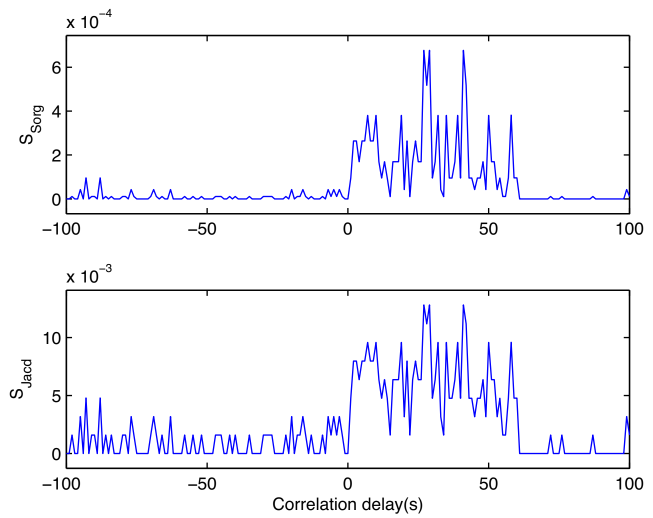

Fig. 11. The estimated Sorgenfrei coefficients (top) and Jaccard coefficients (bottom) for different values of τ for Case I.

$y_a(t)$ are obtained from a refinery plant in Alberta, Canada, as shown in Fig. 12. The data length is $N = 400,000$ with the sampling interval 1 s (about 111 h). Alarm quantities of $x_a(t)$ and $y_a(t)$ are $N_x = 152$ and $N_y = 127$, respectively. No chattering alarms are detected. Using the ODE algorithm with the searching range $\tau \in [-300, 300]$ s, the correlation delay τ is estimated to be $\hat{\tau} = 227$. Fig. 13 shows the sequence of the ROD $\tilde{\lambda}_r(k)$ and the estimated distribution of ROD in the form of histogram; in particular, the RODs are found to span a broad range from −12,587 to 11,599. Observing the RODs, we can see that even the correlation delay has been removed, most alarm points in $y_a(t)$ cannot be well matched with the alarm points in $x_a(t)$.

After removing the correlation delay, the lag factor is calculated to be $\varphi = 3352.244$. Since $y_a(t)$ contains fewer alarm points, the threshold $\varphi_{th} = 853.474$ is calculated from (23) based on the alarm quantity of $y_a(t)$, i.e., $q_r = N_y = 127$ and $p_r = N_y/N = 3.177 \times 10^{-4}$. Because $\varphi > \varphi_{th}$, $x_a(t)$ and $y_a(t)$ are believed to be uncorrelated and the computation is thereby terminated. As a comparison, the correlated alarm detection methods based on Jaccard coefficient S_{Jacd} in (8) and Sorgenfrei coefficient S_{Sorg} in (9) are employed based on $x_a(t)$ and $y_a(t)$. The calculated Sorgenfrei and Jaccard coefficients are shown in Fig. 14. Their maximum values are $S_{Sorg} = 5.180 \times 10^{-5}$ and $S_{Jacd} = 3.597 \times 10^{-3}$; thus, $x_a(t)$ and $y_a(t)$ are claimed to be uncorrelated. This is consistent with the conclusion

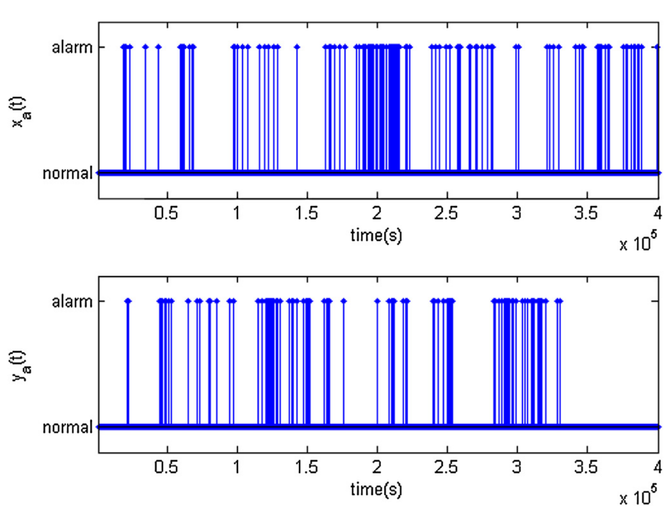

Fig. 12. Samples of $x_a(t)$ (top) and $y_a(t)$ (bottom) for Case II.

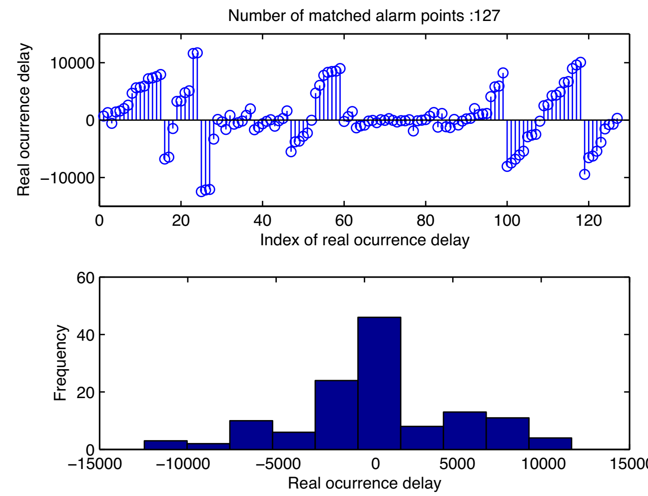

Fig. 13. The sequence of ROD (top) and the histogram of ROD (bottom) for Case II.

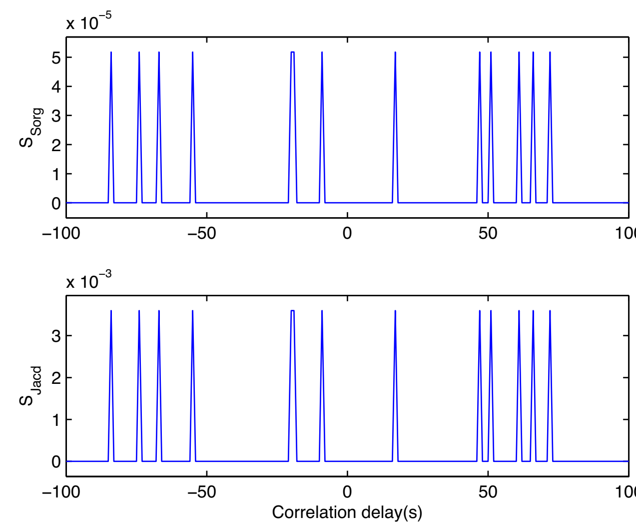

Fig. 14. The estimated Sorgenfrei coefficients (top) and Jaccard coefficients (bottom) for different values of τ for Case II.

obtained using the proposed method. Considering the fact that the process signals associated with $x_a(t)$ and $y_a(t)$ are located at different and disconnected units, the conclusion that $x_a(t)$ and $y_a(t)$ are uncorrelated is reasonable.

5. Conclusion

This paper proposed a new method to detect correlated alarms and quantify the correlation level. First, the occurrence delay was defined in Definition 1 and was shown to be the main cause of erroneous small values of Sorgenfrei and Jaccard coefficients that require the alignment of alarm activations. To tolerate the presence of occurrence delays, the binary alarm signals were transformed to continuous-valued pseudo alarm signals via (11) and (12), so that the Pearson's correlation coefficient r_{xy} in (14) can be used to quantify the correlation level. Second, the ODE algorithm was provided to estimate the correlation delay τ in order to be removed from occurrence delays to reach the RODs. The ODE algorithm was shown to perform better than the existing methods based on Sorgenfrei and Jaccard coefficients. This is also owing to the presence of occurrence delays causing errors in the alignment of alarm activations. Third, a statistical test based on the RODs was proposed to detect correlated alarms. That is, if (21) is satisfied, then the alarm signals $x_a(t)$ and $y_a(t)$ are claimed to be correlated. A rule of thumb is to have at least 27 alarm activations to make the statistical test reliable, while the counterparts in literature requires at least 300 alarm activations. Thus, the proposed statistical test is much less demanding on sample lengths of $x_a(t)$ and $y_a(t)$. Numerical examples were provided to support the obtained results, and industrial case studies showed that the proposed method performed well in detecting correlated alarms and uncorrelated ones.

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