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A correlation consistency based multivariate alarm thresholds optimization approach

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ABSTRACT

Different alarm thresholds could generate different alarm data, resulting in different correlations. A new multivariate alarm thresholds optimization methodology based on the correlation consistency between process data and alarm data is proposed in this paper. The interpretative structural modeling is adopted to select the key variables. For the key variables, the correlation coefficients of process data are calculated by the Pearson correlation analysis, while the correlation coefficients of alarm data are calculated by kernel density estimation. To ensure the correlation consistency, the objective function is established as the sum of the absolute differences between these two types of correlations. The optimal thresholds are obtained using particle swarm optimization algorithm. Case study of Tennessee Eastman process is given to demonstrate the effectiveness of proposed method.

1. Introduction

The distributed control system is widely used in modern industries to monitor and control the processes, in which the alarm systems play an essential role. The vitally important aspect of alarm systems is to ensure the safety of environment, equipment and personnel. In alarm systems, almost all variables are configured with high and low alarms, especially some key variables with the four kinds of alarms: the high alarms, the low alarms, the high-high alarms and the low-low alarms. If one variable exceeds the configured alarm limit, an alarm occurs and reminds the operators to take proper actions to avoid hazardous events. There is no question that the growing integration and complexity of the industry process have put higher requirements on alarm systems and operators. One of the major problems in the alarm systems is the alarm flooding, which distracts the operators' attention and thus increases the probability of accidents. The HSE (Health and Safety Executive) points out that the problems in alarm systems have led to many financial loss or damage of environment and equipment [1], such as the explosion and fire at the Milford of Haven Refinery in the UK and the fire at the England–France Channel Tunnel. With the guidance of the ISA (International Society of Automation) 18.2 [2] and the EEMUA (Engineering Equipment & Materials User's Association) [3], the alarm management has drawn a lot of attention recently.

It is obvious that the alarm thresholds directly affect the quality of the generated alarms. An improper alarm threshold is normally the main reason of false alarms and missed alarms. The relationship among the alarm thresholds, the false alarm rate and the missed alarm rate can be visualized by Receiver Operating Characteristic (ROC) curve [4]. Theoretically, for a process variable, its best alarm limit refers to the value that makes both false alarm rate and missed alarm rate reach the minimum value, which is generally accepted in practice. A series of methods like the filters [5–8], the dead bands [9] and the delay timers [10] have been used to deal with the alarm thresholds. In addition, some dynamic methods have also been investigated. Zhu [11] employed Bayesian theory to determine the dynamic alarm thresholds with a given confidence interval during the process transition, but the correlation among the variables is not taken into consideration. Zang [12] employed joint probability density functions to analyze the false alarm rate and missed alarm rate with Bayesian inference involved. Han [13] combined FAP, MAP and correlation consistency to optimize the multivariate alarm thresholds. However, in these methods, the normal data and the abnormal data must be known in advance. To avoid the distinction of the normal and abnormal data, Yang [14] proposed the concept that the optimal alarm limits can be selected by comparing the correlation coefficients difference between alarm data and process

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data. But in this method, the influences of other variables are ignored, and the time-lagged causal relationship has some limitations such as the circles of the influences.

Chemical processes usually have the characteristics of strong relevance and complex relationships. One variable can be affected by several other variables. In order to show the interactions among the variables and select the key correlated variables for alarm thresholds optimization, the Interpretative Structure Modeling (ISM) method is introduced in this paper.The ISM method is a widely used approach for system structure modeling. It has gained wide popularity in many fields, such as risk analysis of supply chain [15], modeling and analysis of key factors [16,17] and fault detection [18]. Especially, we have successfully applied the ISM into causal model construction and alarm root-cause diagnosis [19,20]. All experiments show the effectiveness of the ISM method in revealing the structure of the system.

Motivated by the above consideration, we propose a new multivariable alarm thresholds optimization methodology. Firstly, the correlations of the process variables are analyzed by the ISM method. The key correlated variables can be selected here to perform alarm thresholds optimization. Then for the selected variables, kernel density estimation is adopted to describe the correlation of the alarm data. Correlation consistency about the process data and the alarm data is considered to establish the objective function, and the method of PSO is used to determine the optimal thresholds. To show this method, the rest of this paper is organized as follows. Theories about the ISM is introduced in Section 2. Section 3 gives the correlation analysis of the process data and the alarm data. Section 4 shows the specific process of the multivariate alarm thresholds optimization methodology. In Section 5, the method is applied to Tennessee Eastman (TE) process and compared with the method in average alarms rate and peak alarms rate. Conclusions are summarized in final section.

2. Data-driven interpretative structural modeling

Based on the graph theory, the ISM, an effective model for analyzing and revealing the complicated relationships, can be used to change the complex relationships between each element in the system into a clear multi-level hierarchical structure. So in this paper, a data-driven ISM is used to determine the process topological information.

Suppose the element $M_j \in \boldsymbol{R}^L (j = 1, 2, \ldots, N)$ in the system $\mathbf{S}$, so the system $\mathbf{S}$ can be expressed as:

$$\mathbf{S} = \left\{ M_j \,|\, j = 1, 2, ..., N; M_j \in \mathbf{R}^L \right\} \tag{1}$$

Firstly, the correlation coefficient between any two variables in system $\mathbf{S}$ can be represented in matrix $\boldsymbol{r}$:

$$\mathbf{r} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1N} \\ r_{21} & r_{22} & \cdots & r_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ r_{N1} & r_{N2} & r_{N3} & r_{NN} \end{bmatrix}_{N*N} \tag{2}$$

where r_{ij} represents the Pearson coefficient of elements M_i and M_j.

Then, the inverse matrix $\boldsymbol{c}$ can be calculated:

$$\mathbf{c} = inv(\mathbf{r}) = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1N} \\ c_{21} & c_{22} & \cdots & c_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ c_{N1} & c_{N2} & c_{N3} & c_{NN} \end{bmatrix}_{N*N} \tag{3}$$

Table 1
The scope of partial correlation coefficient and its corresponding relationship.

The scope of partial correlation coefficient	Corresponding relationship
$0 < \lvert p_{ij} \rvert < 0.1$	No relationship
$0.1 \le \lvert p_{ij} \rvert < 0.3$	Low correlation
$0.3 \le \lvert p_{ij} \rvert < 0.5$	Medium correlation
$0.5 \le \lvert p_{ij} \rvert < 0.8$	Strong correlation
$0.8 \le \lvert p_{ij} \rvert < 1$	Extremely strong

Table 2
Definition of a_{ij} in adjacency matrix.

		p_{ij}	a_{ij}	a_{ji}
$i \ne j$	$\lvert p_{ij} \rvert \ge \varepsilon$	> 0	1	0
		< 0	0	1
	$\lvert p_{ij} \rvert < \varepsilon$	–	0	0
$i = j$	–	–	0	0

Finally, the partial correlation coefficient p_{ij} between element M_i and M_j is defined:

$$p_{ij} = -\frac{c_{ij}}{\sqrt{c_{ii} * c_{jj}}} (i, j = 1, 2, \ldots N) \tag{4}$$

Table 1 shows the relationship between the absolute value of the partial correlation coefficient and the degree of correlation. The larger the absolute value is, the stronger the correlation is.

Given a threshold $\varepsilon (0 < \varepsilon < 1)$, the adjacency matrix $\boldsymbol{A}$ then can be determined by Table 2.

Assuming that $\mathbf{A}_1 = (\mathbf{A} + \mathbf{I}), \mathbf{A}_n = (\mathbf{A} + \mathbf{I})^n$, reachability matrix $\mathbf{R} = \mathbf{A}_{n-1}$ must meet the condition that $\mathbf{A}_1 = (\mathbf{A} + \mathbf{I}) \ne \mathbf{A}_2 \ne \cdots \ne \mathbf{A}_{n-1} = \mathbf{A}_n$, indicating the direct or indirect relationship between the elements.

According to the reachability matrix, each element must belong to the reachability set $P(M_i)$ or antecedent set $Q(M_i)$. The highest-level L1 contains elements which can be reached by other elements while cannot reach any elements. They can be extracted according to the following rule:

$$P(M_i) \cap Q(M_i) = P(M_i) \tag{5}$$

Deleting the corresponding rows and columns of elements in the highest level L1 from reachability matrix $\mathbf{R}$, a reduced matrix **R1** is obtained and used to determine the second level L2. Repeat the above procedure until all the variables are assigned to the appropriate levels. After the hierarchy division, the systemic structure can be expressed in the form of a directed graph called Interpretative Structural Model. In the structure, elements are distributed in layers, and different elements are connected referring to the adjacency matrix.

3. Correlation analysis of process data and alarm data

3.1. Correlation analysis of process data

In order to investigate whether there is some kind of dependency between the variables, correlation analysis is introduced, and the direction of the dependencies and the relevance can be specified as the correlation coefficient, such as the Pearson correlation coefficient, the Spearman and Kendall correlation coefficient. For the continuous data at equal intervals, for example, the process data sampled from the DCS system, the Pearson correlation coefficient can be used. So in