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Review of Multiscale Methods for Process Monitoring, With an Emphasis on Applications in Chemical Process Systems

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ABSTRACT Process monitoring has played an increasingly significant role in ensuring safe and efficient manufacturing operations in process industries over the past several years. Chemical process data is highly correlated and has multiscale characteristics in general. Extensive work has been carried out to overcome this concern for multiscale process monitoring of process plants during the past two decades. The recent success of multiscale methods in monitoring and controlling manufacturing processes has sparked interest in investigating these methods for process monitoring. This article aims to present a concise and critical overview of the applications of multiscale process monitoring methods in chemical processes. First objective is to identify the importance of multiscale methods for process monitoring. The second and main objective is the statistical and critical analysis of methods implementation, application area, types of data used, and various issues mentioned by previous researchers. In addition, the most important critical issues have been identified, and the capabilities and limitations of each method are discussed and highlighted. The reported literature focus mainly on fault detection and do not investigate the root-cause diagnosis of the detected faults. Further, the challenges and prospects in multiscale process monitoring in the chemical process industry have been discussed for advancement.

INDEX TERMS Chemical process systems, feature extraction; fault detection, fault diagnosis, multivariate statistical process monitoring, multiscale process monitoring, wavelet transforms.

I. INTRODUCTION

A. PROCESS MONITORING AND ITS IMPORTANCE

Process monitoring in process industries is a cutting-edge technology that ensures process safety and product quality [1]. Due to recent technological advances in modern industry, manufacturing processes have increased in size, complexity, and intelligence [2]. Early fault detection and diagnosis (FDD) can increase product quality, less downtime, and increase plant safety [3], [4]. Moreover, establishing comprehensive process monitoring systems in process industries may save billions of dollars [5]. A fault diagnostic system must have several characteristics to be effective. These characteristics are advantageous for comparing and standardizing various methods to improve the design and execution of the design system. These characteristics may also aid in the development of effective fault diagnostic methods based on useful parameters [6]. The process monitoring and fault diagnosis system's characteristics are shown in Figure 1.

B. PROCESS MONITORING TECHNIQUES

Process monitoring methods are classified in various ways and available in the literature [6]–[8]. These methods include analytical model-based, knowledge-based, and data-driven methods [9]. Figure 2 shows the classification of fault detection and diagnosis methods. Model-based approaches are based on the primary principle of constructing the mathematical model of the system. These approaches include an awareness of the system's physical characteristics in the

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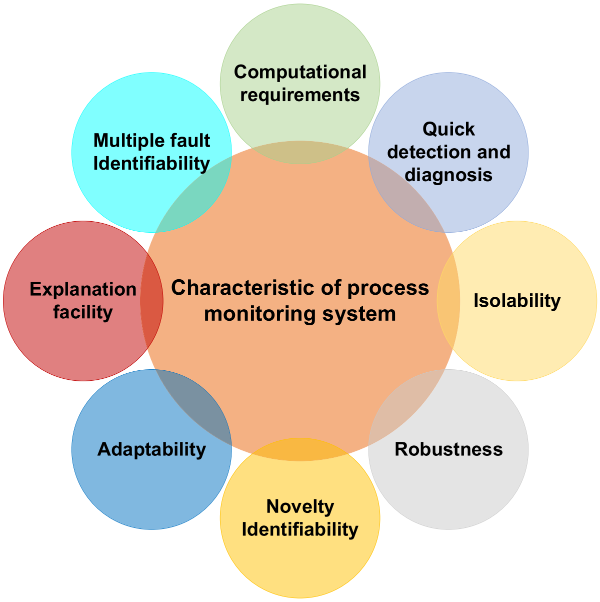

FIGURE 1. Features of the process monitoring system [8].

problem identification and diagnostic process. However, creating accurate models of large-scale and complex systems is difficult and sometimes impossible [10], [11]. Additionally, knowledge-based approaches use expert systems that are rule-based and depend on the skill and experience of plant operators. However, developing a comprehensive knowledge base is time-consuming and difficult, especially in the large-scale processes [12], [13]. Data-driven techniques do not need a mathematical model or expert knowledge. These approaches have been more popular in recent years, particularly for complex systems with difficulties creating models and expert knowledge [14]–[16].

Multivariate statistical process monitoring (MSPM) techniques are capable and are increasingly implemented in monitoring chemical processes [17]–[19]. The key idea behind the MSPM techniques is to extract process features through a specific multivariate analysis process. Highly dimensional information is then projected into less dimensional space, and the statistics are evaluated. Leading MSPM techniques are the principal component analysis (PCA) [14], [20], [21] and partial least squares (PLS) [22], [23], commonly used for the monitoring of the chemical processes. Although, these techniques for monitoring chemical processes have been very effective, they have certain limitations, such as the presumption of linear relationships among variables, as essential details can be overlooked when nonlinear systems are considered. However, most of these assumptions can easily be infringed in reality. Therefore, several improvements of MSPM techniques for process monitoring have been made in recent years. Although conventional MSPM techniques and extensions have been successful in many practical situations, they are generally limited to the single-scale analysis of events corresponding to the sampled frequency. Most existing methods are based on fixed-scale data, while the multiscale scheme uses decomposition techniques to depict data on several scales. However, a systematic review of these recently developed MSPM methods has not been reported yet.

C. PREVIOUS REVIEWS AND THE AVAILABLE GAP

Many excellent review articles in process monitoring have been published in the past. Fault diagnostic approaches based on quantitative models [6], qualitative models [7], and historical process knowledge [8] have been thoroughly analyzed in a series of papers. Qin [24] has reviewed data-based process monitoring methods for fault detection, identification, reconstruction, and diagnosis. Ge *et al.* [13] reviewed data-based process monitoring methods for nonlinear, non-Gaussian, multimode, and dynamic processes. Gao *et al.* [25], [26] have systematically investigated the use of fault diagnostic methods. A comprehensive bibliometric analysis of data-based fault detection and diagnostic methods for process systems has recently been presented [27]. Nor *et al.* [28] have reviewed data-based FDD methods for chemical processes. Other significant data-based fault detections and diagnostic studies have also been reported [29]–[34]. The above reviews cover different aspects of data-based fault detection and diagnosis methods by various aspects, as shown in Table 1.

The purpose of this review paper is to guide the selection of multiscale fault detection and diagnosis procedures. As mentioned earlier, none of the available reviews covered the multiscale process monitoring methods. Therefore, this review paper aims to provide a comprehensive insight into multiscale fault detection and diagnosis methods for chemical processes. Thus, this work offers excellent knowledge for those interested in developing a multiscale fault detection and diagnostic framework for the chemical process. It would serve as inspiration for the future valuable addition in the state of knowledge relevant to recent developments in fault detection and diagnosis in chemical processes.

The rest of the paper is structured as follows. The motivation for multiscale process monitoring is provided in Section II. Multiresolution techniques used in multiscale process monitoring methods are discussed in Section III, followed by a statistical analysis of multiscale fault detection and diagnosis methods in Section IV. A detailed review of multiscale process monitoring methods based on the promising issues has been discussed in Section V. Finally, some future challenges and recommendations are discussed in Section VI, followed by the findings of this review article.

II. MOTIVATION FOR MULTISCALE PROCESS MONITORING METHODS

Multiscale process monitoring is an important extension of the statistical process monitoring methods used for highly correlated, noisy data. These methods have been widely used to monitor chemical processes in recent years. The motivation for the multiscale process monitoring is presented in the following sub-sections.

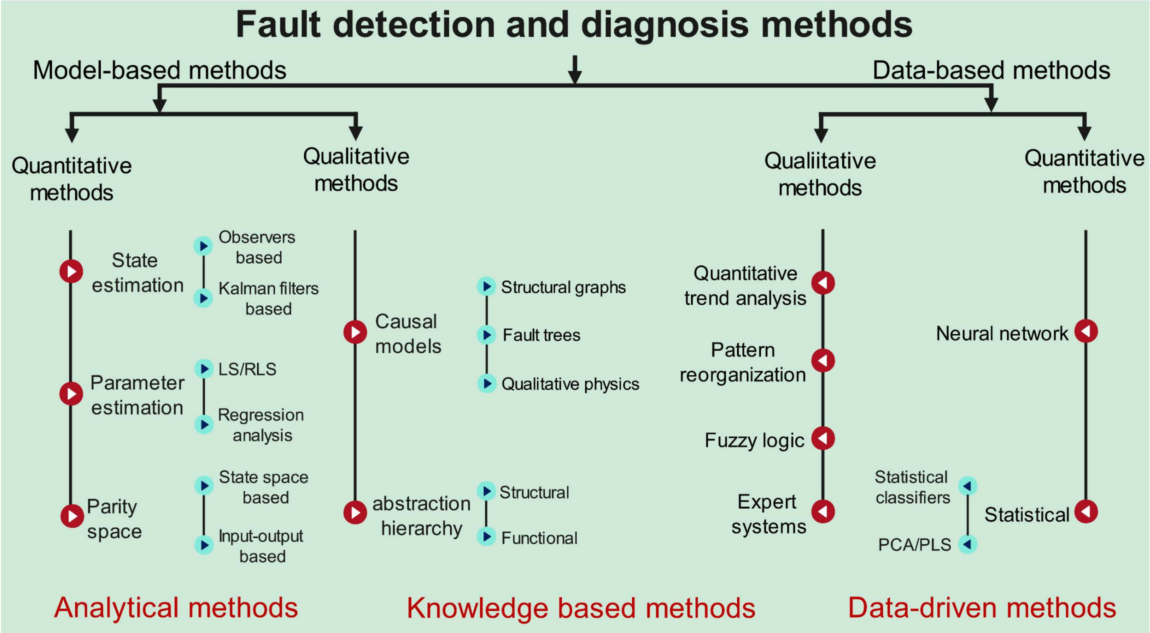

FIGURE 2. **Classification of fault detection and diagnosis methods [9].**

A. UNIVARIATE STATISTICAL PROCESS MONITORING

Univariate statistical process monitoring methods, often known as statistical process control (SPC) methods, evaluate each variable individually [41]. Walter Shewhart invented the first SPC chart, which is used for process monitoring without the usage of a filter. This chart identifies the typical significant faults. Other SPC charts, such as the cumulative sum (CUSUM) and exponentially weighted moving average (EWMA), detected minor faults using linear filters. While these techniques continue to be prevalent in the process industry, their efficacy degrades when highly correlated variables are used [42]. Multivariate extensions of Shewhart control charts are used when process parameters of the underlying process are known or unknown. Multivariate CUSUM (MCUSUM) and multivariate EWMA (MEWMA) have been developed for the detection of small changes [43] and have provided unsatisfactory results for highly correlated process variables [44].

B. MULTIVARIATE STATISTICAL PROCESS MONITORING

Multivariate process monitoring (MSPM) methods can be used to evaluate highly correlated and high-dimensional process data. The main concept of MSPM methods is the characteristics of the process that can be achieved through a particular analysis process. Thus, higher dimensional information is projected into a less dimensional space, followed by the evaluation of statistics [45]. Figure 3 shows the classification of well-known MSPM methods.

PCA and PLS are the most widely used MSPM methods. PCA-based monitoring methods consider all process faults, while PLS-based monitoring methods emphasis on quality-related faults. As the complexity of industrial processes have increased due to the recent technological advances in modern industry, it is necessary to ensure process safety, product quality and production efficiency [2]. Therefore, quality related process monitoring is much more significant than simply monitoring the fluctuations and anomalies of process variables [46], [47]. Both methods presume that the Gaussian distribution obeys the data. Independent component analysis (ICA) requires high-level statistics to solve non-Gaussian problems. More important information can be revealed in non-Gaussian data [48]. Gaussian Mixture Model (GMM) is another way of handling non-Gaussian data by treating a complex process as a linear combination of several Gaussian models [49].

C. RECENT DEVELOPMENTS IN MSPM METHODS

Generally, two types of processes are used in industry including batch processes and continuous processes. The process data obtained from process industry exhibit multimodal distribution, dynamics, nonlinear relationships between variables, non-Gaussian, and time-varying and multiscale [13]. Several enhancements to conventional MSPM approaches have been made in recent years, and many other data-based methods have also been introduced for process monitoring [50]–[52].

In practical applications, the process data are always contaminated by random noises. Therefore, it is essential that process monitoring should also be carried in a statistical manner, and the monitoring decisions are made through a probabilistic way. To address this problem, PCA based monitoring method formulated into a probabilistic framework known as probabilistic PCA (PPCA) [53]. In the probabilistic models a unified likelihood-based monitoring statistic is used instead

TABLE 1. Recent review papers coverage in comparison with this review paper.

Year	Reference	Field	Remarks
2011	Ma and Jiang [35]	Nuclear power industries	Review of FDD methods and their applications in the nuclear power industry.
2012	Das et al. [30]		Review and categorize various process monitoring and fault detection techniques and into data-based, model-based, and hybrid approaches.
2013	Zheng et al. [36]	Proton Exchange Membrane Fuel Cell system	Review and comparison of non-model-based methods, including artificial intelligence, statistical, and signal processing.
2013	Ge et al. [13]	Industrial processes	Review of recent developments in data-driven process monitoring methods for industrial processes focused on considering different data characteristics, including non-Gaussian, nonlinear, time-varying, and multimode, dynamic, and batch processes.
2014	Yin et al. [31]	Industrial Process	Reviews data-driven process monitoring and fault diagnostic methodologies from an application point of view in many industrial processes and provides a basic framework for monitoring under different industrial operating conditions.
2015	Agrawal et al. [37]	Coal mills	Comparative study of various control and fault diagnostic techniques, including quantitative, signal, qualitative, and process-historical approaches to coal mills and possible directions for future research.
2016	Severson et al. [4]	Industrial systems	Review of process monitoring methods and discuss current issues and promising future directions.
2016	Tidriri et al. [33]	Process industries	Comparative analysis of model-based and data-based process monitoring methods highlights their features and points out the benefits and limits of each approach.
2017	Ge [34]	Industrial processes	Review of data-driven process monitoring methods focused on addressing plant-wide process issues.
2018	Alauddin et al. [27]	Process Systems	Bibliometric analysis of data-driven FDD approaches addresses key areas, contributing authors, key sources, and actively involving countries in this research area.
2019	Nor et al. [28]	Chemical process systems	Review data-driven FDD frameworks and their challenges and guide applying such methods in chemical processes.
2019	Jiang et al. [38]	Industrial Processes	Review of data-driven multivariate process monitoring techniques for industrial plant-wide processes, emphasizing large-scale and multi-unit operations.
2020	Park et al. [39]	Industrial processes	Review of current research and developments of FDD approaches for process monitoring.
2021	Taqvi et al. [40]	Process industries	Overview and categorize data-driven approaches in fault detection and diagnosis in process industries.
2021	This Review	Chemical process systems	Review of multiscale process monitoring methods and their applications in chemical process systems. Some challenges and future recommendations were also discussed.

of the T^2 and SPE control charts [54]. Furthermore, PPCA framework has also been extended to handle non-Gaussian data to improve the fault detections [55].

The process data collected from chemical processes usually involve high noise levels and autocorrelation and may also vary from normality and impact MSPM process monitoring methods [56]. Such techniques are also based on a single-scale representation of measurements and cannot capture the information from multiscale representations of measurements [57]. Wavelet-based multiscale process monitoring methods have been developed to address these problems. Process monitoring models have been developed in these techniques by using wavelet coefficients at each scale [57]–[59]. Instead of wavelet transforms (WT), some researchers used empirical mode decomposition (EMD) and singular spectrum analysis (SSA) to decompose the process variables before MSPM methods [60], [61]. EMD and SSA both are merely relying upon data-adaptive basis functions. Thus, these techniques are more helpful in analyzing the nonstationary signals emanating from nonlinear systems [62]. Multiscale process monitoring techniques have effectively been used to analyze chemical processes over the last two

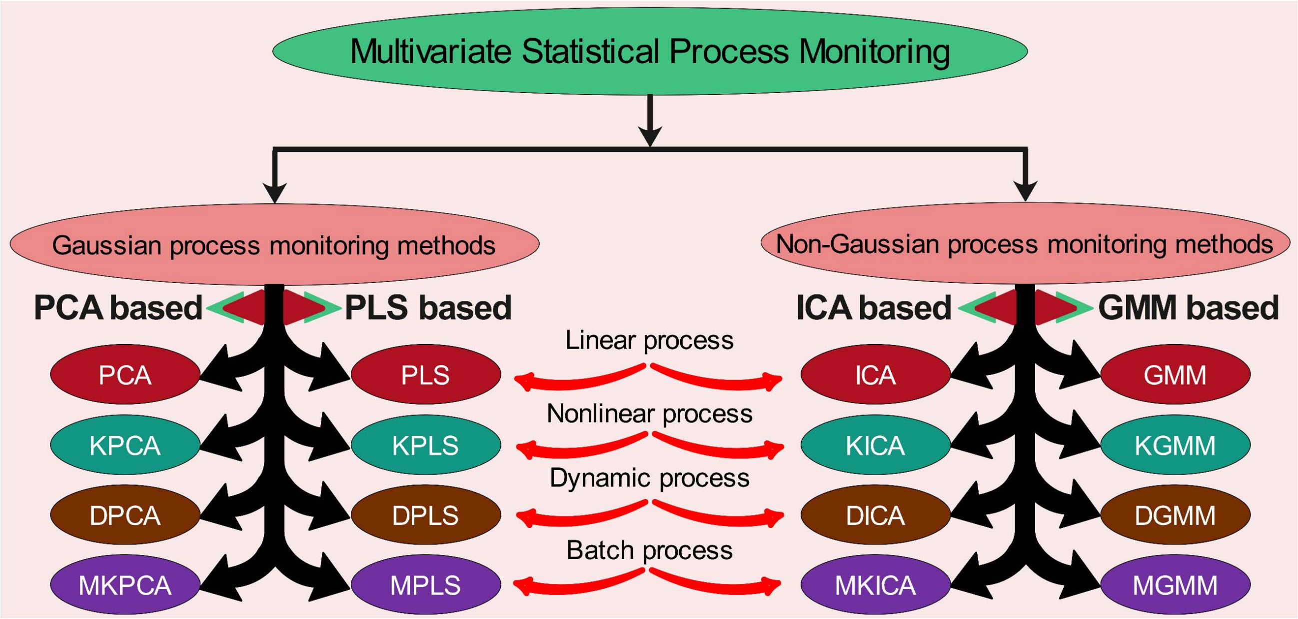

FIGURE 3. Multivariate statistical process monitoring methods and their modifications [63].

decades. Various multiscale process monitoring techniques have been applied based on the process data obtained from different chemical processes.

III. MULTIRESOLUTION TECHNIQUES IN MULTISCALE PROCESS MONITORING METHODS

The demand for operational safety and product quality are critical issues in modern industrial processes. Although, the widespread use of sensor networks, advanced data acquisition technology, and the extensive use of distributed control systems (DCS) have added significant benefits to all process industries [44], they are becoming increasingly integrated, automatic, more complex, and intelligent operations. These developments in modern industrial processes increase the need of efficient process monitoring systems [2]. Conventional MSPM techniques and their extension focus on analyzing single-scale phenomena, typically the sampling frequency. Therefore, the applications of these techniques are restricted to only a single scale and cannot derive the amount of information from process data showing multiscale phenomena [64]. The multiscale approach can obtain information through different decomposition techniques in different scales.

WT is the most effective multiresolution analysis (MRA) tool and helps decompose the original process measurements into their multiscale components according to time and frequency characteristics [14]. The process signals, which have distinct physical patterns or disruptions, decompose, and are viewed as several signals at different resolution scales.

The scaled version of the original signal is achieved by projecting it on an orthogonal signal to obtain coarse approximate coefficient scale and is given as [65]:

$$\varphi_{ij}(t) = 2^{-j/2}\varphi(2^{-j/2}t - k) \tag{1}$$

where, k and j are discretized translation and dilation parameters, respectively. The discrete wavelet function for detail scale is given as [65]:

$$\Psi_{ij}(t) = 2^{-j/2}\Psi(2^{-j/2t-k}) \tag{2}$$

The coarse approximate and detail signal coefficients are computed using the low pass filter (H) and high pass filter (G) given as [66]:

$$a_s = Ha_{s-1}, \quad d_s = Ga_{s-1} \tag{3}$$

where, a_s and d_s are the approximate and detail scale coefficients, respectively. The original signal can be obtained by computing the sum of the last scaled signal and all detail signals:

$$x(t) = \sum_{k=1}^{n2^{-j}} a_{jk}\varphi_{jk} + \sum_{j=1}^{j}\sum_{k=1}^{n2^{-j}} d_{jk}\Psi_{jk}(t) \tag{4}$$

where j and n are the level of decomposition and original signal length, respectively.

In WT, determining the optimal decomposition level is important. At the highest decomposition level, the approximation function adequately reflects the actual deterministic signal with the least amount of noise. Each variable in a multivariate scenario may have a distinct optimum decomposition level. For computational simplicity, only a single decomposition level will be applied to all variables in most practical applications. As a result, the decomposition level chosen must be appropriate or optimal to ensure that the underlying characteristics of each variable are appropriately retained in the approximation function with the least amount of noise [67].

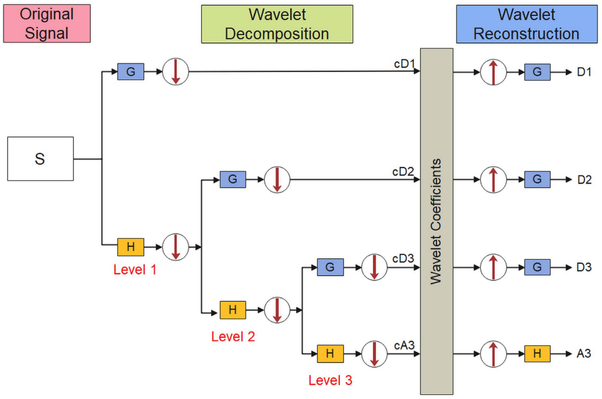

FIGURE 4. The basic idea in multiresolution analysis with wavelet transform.

Multiscale representation of signal up to level 3 is illustrated in Figure 4. First, the original signal (S) is decomposed into approximation and detail coefficients. The approximation function low-frequency signal, which contains the essential underlying deterministic features. The detail function includes the high-frequency component, which is mainly noises. The approximation function is further decomposed into even coarser approximation until the average signal has been approximated. This reconstruction perfectly composes the original signal if all wavelet coefficients are used.

Recently EMD has attracted much attention when decomposing the time-series signal into different time scales. Unlike wavelet-based algorithms where the signal is decomposed in the transform domain, EMD adaptively sets the decomposition functions directly from data instead of using a fixed wavelet function across the entire analysis; therefore, this algorithm is a better choice for handling data collected from non-stationary processes [62]. The following are the two conditions that need to be met for a component to be considered an intrinsic mode function (IMF) [68]:

1. Total zero crossings and the total extrema in the whole data set should be equal or vary by at most one.
2. The mean value of the envelope from maxima and minima should be equal to zero at any component interval.

Among these decomposition frameworks, the WT has dominated the publication landscape over the years and will be referred to more extensively.

IV. STATISTICAL ANALYSIS OF MULTISCALE PROCESS MONITORING METHODS

The available literature based on multiscale process monitoring has been statistically reviewed and summarized in Figure 5. Various fault detection and diagnosis techniques have been used for multiscale process monitoring. These include conventional process monitoring methods such as (CUSUM and EWMA), multivariate (PCA and PLS), and their various extensions. Figure 5(a) shows the most widely used methods involved in multiscale process monitoring. PCA is the most widely used method in multiscale process monitoring, followed by KPCA, PLS, KPLS, NLPCA and KFDA.

Validation of multiscale process monitoring approaches has been done using various applications. Figure 5(b) illustrates the most often used applications in this field of study. The TE process is widely used by researchers, with a share of about 22.22%. The CSTR system, Industrial processes, and simulated numerical data are the next most used application areas, with 15.15%, 16.16%, and 14.14%, respectively.

The performance of the multiscale process monitoring methods was evaluated using process data from various diverse application areas. Figure 5(c) shows the distribution of data types used in multiscale process monitoring. Two types of datasets have been used for multiscale process monitoring, including real-time and simulated data. Figure 5(c) shows that the portion of the real-time dataset used is only 23.23%, acquired from either industrial processes or pilot plants. On the other hand, the rest of the portion includes simulated datasets. The characteristics of simulated datasets usually are known, which can help highlight the effectiveness of a specific method.

Various issues arise in the application of multiscale process monitoring. The major issues identified based on careful study of the research articles related to multiscale process monitoring are presented in Figure 5(d). The figure shows the percentage of papers that dealt with each of them. Although some of these issues are not unique to multiscale process monitoring methods alone, we are reviewing them within the context of multiscale process monitoring. Research articles based on multiscale process monitoring are devoted to discussing these issues. A list of all the research articles reviewed is then provided in Table 2. The table also shows the decomposition technique used, the method used, the case studies used, and, more importantly, the issues addressed. The purpose of this table is to help the reader choose a specific issue of interest and to browse the column for papers that deal with it.

V. REVIEW OF MULTISCALE PROCESS MONITORING METHODS

As identified and presented in Table 2, significant issues related to multiscale process monitoring are thoroughly discussed in this section. We first converse why they are important and then give examples of how many researchers have addressed them over the years.

A. MULTISCALE METHODS FOR QUALITY-RELATED PROCESS MONITORING

MSPM methods are more beneficial for extracting meaningful information from the highly correlated process and quality variables because quality variables are measured at lower frequencies and typically have significant time delay [69]. Monitoring quality variables is essential for preventing system breakdowns and evading substantial financial losses. A few researchers have also developed a quality-related multiscale process monitoring technique.

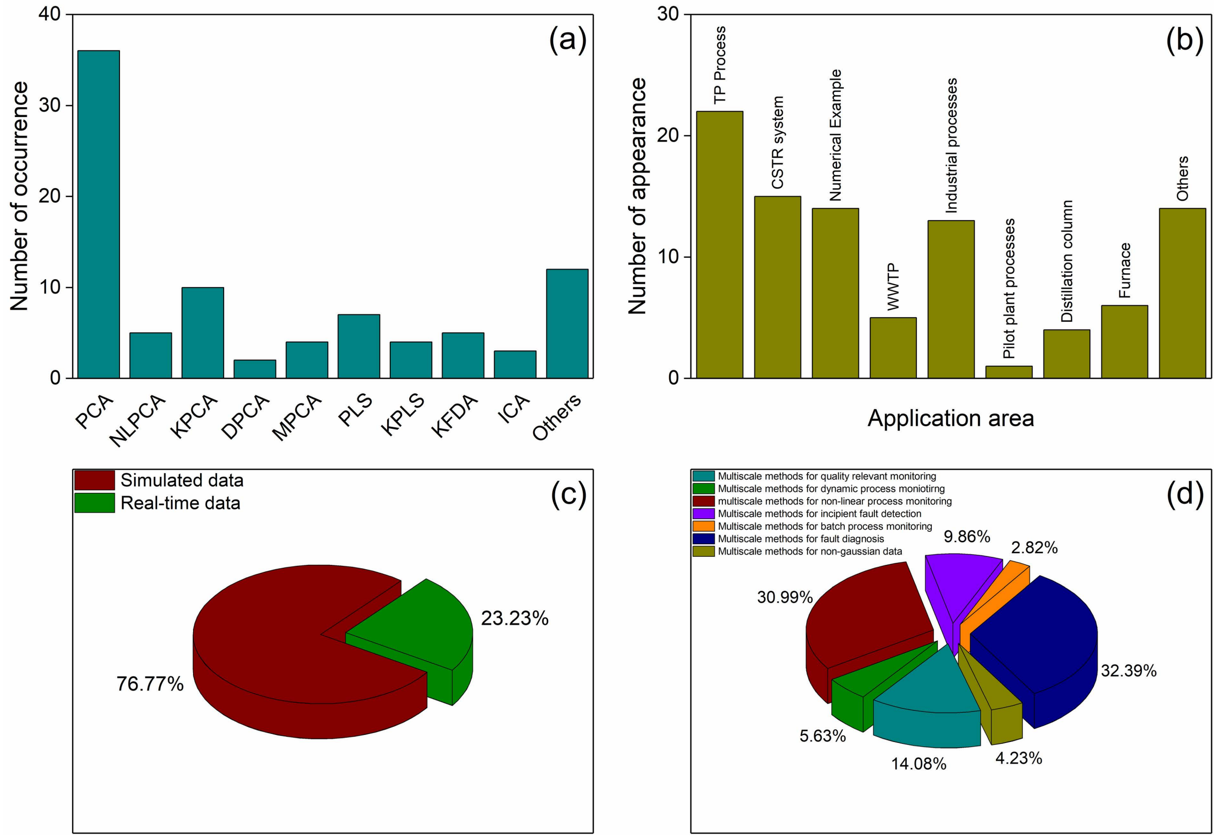

FIGURE 5. **(a) commonly used methods involved in multiscale process monitoring, (b)-Types of case studies used in multiscale process monitoring, (c)-Frequently used application area in multiscale process monitoring, and (d)-Issues arise in multiscale process monitoring.**

Partial least squares (PLS) technique is the MSPM method associated with quality-relevant monitoring, and it finds a relationship between the process and quality variables [70]. Teppola and Minkkinen [71] proposed a quality-related multiscale process monitoring scheme combining wavelets with PLS. The PLS model is based on filtered measurements obtained by removing low-frequency scales in this approach. Lee *et al.* [72] proposed a multiscale technique combining PLS and WT for sensor fault detection. The feasibility of the proposed technique was confirmed by using the real industrial dataset from the biological wastewater treatment process. The monitoring results were also compared to those of the standard PLS method.

Madakyaru *et al.* [73] proposed a MSPLS model based on generalized likelihood ratio (GLR) tests. In this approach, a modelling framework is created by integrating WT with PLS, and then GLR testing is used to improve the fault detection. The proposed methodology proved immensely influential in the early detection of minor faults with incipient behaviour in distillation columns. Similar work is proposed by Botre *et al.* [74], where efficiency and robustness are demonstrated through simulated continuous stirred tank reactor (CSTR) and Tennessee Eastman process (TEP) data.

Zhang and Hu [75] proposed a multiscale KPLS (MSKPLS) method combining kernel PLS (KPLS) and wavelet analysis for investigating the multiscale nature of the nonlinear process. The feasibility of the proposed method was tested for a real industrial data set, and the process monitoring abilities were compared with the standard KPLS method.

B. MULTISCALE METHODS FOR NONLINEAR PROCESS MONITORING

Multiscale process monitoring frameworks using conventional MSPM methods have been used effectively in the process industry. Conventional MSPM methods underperform in complex industrial processes with nonlinear features due to their assumption of linear correlations in the process data. In recent years, nonlinear process monitoring has become a hot area of research in this field, and some nonlinear multiscale approaches have been developed.

Shao *et al.* [76] proposed a multiscale NLPCA process monitoring approach based on input-training neural network (IT-NN) where non-parametric control limits were employed instead of linear control limits to improve online performance monitoring. This technique was modified using a multi-level wavelet decomposition to enhance the process monitoring [77]. Geng and Zhu [78] proposed an adaptive multiscale NLPCA approach to monitor slow and weak changes in process variables. Maulud *et al.* [67], [79] have developed a new multiscale approach using optimal wavelet decomposition and the orthogonal NLPCA. They only used approximation and highest detail functions, simplifying the overall model structure and improving interpretation at each scale. In this work, optimal decomposition level was determined by a PCA based graphical method.

The kernel learning methods recently received significant attention in the chemical industry and have been coupled with conventional MSPM process monitoring methods [80]–[83]. Several researchers have proposed KPCA and KPLS based multiscale nonlinear process monitoring methods [84]–[86]. Choi *et al.* [84] proposed a new multiscale nonlinear process monitoring technique using KPCA to detect and identify faults. This approach has been extended by Deng and Tian [85] to nonlinear dynamic processes that can effectively extract autocorrelation, cross-correlation, and nonlinearity from the process data. Zhang and Ma [86] further developed this approach to improve diagnostic capabilities. Further study proposed a nonlinear system monitoring approach based on KPLS at different levels. Zhang and Hu [75] have extended this approach to monitoring online processes in nonlinear processes.

The Fisher discriminant analysis (FDA) does better than the PCA approach to classification problems in many cases. Although it shows limited performance in nonlinear systems due to its linearity, it is better suited to classification problems [87]. Liu *et al.* [88] proposed a multiscale classification method to obtain the most discriminatory characteristics of the scale. The effects of feature extraction investigated the classifier performance, and a multiscale classifier was developed to classify the faults better. This method can be applied to relatively large multi-class issues. Nor *et al.* [89] proposed a novel multiscale approach by combining KFDA with wavelets for nonlinear process monitoring. In this approach, XmR and T^2 statistics used fault detection. This approach was further extended to enhance the performance of fault classification and developed a robust multiscale feature extraction and fault classification method [90].

C. MULTISCALE METHODS FOR DYNAMICS PROCESS MONITORING

Due to random noise and process disturbances, a dynamic relationship exists among process variables in modern chemical processes. Information on this dynamic behaviour is not included in conventional process monitoring methods, leading to misleading results. Changes in dynamic relationships among process variables can not be investigated efficiently, resulting in significant process failure due to dynamic relationships, intermittent noises, and other disturbances. Substantial research has improved monitoring performance in dynamic industrial processes in recent years.

Haitoa *et al.* [91] proposed a multiscale framework for monitoring dynamic multivariate processes at different scales by combining wavelets and PCA. This framework enhances the suitability of PCA for monitoring processes based on auto-correlated data. Yoo *et al.* [92] have developed a multiscale approach to dynamic processes using dynamic PCA for WWTP. Similar faults have been detected and isolated by incorporating D statistics into the algorithm. Alabi *et al.* [93] have developed a multiscale dynamic process monitoring approach by integrating WT with generic dissimilarity measure (GDM) to improve performance monitoring. Kini and Madakyaru [94] developed a multiscale DPCA framework where T^2 and SPE statistics were used for fault detection. The effectiveness of this framework is demonstrated by using dynamic multivariate data acquired from the TEP.

D. MULTISCALE METHODS FOR INCIPIENT FAULT DETECTION

Early detection of incipient faults in modern chemical process systems is increasingly becoming important, as these faults can slowly develop into severe abnormal events, which leads to the failure of critical equipment. It is critical to detect even the most minor irregularities to ensure the safety of the process and the highest level of product quality. Detecting minor or incipient anomalies in modern chemical process systems is essential for process safety and maintaining product quality. Because they are camouflaged by noise and process control, these faults are difficult to detect early. They are common in complex processes and may quickly increase if no action is taken. Multiscale methods for detecting minor faults are reviewed as follows.

Kano *et al.* [18] proposed a multiscale method for incipient fault detection using dissimilarity analysis (DISSIM). Although DISSIM is mathematically comparable to PCA, its statistical index differs from T^2. A new multiscale fault detection method based on Ensemble Empirical Mode Decomposition (EEMD) is proposed, effectively detecting three specific faults in the TEP that were previously undetectable using previously reported methods [95]. In this method, faults signatures are extracted using EEMD based PCA, and then half-normal probability and Cumulative Sum (CUSUM) are used for fault detection. The proposed method is further extended where CUSUM based on T^2 and SPE statistics improves fault detection [60]. Recently, a new multiscale framework has been proposed to detect incipient faults. In this framework, wavelet-based PCA is used to extract the fault signatures, and then CUSUM and EWMA based on T^2 and SPE statistics are developed to improve the fault detection. The results show that EWMA based SPE statistics successfully detect the incipient faults present in the simulated data obtained from the CSTR system [96]. Žvokelj, *et al.* proposed a multivariate and multiscale fault detection methods to detect incipient failure of large slewing bearings based on Acoustic Emission (AE) signals by integrating EEMD with PCA [97], KPCA [98] and ICA [99].

E. MULTISCALE METHODS FOR FAULT DIAGNOSIS

Multiscale methods for fault detection have been thoroughly reviewed in previous sections. Although fault diagnosis is essential in process monitoring, it is relatively limited while employing multiscale methods. It is challenging to analyze the simultaneous impact of multiscale variables on monitoring statistics. Generally, fault diagnosis is accomplished via

TABLE 2. Comprehensive overview of published literature on multiscale fault detection and diagnosis.

Sr. No	Year	Decomposition Technique	Monitoring method	Issue addressed								Application area	Types of case study		Reference
				A*	A	B	C	D	E	F	G		Simulated	Real-time	
1	1998	WT	PCA	✓								NE, FCCU	✓		Bakshi [58]
2	1999	WT	NLPCA	✓					✓			ISD		✓	Shao et al. [76]
3	1999	WT	PCA	✓			✓					NE	✓		Haitao et al. [91]
4	1999	WT	PCA	✓				✓				DC, CSTR	✓		Luo et al. [115]
5	2000	WT	NLPCA	✓		✓						NLIP		✓	Fourie & de Vaal [77]
6	2000	WT	PCA, MPCA, DISSIM	✓								TEP	✓		Kano et al. [116]
7	2000	WT	PLS	✓	✓							WWTP		✓	Teppola & Minkkinen [71]
8	2001	WT	PCA	✓								WWTP		✓	Rosen & Lennox [117]
9	2002	WT	PCA	✓					✓			IBD, ITRS	✓	✓	Misra et al. [100]
10	2002	WT	PCA, MPCA, DISSIM	✓				✓				NE, TEP	✓		Kano et al. [18]
11	2002	WT	DPCA	✓			✓					WWTP	✓	✓	Yoo et al. [92]
12	2002	WT	PCA	✓					✓			WWTP		✓	Lennox & Rosen [118]
13	2003	WT	PCA	✓					✓			TEP, TTS	✓		Lu et al. [101]
14	2004	WT	PCA	✓					✓			NE, CFT	✓	✓	Zhiqiang & Qunxiong [103]
15	2004	WT	PCA	✓					✓			CSTR	✓		Yoon & MacGregor [59]
16	2005	WT	PCA	✓								PSP		✓	Wang & Romagnoli [119]
17	2005	WT	MPCA	✓						✓		SBRS		✓	Lee et al. [111]
18	2005	WT	NLPCA	✓		✓						ECF		✓	Geng & Zhu [78]
19	2005	WT	NLPCA	✓		✓						CSTR	✓		Maulud et al. [79]
20	2005	WT	GDM	✓			✓					TEP	✓		Alabi et al. [93]
21	2006	WT	PCA	✓								SS	✓		Reis & Saraiva [120]
22	2006	WT	NLPCA	✓		✓						CSTR	✓		Maulud et al. [67]
23	2006	WT	PCA	✓								NE	✓		Zhang & Wang [121]
24	2006	WT	KPCA	✓		✓						CSTR	✓		Deng and Tian [122]
25	2006	WT	PCA	✓								NE, CSTR	✓		Reis & Saraiva [123]
26	2007	WT	MPCA	✓					✓	✓		PFP	✓		Alawi & Morris [112]
27	2007	WT	PCA	✓								BWWTP	✓		Borowa et al. [124]
28	2008	WT	PCA	✓								SM, FFE		✓	Reis et al. [125]
29	2008	WT	PCA	✓					✓			CS		✓	Xu et al. [126]
30	2008	WT	KPCA	✓		✓						TEP	✓		Tian & Deng [105]
31	2008	WT	PCA, KPCA	✓		✓			✓			CSTR	✓		Choi et al. [84]
32	2008	WT	ICA	✓							✓	TEP	✓		Salahshoor & Kiasi [113]
33	2009	WT	PLS	✓	✓							SDS, BAFP	✓	✓	Lee et al. [72]
34	2010	WT	PCA	✓								PMP	✓		Xia and Pan [127]

TABLE 2. ***(Continued.)*** **Comprehensive overview of published literature on multiscale fault detection and diagnosis.**

35	2010	WT	PCA, KFDA	✓		✓			✓			IPPP,TEP,CSTR	✓	✓	Liu et al. [88]
36	2010	EEMD	PCA	✓				✓				LSBTS	✓		Zvokelj et al. [97]
37	2011	EEMD	KPCA	✓		✓		✓				NE, BF, LSBTS	✓	✓	Zvokelj et al. [98]
38	2011	WT	KPCA, KPLS	✓		✓			✓			FMF, CAP	✓		Zhang and Ma [86]
39	2011	WT	PCA	✓					✓			HHS	✓		Giantomassi et al. [128]
40	2011	WT	PCA	✓					✓			PMP		✓	Ferracuti et al. [102]
41	2011	WT	KPLS	✓	✓	✓			✓			NE, PFP, EFMF	✓	✓	Zhang and Hu [75]
42	2011	WT	PLS	✓	✓							TEP	✓		Roodbali & Shahbazian [129]
43	2012	WT	KPCA	✓		✓						NE, EFMF, TEP	✓		Zhang et al. [64]
44	2013	WT	PCA	✓								NC		✓	Harrou et al. [130]
45	2013	WT	PCA	✓		✓						NE, TEP	✓		Shi et al. [131]
46	2013	WT	PCA	✓					✓			TEP	✓		Lau et al. [106]
47	2013	EEMD	KPCA, SKC	✓		✓						CSTR	✓		Deng and Tian [132]
48	2014	WT	PCA	✓								STP		✓	Mirin & Wahab [133]
49	2015	EEMD	KPLS	✓	✓	✓						NE, PFP	✓		Liu & Zhang [134]
50	2015	WT	KFDA	✓		✓						TEP	✓		Nor et al. [89]
51	2016	WT	GMM, KFDA	✓					✓			TEP	✓		Nor et al. [135]
52	2016	EEMD	ICA	✓					✓		✓	LSBTS	✓	✓	Zvokelj et al. [99]
53	2016	WT	PLS	✓	✓							DC	✓		Madakyaru et al. [136]
54	2017	WT	PCA	✓								SD, TEP	✓		Sheriff et al. [14]
55	2017	WT	EWMA, KPLS	✓	✓	✓						CSM	✓		Mansouri et al. [137]
56	2017	WT	GMM, KFDA	✓		✓			✓			TEP	✓		Nor et al. [90]
57	2017	WT	PLS	✓	✓							DC	✓		Madakyaru et al. [73]
58	2017	WT	KPCA	✓		✓						CSTR	✓		Sheriff et al. [138]
59	2017	WT	PLS	✓	✓							TEP, CSTR	✓		Botre et al. [74]
60	2017	WT	PCA	✓					✓			TEP	✓		Zhang et al. [139]
61	2018	WT	PLS	✓	✓							SFSS	✓		Chaabane et al. [140]
62	2018	EEMD	PCA, CUSUM	✓				✓				TEP	✓		Du and Du [95]
63	2018	EEMD	PCA, CUSUM	✓				✓	✓			TEP	✓		Du and Du [60]
64	2019	WT	PCA	✓								AHWR	✓		Yellapu et al. [141]
65	2019	WT	DPCA	✓			✓					TEP	✓		Kini & Madakyaru [94]
66	2019	WT	PCA	✓								CSTR	✓		Nawaz et al. [142]
67	2019	WT	KFDA	✓		✓			✓			TEP	✓		Nor et al. [107]

TABLE 2. ***(Continued.)*** **Comprehensive overview of published literature on multiscale fault detection and diagnosis.**

68	2020	WT	KPCA	✓		✓			✓			CSTR	✓	Nawaz et al. [104]
69	2021	WT	PCA	✓								AHWR	✓	Yellapu et al. [143]
70	2021	WT	ICA	✓							✓	NE, QTP, DC	✓	Kini & Madakyaru [114]
71	2021	WT	PCA, CUSUM, EWMA	✓				✓				CSTR	✓	Nawaz et al. [96]
72	2021	WT	KPCA	✓		✓			✓			CSTR	✓	Nawaz et al. [144]
73	2021	WT	PCA	✓								NE,TEP	✓	Sheriff et al. [145]

Name of Issue: (A*)-fault detection, (A)- multiscale methods for quality relevant process monitoring, (B)- multiscale methods for nonlinear process monitoring, (C)- multiscale methods for dynamic process monitoring, (D)- multiscale methods for incipient fault detection, (E)- multiscale methods for fault diagnosis, (F)- multiscale methods for batch process monitoring, (G)-multiscale methods for non-Gaussian data.

fault identification and classification. In fault identification, the faulty variables are identified based on their influence on the value of the statistical index. Identifying faulty variables is beneficial for highly integrated, large-scale, and complex plants [10]. There is no need for fault information for diagnosis through fault identification. If prior knowledge about the fault is available, the learning problem would be to find the boundary between normal and faulty samples. This learning problem is related to fault classification, and the three common approaches are similarity factors, discriminant analysis, and support vector machines (SVM).

Contribution plots are the most popular tool for identifying which variables push the statistics beyond control limits. Shao *et al.* [76] proposed a wavelet-based nonlinear PCA algorithm for process monitoring and applied differential contribution plots to find faulty variables of an industrial drying process. Many researchers have also used contribution plots with MSPCA process monitoring approaches to determine the faulty variables [100]–[102]. Zhiqiang and Quanxiong [103] used contribution plots for fault identification in the wavelet-based adaptive MSPCA method. Many researchers applied contribution plots to identify the faulty variables using kernel-based nonlinear multiscale techniques [75], [84], [86], [104]. Similarity factor was integrated with MSPCA to identify the fault type and reveal the fault source [85], [105].

Lau *et al.* [106] have implemented Adaptive Neuro-Fuzzy Inference System (ANFIS) fault classification with MSPCA to diagnosis selected fault cases in the TEP. Nor *et al.* [107] proposed a new multiscale fault diagnosis method by combining the multiscale KFDA and the ANFIS classification model. The fault classification performance was evaluated using the TEP, and the results indicated that the proposed multiscale KFDA-ANFIS framework improved over the multiscale PCA-ANFIS and FDA-ANFIS.

SVM is a well-known classification tool, proposed initially by Cortes and Vapnik [108]. Liu *et al.* [88] proposed a multiscale fault diagnosis method and applied the SVM classifier based on classification distance, using 4-fold to obtain the optimal parameters. Nor *et al.* [90] incorporated the SVM classifier with multiscale KFD, and the performance accuracy was compared to the multiscale KFD-GMM of the faults in the TEP.

F. MULTISCALE METHODS FOR BATCH PROCESS MONITORING

Batch processes often operate in different phases of operation. The batch operations are becoming increasingly complicated due to frequent start-ups and shutdowns. As a result, monitoring tasks in batch processes are becoming more challenging to perform. Multiway PCA [109] and multiway PLS [110] are still used to monitor batch processes.

Lee *et al.* [111] proposed a multiway MSPCA approach for batch processes that combines WT and multiway PCA and has been effectively used in the sequencing batch reactor process for biological wastewater treatment. The proposed approach aids in detecting early faults and detecting less apparent faults. Alawi and Morris [112] proposed a multiscale multi-block modeling approach for batch process monitoring and compared it with the conventional MPCA approach using simulated data obtained from the penicillin fermentation simulation benchmark.

G. MULTISCALE METHODS FOR NON-GAUSSIAN DATA

Contrary to the eminent advances in MSPCA and MSPLS fault detection methods, ICA has received significantly less attention in the field of wavelet-based process monitoring despite ICA being a better choice for monitoring non gaussian data. A few researchers have also developed a multiscale process monitoring methods to handle non-Gaussian data.

Salahshoor and Kiasi [113] proposed a multiscale-ICA technique by integrating with wavelet analysis and ICA for non-gaussian data. They used Daubechies 3 up to level 3 and found that the proposed technique was effective for TE process data. Zvokelj *et al.* [99] proposed a new multiscale process monitoring technique by combining EEMD with ICA. They found that this technique is also suitable for detecting incipient faults in large slewing bearing systems. Recently, Kini and Madakyaru [114] proposed a wavelet based multiscale fault detection technique by combing wavelets with

ICA. The effectiveness of the proposed technique was illustrated by using three different case studies and found that this technique can enhance the detection rate in noisy process environments.

VI. CHALLENGES AND OPPORTUNITIES

The increasing complexity of industrial systems and their related performance requirements have created a need to develop new approaches for their supervision. This review unravels how multiscale approaches have been applied for process monitoring within various industrial applications. Despite many advances in multiscale process monitoring research, more challenges are still emerging. Multiscale will likely have a role in addressing these challenges towards safer operations in the industry. A few of these challenges are discussed as follows.

A. ONLINE PROCESS MONITORING

Plant safety and product quality are two essential elements of today's process industry. Implementing a distributed control system and modern mearing techniques adds to the complexity of modern chemical plants. Therefore, it is important to identify and correct anomalies immediately during the process. This issue can be solved by employing online process monitoring, which will be helpful for efficient quality control of final products and process optimization. However, not enough attention is given to the issue of online process monitoring in multiscale methods. Therefore, developing a methodology for online process monitoring is of great interest that needs further research in the future.

B. FAULT IDENTIFICATION AND SMEARING EFFECT

The increasing complexity of chemical process systems makes it much more difficult to diagnose faults. A diagnostic tool is needed for fault identification after the fault has been detected in a process. Identifying a faulty variable is critical in analyzing the causes of abnormalities present in the process. In real systems, there is a possibility that avoiding a specific fault may result in the occurrence of another subsequent fault. Contribution plots are commonly used to determine fault variables, but this technique suffers from the smearing effect, which can mislead the faulty variables of the detected faults. However, insufficient attention is paid to fault identification in multiscale process monitoring. Identifying a faulty variable correctly in multiscale process monitoring is an open question that needs further research in the future.

C. ADAPTIVE FAULT DETECTION AND DIAGNOSIS

One of the most challenging monitoring processes is the detection of minor or incipient irregularities in highly correlated multivariate process data. Indeed, early detection of these incipient irregularities can help prevent significant damages and financial losses. Unfortunately, it is challenging to detect incipient abnormalities as they are too weak to

TABLE 3. List of abbreviations.

Abbreviations used in the manuscript text:	
ANFIS	adaptive neuro-fuzzy inference system
ANN	artificial neural network
CUSUM	cumulative sum
DCS	distributed control system
DKPCA	dynamic KPCA
DPCA	dynamic PCA
EEMD	ensemble empirical mode decomposition
EMD	empirical mode decomposition
EWMA	exponentially weighted moving average
FDA	fisher discriminant analysis
FDD	fault detection and diagnosis
FDI	fault detection and identification
GLRT	generalized likelihood ratio test
GMM	gaussian mixture model
ICA	independent component analysis
IT-NN	input-training neural network
IMF	intrinsic mode functions
KFDA	kernel FDA
KGMM	kernel GMM
KICA	kernel ICA
KPCA	kernel PCA
KPLS	kernel PLS
MCUSUM	multivariate CUSUM
MEWMA	multivariate EWMA
MGMM	multi-way GMM
MKICA	multiway KICA
MKPCA	multiway KPCA
MSNLPCA	multiscale NLPCA
MSPLS	Multiscale PLS
MSPM	multivariate statistical process monitoring
NLPCA	nonlinear PCA
PCA	principle component analysis
PLS	partial least square
PPCA	probabilistic PCA
SPC	statistical process control

TABLE 3. ***(Continued.)*** **List of abbreviations.**

SSA	singular spectrum analysis
SVM	support vector machines
WT	wavelet transforms
Abbreviations for the case studies used in Table 2 are:	
AHWR	advanced heavy water reactor
BAFP	biological anaerobic filter process
BF	bearing fault
BWWTP	biological wastewater treatment plant
CAP	continuous annealing process
CFT	cracking furnace tube
CS	chiller system
CSM	cad system in E. coli model
CSTR	continuous stirred tank reactor
DC	distillation column
ECF	ethylene cracking furnace
EFMF	electro fused magnesium furnace
FCCU	fluidized catalytic cracker unit
FFE	furnace feed event
FMF	fused magnesium furnace
HHS	home heating system
IBD	industrial boiler data
IPPPP	industrial polypropylene production process
ISD	industrial spray dryer
ITRS	industrial tubular reactor system
LSBTT	low speed bearing test stand
NC	ne concentrations
NE	numerical example
NLIP	nonlinear industrial process
PFP	penicillin fermentation process
PMP	polymerization process
PMP	paper mill plant
PSP	pilot scale plant
SBRS	sequencing batch reactor system
SDS	simulated datasets
SD	synthetic data
TEP	Tennessee Eastmann process
WWTP	wastewater treatment processes
TTS	three tank process
SS	simulated system
SM	sensor malfunction
LSBTS	laboratory slewing bearing test stand
STP	sewage treatment process
SFSS	steel-frame scale structure
QTP	quadruple tank process

detect conventional MSPM methods. As mentioned in the above discussion, a few techniques attempt to handle such irregularities. The key limitation of these studies is the use of conventional PCA methodology, a linear technique. However, most chemical processes are nonlinear and may have specific dynamic characteristics. Therefore, developing a nonlinear multiscale method for detecting incipient faults is of great interest in the future.

D. MULTIMODE PROCESS MONITORING

The conventional MSPM methods and their extensions assume that the process is operated under single steady state conditions. Since the modern industrial processes are linked with different operations, where operating conditions are change frequently. In this situation, the currently used monitoring technique may not perform well and may cause false alarm(a). Therefore, to keep the industrial process under control, monitoring process should be updated according to the change of operating conditions.

VII. CONCLUSION

This study aims to provide an overview of multiscale process monitoring and its use in chemical process systems. This review article firstly discussed the statistical process monitoring and recent developments in MSPM methods. A statistical analysis of the existing literature on multiscale process monitoring methods is also presented, based on the methods used, application area, types of data, and the issues addressed within these methods by various researchers. These issues include monitoring quality-related processes, monitoring nonlinear processes, handling batch process data, accounting for process dynamics, and performing fault diagnosis. Multiscale process monitoring research has significantly progressed by addressing these issues in the last two decades.

Finally, future research prospects for multiscale process monitoring research have been discussed. This article shall contribute to a better understanding of the role of multiscale process monitoring and provide new insights for researchers in the field.

APPENDIX

The list of abbreviations is listed in Table 3.

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