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# Root-cause analysis of occurring alarms in thermal power plants based on Bayesian networks☆

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ABSTRACT

The paper proposes a method to analyze root causes of occurring alarms, for a special type of alarm variables in thermal power plants, where alarms are arisen from binary-valued root-cause variables. A Bayesian network with one child node and multiple parent nodes is used to describe the relationship between an alarm variable and root-cause variables. Probability parameters in the network are updated recursively. Root causes of occurring alarms are determined from the parent node set with the largest posterior conditional probability. The proposed method can remove negative effects of false and missing alarms in the nodes, handle the co-existence of multiple root causes, and detect the incompleteness of known root causes. Industrial examples are provided to illustrate the effectiveness of the proposed method.

## 1. Introduction

Industrial alarm systems are critically important for modern industrial plants to ensure safe and efficient operations and to prevent the deterioration of near misses to accidents [15,21,9]. Their main functionalities are the detection and communication changes of alarm states to industrial plant operators, who take corrective actions accordingly to deal with abnormalities causing the occurrences of alarms. Topics on industrial alarm systems have received persisting attentions from both industry and academic communities [17,16,2,22,13,26,11].

One major topic is to find root causes of occurring alarms. McDonald et al. [19], Cheon et al. [5], Miao et al. [20], Dahlgren et al. [7] exploited process knowledge of power systems to formulate specific rules or expert systems to analyze faults from alarms. Wen & Chang [29] and Wen et al. [30] explained occurring alarms from knowledge-based tables describing the relations between abnormal events and alarm variables. Dashlstrand [8] and Souza et al. [24] used multilevel flow models or fuzzy neural networks to analyze root causes of alarms. Simeu-Abazi et al. [23] exploited dynamic fault trees to locate faults from alarms with application to avionic systems. Guo et al. [12] and Wei et al. [28] determined fault causes based on rule networks or temporal constraint networks between cause hypothesis and alarms for digital power substations. Wee et al. [27] learned a Bayesian belief network and a fuzzy cognitive map from data to inference the root causes of faults. Gao et al. [10] constructed an interpretive structural model for analyzing alarm root causes, according to process knowledge and correlation coefficients of alarm variables.

This paper proposes a method to analyze root causes of occurring alarms, for a special type of industrial alarm variables. This type of alarm variables is known to switch between non-alarm and alarm states, owing to status changes of multiple root-cause variables. The alarm variable and root-cause variables take binary values, namely, ‘1’ for the alarm state and valid status, and ‘0’ for the non-alarm state and invalid status. This type of alarm variables often appears in thermal power plants (to be clarified later in Section 4). To the best of our knowledge, the root-cause analysis for such a special type of alarm variables have not been investigated in the literature with only two exceptions, that is, Yu & Yang [31] and Hu et al. [14] generalized transfer entropies to binary-valued alarm variables to infer cause-effect relationships. A certain number of alarm occurrences (e.g., at least 50 alarm occurrences as stated in Section 3.2 of Hu et al. [14]) are required to obtain reliable estimates of transfer entropies and to infer whether alarm variables have causal relationships in a large time window. By contrast, the proposed method is to analyze root causes of the alarm

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occurring recently in a short time window. Thus, the proposed method and the counterparts in Yu & Yang [31] and Hu et al. [14] are associated with different objectives.

The main idea of the proposed method is as follows. The relationship between the alarm variable and root-cause variables is described by a Bayesian network with one child node and multiple parent nodes. The probability parameters in the Bayesian network are updated recursively from observed data samples. Root causes of an occurring alarm are determined from the parent node set having the largest posterior conditional possibility. The proposed method can effectively deal with three challenges frequently appeared in industrial environments. That is, it removes negative effects of false and missing alarms, handles the co-existence of multiple root causes, and detects the incompleteness of known root causes. By contrast, a common practice, which finds root causes manually by comparing data samples of the alarm variable and root-cause variables, cannot well deal with these challenges. Bayesian networks have been extensively exploited in literature for fault diagnosis [3]. However, very few studies, e.g., Cai et al. [4], have exploited Bayesian networks for industrial alarm systems; in addition, the first and third challenges have not been explicitly considered therein.

A preliminary version of the proposed method was presented in a conference paper [25]. The proposed method makes significant improvements. In particular, root causes are analyzed to handle the above-mentioned three challenge, and the design of an updating rate parameter is greatly simplified. The proposed method has been successfully applied to a large number of industrial alarm variables. Two representative industrial examples, instead of simulated ones, are provided to illustrate the effectiveness of the proposed method in practice.

The rest of the paper is organized as follows. Section 2 describes the problem to be solved. The proposed method is presented in Section 3. Section 4 provides industrial examples for illustration. Section 5 gives some concluding remarks.

## 2. Problem description

Consider an alarm variable $X_a$ taking the value '1' for the alarm state and '0' for the non-alarm state. It is assumed that $X_a = 1$ can be arisen from the status changes of $n$ mutually independent root-cause variables, denoted by $X_1, X_2, \ldots, X_n$. The assumption is usually fulfilled by exploiting some process knowledge. Let the root-cause variables take binary values, i.e., $X_i = 1$ (or $X_i = 0$) for $i \in [1,n]$ represents the status that the $i$-th root-cause variable $X_i$ is valid (or invalid). If $X_i = 1$, then $X_a$ will run into the alarm state. Given the observed data set $D := \{X(1), \ldots, X(t-1), X(t)\}$ with $X(t) := [X_1(t), X_2(t), \ldots, X_n(t), X_a(t)]^T$, the objective is to analyze root causes of an occurring alarm in $X_a(t) = 1$ under the above assumption.

A common practice to reach such an objective is to analyze root causes manually by looking at observed data samples. If $X_a(t) = 1$, then root causes are the ones with $X_i(t) = 1$ for $i \in [1,n]$. However, the common practice often yield inaccurate results due to the following three challenges. First, either $X_a$ or $X_i$ may take the value of '1' for a short time duration owing to random noises. Thus, $X_a$ or $X_i$ is contaminated by false alarms, which result in failures of root-cause analysis. Second, multiple root causes may exist simultaneously, instead of the presence of single one root cause. The common practice is manually done by industrial operators. They tend to focus on the first-appeared root cause, and overlook other co-existing root causes. Third, the root causes $X_1, X_2, \ldots, X_n$ may be incomplete. One common reason for the incompleteness is that measurements of some other root-cause variables are unavailable at control centers of industrial plants. The verification of these root causes have to be done on site by industrial engineers. As a result, these root causes are not in the set $\{X_1, X_2, \ldots, X_n\}$, so that they cannot be handled by the common practice. Due to the three challenges, a new method is needed to analyze root causes of occurring alarms in $X_a$.

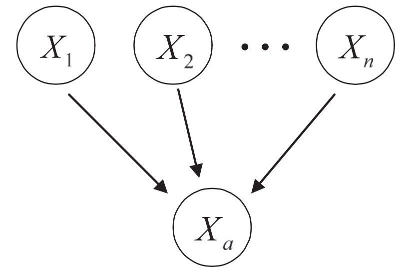

**Fig. 1.** The diagram of a Bayesian network.

## 3. The proposed method

This section first updates probability parameters in a Bayesian network, and analyzes alarm root causes afterwards.

### 3.1. Updating probabilities in a Bayesian network

A Bayesian network depicted in Fig. 1 is used to describe the relationship between the alarm variable $X_a$ and root cause $X_1, X_2, \ldots, X_n$. It is a graphical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph; random variables are represented by nodes in the network and take some discrete values [18]. For the Bayesian network in Fig. 1, $X_1, X_2, \ldots, X_n$ are the parent nodes of $X_a$, and they take binary values '0' and '1' in this context. Denote $\theta_{i,0}$ and $\theta_{i,1}$ as the probabilities of $X_i$ with $i \in [1,n]$ taking the value '0' and '1', respectively, i.e.,

$$\theta_{i,0} := P(X_i = 0), \quad \theta_{i,1} := P(X_i = 1), \quad i \in [1,n].$$

Let $R := \{X_1, X_2, \ldots, X_n\}$ be the parent node set of $X_a$, and $r_j$ with $j \in [1, 2^n]$ be the $j$-th set of possible values taken by the parent nodes of $X_a$. For instance, if $n = 2$, then there are four sets in $R$, namely, $r_1 := \{0,0\}, r_2 := \{1,0\}, r_3 := \{0,1\}$ and $r_4 = \{1,1\}$. The parameters $\theta_{a,0|j}$ and $\theta_{a,1|j}$ respectively represent the prior conditional probabilities of $X_a = 0$ and $X_a = 1$ given the condition that $R$ takes the value $r_j$, i.e.,

$$\theta_{a,0|j} := P(X_a = 0|R = r_j), \quad \theta_{a,1|j} := P(X_a = 1|R = r_j), \quad j \in [1, 2^n].$$

Clearly, these parameters need to satisfy the constraints, $\theta_{i,0} + \theta_{i,1} = 1, \forall i \in [1,n]$ and $\theta_{a,0|j} + \theta_{a,1|j} = 1, \forall j \in [1, 2^n]$.

For the purpose of online root-cause analysis, the probability parameters in the set $\theta := \{\theta_{i,0}, \theta_{i,1}, \theta_{a,0|j}, \theta_{a,1|j}\}$ for $i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, 2^n$ in the Bayesian network need to be learned from observed data samples in a recursive manner. More precisely, the parameter set $\theta$ needs to be updated based on a priori parameter set $\bar{\theta}$ and the observed data samples of $X_1, X_2, \ldots, X_n$ and $X_a$.

Bauer et al. [1] proposed a batch learning algorithm being applicable to the historical data set $D := \{X(1), \ldots, X(t-1), X(t)\}$ with $X(t) := [X_1(t), X_2(t), \ldots, X_n(t), X_a(t)]^T$. The posterior estimate $\hat{\theta}$ is obtained by maximizing a function $F(\theta) = \lambda L_D(\theta) - d(\theta, \bar{\theta})$, i.e.,

$$\hat{\theta} = \underset{\theta}{\operatorname{argmax}} (\lambda L_D(\theta) - d(\theta, \bar{\theta})). \tag{1}$$

Here $L_D(\theta)$ is the averaged logarithm likelihood,

$$L_D(\theta) = \frac{1}{t} \sum_{l=1}^{t} \ln P_\theta(X(l)),$$

where $X(l_1)$ and $X(l_2)$ are assumed to be independent with each other for all indices $l_1 \neq l_2$. The penalty term $d(\theta, \bar{\theta})$ is a measure of $\chi^2$ distance between $\theta$ and $\bar{\theta}$. The constant $\lambda$ is an updating rate parameter. Cohen et al. [6] further developed an online updating algorithm based on the batch solution in (1). The historical data set $D$ is replaced by the current sample $X(t)$, while $\hat{\theta}(t-1)$ and $\hat{\theta}(t)$ take the place of $\bar{\theta}$ and $\hat{\theta}$, respectively.

The main idea of the online updating algorithm in Cohen et al. [6] is adopted here for updating probability parameters of the Bayesian