An Industrial Multilevel Knowledge Graph-Based Local–Global Monitoring for Plant-Wide Processes

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***Abstract*— In order to satisfy safety requirements of modern plant-wide processes, multiblock-based distributed monitoring strategies are often used to obtain higher monitoring performance, and their two critical issues refer to suitable multiblock partition for reducing uncertainties and local–global fault interpret perception for practical physical meaning. To handle these problems, a novel multilevel knowledge-graph (MLKG) based on combining domain expert knowledge and monitoring data are constructed to describe characteristics of plant-wide processes. And then numerous monitoring variables of each node (block) can be used to calculate the node status which can be used to realize fault detection by exceeding corresponding thresholds. Creatively, numerous node statuses of multilevel can be aggregated into the top-level node status to globally characterize the system health to realize fault detection. Finally, methods such as variables contribute rate can be adopted to locally locate the fault to achieve fault location, which can be regarded as an attempt to interpret the fault detection results. Results of benchmark and practical-case-application can be used to demonstrate the effectiveness and applicability of this proposed method.**

***Index Terms*— Fault detection, fault location, multilevel knowledge graph (MLKG), plant-wide process monitoring.**

I. Introduction

MOST modern plant-wide processes tend to develop increasing large-scale, complicated, and intelligent ones, which make traditional process monitoring methods increasingly difficult to ensure safety and reliability. Fortunately, some studies have shown that multiblock-based distributed monitoring strategy can be regarded as the most potential one to establish a sub-system monitoring model to solve this problem [1]. The key of this strategy can be regarded as that suitable block partition should be able to get an accurate description of faults by maintaining the associations within and between different blocks to avoid destroying the variables dependencies [2]. Local faults in each block can be quickly and sensitively reflected in global statistics, while global faults should be analyzed in time to realize the accurate location of monitoring variables [3]–[5]. This local–global monitoring can be regarded as the core challenge of distributed monitoring strategy, and this difficulty is often interfered with by uncertainties or noises which hinder conventional methods from achieving the purpose of local–global monitoring.

Multiblock-based distributed process monitoring has attracted more and more scholars' attention by its super performance on effectively reducing calculation complexity, mining local information, improving monitoring accuracy, reducing related costs, etc. For example, Chen *et al.* [2] proposed a new data-driven fault detection method based on distributed canonical correlation analysis to reduce uncertainties using correlation information from the neighboring nodes; Jiang *et al.* [6] proposed a local–global modeling and distributed computing framework to achieve efficient fault detection and isolation for nonlinear plant-wide processes; Khatib and Daoutidis [7] presented two methods for distributed data-driven monitoring system, and the first one is used to select a suitable distributed decomposition pattern, while the second one is employed to find the minimum number of distributed monitoring locations. Most of these methods focused on hunting for suitable blocks partition to obtain comparable results based on uncertain, subjective, and few experiences, and it is still a big challenge for complex industrial processes to achieve suitable multiblocks [8].

One of these difficulties in suitable multiblocks refers to the difficulties in obtaining accurate model or expert knowledge, while the other one is the correlation between monitoring variables which are too complicated to make monitor performance often decrease by an inappropriate partition with splitting these corresponding dependencies. In order to maintain the integrity of the correlations between variables, many scholars around the world have made some attempts to achieve plant-wide process monitoring. For example, Liu *et al.* [9] proposed a variational Bayesian mixture of canonical correlation analysis-based process monitoring method to predict and diagnose hard-to-measure quality-related variables, which mainly maintain the correlations between quality-related variables to make the proposed scheme insensitive to disturbance, measurement noises, and model discrepancies; Huang *et al.* [10] proposed a double layer distributed monitoring method based on multiblock slow feature

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analysis and multiblock independent component analysis, and this proposed method mainly considered the sequential correlation matrices in static and dynamic blocks; Tian *et al.* [11] proposed a weighted copula-correlation-based multiblock principal component analysis (PCA) to hunt suitable methods to effectively achieve the selection of variables for each sub-block. Ma *et al.* [12] proposed multistep dynamic slow feature analysis to complete the full-condition monitoring by dividing dynamic structures more precisely. Most correlations of these methods are flat, and most of them are primarily calculated by historical datasets, which make these correlations more easily influenced by the relative under-completeness between online and offline data.

This article aims to propose a local–global monitoring method based on industrial multilevel knowledge graph (MLKG) which can be used to integrate all types of knowledge to solve the under-completeness problem, such as mechanism knowledge, experience knowledge, and data knowledge. The industrial knowledge can be considered as the correlations between features or variables, and the correlations in practice should be solid (hierarchical) instead of flat (calculated by a large amount of literature [9]–[12]). Recently, these hierarchical correlations between features or variables have attracted much more scholars' attention. For instance, Tootooni *et al.* [13] used a spectral graph theoretic approach to monitor complex process dynamics manifest in multivariate time series data; Chen *et al.* [14] developed a novel graph convolutional network framework for fault location in power distribution network; Zhang *et al.* [15] combined graph convolution operators, graph coarsening methods, and graph pooling operations to develop a deep graph convolutional network to deliver acoustic-based fault diagnosis of roller bearings; Liao *et al.* [16] proposed a novel method for transformer fault diagnosis based on graph convolutional network to improve the diagnosis accuracy; Chen *et al.* [17] proposed a fault diagnosis method based on the graph convolutional network using the available measurements and the prior knowledge. Liu *et al.* [18] handled the fault classification with label-noise in training samples by initially proposing a manifold-preserving sparse graph-based ensemble Fisher discriminant analysis model. However, most MLKGs in literature are just used to describe the associations between variables in multiple levels instead of the utilization to achieve suitable blocks partition.

MLKG can be considered as one of the most hot topic in describing the solid (hierarchical) correlations, such as the MLKG in [19] mainly consists of production level, process level, energy saving and emission reduction level, and raw material level. The knowledge graph can be considered as a type of graph model in essence, and its main special characteristics are the nodes and their corresponding associations (relations), whose idea is consistent with the blocks (nodes) and their corresponding correlations (associations) in plant-wide distributed process monitoring. Inspired by this consistency, plant-wide processes can be separated as numerous sub-processes (blocks) which can be described by the nodes and their corresponding associations in MLKG. The features of nodes and their corresponding associations can be used to design the local observers for each node (subprocess) to determine operation states, and then to provide evidence to globally monitor system behaviors. It should be noted that it would be more efficient for better monitoring performance to consider its local and its neighbor information by considering the correlations between different operation nodes [20].

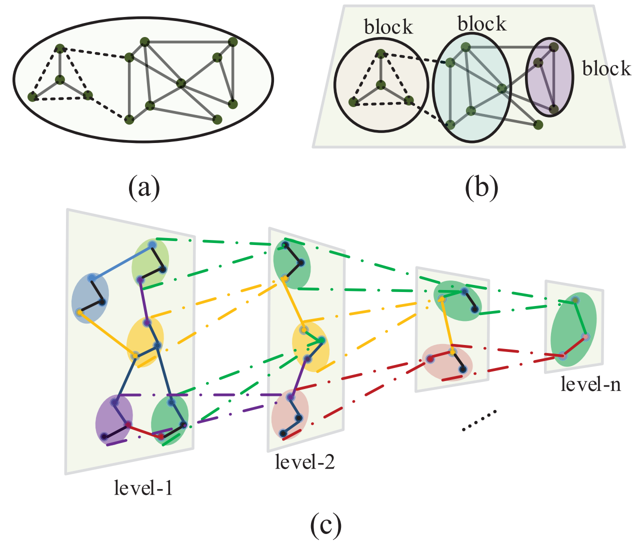

Fig. 1. Schematic of plant-wide process monitoring strategy. (a) Centralized solution. (b) Decentralized solution. (c) Proposed plant-wide solution.

In fact, the idea behind this plant-wide process monitoring method can be simply considered as to reduce uncertainties in local nodes, and it should be noted that the correlation projections are learned from the process data to reflect the possible changes. The innovation and the contribution of this article can be considered as follows.

1) A new MLKG construction method is addressed into plant-wide process monitoring, and this can be utilized as a basis to broaden the research on fault detection.
2) A new local–global monitoring framework is proposed to achieve efficient performance for plant-wide processes, and this method attempts to interpret the detection results interpretably.
3) A new and well-considered correlations representation between nodes (sub-blocks) is addressed, and the variables in each block on each level are from itself and its neighbors, which can be used to reduce the uncertainties in local information to enhance monitor performance.

The remainder of this article can be organized as follows. Section II illustrates the problem formulations. In Section III, the proposed local–global fault detection and location framework is addressed, including method framework, MLKG construction, fault detection, and fault location. The results of the benchmark on the Tennessee Eastman (TE) chemical process and case study on cobalt-nickel removal from zinc solution are used to demonstrate the monitoring performance and effectiveness in Section IV. The last section mainly focuses on the conclusion and further work.

II. Problem Formulation

Currently, plant-wide process monitoring can be mainly considered as two solutions: centralized, decentralized

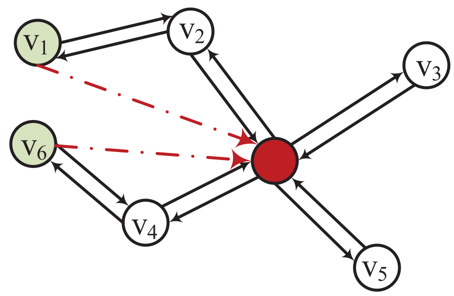

Fig. 2. Schematic of knowledge source atlas.

(distributed) strategies, as shown in Fig. 1(a) and (b). The key centralized solution is to collect all variables to perform process monitoring, and it is not suitable for plant-wide processes by incomplete samples between online and offline [21]. Plant-wide processes push out decentralized solutions to address the problem on large amounts of monitoring data, and its core idea focuses on partitioning processes into several sub-processes (or operation units, or nodes) [2]–[6]. Then, the following step is to design the local observers for each node to determine operation states and to provide evidence to globally monitor system behaviors. And the local monitor design belongs to the multivariate statistical analysis, and it is still in the continuous development stage in the distributed monitoring system. The typical methods to achieve local faults detection can be regarded as PCA [22], independent components analysis (ICA) [23], canonical correlation analysis (CCA) [24] and partial least squares (PLS) [25], [26].

Due to the increasing advancement of modern plant-wide processes, a fault that occurs in each node often affects a small part of process variables instead of the whole process [2]. However, few reports considered the correlations between different nodes to reduce the uncertainties by using neighboring nodes' information. Therefore, the local observers should be gifted by the ability not only to locally and sensitively perceive the local monitoring variables changes, but also on producing reliable evidence to realize the global monitor for plant-wide processes, as shown in Fig. 1(c). This idea of distributed monitoring can be regarded as to follow the solid (hierarchical) correlations which respect the fact that different data sources reflecting the same object status have overlapping information instead of variable reduction. As shown in Fig. 2, information reflecting node status is generally collected on multilevels, including market information, actuators, materials, intermediate products, and other node statuses that are associated with the node of interest. Due to the noises and uncertainties during its practical operations, knowledge of the component of interest (red node in Fig. 2) can be defined as apparent one and latent one, which can be simply described as v_2, v_3, v_4, v_5 and v_1, v_6, respectively. The apparent part (black solid line) is relatively easy to obtain by domain experts, while the latent part (red dotted line) needs to be calculated. And latent correlations between nodes can be quantified and constructed only by designing suitable methods, and this latent knowledge is very important for reducing noises and uncertainties to improve the process monitoring performance.

Under the solution shown in Fig. 1(c), the proposed method seeks to find out a local–global (node-level) plant-wide monitoring framework. And this framework intends to solve the following three items.

1) Correlations between monitoring variables or nodes of interest should be quantified to construct the MLKG, which can be used to describe characteristics of plant-wide processes.
2) Information collected to achieve process monitoring should contain the local data (data available at the node itself) and the data from its neighboring nodes, which can be solved by searching MLKG.
3) The noises and uncertainties of local nodes can be reduced by rich information to enhance the global–local monitoring performance (such as accuracy, etc.), which can be achieved by local and neighbor nodes information.

III. Plant-Wide Process Monitoring

A. Framework of the Proposed Method

This new local–global plant-wide process monitoring involves three steps: off-line MLKG, global fault detection of one node in top-level, and local fault location of numerous nodes in bottom-level, as shown in Fig. 3. The off-line MLKG comprehension is significant for plant-wide process monitoring performance, but it can be considered as a time-cost issue. Generally, the MLKG is constructed from the history data (off-line) of the normal state, which is enough to fault state. Global fault detection at top-level can be considered as to perceive the information changes in plant-wide process, which will exceed the corresponding thresholds when fault occurs. And then local fault location at bottom-level can be regarded as to find out the reason causing the faults, and this requirement has attracted increasing scholars attentions around the world [27], [28].

This new plant-wide process monitoring framework employs the entities and their correlations between each other to completely describe the information source of the component of interest on each level, and this idea can be used to implement an explainable and credible manner for plant-wide processes monitoring. And then the status statistics (used to detect faults) can be calculated one by one level without any information loss by the data reflecting raw materials, device states, and some other things. Once the fault is detected, its location should be precisely located as soon as possible to make fault detection results have practical application meaning.

B. Multilevel Knowledge-Graph Construction

The knowledge graph is generally composed of pieces of triples, viz [head (H-node), relation (r), tail (T-node)]. The head and tail can be similarly considered as either the concept, physical entity, or ontology, such as sensor measurements and devices states, while the relation represents the association between head and tail. MLKG of plant-wide process needs to solve four main issues: definition of multilevel, definition

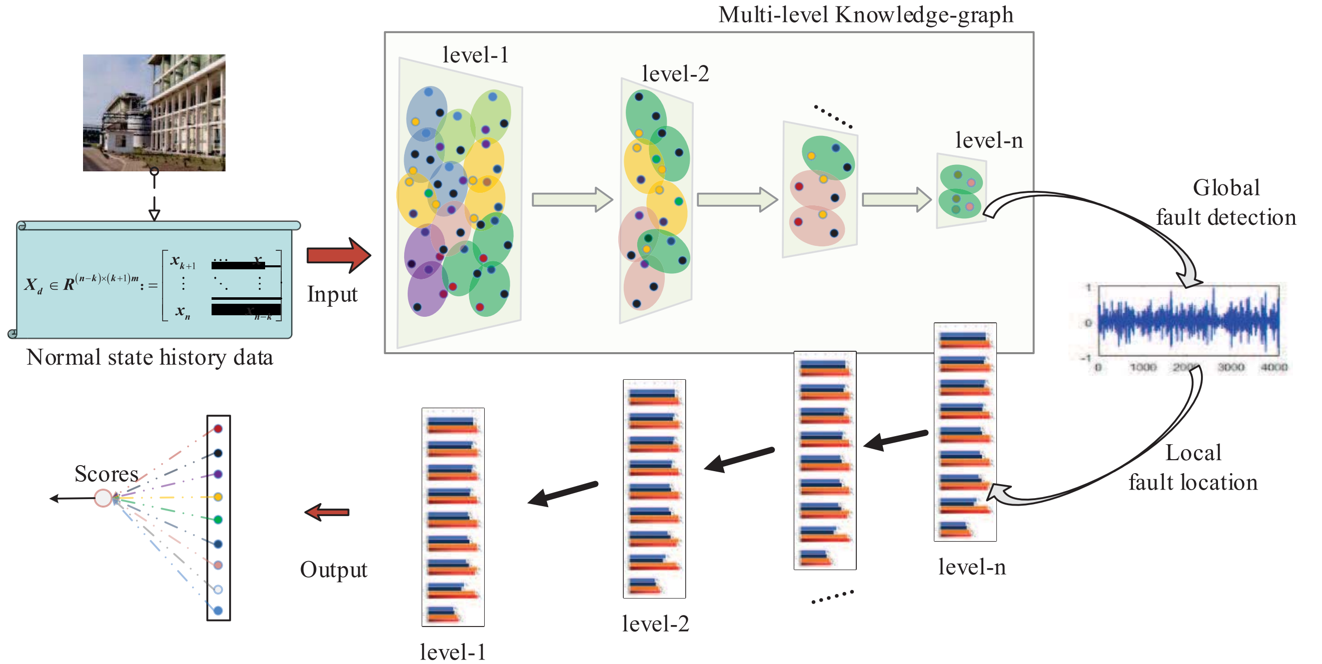

Fig. 3. Framework of MLKG-based local–global monitoring method for plant-wide processes.

of head and tail entity, the definition of inner-level relations, and definition of extra-level relations.

Definition 1 (Multilevel Construction): The multiple levels $l(z)$ for a given plant-wide process is a function of sensor measurements, status of related components data z where this article simply implies as $l(z) = \{sensors, devices, sub-processes, process\}$.

Definition 2 (Head and Tail Entity): The head and tail entity refer to the components of interest (or operation units, or nodes) and their related monitoring variables which mainly consist of a large number of key market information, sensor measurements, and status of components in the last level (if they have any). This definition can be described as follows:

$$\mathbf{X}^{ij}_{n\times m} = [(\mathbf{X}^{ij}_{n\times m_1})', \mathbf{Y}^{c}_{n\times m_2}, \mathbf{Y}^{s}_{n\times m_3}, \mathbf{Y}^{d}_{n\times m_4}, \mathbf{Y}^{b}_{n\times m_5}] \quad (1)$$

where $\mathbf{X}^{ij}_{n\times m}$ is the ith node on the jth level in MLKG, while the $(\mathbf{X}^{ij}_{n\times m_1})'$ represents its related variables or node status on the (j-1)th level in MLKG. $\mathbf{Y}^{c}_{n\times m_2}, \mathbf{Y}^{s}_{n\times m_3}, \mathbf{Y}^{d}_{n\times m_4}$ are the observer matrix corresponding to control parameters, system operation states and indicator parameters, respectively. $\mathbf{Y}^{b}_{n\times m_5}$ means market information data. $m_i, i = 1, 2, 3, 4, 5$ is the final number of features, while n is the sample number.

Definition 3 (Inner-Level Relation): A necessary message (knowledge itself) is a piece of rule that is summarized by humans or learned by desired algorithms from the component of interest and its monitoring variables (shared knowledge). If this piece of rule exists, then the inner-level relation exists.

Taking Fig. 4 as an example, the defined rule can be obtained by domain expert knowledge, and it represented as (head (information source), relation, tail (node)). The relation can be divided into apparent and latent one. The apparent one can be defined by expert knowledge (gray circle and gray line in Fig.4(a)), while latent one can be defined by the similarity indices exceeding their thresholds (red circle and red line in Fig.4(a)). The similarity indices between a pair of variables (corresponding to gray circle and red circle) can be calculated by normalized mutual information entropy, as shown in Fig. 4(b)

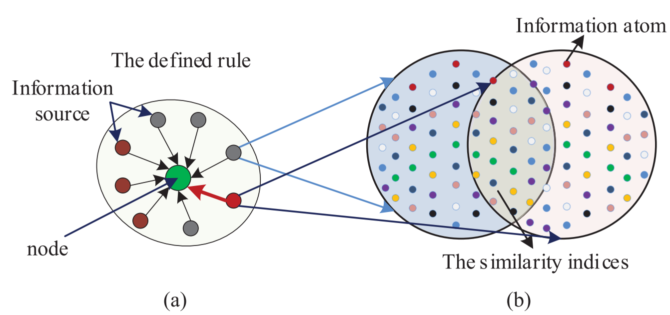

Fig. 4. Schematic of shared knowledge. (a) Component of interest and its monitoring variables. (b) Principle of the existence or nonexistence by shared knowledge.

$$H(S) = -\sum_{i} p(s_i)\log p(s_i) \quad (2)$$

$$H(V) = -\sum_{i} p(v_i)\log p(v_i) \quad (3)$$

$$I(S;V) = \sum_{s_i}\sum_{v_j} p(s_i, v_j)\log\frac{p(s_i, v_j)}{p(s_i)p(v_j)} \quad (4)$$

$$\mathrm{NMI}(S;V) = \frac{2\times I(S;V)}{H(S)H(V)} \quad (5)$$

where $H(\cdot)$ is the information entropy. $p(\cdot)$ is the marginated distribution probability. $S = \{s_i\}$ and $V = \{v_j\}$ are a pair of monitoring variables of interest, respectively. NMI(S, V) is the normalized mutual information entropy between a pair of monitoring variables. Due to uncertainties or noises in variables, the information entropy would be unstable by insufficient sequence length. Therefore, this article employs all historical data signal segments to calculate a series of information entropies which can be used to obtain the final information entropy with their average.

Correspondingly, relations definition between key components and their monitoring variables refer to calculate a series of NMIs, which can be used to determine the inner-level relations between different entities. The corresponding thresholds (hyper-parameter, and it can be pre-determined by expert knowledge), which is described as follows, mathematically:

$$r_{kl} = \begin{cases} 1, & \mathrm{NMI}_l \geq \mathrm{Thr} \\ 0, & \mathrm{NMI}_l < \mathrm{Thr} \end{cases} \tag{6}$$

where r_{kl} means the relation between head-node (n_k) and tail-node (n_l). Thr is the threshold (hyper-parameter), and it is pre-determined by expert knowledge. NMI_l is the NMI between a pair of (head, tail)-nodes (n_k, n_l).

Definition 4 (Extra-Level Relation): Multiple pieces of the necessary message (knowledge themselves) are mastered by all individuals, where can define by the number of the same monitored variables accounts for the percentage of the number of monitored variables of the node of interest.

The definition of extra-level relations can be regarded as the element in the adjacency matrix A (only defined 0 and 1), which are denoted as follows, mathematically:

$$a_{ij}^{\mathrm{in}} = \begin{cases} 1, & \mathrm{len}(\mathbf{V}_i \cap \mathbf{V}_j)/\mathrm{len}(\mathbf{V}_i) \geq T_{\mathrm{num}} \\ 0, & \mathrm{else} \end{cases} \tag{7}$$

$$a_{ij}^{\mathrm{out}} = \begin{cases} 1, & \mathrm{status}_j \in \mathbf{V}_i \\ 0, & \mathrm{else} \end{cases} \tag{8}$$

where a_{ij} means the relation between node N_i and N_j. $a_*^{\mathrm{in}}, a_*^{\mathrm{out}}$ mean that nodes of interest are from the same level or different level. $\mathbf{V}_i, \mathbf{V}_j$ are the monitoring variables sets of ith and jth node, respectively. $\mathrm{len}(\cdot)$ means the number of monitoring variables. status_j means the status of jth node. T_{num} is another threshold (another hyper-parameter) that can be pre-determined by expert knowledge. Equation (7) means the percentage of the common monitoring variables to the number of monitoring variables in ith node, while (8) means as long as the monitoring variables of ith node contains the status of jth node (not belong to the same level), the relation between them exists.

MLKG can be considered as a high-level knowledge organization in plant-wide processes. Its purpose can be summarized as 1) to integrate; 2) to disambiguate; 3) to verify; and 4) to update the heterogeneous data of knowledge from different knowledge sources under a unified framework, and this can be used to form a high-quality knowledge base by integrating information, data, methods, experience, and human thoughts. It should be noted that the knowledge framework can be regarded as the first key issue, and followed is knowledge integration and knowledge inference. This article regards the MLKG as a kind of knowledge base which describes the associations between key components in plant-wide processes,

Algorithm 1 MLKG Construction

Input: Levels, **L**; Variables, **V**; Prior-knowledge, **U**; Key components of interest, **N**.
Output: MLKG, $\mathbf{G}_l$.
1: **for** each level l in **L** **do**
2: $\mathbf{NMI}s$ between monitoring variables **V** calculated by (2)–(5);
3: **for** each node n in key components of interest **N** **do**
4: Related monitoring variables set $\mathbf{V}_n$ initially defined by $prior$-knowledge **U**;
5: Update the monitoring variables set $\mathbf{V}_n$ of node n with $\mathbf{NMI}s$ by (6);
6: **end for**
7: Update knowledge graph $\mathbf{G}_l$ of different nodes inside and outside the level by (7)–(8).
8: **end for**

and the whole system status can be equivalent to the node status at the top level while every key component status (including physical entity and virtual process) can correspond to node status on each level.

C. Global Fault Detection on Top-Level

Suppose tails (T-nodes) are the considered objects, and the statuses of these objects can be reflected by a large number of monitoring variables (including sensor measurements, statuses of related components) which can be donated by heads (H-nodes), while their relations can be settled by (6). And these associations (relations) can be used to construct the adjacent matrix, as shown in the following:

$$\mathbf{A} = \begin{bmatrix} a_{11} & \cdots & a_{1l} \\ \vdots & \ddots & \vdots \\ a_{k1} & \cdots & a_{kl} \end{bmatrix} \tag{9}$$

where a_{ij} means the relation between the ith tail (T-node) and the jth head (H-node). **A** means that a knowledge graph has k nodes, while each node can be described by l monitoring variables and node statuses. The feature matrix (monitoring variables) of the ith node can be calculated as follows:

$$\begin{cases} \mathbf{X}_i = \mathbf{Y}_\nu \\ \nu = \arg_j a_i(j) := \{j \mid \forall \iota : a_{i\iota} = 1\} \end{cases} \tag{10}$$

where $a_{i\iota} \in \mathbf{A}$ means to select the related monitoring variables or node statuses to describe the considered object. $\mathbf{X}_i, \mathbf{Y}_\nu$ are the feature matrix of the object of interest, practical observers, respectively.

Suppose the feature observation matrix presented as matrix $\mathbf{X}_{n\times m}$ after normalized (n is the sample number, while m is the number of monitoring variables and node statuses). And this article uses the PCA to achieve the node status description to illustrate the basic theory. The normalized observation matrix $\mathbf{X}_{n\times m}$ can be decomposed into principal components and residual matrix:

$$\mathbf{X}_{n\times m} = \mathbf{T}\mathbf{P}^T + \mathbf{E} \tag{11}$$

where $\mathbf{T} \in \Re^{n\times\kappa}$, $\mathbf{P} \in \Re^{n\times\kappa}$ are principal component score and their loading matrix, respectively. $\mathbf{E} \in \Re^{n\times m}$ is the residual matrix. $k \le m$ is the number of principal components, and this can be calculated by the contribution rate of cumulative principal variance.

The Hotelling's statistics $\mathbf{T}^2$ and $\mathbf{Q}$ are employed to monitor the changes of principal component subspace and residual subspace to detect changes [29]

$$\begin{cases} \mathbf{T}^2 = x\mathbf{P}\Lambda^{-1}\mathbf{P}^T x^T \le \dfrac{\kappa(n-1)}{n-\kappa} F_{\kappa,n-\kappa,\alpha} \\ \mathbf{Q} = x(\mathbf{I}-\mathbf{P}\mathbf{P}^T)x^T \le g\chi^2_{h,\alpha} \end{cases} \tag{12}$$

where $\Lambda = \mathrm{diag}(\lambda_1, \lambda_2, \ldots, \lambda_m)$ is the diagonal matrix. $F_{\kappa,n-\kappa,\alpha}$, $\chi^2_{h,\alpha}$ are the F-distribution and χ^2-distribution with κ and n-κ degrees under the confidence limit α, $g = \delta/2\mu$, and $h = 2\mu^2/\delta$ with μ and δ denoting the estimated mean and variance of the $\mathbf{Q}$, respectively.

This article mainly employs the statistic characteristics of $\mathbf{Q}$ to measure the possibility of the correlations between normal monitoring features to show the fault conditions, and this article also employs the statistic characteristics of $\mathbf{T}^2$ to measure the distance or similarity between the existing samples and original principal component subspace. Due to the fact that principal component subspace is mainly used to reflect the changes of normal operation, while residual subspace is mainly employed to reflect the changes of faulty noise. Therefore, Hotelling's statistics $\mathbf{T}^2$ and $\mathbf{Q}$ are very suitable to detect the fault of the component (node) of interest on the global level.

In addition, the status of nodes in top-level is calculated by (12) from the sensor measurements and the status of the related node on the last level. Loop like this, until the sensor measurements are on the bottom level. Once the fault is detected on top-level, the source of fault occurring reasons will be locally located immediately.

D. Local Fault Location on Bottom-Level

Local fault location generally refers to the separation of special variables, which causes the fault or faulty status of a related component. This article employs the variable contribution rate to illustrate the basic idea, and the variable contribution rate can be regarded as the most commonly used method of fault location. Furthermore, the variable contribution rate in this article has some differences from the traditional one, and these differences rely on the variables, which not only refer to the sensor measurements (monitoring variables) on the bottom level but also refer to the status of related components on the last level. Loop like this, until locating the final reason for a fault occurring. The $\mathbf{Q}$-based contribution rate can be calculated as follows:

$$\mathbf{Q} = \|\tilde{C}x\|^2 = \sum_{i=1}^{m} \mathrm{Cont}_i^{\mathbf{Q}}$$
$$\mathrm{Cont}_i^{\mathbf{Q}} = (\xi_i^T \tilde{C}x)^2 \tag{13}$$

where $\mathrm{Cont}_i^{\mathbf{Q}}$ represents the contribution of each variable to statistics $\mathbf{Q}$, and $\tilde{C} = \mathbf{I} - \mathbf{P}\mathbf{P}^T$, ξ_i represents the i-th column of unit matrix $\mathbf{I}_m$. Similarly, the $\mathbf{T}^2$-based contribution rate can be calculated as follows:

$$\mathbf{T}^2 = (x^T\mathbf{D}x) = \|\mathbf{D}^{1/2}x\|^2 = \sum_{i=1}^{m} \mathrm{Cont}_i^{\mathbf{T}^2}$$
$$\mathrm{Cont}_i^{\mathbf{T}^2} = (\xi_i^T\mathbf{D}^{1/2}x)^2 = x^T\mathbf{D}^{1/2}\xi_i\xi_i^T\mathbf{D}^{1/2}x \tag{14}$$

where $\mathrm{Cont}_i^{\mathbf{T}^2}$ represents the contribution of each variable to statistics $\mathbf{T}^2$, and $\mathbf{D} = \mathbf{P}^T\Lambda^{-1}\mathbf{P}$, ξ_i represents the i-th column of unit matrix $\mathbf{I}_m$.

Variable contribution rate is regarded as the effective method to location the status change on each level, which can be used to trace the main components or monitor variables to construct the path of fault occurring. And this backtracking can be mathematically described as follows:

$$\mathbf{C} = \{c_i^l\},\ l = \{\text{devices, subprocess, process}\}$$
$$c_i^\star = \begin{cases} 1, & \mathrm{Cont}_i^\star \ge \dfrac{1}{m} \\ 0, & \text{else} \end{cases} \tag{15}$$

where $\mathbf{C}$ is local fault location results. c_i^l represents the result of ith node on lth level. $\mathrm{Cont}_i^\star$ is the variable contribute rate of ith node, such as $\mathrm{Cont}_i^{\mathbf{Q}}$ and $\mathrm{Cont}_i^{\mathbf{T}^2}$. Once the fault is detected, the variable with a larger contribution rate can be considered as the fault reason. This backtracking can be realized level by level, and it may be regarded as a method of tracing a binary tree (unintentionally formed). However, the final reason requires further analysis and determination of operators with process background knowledge.

Algorithm 2 Fault Detection and Location

Input: MLKG, $\mathbf{G}_l$; Variables, $\mathbf{V}$; Components of interest, $\mathbf{N}$.
Output: Result of fault detection r and location l.

1: **for** each node n in key components of interest $\mathbf{N}$ **do**
2: Related monitoring variables set $\mathbf{V}_n$ defined by MLKG, $\mathbf{G}_l$;
3: Hotelling's statistics $\mathbf{T}^2$ and $\mathbf{Q}$ and their corresponding control limits $\mathbf{T}^2_{UCL}$, $\mathbf{Q}_{UCL}$ can be calculated by (12);
4: Result of fault detection can be determined by judging whether the statistics $\mathbf{T}^2$ and $\mathbf{Q}$ exceeding their corresponding control limits $\mathbf{T}^2_{UCL}$, $\mathbf{Q}_{UCL}$.
5: Result of fault location can be settled by (13)–(14).
6: **end for**

E. Local–Global Plant-Wide Process Monitoring

Generally, this local–global plant-wide process monitoring consists of two phases: off-line modeling and online monitoring. The details of this new local–global fault detection and location can be summarized as follows, and its flowchart is illustrated in Fig. 5.

1) Off-Line Modeling:

1) *Step* 1: Monitoring variables $\mathbf{V}$, key components of interest $\mathbf{N}$ and multilevels $\mathbf{L}$ are collected and defined, while domain expert knowledge $\mathbf{U}$ is also collected.
2) *Step* 2: MLKG $\mathbf{G}$ can be constructed by collected information by Algorithm 1.
3) *Step* 3: Statistics $\mathbf{T}^2$, $\mathbf{Q}$ of each node in MLKG can be calculated by (12). Naturally, their corresponding

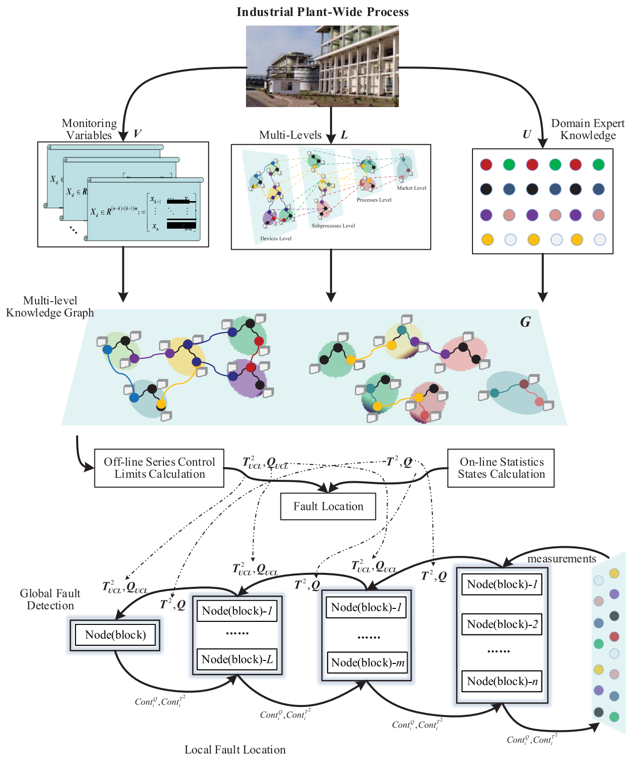

Fig. 5. Flowchart of local–global monitoring.

control limits $\mathbf{T}^2_{\mathrm{UCL}}$, $\mathbf{Q}_{\mathrm{UCL}}$ of $\mathbf{T}^2$, $\mathbf{Q}$ statistics can be also obtained by corresponding F-distribution and χ^2-distribution with κ and n-κ degrees, respectively.

Off-line modeling phase of MLKG-based local–global fault detection mainly involves the calculation of each node statistics $\mathbf{T}^2, \mathbf{Q}$ and their control limits $\mathbf{T}^2_{\mathrm{UCL}}$, $\mathbf{Q}_{\mathrm{UCL}}$. Once each node statistics $\mathbf{T}^2, \mathbf{Q}$ and their control limits $\mathbf{T}^2_{\mathrm{UCL}}, \mathbf{Q}_{\mathrm{UCL}}$ are over, the fault detection and location in process monitoring can be achieved by this method. And on-line monitoring can be realized as follows.

2) On-Line Monitoring:

1) *Step* 1: A set of monitoring variables $\mathbf{V}$ of time series of interest is collected.
2) *Step* 2: MLKG corresponding to this monitoring variables $\mathbf{v}$ can be constructed timely.
3) *Step* 3: Statistics $\mathbf{T}^2$, $\mathbf{Q}$ of each node in MLKG can be calculated by (12).
4) *Step* 4: Fault detection can be achieved by its statistics $\mathbf{T}^2$, $\mathbf{Q}$ exceeding their control limits $\mathbf{T}^2_{\mathrm{UCL}}$ and $\mathbf{Q}_{\mathrm{UCL}}$.
5) *Step* 5: Correspondingly, fault location can be settled down by (13) and (14), iteratively.

In general, the purpose of global fault detection can be regarded as the timely perception of system status changes, while local fault location can be regarded as an attempt to trace the cause of the change in the operation status in a top-down manner. The departure of local fault location should be used to interpretably describe that how the cause of the change on the bottom level leads to the failure on system operation status level by level.

IV. Experimental Studies

A. Benchmark Experiment

1) Plant-Wide Process Description: TE chemical process is designed as a benchmark for process control and related research area, and it mainly consists of five major operation units (including reactor, product condenser, vapor-liquid separator, recycle compressor, and product stripper). Four reactants A, D, C, and E are fed into the reactor which outputs two liquid products G and H and one by-product F. All of these simple products information can be used to provide mechanism knowledge in MLKG. In this process, it has 22 process measurement variables (v_0-v_{21}), 12 control parameters (v_{22}-v_{32}), and 19 indicator variables (v_{33}-v_{51}), which can be employed to construct MLKG with domain expert knowledge by Algorithm 1. In order to validate the process monitoring performance, one normal state and 21 type faults have been simulated, respectively. The train datasets of 22 states are composed of 480 data samples, while the test datasets are composed of 960 samples (each fault starts to appear at time $k = 161$). More details had been elaborated in many literature works, such as [30], [31].

Fig. 6 shows the flowchart of global–local fault detection and location for the TE process. The first issue of this flowchart is to collect domain expert knowledge by subjectively observing the TE chemical process, and parts of expert knowledge on the initial variables of key components are shown in Table I. There are 52 monitoring variables that are used to calculate the correlations matrix by (2)–(5), and this correlations matrix is significant for MLKG construction by algorithm 1. The MLKG for TE process description can be easily achieved by algorithm 1, which is utilized to realize global fault detection and local fault location level by level.

2) Multilevel Knowledge-Graph Construction: The levels $\mathbf{L}$ are defined four: sensors level, devices level, subprocess level, and process level. The monitoring variables $\mathbf{V}$ are divided into two main parts: one consists of 22 sensor measurement variables and 12 control parameters, while another one consists of 19 indicator variables. The domain expert prior-knowledge $\mathbf{U}$ is subjectively summarized from Fig. 6, and it is represented by initial monitoring variables of key components of interest $\mathbf{N}$, and the final monitoring variables can be determined by checking correlation matrix (52×52 matrix).

Due to the limited space and the necessity of illustrating this new method, there is no need to present the detailed form of MLKG. And this benchmark mainly discusses four main devices (reactor, separator, stripper, and compressor) to demonstrate the effectiveness of this new method. In fact, the MLKG for TE process consists of 22 nodes, and the status of each node in devices level is only reflected by numerous monitoring variables, while the status of each node in subprocess level and process level are not only calculated by monitoring variables but also reflected by the node status on the last level, such as the status of subprocess-1 are also influenced by the status of key components in devices level. Furthermore, the monitoring variables in different nodes are more likely to duplicate, which is different from traditional ones.

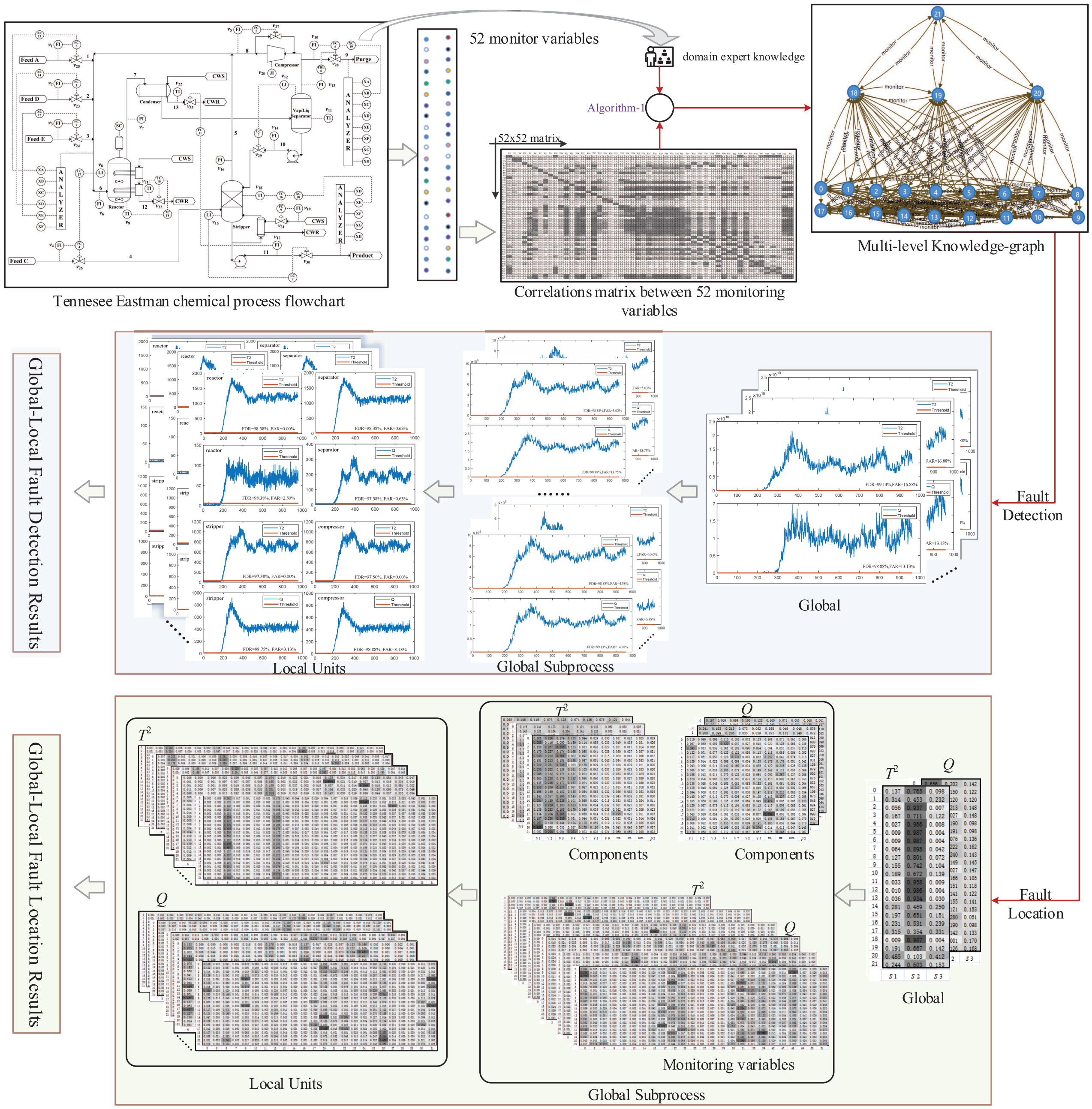

Fig. 6. Flowchart of local–global monitoring for TE process.

Table I shows expert *prior*-knowledge of the initial and final variables calculation of key components. The initial variables of key components (reactor, separator, stripper, and compressor) are defined by domain expert knowledge, while the final variables of key components are determined by checking MLKG. Furthermore, the final variables can be utilized to define the healthy status of key components to realize the global fault detection in one node on the top level.

3) Global Fault Detection: Fault detection rates (FDRs) and false alarm rates (FARs) for key components of interest on multilevels in TE are shown in Tables II and III, respectively. All the results of global fault detection are achieved by the configuration on hyper-parameters of this proposed method, such as Thr $= 0.9$, $T_{\text{num}} = 0.8$, confidence $\alpha = 0.01$, etc. In several simple faults, the performance of the proposed method has been verified, such as fault-1, 2, 4, 5, 6, 7, 8, 12, 13. The global FDRs of these simple faults have little distance from 100%, while their global FARs can reach as low as 20%. And in some hard tasks, the global FDRs of fault-3, 9, 15, 19, 20, and 21 can reach as high as 37.38%, 34.63%, 38.75%, 81.13%, 88.25%, and 74%, respectively, which means this proposed method can be utilized to solve some hard problems. As for the reasons for describing the difference in the performance between simple tasks and hard tasks, it should be noted that associations between nodes are not considered in this article, which is very significant for fault detection.

TABLE I

EXPERT *prior*-KNOWLEDGE OF THE INITIAL AND FINAL VARIABLES CALCULATION OF KEY COMPONENTS IN TE

Level	Components	Initial variables	Final variables
devices	reactor	3, 5, 6, 7, 8, 20, 31	3, 5, 6, 7, 8, 10, 11, 12, 13, 14, 16, 17, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31
	separator	4, 9, 10, 11, 12, 13, 21, 26, 27, 28	0, 4, 5, 6, 7, 9, 10, 11, 12, 13, 14, 16, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32
	stripper	5, 6, 7, 8, 13, 28, 14, 15, 16, 17, 18, 29, 30	4, 5, 6, 7, 8, 10, 11, 12, 13, 14, 15, 16, 17, 18, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32
	compressor	4, 5, 6, 7, 8, 10, 11, 12, 19, 26	4, 5, 6, 7, 8, 10, 11, 12, 13, 14, 16, 17, 19, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32
subprocess	subprocesss-1	34, 35, 36, 37, 38, 39, valve1, valve2, valve3, valve5, valve10, reactor, stripper, compressor, condenser, separator	3, 4, 5, 13, 16, 24, 26, 27, 31, 32, 33, 34, 35, 36, 37, 38, 39, 41, 42, 43, 44, 45, 46, 51, valve1, valve2, valve3, valve5, valve10, reactor, stripper, compressor, condenser, separator
	subprocesss-2	40, 41, 42, 43, 44, 45, 46, 47, valve5, valve6, valve7, pump1, reactor, stripper, compressor, condenser, separator	0, 4, 5, 13, 16, 24, 26, 27, 28, 31, 32, 33, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 48, 51, valve5, valve6, valve7, pump1, reactor, stripper, compressor, condenser, separator
	subprocesss-3	48, 49, 51, 52, valve7, valve8, valve9, valve1, valve2, valve3, valve4, pump2, reactor, stripper, compressor	0, 5, 7, 9, 11, 13, 14, 16, 17, 22, 23, 25, 27, 28, 29 30, 31, 33, 39, 42, 47, 48, 49, 50, 51, valve7, valve8, valve9, valve1, valve2, valve3, valve4, pump2, reactor, stripper, compressor
process	process	subprocesss-1, subprocesss-2, subprocesss-3	

The number in variables column are the monitoring variables, which corresponding to 22 (0-21) process measurement variables and 12 (22-32) control parameters and 19 (33-51) indicator variables.

TABLE II

FDRS OF KEY COMPONENTS OF INTEREST ON MULTILEVELS IN TE

	Process		Subprocess-1		Subprocess-2		Subprocess-3		Reactor		Separator		Stripper		Compressor	
	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q
1	100.0	100.0	100.0	100.0	99.88	99.88	99.88	99.88	99.00	99.88	99.13	99.75	99.25	99.75	99.13	99.75
2	99.13	98.88	98.88	98.88	98.88	99.13	98.75	99.00	98.38	98.38	98.38	97.38	97.38	98.75	97.50	98.88
3	37.38	23.25	20.63	31.75	19.88	30.38	20.25	18.38	5.63	2.00	3.63	6.25	5.38	2.88	4.63	2.75
4	100.0	100.0	100.0	100.0	100.0	99.88	100.0	100.0	68.38	100.0	72.50	100.0	43.50	100.0	41.50	100.0
5	100.0	100.0	100.0	100.0	100.0	100.0	42.88	40.25	26.50	19.13	26.50	25.25	26.50	24.50	26.63	28.00
6	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	99.38	100.0	99.88	100.0	99.75	100.0
7	100.0	99.75	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	42.13	100.0	80.00	100.0	75.13
8	98.63	98.00	98.50	98.50	98.38	98.38	98.13	98.13	96.63	94.50	96.88	87.63	96.50	95.38	96.38	95.75
9	34.63	20.38	18.88	31.13	18.00	25.75	17.13	18.38	4.63	3.50	2.63	4.88	3.25	3.75	3.88	3.63
10	81.00	63.38	73.00	73.88	72.63	70.75	72.63	77.25	45.88	43.38	35.13	29.25	42.75	45.88	43.75	38.38
11	92.25	82.25	88.75	90.88	89.50	89.25	86.75	86.75	60.50	69.38	46.38	65.50	52.75	76.88	52.13	77.63
12	100.0	99.63	100.0	100.0	100.0	100.0	99.13	99.63	98.88	93.13	98.00	91.38	98.63	90.00	98.75	92.25
13	96.38	95.50	95.75	96.38	95.88	96.00	95.88	95.88	94.38	95.13	93.63	94.63	94.63	94.50	94.00	95.13
14	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	99.25	79.75	90.63	88.00	86.25	87.50	86.63
15	38.75	23.38	29.38	32.88	26.38	31.38	23.63	27.50	8.38	4.38	5.50	8.38	8.63	3.38	7.00	4.88
16	81.63	63.50	71.38	73.63	69.88	71.88	73.38	75.88	27.25	42.13	19.63	24.13	30.75	42.63	25.88	37.50
17	97.63	95.88	96.75	97.13	96.50	96.50	96.38	97.25	86.50	96.75	48.50	56.38	66.50	65.63	66.13	66.13
18	93.50	91.75	92.25	92.88	92.00	92.50	92.13	92.38	89.50	90.75	89.63	90.50	89.38	90.88	89.50	91.00
19	81.13	46.88	67.50	75.50	66.38	72.88	54.88	58.88	4.75	33.38	16.25	22.38	19.25	22.13	17.50	26.00
20	88.25	77.88	86.25	87.25	85.88	86.63	73.75	72.13	4.25	63.50	43.63	58.00	41.13	61.13	46.50	58.25
21	74.00	60.13	67.00	71.00	67.50	68.00	52.38	65.50	45.63	43.88	41.50	50.63	48.38	43.25	42.88	49.13

Each node on multilevel can get high detection accuracy, such as the FDRs of the node on top-level (process) for fault-2 are 99.13% (T^2), 100.0% (Q) that are basically the same as the FDRs of subprocess-1, 2, 3 on subprocess level and the FDRs of key components of interest (reactor, separator, stripper, and compressor) on devices level. This demonstrates that noises and uncertainties of a local node have been effectively reduced, which manifests the importance of combining the local data (data available at the node itself) and the data from its neighboring nodes.

Fig. 7 shows the Hotelling's statistics T^2 and Q on global-process level to local-compressor level, which can be employed to demonstrate the effectiveness and reasonable of the consideration on the head and tail entity that should refer to the components of interest (or operation units, or nodes) and their related monitoring variables. Furthermore, status changes of each node on the bottom level can evolve into the status change of the node on the top level without any information loss.

4) Local Fault Location: Fault location will make results of global fault detection have their practical physical meaning, which is comprehensively realized by a top-down manner. This top-down manner firstly starts on process-level to identify the nodes on subprocess level nodes that have a greater impact, and then the identified subprocess level node utilizes this top-down manner to identify nodes with greater influence on devices-level. This cycle continues until the final information (monitoring variables), and due to the limited space, this article just employs the results of fault location at time $k = 200$ to

TABLE III
FARs OF KEY COMPONENTS OF INTEREST ON MULTILEVELS IN TE

	Process		Subprocess-1		Subprocess-2		Subprocess-3		Reactor		Separator		Stripper		Compressor	
	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q
1	16.25	11.88	6.88	17.50	6.88	8.13	10.00	10.63	0.63	3.13	0.00	1.25	0.00	3.75	0.00	3.13
2	16.88	13.13	5.63	13.75	4.38	14.38	10.00	6.88	0.00	2.50	0.63	0.63	0.00	3.13	0.00	3.13
3	45.00	26.88	20.00	41.88	23.75	30.63	8.75	18.75	1.25	1.25	1.88	0.63	1.25	3.13	1.25	3.75
4	13.75	10.63	7.50	14.38	6.25	13.13	7.50	9.38	1.25	0.00	0.63	2.50	1.25	0.00	0.63	0.00
5	13.75	10.63	7.50	14.38	6.25	13.13	9.38	7.50	1.25	0.00	0.63	2.50	1.25	0.00	0.63	0.00
6	17.50	8.13	5.00	13.75	3.75	10.63	3.75	8.13	0.63	1.25	0.63	3.13	0.63	0.00	1.25	0.00
7	16.25	11.88	9.38	13.75	6.88	10.63	6.88	10.63	1.25	0.63	0.00	5.00	0.63	0.63	0.63	0.63
8	18.75	13.75	8.75	15.00	7.50	16.88	10.00	7.50	1.88	2.50	0.63	3.13	0.00	1.25	0.00	1.25
9	41.88	25.00	28.13	32.50	28.13	31.88	26.25	24.38	5.00	3.75	4.38	6.88	7.50	3.13	11.25	2.50
10	16.25	10.63	6.25	10.63	5.63	16.25	10.63	10.00	1.88	3.13	2.50	1.25	3.13	1.25	1.88	0.63
11	20.63	13.75	8.75	15.63	8.13	19.38	8.13	13.13	1.88	4.38	1.25	0.00	1.25	2.50	1.25	1.25
12	16.88	12.50	8.13	11.88	8.13	15.00	8.13	9.38	0.63	2.50	0.63	0.00	2.50	2.50	1.88	1.88
13	16.88	9.38	5.63	10.63	6.25	10.00	5.63	6.88	0.63	0.00	0.63	1.88	0.63	3.75	0.63	3.75
14	21.88	14.38	8.75	16.25	4.38	18.13	9.38	14.38	0.63	1.25	0.00	1.25	0.63	0.00	0.63	0.00
15	17.50	15.63	4.38	16.25	3.75	12.50	5.00	11.25	0.00	3.75	1.25	0.00	0.00	0.63	0.00	0.63
16	50.00	31.88	38.13	38.13	36.88	36.88	28.13	30.00	10.0	5.63	8.13	2.50	10.63	4.38	8.75	4.38
17	21.25	8.75	11.88	15.63	16.88	16.88	11.88	14.38	1.88	0.63	1.88	5.00	2.50	1.88	1.88	1.25
18	16.88	13.13	5.63	14.38	6.25	11.88	5.00	10.00	1.25	1.25	0.63	1.25	1.25	1.88	0.63	2.50
19	11.25	9.38	4.38	8.75	5.00	8.75	8.13	6.88	0.00	1.88	0.63	0.63	0.63	1.25	0.63	1.88
20	16.25	6.25	6.25	12.50	1.88	10.00	5.00	5.63	0.00	0.00	0.63	1.25	0.63	0.63	0.63	0.63
21	33.75	15.63	16.25	30.00	14.38	26.88	10.63	22.50	1.25	1.88	2.50	1.25	0.63	3.75	0.63	3.13

TABLE IV
COMPARISON STUDY WITH THE STATE OF THE ART IN GLOBAL DETECTION RATES (FDR) FOR TE PROCESS

	PCA		Global-SAE		Global-KPCA		WCMBPCA		HBN		DPLS-RG		MLKG-MB	
	T^2	Q	T^2	Q	T^2	Q	BIC_{T^2}	BIC_{SPE}	T^2	Q	T^2	Q	T^2	Q
1	99.2	99.7	100	100	100	100	99.8	99.8	99	88	100.0	99.1	**100.0**	**100.0**
2	98.0	98.6	99	99	99	100	98.5	98.6	94	89	98.5	16.3	**99.13**	98.88
3	0.2	0.9	12	28	9	12	–	–	2	0	–	–	**37.38**	**23.25**
4	54.4	96.2	100	100	79	100	100.0	97.9	2	0	100.0	0.1	**100.0**	**100.0**
5	22.5	25.4	70	100	30	51	28.0	100.0	35	27	100.0	87.0	**100.0**	**100.0**
6	99.2	100.0	100	100	13	100	99.5	100.0	99	99	100.0	100.0	**100.0**	**100.0**
7	100.0	100.0	100	100	100	100	95.5	100.0	56	40	100.0	100.0	**100.0**	99.75
8	97.5	97.5	99	99	98	99	97.8	97.8	93	86	97.9	74.6	98.63	98.00
9	0.6	1.9	11	24	8	10	–	–	1	0	–	–	**34.63**	**20.38**
10	33.4	34.1	50	92	52	82	49.3	75.8	79	52	88.0	14.6	81.00	63.38
11	20.6	64.4	86	84	65	85	72.9	57.1	17	10	79.1	1.9	**92.25**	82.25
12	97.1	97.5	99	100	99	99	98.9	99.4	97	83	99.9	72.5	**100.0**	**99.63**
13	94.0	95.5	96	96	95	96	95.0	95.0	91	78	95.3	89.0	**96.38**	**95.50**
14	100.0	98.9	100	100	100	100	100.0	99.9	99	63	100.0	0.6	**100.0**	**100.0**
15	1.2	2.7	21	30	11	21	–	–	1	1	–	–	**38.75**	**23.38**
16	15.7	24.5	36	96	37	78	26.6	78.0	20	11	92.0	10.0	81.63	63.50
17	74.1	89.2	97	96	84	98	94.5	91.9	91	66	97.0	28.3	**97.63**	95.88
18	88.7	89.9	92	92	19	91	90.3	89.6	85	82	90.4	86.5	**93.50**	**91.75**
19	13.9	28.0	75	92	24	65	4.0	52.4	1	2	93.1	0.6	81.13	46.88
20	31.5	60.2	75	86	58	75	55.3	65.1	74	54	91.1	16.3	88.25	77.88
21	26.4	43.0	63	58	49	66	44.0	52.0	28	12	54.6	7.4	**74.00**	60.13

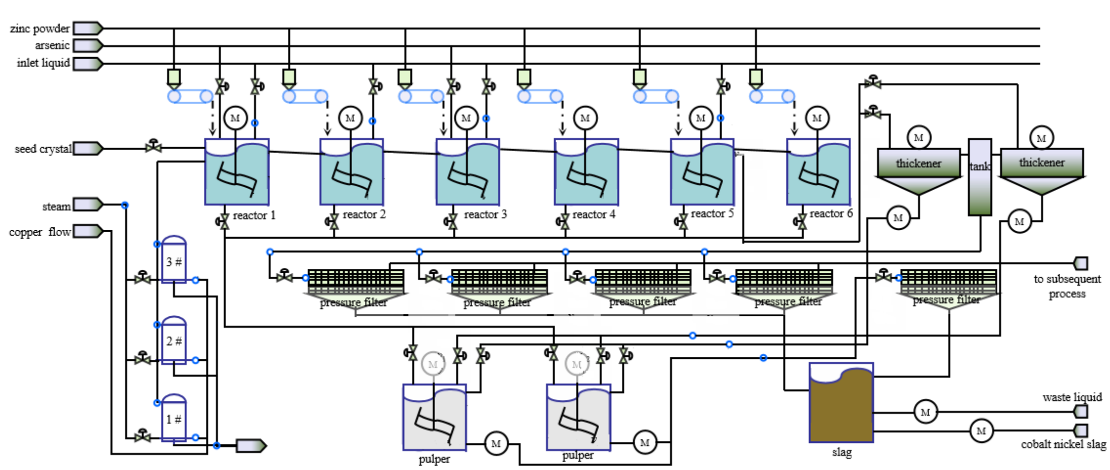

Fig. 9. Flowchart of practical process of Cobalt–Nickel removal from zinc solution.

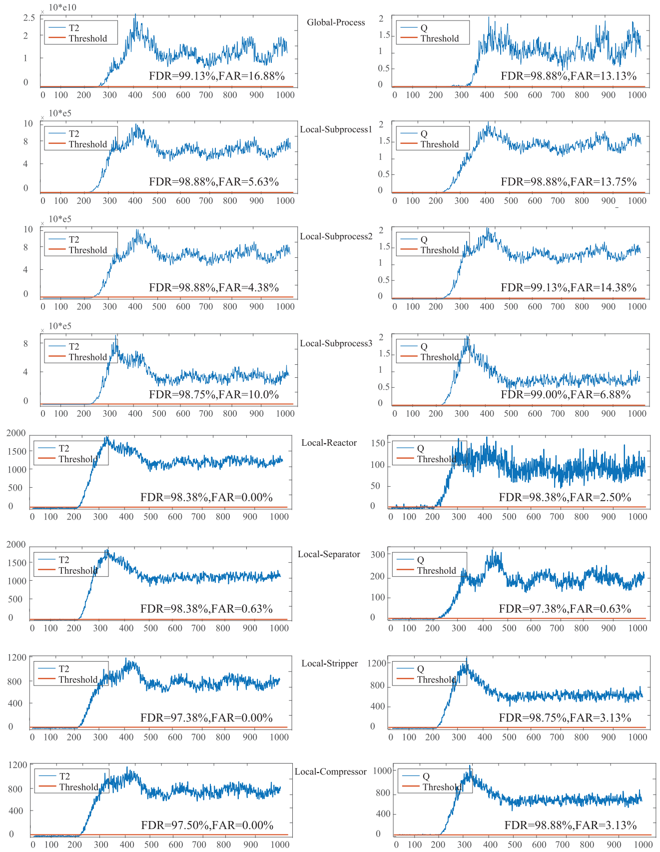

Fig. 7. Results of global–local detection for fault2.

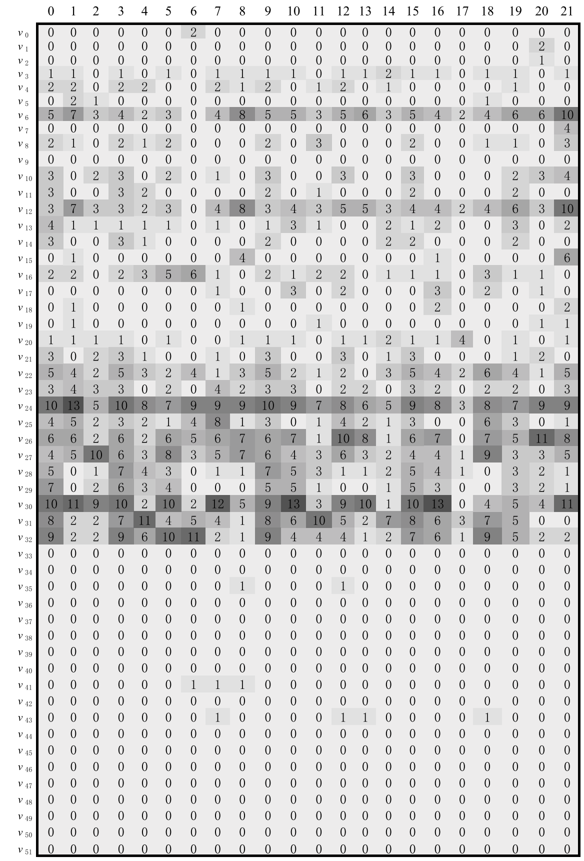

Fig. 8. Results of fault location for plant-wide TE process.

illustrate the effectiveness and applicability of this proposed method in Fig. 8.

5) Comparison With the State of the Art: Table IV shows some related monitoring results (global FDR) of multiblock-based distributed process monitoring, including PCA in [10], global sparse auto-encoder (Global-SAE) and global kernel PCA (Global-KPCA) in [6], weighted copula-correlation based multiblock PCA (WCMBPCA) in [11], hierarchical Bayesian Network (HBN) in [32], distributed partial least squares based residual generation (DPLS-RG) in [33], and this proposed method (MLKG-based multiblocks (MLKG-MBs)). In distributed plant-wide process monitoring, the FDRs of some simple tasks can be obtained as to 100% (fault-1, 4, 5, 6, 7, 12, 14) which can be used to demonstrate the effectiveness of this proposed method. However, the FDRs of some semi-hard tasks (fault-11, 13, 17, 18, 21) are higher than other recent reports, which means this proposed method can be used to obtain the state-of-the-art performance. In particular, the hard tasks (fault-3, 5, 9) can reach 37.38%, 34.63%, and 38.75%, respectively, which are much higher than other methods. Finally, all these results can be used to demonstrate that the noises and uncertainties of each node can be effectively reduced by this new method, which is hardly realized by traditional methods.

B. Practical Case Application

1) Plant-Wide Process Description: Zinc is one of the most used nonferrous metals, and it has been widely used in numerous industries, such as replacement electroplating, alloy, and pharmaceutical production. Zinc hydrometallurgy accounts for more than 85% zinc production, and it mainly consists of five processes: roasting, leaching, purification, electrolysis, and casting. In this process, purification can be regarded as one of the most important processes to obtain a qualified solution. Cobalt–Nickel removal from zinc solution is one of the purification processes, and its purpose is to remove cobalt and nickel impurities to keep the performance of producing zinc, as shown in Fig. 9. Its function in zinc hydrometallurgy is to add the impurity removal agent (zinc elemental powder) and catalyst to reactors, and then complex redox reaction happens with impurity metal ions in leachate, and finally alloy or metal compound precipitation can be formed to gradually reduce the concentration of impurity ions until make it tend to the range of technical indicators [34].

Cobalt–Nickel removal from zinc solution consists of three heaters, six reactors, two thickeners, five filters, and so on. And the monitoring variables in practical usage mainly refer to 65 variables (v_0-v_{64}), including pressure, temperature, flow, and liquid level. The MLKG of this practical cobalt–nickel removal process can be constructed by algorithm 1, and its global–local fault detection and location can be achieved by algorithm 2. Furthermore, this case study has selected seven faults to demonstrate the effectiveness and applicability of this proposed method, and these seven faults occur in seven different modes (mode12, mode15, mode18,

TABLE V

EXPERT *prior*-KNOWLEDGE OF THE INITIAL AND FINAL VARIABLES CALCULATION OF KEY COMPONENTS IN PRACTICAL PROCESS OF COBALT-NICKEL REMOVAL FROM ZINC SOLUTION

Level	Components	Initial variables	Final variables (mode-12)
devices	heater-2	17, 4, 57, 49, 43, 44	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 14, 16, 17, 18, 22, 23, 24, 25, 27, 28, 29, 33, 38, 39, 40, 42, 43, 44, 45, 47, 48, 49, 50, 51, 52, 53, 54, 55, 57, 58, 59, 60, 61, 62, 63
	reactor-2	51, 46, 20, 32, 3, 12, 28, 7, 60	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 27, 28, 29, 30, 31, 32, 33, 34, 37, 38, 39, 40, 41, 42, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 57, 58, 59, 60, 61, 62, 63
	reactor-4	53, 47, 34, 14, 9, 62	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 22, 23, 24, 25, 27, 28, 29, 31, 32, 33, 34, 37, 38, 39, 40, 42, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 57, 58, 59, 60, 61, 62, 63
	thickener-1	41, 55, 54	0, 1, 2, 3, 4, 5, 8, 9, 10, 19, 20, 21, 27, 28, 29, 30, 39, 40, 41, 42, 49, 50, 51, 52, 53, 54, 55, 57, 58, 61, 62, 63
	filter-2	37, 22, 40	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 14, 16, 17, 18, 22, 23, 24, 25, 27, 28, 29, 31, 32, 33, 34, 37, 38, 39, 40, 42, 45, 48, 55, 57, 58, 59, 60, 61, 62, 63
	filter-4	37, 24, 40	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 14, 16, 17, 18, 22, 23, 24, 25, 27, 28, 29, 31, 32, 33, 34, 37, 38, 39, 40, 42, 45, 48, 55, 57, 58, 59, 60, 61, 62, 63
	pulper-1	45, 46, 47, 48, 25, 38, 41, 42	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 14, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 27, 28, 29, 30, 38, 39, 40, 41, 42, 45, 46, 47, 48, 49, 55, 57, 58, 59, 60, 61, 62, 63
	slag	40	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 16, 17, 18, 22, 23, 24, 25, 27, 28, 29, 38, 39, 40, 42, 45, 48, 55, 57, 58, 59, 60, 61, 62, 63
subprocess	subprocesss-1	heater-1, heater-2, heater-3, reactor-1	
	subprocesss-2	heater-3, mixture, reactor-1, reactor-2, reactor-3, reactor-4, reactor-5, reactor-6, pulper-1, pulper-2, thickener-1, thickener-2	
	subprocesss-3	reactor-5, reactor-6, pulper-1, pulper-2, thickener-1, thickener-2, storage-tank, filter-1, filter-2, filter-3, filter-4	
	subprocesss-4	storage-tank, filter-1, filter-2, filter-3, filter-4, slag	
	subprocesss-5	pulper-1, pulper-2, filter-5, slag	
	subprocesss-6	reactor-1, reactor-2, reactor-3, reactor-4, reactor-5, reactor-6, thickener-1, thickener-2, pulper-1, pulper-2, filter-5	
	subprocesss-7	filter-1, filter-2, filter-3, filter-4, filter-5, slag	
process	process	subprocesss-1, subprocesss-2, subprocesss-3, subprocesss-4, subprocesss-5, subprocesss-6, subprocesss-7	

The number in variables column are the monitoring variables, which corresponding to 65 $(0-64)$ process monitoring variables.

TABLE VI

FDRS OF KEY COMPONENTS OF INTEREST ON MULTILEVELS IN PRACTICAL PROCESS OF COBALT-NICKEL REMOVAL FROM ZINC SOLUTION

	Process		Subprocess-1		Subprocess-2		Subprocess-3		Subprocess-4		Subprocess-5		Subprocess-6		Subprocess-7	
	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q
1	99.93	99.53	99.70	90.83	99.90	97.57	99.87	98.10	99.63	95.50	99.77	64.53	99.93	96.93	99.73	76.93
2	100.0	99.95	100.0	78.70	100.0	99.85	100.0	98.00	100.0	84.70	100.0	79.95	100.0	99.70	100.0	57.30
3	100.0	99.88	100.0	74.76	100.0	98.80	100.0	94.72	100.0	87.08	99.96	64.28	100.0	97.20	100.0	77.56
4	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	72.03	57.79	76.85	20.77	100.0	100.0	75.39	26.03
5	100.0	99.84	99.24	97.52	98.04	99.80	99.04	99.52	87.76	46.12	90.00	17.00	98.76	99.84	88.40	34.04
6	100.0	100.0	99.96	64.18	100.0	100.0	99.91	98.67	99.69	79.47	99.51	99.51	100.0	100.0	99.51	77.20
7	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	heater2		reactor2		reactor4		thickner1		filter2		filter4		pulper1		slag	
	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q
1	99.80	69.50	99.73	85.57	99.57	71.30	98.40	47.60	99.50	76.87	99.37	78.70	99.60	84.83	99.40	78.47
2	99.95	83.35	100.0	93.80	100.0	70.80	100.0	94.25	99.90	61.55	99.90	61.55	100.0	89.15	99.70	60.15
3	99.96	71.60	99.92	80.60	99.96	74.36	99.48	56.40	99.88	61.44	99.88	61.08	99.88	73.84	99.76	52.32
4	67.20	31.31	74.48	36.83	70.61	70.61	61.17	21.73	62.45	23.97	62.45	23.97	66.59	26.56	66.77	21.76
5	83.64	42.40	85.12	46.44	85.44	46.40	75.24	34.44	81.84	35.36	81.84	35.36	85.04	35.60	83.16	36.28
6	99.29	81.33	100.0	100.0	99.47	73.20	99.20	42.31	98.76	77.42	98.76	75.96	98.98	76.98	98.09	75.78
7	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

mode19, mode20, mode23, and mode24) at corresponding time $k = 3000, 2000, 2500, 2000, 2500, 2250$, and 1250. Honestly, there are no exact records to explain these fault occurs except for the exact time (confirmed by skilled workers) of faults occurring in each mode.

2) Global Fault Detection: Due to the limited space, details of MLKG for this practical case application and flowchart of global–local fault detection and location are not illustrated in this article. And this practical case application mainly discusses eight devices (heater-2, reactor-2, reactor-4, thickner-1, filter-2, filter-4, pulper-1, and slag), all seven subprocess node and the node on top-level. Table V shows the expert *prior*-knowledge of the initial and final variables calculation of key components in the practical process of Cobalt–Nickel removal from zinc solution, and this knowledge can be regarded as the basis to achieve the MLKG construction.

FDRs and FARs of this practical case application on multi-levels are shown in Tables VI and VII, respectively. All these results are obtained by the configuration on hyperparameters, such as Thr $= 0.9$, $T_{\text{num}} = 0.8$, confidence $\alpha = 0.01$, etc. The performance on FDRs of this new method on seven faults detection can reach as high as 100%, which FARs can get as low as 20%. However, global fault detection for fault-4 has failed on FARs which means some other unknown behaviors occur during this fault happen. Furthermore, the FARs of subprocess-2, subprocess-3, and subprocess-6 are as high as 100%, which means the unknown behaviors may occur in subprocess-2, subprocess-3, and subprocess-6 on subprocess-levels that are caused by the unknown associations between key components.

Fig. 10 shows the Hotelling's statistics T^2 and Q on the global-process level to local-slag level, which describes the

TABLE VII

FARs of Key Components of Interest on Multilevels in Practical Process of Cobalt-Nickel Removal From Zinc Solution

	Process		Subprocess-1		Subprocess-2		Subprocess-3		Subprocess-4		Subprocess-5		Subprocess-6		Subprocess-7	
	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q
1	17.80	14.23	10.20	3.67	3.67	8.67	11.40	8.07	9.07	5.27	8.20	4.10	12.03	8.73	7.43	8.13
2	19.70	16.00	9.25	5.05	15.35	10.50	13.15	4.60	8.10	4.70	8.10	2.00	15.35	9.15	5.15	4.75
3	17.08	13.24	9.76	4.52	15.24	9.32	11.52	6.36	7.20	6.36	8.52	2.92	14.11	7.56	5.48	5.16
4	100.0	100.0	10.46	1.60	100.0	100.0	100.0	100.0	10.34	4.40	7.54	4.46	100.0	100.0	7.77	6.46
5	20.48	17.52	13.16	2.40	15.16	10.48	15.36	6.08	9.36	5.48	9.04	2.28	15.36	9.48	9.16	5.44
6	20.62	16.58	9.91	4.76	15.73	11.16	13.33	10.80	9.16	6.71	8.40	6.36	15.78	10.58	9.38	8.58
7	16.32	15.12	10.56	1.84	14.08	10.56	12.48	9.92	10.96	6.32	8.80	1.84	13.44	10.24	8.56	7.44
	heater2		reactor2		reactor4		thickner1		filter2		filter4		pulper1		slag	
	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q	T^2	Q
1	0.87	3.70	0.83	5.03	0.60	4.43	1.13	2.57	0.70	3.60	0.57	3.47	0.60	3.90	0.77	3.43
2	0.70	3.95	0.40	5.95	0.60	3.95	0.90	3.50	0.60	2.45	0.60	2.45	0.80	4.05	0.70	2.55
3	1.08	4.56	1.04	6.00	1.12	4.28	0.80	2.88	1.28	3.04	1.28	3.12	0.72	4.00	1.24	2.64
4	0.74	4.11	0.86	4.91	1.20	4.63	0.91	2.51	1.20	3.37	1.20	3.37	0.97	3.49	1.43	2.69
5	0.80	5.28	0.92	6.12	0.84	4.80	1.24	3.28	0.64	4.60	0.64	4.60	0.64	4.20	0.76	3.36
6	0.89	3.47	0.95	4.67	1.07	4.00	0.93	2.76	1.07	2.80	1.11	2.71	1.11	3.51	1.02	2.84
7	0.48	4.48	0.32	5.12	0.64	4.64	0.96	2.64	0.24	4.72	0.16	3.76	0.32	4.48	0.72	3.20

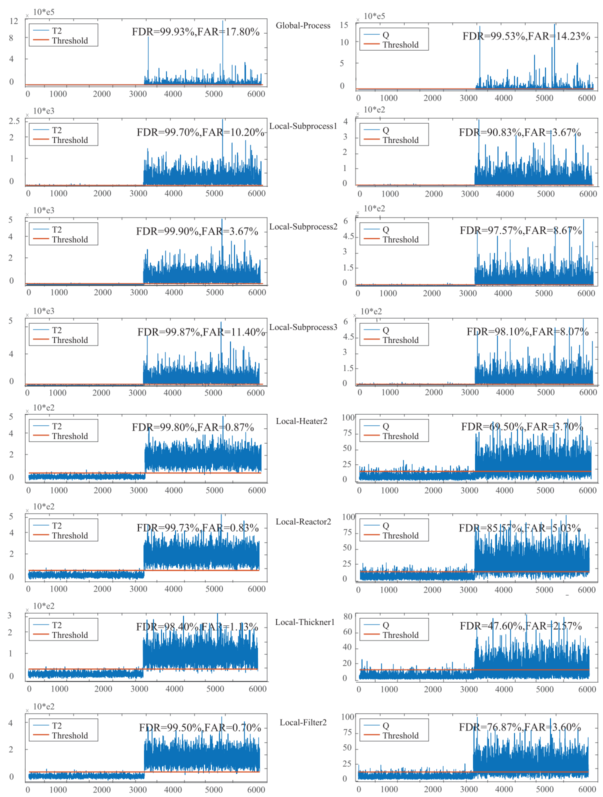

Fig. 10. Results of global–local detection for fault1 in practical process of Cobalt–Nickel removal from zinc solution.

process of information transmission. For instance, the status changes of the components of interest on the bottom level can evolve to the status change of the node on the top-level. Similarly, these results can also be employed to demonstrate the effectiveness and reasonable of the consideration on the definition of head and tail entity.

3) Local Fault Location: The practical physical meaning of local fault location is very significant for the practical production process, which is the information supports for decision marking and enterprise profit. Similarly, the fault location in this practical-case-application is achieved by a top-down manner which firstly starts on the process level to identify the nodes on the subprocess level that have great impacts. And then, the identified nodes on the subprocess level utilize the top-down manner again to identify nodes on the devices level. Finally, results of fault location for the practical process of Cobalt–Nickel removal from zinc solution can be obtained, as shown in Fig. 11.

It is worthy to note that these seven faults are collected from seven continuous production modes. For instance, fault1 (1-1) is very different from its normal status (1-0), while fault2 (2-1) occurs in its normal status (2-0) that is adjusted to normal state based on fault1 condition. Therefore, fault detection and location can be considered as a frequently training stage to adapt to the condition which occurs in the practical process.

TABLE VIII

Detection Accuracy of PCA and This Proposed Methods (FAR, FDR)

No.	PCA		This paper	
	T^2	Q	T^2	Q
1	(0.7, 99.70)	(5.6, 85.00)	(17.80, 99.93)	(14.23, 99.53)
2	(0.8, 100.0)	(6.2, 95.40)	(19.70, 100.0)	(16.00, 99.95)
3	(0.8, 100.0)	(5.4, 85.20)	(17.08, 100.0)	(13.24, 99.88)
4	(0.8, 99.90)	(8.0, 100.0)	(100.0, 100.0)	(100.0, 100.0)
5	(1.2, 99.90)	(6.5, 85.70)	(20.48, 100.0)	(17.52, 99.84)
6	(0.5, 100.0)	(8.8, 100.0)	(20.62, 100.0)	(16.58, 100.0)
7	(0.5, 100.0)	(9.3, 100.0)	(16.32, 100.0)	(15.12, 100.0)

FAR = False Alarm Rate. FDR = Fault Detection rate.

4) Comparison and Discussion: Table VIII presents the performance of PCA and this proposed method (FAR and FDR). These results can be used to demonstrate the super performance on process monitoring, such as this new method can reach as high as 100.0% for fault5, while PCA cannot. However, the results of this new method cannot reach the accuracy of the result based on the T_2 statistics, while its Q statistics have worse results. All of these would provide decision-markers with conflicting information, which makes it difficult to make decisions. The FDR results of seven faults by the new proposed method can realize consistent accuracy. All these comparisons can be employed to demonstrate the effectiveness and reasonable of this local–global fault detection and location framework which is very beneficial for plant-wide process monitoring. Therefore, this local–global fault detection and location framework with MLKG can be applied to prac-

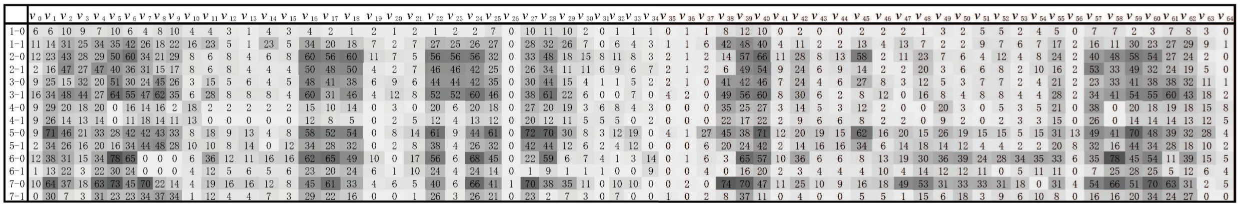

Fig. 11. Results of fault location for practical process of Cobalt–Nickel removal from zinc solution.

tical process monitoring in cobalt–nickel removal from zinc solution.

V. Conclusion and Discussion

This article presents a multiblock partition method based on MLKG to satisfy the requirements of multiblocks or distributed monitoring strategies, which can be used to achieve decentralized process monitoring. This method is trying to solve three main issues: the first one is to quantify the correlation between monitoring variables and node of interest to construct MLKG, and the second one is to describe the node characteristics by collecting information from the local data (data available at the node itself) and the data from its neighboring nodes, while the last one is to achieve local–global fault perception by reducing noises and uncertainties of the local node to enhance the performance of fault detection and location. When these three problems are well-solved, plant-wide process monitoring performance will increase. The effectiveness and applicability of this new method are demonstrated by benchmark on TE chemical process and practical application on cobalt–nickel removal from zinc solution.

However, this study of industrial MLKG-based local–global monitoring for plant-wide processes can be regarded as the preliminary one and its open discussion is very worthy to note in our future works. And this discussion should include the following items.

1) Fault diagnosis and recognition should be performed well in future works instead of only fault detection and isolation. The potentiality of industrial MLKG for fault diagnosis should be deeply discussed and this item has become the first one to be considered.
2) Industrial MLKG does not deal with the time-varying correlation which will cause the variable correlations change and additional discussions on this change should be required.
3) Multiple levels are predefined from bottom (sensors) to top (process), and this definition does not consider quality-related monitoring, multimode monitoring, nonlinear monitoring, and so on. All of these unconsidered ones should be solved in future work.
4) Other details of this proposed method need to be deeply analyzed and discussed, such as the calculation of inner-level relation and extra-level relation instead of normalized mutual information entropy, and node status definition instead of PCA. All of these issues should be well solved when this proposed method is applied to practical industrial processes.

For future work, these issues will be well solved to broaden the future horizon of the research on industrial MLKG-based local–global monitoring for plant-wide processes. Future works need to promote the deep integration of industrial intelligence and the real economy on the basis of the full-processes monitoring of typical process industries.

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