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Perspectives on nonstationary process monitoring in the era of industrial artificial intelligence

Chunhui Zhao

State Key Laboratory of Industrial Control Technology, College of Control Science and Engineering, Zhejiang University, Hangzhou, 310027, China

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ABSTRACT

The development of the Internet of Things, cloud computing, and artificial intelligence has given birth to industrial artificial intelligence (IAI) technology, which enables us to obtain fine perception and in-depth understanding capabilities for the operating conditions of industrial processes, and promotes the intelligent transformation of modern industrial production processes. At the same time, modern industry is facing diversified market demand instead of ultra-large-scale demand, resulting in typical variable conditions, which enhances the nonstationary characteristics of modern industry, and brings great challenges to the monitoring of industrial processes. In this regard, this paper analyzes the complex characteristics of nonstationary industrial operation, reveals the effects on operating condition monitoring, and summarizes the difficulties faced by varying condition monitoring. Furthermore, by reviewing the recent 30 years of development of data-driven methods for industrial process monitoring, we sorted out the evolution of nonstationary monitoring methods, and analyzed the features, advantages and disadvantages of the methods at different stages. In addition, by summarizing the existing related research methods by category, we hope to provide reference for monitoring methods of nonstationary process. Finally, combined with the development trend of industrial artificial intelligence technologies, some promising research directions are given in the field of nonstationary process monitoring.

1. Introduction

With the development of technologies such as the Internet of Things (IoT), artificial intelligence (AI), cloud computing, etc., the third industrial revolution characterized by automation is turning to the fourth industrial revolution, i.e., Industry 4.0, which is characterized by intelligence [1–4]. Due to automation requirements, a large number of sensors are installed on industrial equipment to collect and transmit various parameters in the industrial production process in real time. The development of the IoT technology [5,6] has significantly improved the level of industrial informatization. People can conveniently and quickly collect, transmit and store a large number of multi-category process data, providing rich data support for in-depth analysis and understanding of the process. Therefore, the perception of the condition of the industrial production process tends to be refined. However, unprocessed raw data has a distinctive feature of low value density, and requires proper data analysis to form valuable information for production managers. AI technology [7–11] gives us the means to extract effective information from large-scale and multi-type data. At the same time, the development of cloud computing makes it possible to use large-scale data to train models, which can greatly reduce the cost of model training [12], laying a strong foundation for computing resource management for the large-scale application of artificial intelligence technology in the industrial field. According to the original definition, IAI [1] is to combine artificial intelligence technology with specific industrial scenarios to realize innovative applications, such as design model innovation, production intelligent decision-making, and resource optimization allocation, so that industrial systems have self-perception, self-learning, self-execution, self-decision, and self-adaptive ability to adapt to the changing industrial environment, and complete a variety of industrial tasks, and ultimately achieve the purpose of improving enterprise insight, improving production efficiency or equipment product performance. In traditional industrial processes, it is difficult to obtain the mechanism models of many devices or systems, so data-driven methods [13–20] that do not require accurate models of industrial systems are the most widely used in industrial artificial intelligence. By analyzing industrial data, data-driven methods can extract key features, mine potential patterns contained within the data, and complete tasks, such as anomaly identification and fault classification. Here, the common term of industrial data is used instead of industrial big data because the focus of the current work is not to show how big the data is and what special methods should be developed for big data.

E-mail address: chhzhao@zju.edu.cn.

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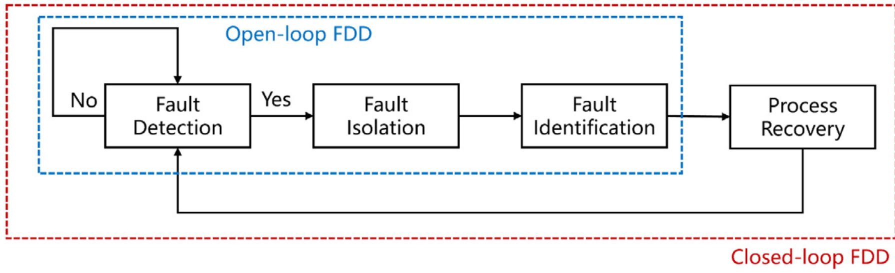


Fig. 1. The illustration of process monitoring loop.

Intelligent process monitoring in complex industrial environments is an important research direction of industrial artificial intelligence [1], which is crucial to the long-term safe and reliable operation of automatic control systems. Many process monitoring systems are implemented in the form of a loop that consists of fault detection, fault isolation, fault identification, and process recovery [21] as shown in Fig. 1. Here, we focus on the first three parts and follow the definition of a fault [22], which is an unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable/usual/standard operating conditions. We call fault isolation and identification as fault diagnosis in a narrow sense [21] since fault diagnosis in a broad sense is equivalent to process monitoring. Therefore, we can abbreviate fault detection and fault diagnosis as FDD, i.e., process monitoring. Fault detection [23–26] refers to the use of process data to evaluate the operating state of industrial processes and determine whether there is an abnormality, which is the starting point and basis for fault diagnosis. Fault diagnosis [27–30] is based on the existing process parameters, combined with the known structural characteristics and historical operation and maintenance records, etc., to predict, analyze and judge the faults that may occur or have occurred in the process, and determine the fault location, time and magnitude. It is noted that two special terms are defined in the present work, i.e., open-loop FDD and closed-loop FDD, which are distinguished by whether the part of process recovery is included which is deemed to be the feedback based on FDD results. The specific explanation will be talked in Section 5. At present, many scholars have carried out specific research in the field of industrial process operating condition monitoring [31–35] which may cover different applications including to petrochemical, power generation, metallurgy, papermaking and steelmaking. In the core database of Web of Science (WoS), according to the results searched by full-text/keywords "fault detection" or "fault diagnosis" or "process monitoring", the number of SCI scientific research articles is showing an upward trend year by year as shown in Fig. 2 (a), and is currently maintained at least 1000 per year, indicating that its research has attracted the increasing attention of researchers and has become the hot spot. As such, many reviews have been published for industrial process monitoring over the last twenty years [13,15,17,36–40].

However, most of the published literature review in the field of process monitoring summarizes the commonly used process monitoring methods for data analysis for stationary processes. Stationarity means that the mean and variance of the time series do not change with time [41], which is a long-term stable relationship. In contrast, the operating conditions of industrial processes obviously do not meet the definition of stationarity. Nonstationary changes are typical characteristics of modern industrial processes. Due to time-varying factors such as changes in production conditions, catalyst deactivation, unknown external disturbances, and switching of equipment on and off, the statistical characteristics of industrial process parameters often change over time. At the same time, in the process industry transformation from "mass production" to "customized production", enterprises change product types according to diversified market demands and thus adjust the production settings at various stages, which increases the range and degree of nonstationary variation of the process. For nonstationary processes, the traditional monitoring methods based on the independent and identical distribution (IID) assumption are no longer applicable. In addition, the normal process state changes are very similar to the changes caused by faults in some process parameters, and the coincidence of these changes brings great difficulties to the timely detection of abnormal conditions and the accurate diagnosis of fault causes. In comparison with the searching requirement shown in Fig. 2(a), "nonstationary" is added and the number of SCI scientific research articles is shown in Fig. 2(b), revealing a similar upward trend for full-text searches but a significantly smaller number per year. Up to 100 publications are available per year. Using VOSviewer [42], Fig. 3 depicts the map of co-occurrence clustering result of the keywords in publications in the WoS core database referring to "nonstationary" and "process monitoring" or "fault detection" or "fault diagnosis" through "full text" search. It can be observed that the major research fields include "fault diagnosis", "empirical mode decomposition","time–frequency analysis", "fault detection","signal processing", etc. Nonstationary monitoring is more demanding and difficult than steady-state condition monitoring, and there are still many problems and challenges that need to be discussed and studied in depth.

This article does not review the entire process monitoring field which, according to the WoS core database in Dec. 2021 shown in Fig. 2(a), has had over 248 604 publications searched by full-text since 2002. In this paper, we focus on the nonstationary changes of industrial processes, which only have 1000 publications up to now, and strive to provide some perspectives on the current state of nonstationary process monitoring methods, as well as current challenges and promising future directions for the field. First, the typical problems and complex characteristics caused by the nonstationary changes are analyzed for the purposes of industrial process monitoring, revealing the difficulties for nonstationary condition identification. Second, the conventional monitoring methods for stationary processes are briefly reviewed for comparison. Third, for the research on monitoring of nonstationary industrial process, it is divided into four categories from different analysis angles, i.e., nonstationary time series analysis method, long-term constant analysis method, time-driven multi-mode analysis method and condition-driven multi-mode analysis method. Wherein, the typical representative methods are reviewed in response to the difficult problems caused by nonstationary changes with analysis of both advantages and disadvantages. Fourth, significant and promising research directions in the era of Industry 4.0 and big data are looked forward, including data and knowledge fusion, model generalization and transfer under the cloud–edge collaboration framework, and self-healing regulation of operating conditions.

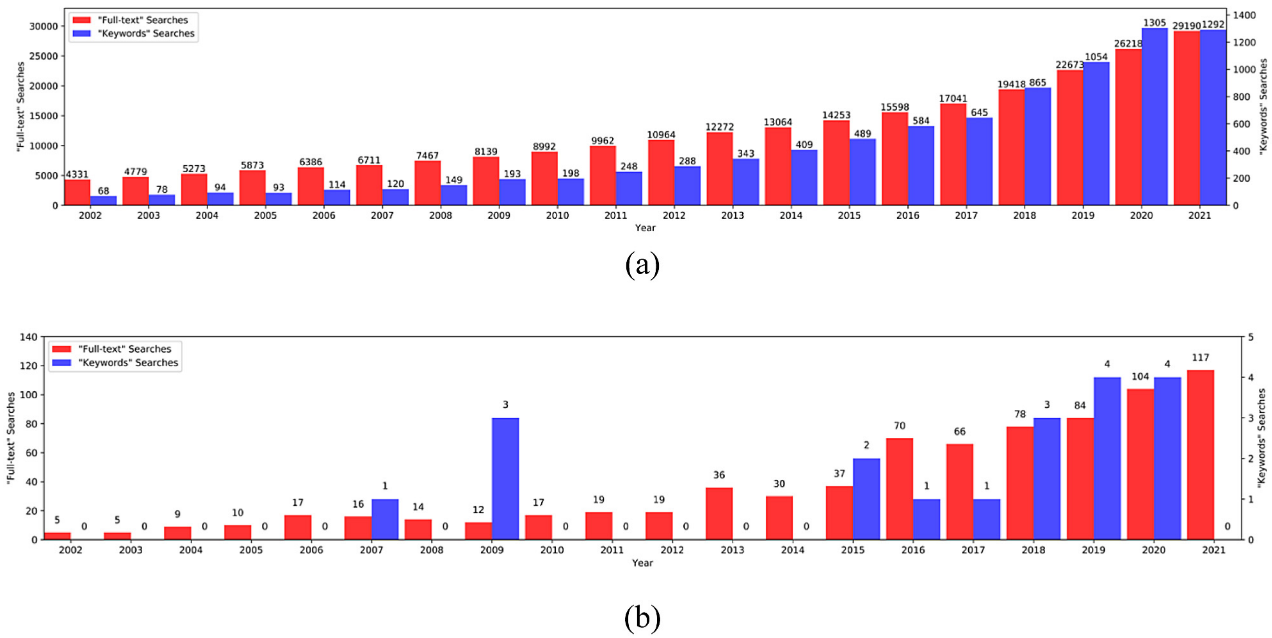


Fig. 2. The development trend of process monitoring from 2002 to 2021. The results are obtained by searching (a) for "process monitoring" or "fault detection" or "fault diagnosis", (b) for "nonstationary" and "process monitoring" or "fault detection" or "fault diagnosis" in the WoS core database through "full text" search and "keyword" search.

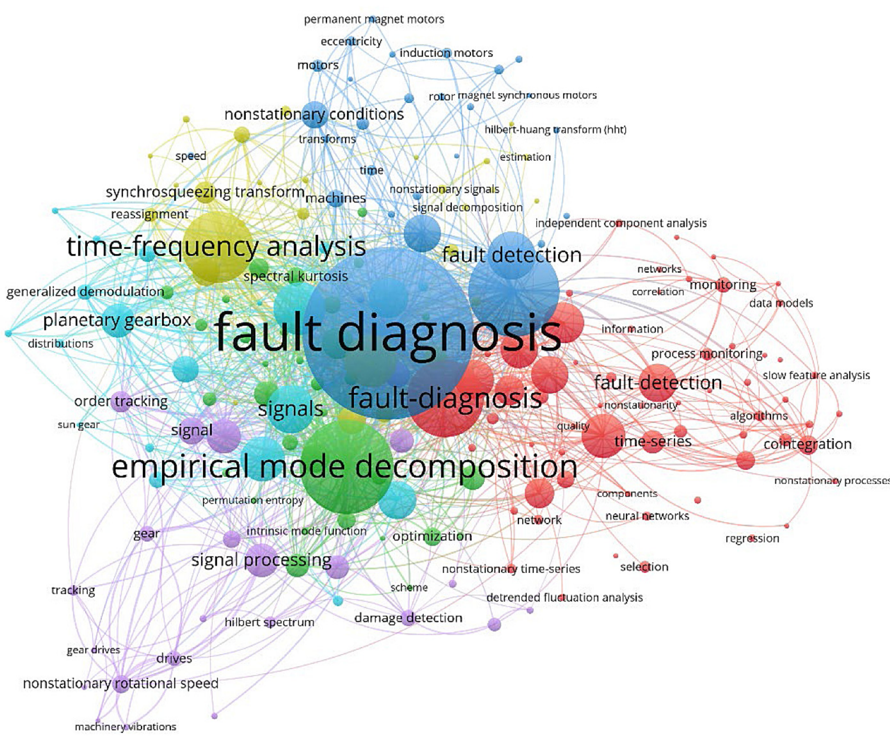


Fig. 3. Map of the co-occurrence clustering of the keywords in publications in the WoS core database referring to "nonstationary" and "process monitoring" or "fault detection" or "fault diagnosis" through "full text" search.

The remainder of this paper is summarized as follows. The second section reveals the complex characteristics of the nonstationary industrial process, analyzes the problems brought to the process monitoring, and summarizes the related difficulties on this basis. In Section 3, we present the review and analysis of conventional process monitoring methods. In Section 4, we sort out and summarize the applicable nonstationary monitoring methods for different problems. In Section 5, we look forward to possible future research directions. The conclusion is given in Section 6.

2. Nonstationary characteristics and monitoring difficulties

This section first makes a comparative analysis and definition of stationary and nonstationary characteristics and then summarizes other complex characteristics displayed in nonstationary industrial processes, with the analysis of difficult problems in the identification of nonstationary operating conditions.

Here, for simplicity, the used notations are given before the following subsections. Given a set of time series $\mathbf{X}(N \times J) = [\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_J]$, $\mathbf{x}_j = (x_1, x_2, \ldots, x_N)^T$, where J is the number of variables (i.e., time series), the subscript j denotes the variable index, and N is the number of samples. Without any special statement, the vector is column one.

2.1. Nonstationarity

To understand nonstationarity, first, we need to define and understand stationary processes. The so-called stationary process is a random process whose statistical properties do not change with the passage of time [41]. Among them, the most widely used is the wide stationary process, which generally specifies the first-order moment and the second-order moment of J-dimensional measurement samples $\mathbf{x}(t)$, as shown in the following formula,

$$\begin{gathered} E(\mathbf{x}(t)) = \boldsymbol{\mu}, Var(\mathbf{x}(t)) = \boldsymbol{\sigma}^2 \\ Cov(\mathbf{x}(t), \mathbf{x}(t+k)) = Cov(\mathbf{x}(t+h), \mathbf{x}(t+k+h)) = \boldsymbol{\rho} \end{gathered} \tag{1}$$

where, the mean $\boldsymbol{\mu}$ and variance $\boldsymbol{\sigma^2}$ of the broad stationary process are constants, and the correlation $\boldsymbol{\rho}$ is only related to the difference between the two times, and does not change with time.

Stationarity makes it easier to analyze problems because of its good statistical properties and ease of processing. However, the observed industrial processes are often affected by some factors and show nonstationarity. Nonstationary properties refer to the change of the mean or variance of a time series over time [41]. Taking the power generation process as an example, due to the influence of variable load peak regulation, the power generation operating state has obvious nonstationary characteristics. As shown in Fig. 4, the load and other parameters fluctuate nonstationarily with time. For practical industrial processes, the operating conditions are often constantly changing due to changes of production requirements, resulting in process variables with time-varying mean and variance, with typical nonstationary characteristics. Generally speaking, industrial processes do not have absolute stationarity, and in a broad sense, they can be regarded as nonstationary processes.

As mentioned before, for nonstationary industrial processes, normal process state changes in some parameters are very similar to the changes caused by faults. This similarity brings great difficulty to the timely detection of abnormal conditions and the accurate diagnosis of fault causes. It may cause normal process changes to be falsely identified as process abnormality, resulting in false alarms, or may cause process abnormality to be masked by normal process changes, resulting in missing alarms. In addition, under nonstationary changes, the fault representation is complex and diverse. For example, the same fault type may have different representations under different working conditions, which causes difficulties in the extraction of fault features, thus affecting the subsequent fault diagnosis performance.

2.2. Other nonstationary related properties

In addition to the nonstationary characteristics, some typical common problems are more serious in comparison with the ideal stationary process due to the frequent switching of operation conditions. Therefore, there are still a lot of difficulties to be solved in nonstationary process monitoring. Some are listed as below which are not limited to:

Nonlinearity: A large number of industrial process monitoring models apply linear assumptions, but nonlinear relationships between operating parameters are very common in practical industrial processes [23,43,44]. Here, the linearity assumption means that for any moment t, there exists a row vector $\mathbf{w}$ $(J \times 1)$ such that the equation $\mathbf{x}(t)^{\mathrm{T}}\mathbf{w} = 0$ holds, where $\mathbf{x}(t)$ denotes the measurement sample. The frequent changes of operating conditions in a nonstationary process tends to exacerbate the nonlinearity of the variable relationship, making the linearity assumption no longer valid.

Non-Gaussian: For conventional process monitoring methods, they in general assume that the data follow or approximately follow Gaussian distribution, i.e. $\mathbf{x} \sim \mathrm{N}(\boldsymbol{\mu}, \boldsymbol{\sigma})$, which is simple and easy to calculate. For nonstationary industrial processes, the data statistical properties change with operation conditions, so that the data are often multi-modal and no longer satisfy the Gaussian distribution [45–47]. It is difficult to characterize and cover the nonstationary data using a single Gaussian model.

Dynamics: The dynamic characteristic means that the industrial process data has time series correlation [48–51], that is, the measured values of the process variable before and after the time no longer satisfy the IID assumption, but are related to each other. This property is influenced by the control strategy imposed on the industrial process and is closely related to the intrinsic mechanisms of the industrial process. For nonstationary processes, the conditions are frequently changed by closed-loop feedback control, and have typical dynamics. The dynamics characteristic can be mathematically expressed as

$$\mathbf{x}(t) = w_1\mathbf{x}(t-1) + w_2\mathbf{x}(t-2) + \cdots + w_s\mathbf{x}(t-s) + r(t) \tag{2}$$

where $\mathbf{x}(t)$ is the vector of process variables at time t, w_i is the regression coefficient for each process variable at different time and $r(t)$ is the residual.

Variable distribution: In traditional data analysis task, in order to ensure the accuracy and high reliability of the trained model, a basic assumption is made that the new test samples ($\mathbf{X}_{\text{test}}$) which formulate a target domain has the same distribution as that of the training samples ($\mathbf{X}_{\text{train}}$) which formulate a source domain used for learning. However, in practice, affected by the switching of working conditions, two domains differ when the marginal distributions $P(\mathbf{X})$ are different, which is the problem of variable distribution [52]. Besides, considering the supervised task, the label space $\mathbf{Y}_*$ is considered as the output of the mapping function of samples $\mathbf{X}_*$. The change in distribution can be mathematically described as for both unsupervised and supervised tasks,

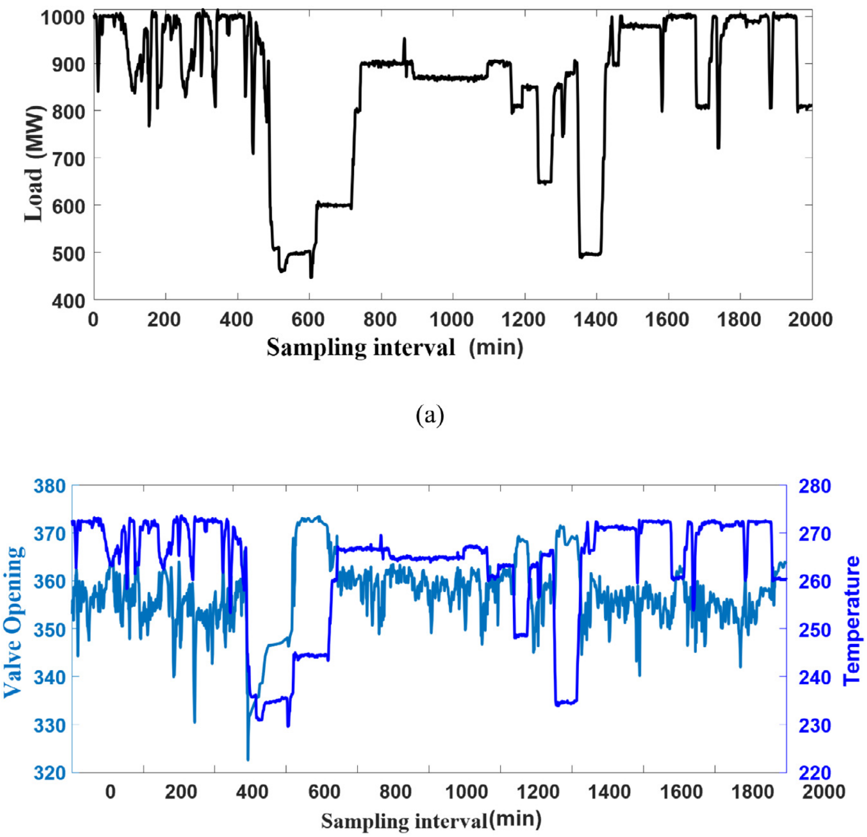
$$P(\mathbf{X}_{\text{train}}) \neq P(\mathbf{X}_{\text{test}}) \text{ or } P(\mathbf{Y}_{\text{train}}|\mathbf{X}_{\text{train}}) \neq P(\mathbf{Y}_{\text{test}}|\mathbf{X}_{\text{test}}) \tag{3}$$

where $\mathbf{X}_*$ means $\{\mathbf{x}|\mathbf{x}_i, i = 1, 2, \ldots, N\}$, $\mathbf{Y}_*$ means the label set, and $\{y|y_i, i = 1, 2, \ldots, N\}$; and P means the function of probability distribution.

Differences in the marginal or condition distribution of the training and test data result in variable distribution, which thus leads to the mismatch of the model in nonstationary processes.

3. Data-driven traditional process monitoring methods

Considering the research changing from stationary to nonstationary, the data-driven traditional process monitoring methods will be introduced first to provide a basis for the nonstationary process monitoring. In recent years, with the rapid development of data measurement and storage technology, data has been accumulated during the operation of industrial systems, including high-frequency and low-frequency sensor measurement signals, process data, and product quality. The data-driven monitoring technology mainly analyzes and mines the collected process data, extracts the implicit information and features underlying the data, and thus reveals the operation state of the process and diagnoses the fault type. The data-driven monitoring method does not need to know the prior knowledge of the object and



(a)

(b)

Fig. 4. Schematic diagram of the nonstationary variable trajectories of a million kilowatt ultra-supercritical unit for (a) power load and (b) other parameters.

the accurate analytical model of the system, and has a strong modeling ability, and thus has gradually become the mainstream direction in the field of industrial process monitoring. Here, we do not elaborate all but only review the current mainstream data-driven traditional process monitoring methods [53–83], which mainly include statistics-based machine learning methods and neural network methods.

Due to its unique advantages in processing high-dimensional coupled data, the statistics-based machine learning methods has developed rapidly in recent decades and has been widely used in various industrial processes, including principal component analysis (PCA) [57–60], partial least square (PLS) [61–64], independent component analysis (ICA) [65,66], slow feature analysis (SFA) [69–71] and linear discriminant analysis (LDA) [72], etc. They use machine learning methods to reduce the dimensionality of high-dimensional redundant process data, eliminate collinearity between variables and extract key features and information, and construct statistical performance indicators for the process monitoring. In this way, the operating status is evaluated, the category of the fault is classified, and the faulty variables can be identified by contribution plot and reconstruction analysis [60,67,73,74]. However, most of the above-mentioned traditional machine learning methods are linear models which have IID assumptions for the data. With the development of industrial intelligence, industrial processes have become increasingly large-scale, with diverse equipment, numerous parameters and mutual influences, and have complex process characteristics, including dynamics, nonlinearity, non-Gaussian, nonstationarity and so on. The traditional methods cannot effectively capture the complex characteristics of the process, and thus cannot realize accurate and efficient working condition identification of complex industrial processes. In order to better adapt to the large-scale and complex modern industrial process, scholars have made a series of improvements and extensions [75–77] on the basis of traditional machine learning methods, which will not be repeated here since it is not the focus in the present work.

Compared with traditional information processing methods, some nonlinear methods have emerged to address the shortcomings of linear methods, including kernel PCA [56] and principal curves [76], etc. The neural network method has obvious advantages in many aspects, mainly in the strong nonlinear expression ability, which increases the adaptability to various changes. The applied research in the field of pattern recognition has always been a hot spot [78–80]. However, the interpretability of its diagnosis process is not strong. Since the neural network information is stored in the form of weights, this implicit knowledge is not easy to understand. In addition, the existing fault diagnosis methods for industrial processes are mainly based on the historical operation data under a certain stable working condition, and the related research on nonstationary industrial processes is still in the ascendant [81–83]. Although the neural network approach has many advantages and has been intensively studied in the problem of industrial process fault diagnosis, it has high requirements on the scale and quality of the training data. Large-scale and high-quality data is an important prerequisite for its good modeling performance. Moreover, most of these methods assume that the training and test data are sampled from the same distribution. However, in real industrial processes, data quality problem, such as insufficient fault history data, missing data, and noise pollution, is very common, and the operating condition of the process during online application may often be different from that when the training data was collected. How to establish an effective monitoring model under the condition of low data quality and insufficient fault samples is a hot research topic at present, which will be discussed later for the nonstationary process monitoring problem.

4. Nonstationary industrial process monitoring methods

The above-mentioned traditional monitoring methods more consider a single operation mode, and the FDD task is carried out for this specific operation mode. However, in the actual operation of nonstationary industrial processes, various factors such as frequent changes in operating conditions, equipment aging, catalyst deactivation, and unknown interference make the mean and variance of process variables change with time, showing obvious nonstationary characteristics [84]. At this time, the process no longer operates under a specific working condition, but frequently alternates between different working conditions, which brings great difficulties to the timely detection of process anomalies. On the one hand, it is difficult to distinguish normal working condition changes from abnormal changes, and fault features are easily masked by nonstationary trends. On the other hand, traditional working condition identification methods cannot accurately describe the relationship between nonstationary variables, which may lead to erroneous monitoring results. In addition, due to changes of working conditions, especially the existence of transitional working conditions, the monitoring of nonstationary industrial processes is more difficult and demanding than that for a single working condition. This section will mainly introduce the basic development history of data-driven nonstationary monitoring methods. First, the nonstationary monitoring methods will be introduced in four categories represented by nonstationary time series analysis method, long-term constant relation analysis method, time-driven multi-mode analysis method and the newly emerging condition-driven multi-mode analysis method as shown in Table 1. Furthermore, other complex characteristics of nonstationary industrial processes are analyzed in depth, and the existing monitoring methods for specific problems are reviewed.

4.1. Nonstationary time series analysis method

The main idea of dealing with nonstationary time series is to convert them into stationary sequences through some preprocessing methods before analyzing them. Some signal processing methods are widely used in the study of nonstationary process monitoring which is also supported by Fig. 3. For example, wavelet transform [85–89], short-time Fourier transform [107–109], and Wigner–Ville distribution [110–113] are used to analyze nonstationary vibration signals to realize process monitoring and fault diagnosis of mechanical equipment. Huang [114] proposed an empirical mode decomposition method that can be used for any type of signal decomposition. As an adaptive time–frequency analysis method, empirical mode decomposition has great advantages in dealing with nonstationary signals [90,91]. The above signal processing methods can effectively deal with vibration signals with nonstationary characteristics. But these methods only analyze a single signal, that is, analyze a single process variable without considering the variable cross-correlation.

In addition to signal processing methods, furthermore, some traditional methods remove nonstationary trends by computing the difference of the original nonstationary time series [115]. Box et al. [116] and Castillo et al. [117] used an ARIMA model to describe the nonstationary nature of the process. Berthouex et al. [118] proposed to use the ARIMA model to predict the operation status of waste water treatment processes. However, after difference processing, some information in the data, such as dynamic information, will be lost, thus affecting the process monitoring effect.

Some scholars have proposed to use adaptive strategy to solve nonstationary problems [92,93,119,120]. The main idea of this strategy is to capture nonstationary changes by continuously updating the predefined models, including model structure and model parameters. Li et al. [92] introduced two recursive PCA algorithms to adaptively update PCA monitoring models, and Yu et al. [93] introduced a recursive exponential slow feature analysis algorithm to solve the model pseudo-update problem and achieve refined adaptive state recognition. Just in time learning (JITL) [121] is deemed to be one special case of adaptive methods. However, some important issues of adaptive monitoring in industrial processes have not been clearly illustrated and addressed. The adaptive update strategy cannot effectively distinguish between normal changes and faults, especially for the slowly changing fault process, it is easy to adapt fault errors, which thus may result in inaccuracy monitoring model. Besides, it is expected that model updating can be efficiently implemented with newly available samples to adapt for the normal slow changes instead of being entirely retrained. Dai et al. [19] proposed an incremental variational Bayesian Gaussian mixture model (IncVBGMM) for developing a fine-scale adaptive monitoring scheme to efficiently accommodate the shifting data distribution caused by different degrees of time-varying behaviors. In addition, the decremental optimization provides an improved lifelong learning capability for IncVBGMM since the redundant components are removed after incremental learning.

4.2. Long-term constant relation analysis method

Another commonly used method is the long-term constant relation analysis method for nonstationary process monitoring, including cointegration analysis (CA) [122] and stationary subspace analysis (SSA) [123,124]. The methods can effectively mine the long-term constant relationship between nonstationary variables and the model can remain valid for a long time. Engle and Granger [122] jointly put forward the cointegration theory in the economic field three decades ago, which believes that there may be a long-term equilibrium relationship between nonstationary variables. That is, each variable fluctuates randomly around a common long-term trend, and is related to the other nonstationary variables. They revealed that it is possible for a linear combination of a set of integrated nonstationary variables to be stationary if the nonstationary variables are integrated of the same order and share common trends. If a nonstationary time series $\mathbf{x}_j$ becomes stationary after being differentiated d times, the nonstationary time series is said to be integrated of order d, which is denoted as $\mathbf{x}_j \sim I(d)$. CA seeks to find the cointegration model which is the linear combination of the nonstationary variables, and it can reflect the long-term equilibrium relation among those nonstationary variables,

$$\boldsymbol{\gamma} = b_1\mathbf{x}_1 + b_2\mathbf{x}_2 + \cdots + b_N\mathbf{x}_J = \mathbf{X}\mathbf{b} \tag{4}$$

where $\boldsymbol{\gamma}$ is the equilibrium error sequence and $\mathbf{b}$ is called the cointegration vector.

Different from traditional PCA, only the equilibrium error sequence $\boldsymbol{\gamma}$ is acquired as a stationary series for process monitoring. However, the cointegration assumption of the data may not be satisfied in the real industrial process. In contrast, stationary subspace analysis (SSA) [123,124] does not need such an assumption and is proposed to separate stationary and nonstationary sources from observed nonstationary multivariate time

Table 1
Comparison of nonstationary monitoring methods for processes under variable working conditions.

Category	Methods	Advantages	Drawbacks	Examples
Typical Nonstationary analysis method	Signal processing methods	Capable of handling nonstationary, nonlinear signals	Limited to high frequency vibration signals	(1) Wavelet transform for fault diagnosis of gearbox vibration signals [85–89] (2) Empirical mode decomposition to deal with nonlinear nonstationary time series [90,91]
	Adaptive strategies	Fast adaptation to new modes and high calculation efficiency	Inability to effectively distinguish between normal variation and slow-change faults	(1) Recursive PCA for adaptive process monitoring [92] (2) Recursive exponential slow feature analysis for adaptive process monitoring [93]
	Cointegration analysis methods	Small number of models, long effective time	Limited to variables with cointegration relationship	(1) Sparse cointegration analysis for distributed process monitoring [94] (2) Cointegration analysis combined with slow feature analysis for full-condition monitoring [95]
Time-driven multi-mode analysis method	Statistical test or stationary indicators determination method	High computational efficiency	Rough mode division, not considering the correlations between multiple variables	(1) Determination of steady operating modes using statistical tests [96–98] (2) Mode division using stability factor [99]
	Characteristic change metrics and mode division strategies	Automatic mode division	Multiple and redundant modes; difficult to confirm the specific mode online	Changes of process characteristics can be inferred from changes of the variable correlations, thus classifying the operating state into different modes [98,100]
	Gaussian mixture model clustering methods	Powerful fitting ability, automatic clustering	Number of modes to be specified in advance	Mode division using GMM for fault diagnosis [101,102]
	Soft transition methods	Better mode split and more sensitive monitoring models	Complex and poorly interpretable mode division results	(1) A soft transition PCA model for multimode monitoring [103] (2) Further development of the soft mode transition approach [104,105]
Condition-driven multi-mode analysis method	Condition mode division method	Starting from the condition axis eliminates the effect of nonstationary problems and captures the essence of the change in working conditions	Without considering the coupling effects of multiple condition variables	A novel method for conditional modes, which facilitates the analysis and extraction of key information within different modes and significantly improves the accuracy of the model [106]

series, which models the observed signal as a linear combination of stationary sources $\mathbf{s}_s\,(R\times 1)$ and nonstationary sources $\mathbf{s}_n\,((J-R)\times 1)$,

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s} = [\mathbf{A}_s\,\mathbf{A}_n]\begin{bmatrix}\mathbf{s}_s\\ \mathbf{s}_n\end{bmatrix} \tag{5}$$

where, $\mathbf{A}\,(J\times J)$ is a time-invariant invertible mixing matrix. Note that the stationary and nonstationary sources are not assumed to be independent.

The aim of SSA is to estimate the inverse of mixing matrix. There are two main algorithms to find the projection matrices. The initial version of SSA extracts the stationary features with the help of the Kullback–Leibler (KL) divergence, thus being referred to as KL-SSA algorithm [123]. In order to reduce the computational cost, the analytic SSA (ASSA) algorithm [124] was developed which transforms the optimization problem of SSA into a generalized eigenvalue problem which can be solve conveniently and efficiently.

In recent years, CA and SSA has received increasing attentions and several applications in industrial field have been reported [84,94,95,125–131]. Different from classical machine learning models, the features extracted in CA are termed as equilibrium errors and can reveal the long-term equilibrium relation. They are assumed to be stationary and can be sequentially ordered according to their stationarity levels that are statistically measurable. Zhao et al. [94] proposed the use of the cointegration analysis (CA) method to estimate the equilibrium errors from the nonstationary multivariate time series for process monitoring. If the cointegration relationship between the variables is broken, that is, the residual sequence after the linear combination is no longer stationary, it deemed that there may be some failure in the system. Sun et al. [125] proposed the concept of sparsity of fault variables for nonstationary processes, which established a sparse reconstruction strategy based on cointegration analysis to automatically and real-time isolate multiple faulty variables. Subsequently, cointegration analysis was further refined to handle other properties that accompany nonstationary processes [84,95,126–128], such as large-scale properties [84], dynamics [95,126], etc. Unlike traditional CA tests, SSA imposes no restriction on integration order of the observed nonstationary variables and the estimated stationary components reflect constant relationships between process variables, which thus can be utilized for reliable process monitoring [129]. An exponential version of SSA (ESSA) method [130] is also developed for monitoring, which solves the singularity issue when solving the generalized eigenvalue problem of ASSA algorithm since the process variables are commonly strongly correlated. Further, it is revealed that the long-term constant relation does not hold forever, that is, the cointegration relationship and stationary subspace model may also drift with time if the time is long enough. In this regard, Yu et al. [131] established a fast incremental learning strategy of cointegration relationship and Chen et al. [130] established the adaptive exponential version of SSA, which makes the predefined model have the ability to quickly adapt to new patterns.

4.3. Time-driven multi-mode analysis method

In recent years, many scholars have carried out research on process monitoring of multiple working conditions, and proposed a multi-mode strategy based on condition division [17,96–98, 100,132–136]. Multimode process monitoring strategy [96–98, 100,132–134] separates the wide-scale nonstationary processes into different steady modes and developed multiple models for different modes. Each model is deemed to represent a specific operation mode and explain the local process characteristics with a high resolution [132,133], which can effectively improve monitoring reliability. The key point is how to divide the whole process into different modes and online judge the mode affiliation of the new sample so that the proper mode model can be correctly adopted for monitoring. Clustering is a typical method that is used to identify the observations that belong to each operating mode. Some popular clustering algorithms [137–140] can be used for mode division, including K-means [137], KNN clustering [138, 139], Fuzzy c-Means [140], and so on. However, the distance between separate samples is used for similarity evaluation, which cannot comprehensively describe the underlying variable correlations. The quality of mode division may directly influence the model performance and thus influence the monitoring performance. Another common method of dividing the steady modes is the stability factor (SF) proposed by Dorr et al. [99], which is used to judge the stationarity of the measured variable, and judge whether the process data is in steady state operation. Zhao et al. [98,100] proposed a recognition for the relationship between the statistical characteristics of data and the internal operation mechanism of the process, and pointed out that the changes in process characteristics can be used to reveal the changes in the correlation of process variables, so that the operation states can be divided into different modes. In this regard, they established a time-driven multi-mode division method which can separate the nonstationary batch process into different modes along time direction. In this way, the variable correlations stay similar with the same mode and behave significantly different for different modes. Assuming each mode follows Gaussian distribution, the Gaussian mixture model clustering method is also used for the identification and judgment of working conditions [101,102]. However, the above methods are mainly aimed at monitoring under different steady-state working conditions, and do not consider the changes and switching between steady-state working conditions [103–105]. In this regard, Zhao et al. [103] established a soft transition PCA model (STMPCA) method, which overcomes the problems of hard division and clustering errors in the establishment of multiple local models. For the transition region, the algorithm uses the 0–1 fuzzy membership degree as the weight coefficient of the two steady-states adjacent to the transition mode, which enhances the sensitivity of the transition monitoring model. Subsequently, Yao et al. [104] used different similarity indicators to analyze the similarity relationship between local models on this basis, and further developed the soft transition method.

For time-driven multi-mode analysis method, it is difficult to determine which mode the current sample belongs to and which model should be used for calculation of monitoring statistics for online application. In general, different models are tried in order to check which can best accommodate the current sample. This is not convenient, and may cause false mode identification results.

4.4. Condition-driven multi-mode analysis method

Previous multi-mode research methods are time-driven. This traditional time axis analysis method usually analyzes the change rule along time, and uses the clustering method to reveal the change of the process operating conditions. In terms of time dimension, the changes of operation modes are more complicated since unexpected frequent switching may happen randomly and at any time. This is termed temporal disorder problem which brings great difficulties to real-time identify the current condition label.

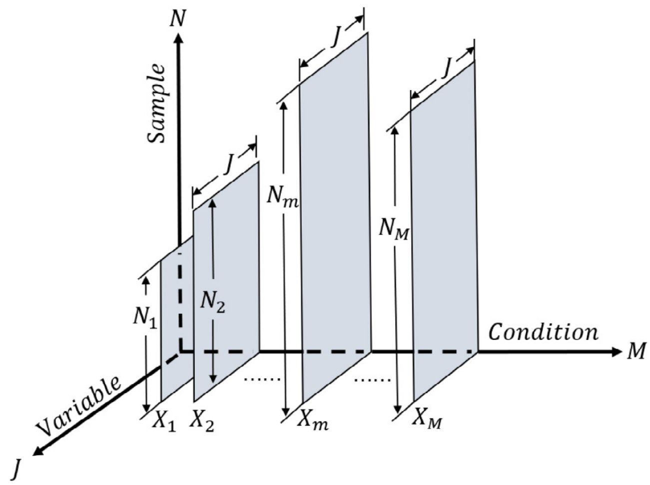


Fig. 5. Illustration of data reorganization from nonstationary data along time axis to different condition slices along condition axis (Each gray slice represents the data samples within the same condition interval, termed condition slice).

Considering the temporal disorder and repeatability of switching in operating conditions, Zhao et al. [106] proposed a condition-driven multi-mode analysis theory for the first time based on the following recognitions: (1) although the process characteristics change with time evolution which is infinite, the process in fact only changes within a certain finite range of operation conditions; (2) despite of changes of operation conditions over time, the underlying variable correlation will be largely similar within the same condition mode and different for different modes; (3) a process may be divided into several condition modes as indicated by changes of its inherent process correlations over conditions. Based on the above recognition, a new data analysis object is proposed to prepare the modeling data. The changes of operation conditions can point to the changes of process characteristics which can thus be used as an indicator to reorganize the data array. The data array reorganization strategy is presented in Fig. 5. The data showing nonstationary changes in time is transformed into a regular data analysis unit on the condition axis, namely the condition slice, through data reorganization. The process characteristics are approximately the same under the same condition slice; according to the change of conditions, the similarity of process characteristics of different condition slices is evaluated so that the similar condition slices can be clustered into one mode and thus the whole process can be divided into different condition modes. Then we can model each condition mode by some popular methods. The new concept of condition mode solves the temporal disorder of working condition switching and the difficulty of online judging the current mode. The idea of condition-driven multi-mode analysis lays the foundation for subsequent nonstationary process monitoring and opens up a new research direction. Based on such a condition-driven idea, a series of work are reported for nonstationary process monitoring, including condition-driven soft transition modeling method [141] and condition-driven regression method for power forecasting [142]. Subsequent issues include the division of condition modes under the coupling influence of multiple condition indicators, and how to better model conditional modes.

Here, we compare four types of nonstationary monitoring methods, from nonstationary time series analysis method, to long-term constant relation analysis method, time-driven multi-mode analysis, and the newly emerging condition-driven multi-modal analysis as summarized in Table 1. Nonstationary time series analysis method and long-term constant relation analysis method often has strict requirements on process data, so it is less suitable for processes with large-scale nonstationary operation and complex coupling of variables. The time-driven analysis method aims to capture the changes of the process along the time axis and then divide the nonstationary process into different operating modes for analysis. For many nonstationary processes, the change of working conditions is quite complicated, and the disorder and repetition in time make the divided modes inaccurate and do not have clear physical meaning. Compared with the time-driven analysis method, the condition-driven concept transforms the data with nonstationary changes in time into regular analysis units along the condition axis, which lays the foundation for the subsequent work condition identification research. The condition-driven idea is a promising research direction which is expected to be widely used in combination with previous modeling methods.

4.5. Nonstationary monitoring method for other typical problems

For nonstationary industrial processes, in addition to the most significant nonstationary characteristics, they also have operating characteristics similar to other industrial production processes. There have been a lot of research results on such common problems. Although many methods may not be directly used in nonstationary processes, these previous research methods are expected to be improved and then applied to nonstationary process monitoring to achieve effective identification of working conditions. The following is a description of the common problems identified from nonstationary industrial processes.

4.5.1. Nonlinear issue

Nonlinearity [143] is an important characteristic of industrial processes, and most of the complex industrial process variables have nonlinear relationships. For a nonstationary process, due to the change of operating conditions, its nonlinearity will be more significant from a global perspective. For nonlinear problem, people often do not specifically consider the difference between stationary and nonstationary processes, and are only limited to the expression of nonlinear relationships based on a large amount of training data. Therefore, here we will review previous work on nonlinear problems.

In the past few decades, various nonlinear methods [56,143–148] have emerged to address the shortcomings of linear methods. The first proposed method for training nonlinear models was a neural network-based approach [143,144]. For example, Kramer et al. [143] proposed the use of auto-associative neural networks to extract nonlinear principal component components of data. Considering that the backpropagation performance of auto-associative neural networks generally decreases with the increase of the number of hidden layers, Tan and Mavrovouniotis [144] proposed a three-layer input training neural network, which overcomes this limitation and makes the neural network easier to train. Dong and McAvoy [76] combined principal component curves and neural networks to solve nonlinear problems. These traditional neural network-based methods require heavy offline model training burden and some smart optimization methods to train the parameters. Due to the poor computer performance, small amount of data and the algorithm limitation at that time, the method based on neural network was not widely used and gradually declined. Subsequently, kernel-based methods have been shown to be effective in solving nonlinear problems, and thus have been rapidly developed [56,146–148]. The main principle is to use the kernel trick to map the data from the low-dimensional input space to the high-dimensional feature space, and then perform the corresponding linear calculation, which has high computational efficiency. Based on kernel technique, traditional machine learning methods can be readily extended to establish their corresponding kernel versions. Commonly used kernel methods include kernel principal component analysis (KPCA) [146], kernel partial least squares (KPLS) [147], kernel independent principal component analysis (KICA) [148, 149], etc. Kernel methods are highly dependent on the selection of kernel functions and related parameters, but such issues are less discussed in the existing literature. In recent years, with the continuous development of AI algorithms and the enhancement of computing power, many methods based on deep neural networks have also been applied to the field of nonlinear process monitoring [44,150,151]. In particular, the auto encoder (AE) [44] with nonlinear dimensionality reduction function has been widely used in the field of fault detection. Yu et al. [44] first applied the AE to industrial processes and considered the denoising function, which converted high-dimensional data into low-level features by training a multi-layer neural network and isolated the key variables that cause faults by combining denoising auto-encoder (DAE) and Elastic Net (EN). Chen et al. [150] proposed a condition-driven soft transition representation method for recognizing and monitoring the steady and transition sub-modes of nonstationary processes, where a conditional discriminative autoencoder (CDAE) network and a transition sub-mode evaluator are designed to describe the steady and transition characteristics, respectively.

However, the work mentioned above all use a single nonlinear analysis method, that is, if most of the process variables are judged to be nonlinear, the nonlinear method is used. In fact, process data are often collected from different devices or components. The internal reaction mechanisms of these devices are different, and the correlations between devices are also extremely complex. As a result, the variable correlations often do not obey a simple linear relationship or a pure non-linear relationship. Instead, they show mixed variable correlations, covering both linear and nonlinear ones. To this end, Li and Zhao et al. [152] proposed a linear evaluation method, which realized the subgroup division by identifying the linear variable relationships, and distinguished linear and nonlinear variables so that they can be modeled differently for monitoring. For the actual nonstationary industrial process, in particular the large-scale process, it is common that both linear and nonlinear relationships exist. The key is how to properly evaluate the variable correlations and thus divide the large-scale process variables into different parts for separate monitoring.

4.5.2. Dynamic issue

Dynamic characteristics refer to the time-related characteristics of industrial process data [18], that is, time-series correlation. Affected by system coupling and complex closed-loop feedback systems, nonstationary process data are often strongly auto-correlated or dynamically cross-correlated, showing obvious dynamic characteristics. Specifically, $\mathbf{x}(t)$ denotes the variable values at the current time t, which will be affected by the values of the variables in the past period $\mathbf{x}(t-1) \sim \mathbf{x}(t-d)$ and meanwhile will have an impact on the values of the variables for the future $\mathbf{x}(t+1) \sim \mathbf{x}(t+d)$ period . Here, the size of the time delay parameter d is determined by the nature of the process. Among them, the time series correlation consists of two parts: the auto-correlation of the variables, i.e., the correlation between $x_i(t)$ and $x_i(t+k), k \in [-d, d], k \neq 0$, and cross-correlation between variables, i.e., the correlations between $x_i(t)$ and $x_j(t+k), k \in [-d, d], i \neq j$.

Table 2
A brief comparison of the typical dynamic analysis methods.

Algorithm		Parameter	Main idea	Separation of dynamic and static information
Dynamic extension	DPCA [154]	The number of features and time lag	Capture as much variations as possible	No
	DFA [155]	The number of features and time lag	Separate the representation for dynamic variations from white noise	Yes
Dynamic feature extraction	DiPCA [156]	The number of features and time lag	Maximize the inner autocovariance of features	Yes
	SFA [157]	The number of features	Learn slowly varying feature from data	Yes
	Second-order ICA [158]	The number of features and time lag	Retrieve mutually temporal uncorrelated features	Yes
State-space	CVA [159]	The number of features, past and future time lags	Maximize the correlation between the future and past data	Yes
	LDS [160]	The number of features	Maximize the conditional expectation of log-likelihood	No

At present, the dynamic analysis mainly considers how to extract the time-series-related correlations contained in the process measurement data. Zheng et al. [153] provides a timely retrospective study of typical methods in dynamic process monitoring with comprehensive comparison. The dynamic methods can be categorized into three groups, including dynamic extension method, dynamic feature extraction method, and state-space method. As shown in Table 2, it compares different dynamic modeling methods [154–160] from multiple aspects, including parameter, main ideas, and the separation of dynamic and static information. In these methods, "dynamic information" often refer to "strong temporal correlation" or "strong predictability", while the left that does not have temporal correlation, for example, white noise, is considered to be "static information". In fact, for dynamic process monitoring, it is necessary to make full use of both information to indicate the change of the process operating condition. Shang et al. [71] and Zhao et al. [95] proposed the idea of simultaneous dynamic and static monitoring to distinguish different process changes in response to various disturbances, covering both position and velocity, which is different from the traditional monitoring method only focusing on the position change. Zhao et al. [106] analyzed the static and dynamic changes of the industrial process under different operating conditions. On the one hand, the process may be under different operating conditions, but show the same process dynamics. On the other hand, even under the same operating condition, the process may show different dynamics in the time direction. Since the operating conditions of a nonstationary process often change according to production needs, the monitoring of nonstationary processes needs to take into account the dynamic change, and carry out refined analysis and monitoring. The most challenge is how to separate the dynamic and static information, which are discussed as below for the typical methods shown in Table 2.

First, for dynamic extension of original machine learning methods [154,161], such as dynamic PCA (DPCA) [154], and dynamic partial least squares (DPLS) [161], they use historical samples to expand the process data matrix, and then directly apply the original analysis algorithm on the expanded data matrix, which are simple to operate and easy to implement, and have been widely used. The data at time t after this expansion operation can be described as

$$\hat{\mathbf{x}}(t,s) = [\mathbf{x}^{\mathrm{T}}(t-s), \mathbf{x}^{\mathrm{T}}(t-s+1), \ldots, \mathbf{x}^{\mathrm{T}}(t)]^{\mathrm{T}} \tag{6}$$

where s represents the step size of the timing expansion.

But these methods perform feature extraction with different objective functions from temporal correlation and cannot guarantee to achieve effective characterization of process dynamics. Moreover, the dynamic expansion of their dependencies may result in a substantial increase in the dimension of variables, making it impossible to achieve optimal dimensionality reduction analysis of the data.

Further, some scholars have proposed direct dynamic feature extraction methods [51,69,70,157,162–164], such as dynamic-inner principal component analysis (DiPCA) [162], slow feature analysis (SFA) [51,69,70,157,164], etc. These methods are all to find a projection direction, so that the features obtained after projection have a higher correlation with the data in the future or in the past.

DiPCA proposed by Dong et al. [162] in 2018 is designed to maximize the inner correlations of the available feature between the current value and its past period, i.e., the multi-order autocorrelation, where the period is defined by time lag. The objective of DiPCA can be written as

$$\max_{\mathbf{w},\boldsymbol{\beta}} \frac{1}{N}\sum_{k=s+1}^{s+N} \mathbf{w}^{\mathrm{T}}\mathbf{x}(k)[\mathbf{x}^{\mathrm{T}}(k-1), \mathbf{x}^{\mathrm{T}}(k-2), \ldots, \mathbf{x}^{\mathrm{T}}(k-s)](\boldsymbol{\beta}\otimes\mathbf{w}),$$
$$\text{s.t. } \|\mathbf{w}\| = 1, \ \|\boldsymbol{\beta}\| = 1 \tag{7}$$

where $\mathbf{w}$ denotes the weight vector from the original variables to the latent features, $\boldsymbol{\beta}$ portrays the dynamic properties of samples at different moments.

In comparison, the goal of slow feature analysis (SFA) [157] is to find a set of projection directions such that the output signal changes as slowly as possible. Given a multidimensional input signal $\mathbf{x}(t) = [x_1(t), x_2(t), \ldots, x_J(t)]^{\mathrm{T}}$, where J is the number of variables. The signals are normalized to a zero mean and a one unit variance to make all the features on the same scale and maintain the relative distance among the different samples. The SFA aims to find a set of projection functions g_j that generates a series of slow features $\mathbf{s}(t) = [s_1(t), s_2(t), \ldots, s_J(t)]^{\mathrm{T}}$, where $j \in [1, 2, \ldots, J]$. The objective function of the SFA is as follows,

$$\begin{aligned} & min \Delta s_j = \langle \dot{s}_j^2 \rangle \\ & \text{s.t. } \langle s_j \rangle = 0(\text{zero mean}) \\ & \langle s_j^2 \rangle = 1(\text{unit variance}) \\ & \forall \ell \neq j, \langle s_\ell s_j \rangle = 0(\text{decorrelation and order}) \end{aligned} \tag{8}$$

where $\langle\cdot\rangle$ indicates time averaging $\langle \dot{s}_j^2 \rangle = \frac{1}{n-1}\sum_{i=2}^{n} \dot{s}_{i,j}^2$, n is the number of samples, and $\dot{s}_j$ represents the first-order derivative of s_j.

In fact, it can be found by derivation that the objective function of SFA minimizes the change speed of the feature and converts it to maximize the first-order autocorrelation of the feature [165]. Generally speaking, the slowest-changing ones among the features can best reflect the essential characteristics of the data, while the fast-changing features can be considered as some noise. The number of slowest features retained is determined according to the actual requirements.

State-space models [159] are the third way to explore dynamic problem. For the above-mentioned dynamic analysis methods represented by DPCA and DiPCA, the main two important operations are to reduce the dimensionality first, and then extract the time series relationship. In comparison, the state space model directly expresses these two operations, and can describe the auto-correlation and cross-correlation of process data simultaneously. In the case of dynamic process modeling, the method of subspace identification is often used to analyze the state space equation. The commonly used method is canonical variate analysis (CVA) [49,159,166,167]. The CVA-based method is simple to solve and can comprehensively analyze the time series dependence of process variables. However, since CVA involves the inversion of the process data matrix in the solution process, the solution will be unstable when the data has collinearity problems, thus affecting the ability of the proposed features to represent the dynamics.

4.5.3. Data insufficiency issue

With the rapid development of deep learning in recent years, deep learning methods represented by autoencoders, deep convolutional networks, and deep belief networks can automatically extract useful deep features from high-dimensional and redundant historical process operation dataset. Although the deep learning methods have higher accuracy than traditional process monitoring methods, they all require a large number of samples to train the network, and the accuracy of these methods will be greatly reduced or even be unsatisfying in the face of small sample data sets. In practical industrial scenarios, the concerned fault cases often have no or very little available data stored. In order to overcome the difficulty of collecting samples for some faults, scholars begin to adopt the method of transfer learning [168–173]. Given a source domain $\mathsf{D}_S = \{(\mathbf{x}_i, y_i)\}_{i=1}^{n_S}$ and learning task T_S, as well as a target domain $\mathsf{D}_T = \{(\mathbf{x}_i, y_i)\}_{i=1}^{n_T}$ and learning task T_T, transfer learning aims to improve the performance of the target predictive function $f_T(\cdot)$ in D_T using the knowledge in D_S and T_S, where $\mathsf{D}_S \neq \mathsf{D}_T$ and/or $\mathsf{T}_S \neq \mathsf{T}_T$. In general, there are some easy-to-obtain faults or historical faults in source domain while there are faults that are difficult or expensive to collect in target domain. The amount of data in the source domain is much larger than that in the target domain, i.e., $n_S \gg n_T$. Lu et al. [168] integrated deep neural networks with maximum average error terms to propose a deep transfer learning method for fault diagnosis that does not require any target fault samples to obtain high-accuracy performance. Wen et al. [169] utilized sparse autoencoders for deep domain adaptation of source and target faults. Chai et al. [170] proposed a fine-grained adversarial network method for cross-domain industrial fault diagnosis based on the idea of adversarial learning. This method performs deep domain adaptation from both the domain level and the fault class level. Compared with the previous work, it can align the conditional distribution of the source domain and the target domain in a finer-grained manner, thereby ensuring the effectiveness of cross-domain diagnosis. In addition, in order to improve the accuracy of the model and ensure that the model can be effectively updated in the incremental data environment, Chai et al. [174] proposed an oblique random forest algorithm with double incremental learning ability, so that the model will be able to update effectively when the samples of existing categories or new categories arrive. Although the above mentioned work does not require the specific number of fault samples in the target domain, deep transfer learning actually solves the domain drift problem, i.e., between the source domain and the target domain, but cannot solve the zero sample problem in the target domain, that is, zero-shot problem.

Zero-shot fault diagnosis [175] is an extremely challenging research task that considers modeling when no target fault samples are available for training. This situation is common in the industrial field, but there is no related research before, which limits the application of traditional data-driven methods in practical processes. Feng and Zhao et al. [175] introduced the concept of zero-shot learning in machine learning field into the industrial field for the first time, and solved the task of zero-shot fault diagnosis by proposing an attribute transfer method based on fault description. As shown in Fig. 6, the traditional fault diagnosis approaches are compared with zero-shot fault diagnosis approaches. The traditional fault diagnosis approaches use data $\boldsymbol{X}_S$ and labels $\boldsymbol{Y}_S$ from seen categories to train the model f. The aim of the model is to minimize the classification loss L,

$$\min L(\boldsymbol{Y}_S, \hat{\boldsymbol{Y}}_S), \hat{\boldsymbol{Y}}_S = f(\boldsymbol{X}_S) \tag{9}$$

However, the traditional diagnosis model cannot be applied to unseen fault data. For zero-sample fault diagnosis, the fault attribute description is considered which is significantly different from that of traditional diagnosis model. It uses the data $\boldsymbol{X}_S$ and attribute descriptions $\boldsymbol{A}_S$ to train transferable attribute predictors g, and transfers the attribute predictors directly to the target fault $\boldsymbol{X}_U$ to obtain the predicted attributes, and then obtains the corresponding category labels $\hat{\boldsymbol{Y}}_U$ through nearest neighbor search in attribute descriptions $\boldsymbol{A}_U$. The process can be formulated as below,

$$\min L(\boldsymbol{Y}_U, \hat{\boldsymbol{Y}}_U), \boldsymbol{Y}_U = f(\boldsymbol{X}_U | \boldsymbol{X}_S, \boldsymbol{Y}_S, \boldsymbol{Z}_S, \boldsymbol{A}) \tag{10}$$

where $\boldsymbol{A} = [\boldsymbol{A}_S, \boldsymbol{A}_U]$ is the attribute description matrix, $\boldsymbol{Z}_S$ is the predicted attributes of seen fault data by $\boldsymbol{Z}_S = g(\boldsymbol{X}_S)$, and the function f includes the training stage of attribute predictors g, the attribute prediction step using predictors g and the nearest neighbor search step.

The method learns to use human-defined fault descriptions rather than collected fault samples to determine fault categories. The defined fault description consists of some attributes of the fault, including the faulty device and location, the effect of the fault, and even the cause of the fault. In fact, the fault description is some form of expert knowledge. For the target fault, its related attributes (or knowledge) can be pre-learned and transferred from the descriptions of other faults in the same industrial system. Then, the target fault can be diagnosed based on the predefined fault description without any additional data training. For the zero-sample fault diagnosis problem, this work theoretically analyzes and explains the effectiveness and feasibility of fault description-based methods. This research has aroused widespread attention to the zero-shot learning method in the field of industrial process monitoring, and improved methods [176–178] have been developed subsequently. Considering that the zero-shot problem caused by various problems is very common in the industrial process, the research on the problem of zero-shot fault diagnosis has very strong practical significance. However, there are still many details to be considered about how to perform zero-shot fault diagnosis in nonstationary scenarios. Fault description [175] is a kind of knowledge in essence, and the combination of knowledge and data will be the key research idea and feasible direction for zero-shot fault diagnosis in the future.

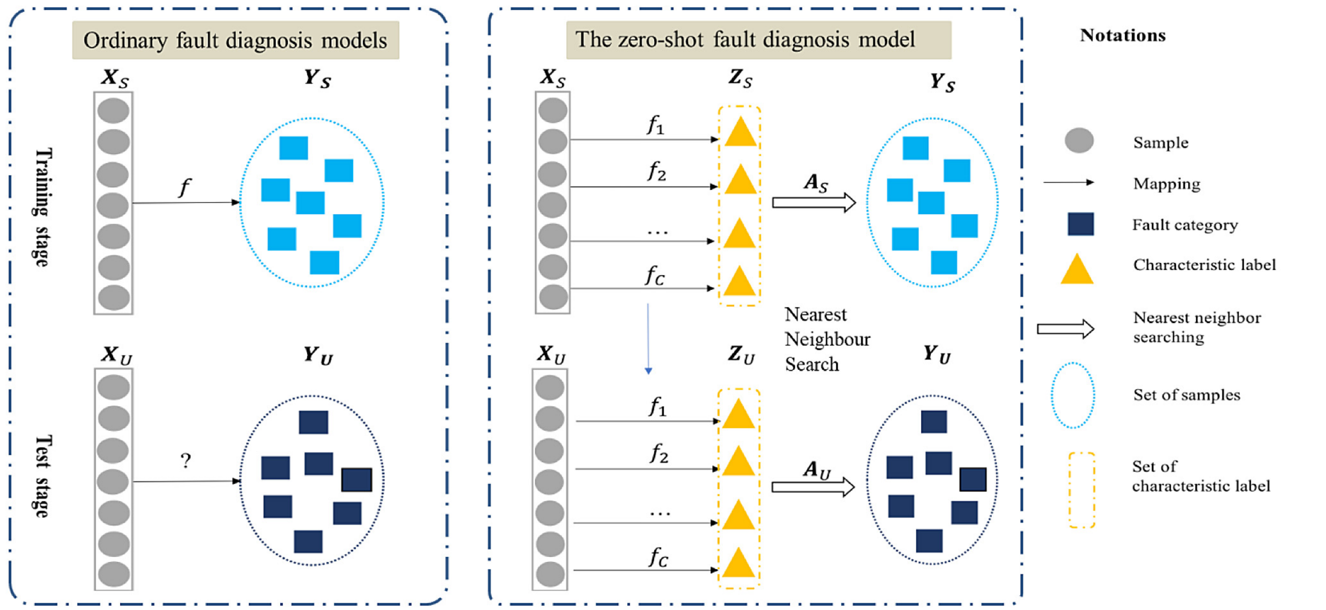


Fig. 6. Schematic comparison of traditional fault diagnosis models and zero-shot fault diagnosis models based on semantic embedding.

4.6. Summary

In addition to the above-mentioned representative process characteristics, industrial system also has strong coupling of process characteristics. The current monitoring technology is mainly oriented to the analysis of single process characteristics such as nonstationary, nonlinear, and dynamic characteristics, and lacks consideration of hybrid characteristics. In practical industrial system, different types of complex characteristics often coexist. How to break through the coupling of complex characteristics and conduct monitoring of industrial system under complex conditions has important research value. Fig. 7 summarizes the time development trend of monitoring methods under the complex characteristics of industrial systems. From the 1990s to the present, it has experienced 30 years of development, covering signal analysis methods, multivariate statistical analysis methods, and emerging methods of machine learning and artificial intelligence in recent years. For the current research situation, the statistics-based machine learning method occupies a dominant position in the field of industrial system monitoring due to its advantages of convenient calculation and clear interpretation. With the rapid development of artificial intelligence technology, methods based on NN have gradually emerged in some specific industrial fields since 2000. The above work has laid a good foundation for the development and deepening of subsequent research.

5. Outlook and prospects

In recent years, the research on working condition identification methods has become a guarantee for the safe and reliable operation of industrial processes, and has become an important symbol of the development level of smart factories. It should be pointed out that previous work in fact is open-loop FDD, which means the FDD results are not used for feedback control to regulate the system. Only by watching rather than intervening in the regulation, the fault cannot be automatically eliminated and most FDD methods will require manual intervention once a fault has been diagnosed. The end goal of process monitoring is process recovery, where the process returns to its normal operation. Therefore, a very promising line is the design of closed-loop FDD as shown in Fig. 1, that is, how to prevent the occurrence of faults or automatically eliminate the influence of the fault, and promote the system to operate in an optimal state. On the one hand, the research area of process monitoring is still very active as researchers aim to tackle some of the drawbacks of previous methods using new techniques. On the other hand, it involves the fourth part of process monitoring loop, i.e., process recovery, requiring extra functions in comparison with previous work, indicating the direction that needs to be focused on in the future.

5.1. Data and knowledge fusion for root cause tracing

After a fault is detected, how to further determine the fault propagation path and trace the root fault variables is also an important step in the fault diagnosis of industrial processes, which helps operators to quickly locate the key equipment and parts of the fault. Although the data-driven fault root cause tracing methods have been widely studied in recent decades, it still has certain limitations. Problems such as pseudo-regression are very common for nonstationary processes. Therefore, the true causal relationship between variables may be masked or distorted, which makes it difficult for purely data-driven methods to accurately trace the propagation path of faults, and thus cannot guarantee the accuracy of locating the root-causing fault variables. In addition, data-driven research has a low usage rate of knowledge and experience resources in fault diagnosis. Different from simply using data-driven methods, one of the current research hotspots is to combine expert knowledge with data analysis to build an intelligent fault diagnosis method. With the development of AI technology, traditional knowledge-driven methods represented by fuzzy logic are gradually replaced by knowledge graph technology. The essence of knowledge graph technology [179,180] is to represent knowledge through visualization methods and to explore the relationship between knowledge, which can reveal the dynamic knowledge development law and realize knowledge sharing. A knowledge graph is a multi-relational graph composed of entities (nodes) and relations (various types of edges), where each edge is represented as a triple of the form (head entity, relation, tail entity) [180]. The triple is also called a fact, indicating that two nodes are connected by a specific relation. Formally, given a knowledge graph consisting of n entities and m relations.

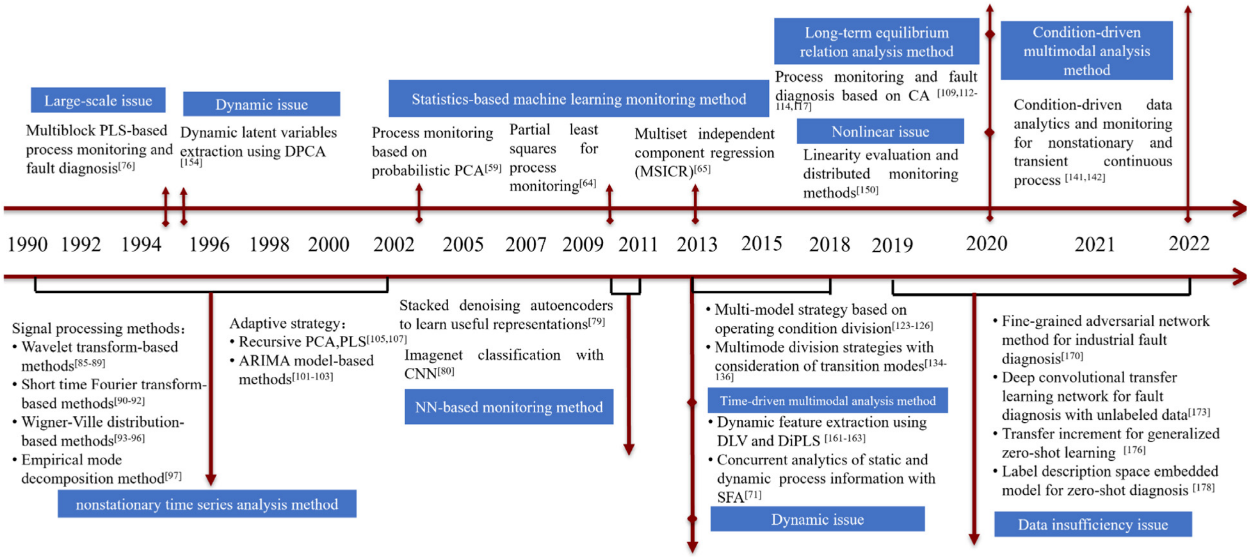


Fig. 7. Schematic diagram of the development trend of industrial process monitoring methods.

Facts observed are stored as a collection of triples $D^+ = \{(h, r, t)\}$, for example (Alfred Hitchcock, Director Of, Psycho). Each triple is composed of a head entity $h \in E$, a tail entity $t \in E$, and a relation between them $r \in R$, where E denotes the set of entities, and R the set of relations. TransE [180] is the most representative knowledge graph model, which assumes the embedded entities h and t can be connected by r with low error, i.e., $h + r \approx t$ when (h, r, t) holds. The scoring function is then defined as the (negative) distance between $h + r$ and t.

The knowledge graph can clearly express the relationship between different faults and fault causes, realize dynamic retrieval of fault information, and effectively trace the causes of process operation faults. The research of industrial fault diagnosis based on knowledge graph is constantly being explored [181,182], trying to build the expert knowledge in the professional field of industrial equipment maintenance into a knowledge graph. It uses speech recognition technology and natural language processing technology to analyze the user's query intention, and queries the knowledge graph to give relevant troubleshooting advices. The main problem is how to collect sufficient expert knowledge and how to build a complete knowledge map. A feasible direction is to use the cloud–edge collaboration framework to realize cross-device and cross-factory knowledge sharing based on similar operating fault data and expert knowledge stored in the cloud. Further, automatic semantic description can be a potential research line to build knowledge base.

5.2. Model generalization and transfer under cloud–edge collaboration

With the development of the industrial internet, the IoTs and the continuous increase of networked devices, the generalization and transfer of data-driven nonstationary and complex industrial process monitoring models have stronger research support and new research focus. The cloud–edge collaboration architecture has been successfully applied in industrial research [183–185]. As shown in Fig. 8, the industrial cloud platform collects and manages data from all edges, trains and optimizes the model, pays attention to the generalization performance of the model, and sends the model to the edge nodes. It should be noted that there are multiple sources of data from each side, due to different conditions, different equipment, different sensors, etc., so the sampling frequency and storage form will also vary. For example, in addition to low-frequency process data such as temperature and pressure, rotating equipment also generates a large number of high-frequency vibration signals, as well as a large amount of image data collected by cameras, thermal imagers, etc. How to reasonably integrate a large number of multi-source heterogeneous data in the cloud for modeling is one of the problems that need to be studied for nonstationary industrial process monitoring in the future.

Under the framework of cloud–edge collaboration, the edge deploys the model, makes it to adapt to the current working condition through model transfer, and realizes distributed intelligence. It needs further research for the generalization and transfer of process monitoring models from factory level, production line level to equipment level. On the one hand, complex industrial processes may generate new operating conditions with factors such as factory-level production plan adjustments and changes in the external environment, but some production lines in other factories may already have similar operating conditions, and the operating conditions data between different factories can complement each other and perform model transfer to solve the model mismatch problem caused by new operating conditions. On the other hand, the process data distribution of the same equipment will change due to the increase of service time and the change of operating conditions. The history model cannot realize accurate working condition identification for the new data distribution, but similar equipment at other edges may provide the data and existing models as reference for the current process monitoring modeling and model transfer. Therefore, it is significant to probe into the generalization and transfer of the process monitoring model based on the industrial cloud. Besides, privacy protection is also one of the future research points. There have been federated learning relevant research [186] for privacy protection study, which, however, is in general carried out for the financial industry, medical industry, e-commerce industry, etc. It distributes model training without sharing data at the edge. The industrial cloud can be jointly built by different groups in the complex manufacturing industry and also has the same need for data privacy protection. However, the generalization and transfer of the existing data-driven monitoring model requires the acquisition of both local data and data from other sources. Thus, it deserves further study for the generalization and transfer methods without data sharing in industrial process monitoring field.

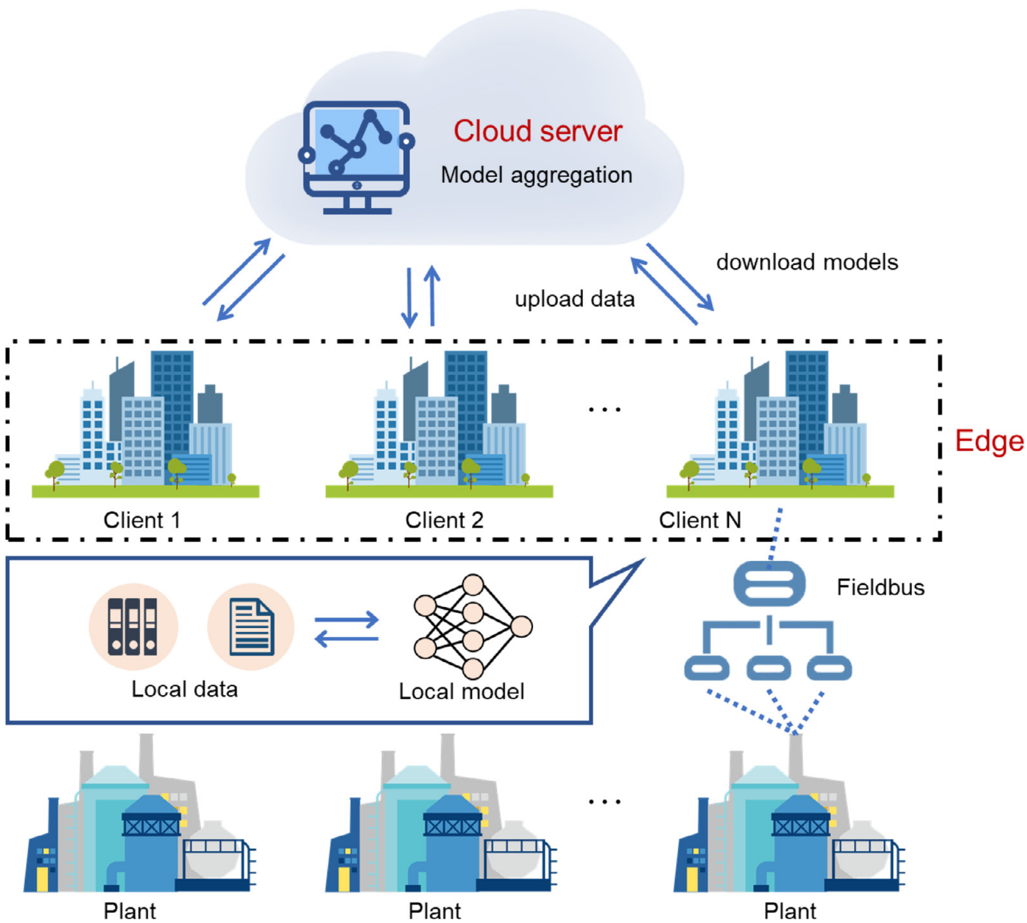


Fig. 8. Schematic diagram of cloud–edge collaboration framework for industrial scenarios.

5.3. Process recovery for closed-loop FDD

The nonstationary process monitoring methods described above are limited to identifying normal or abnormal operation conditions and diagnosing the cause of the fault, but this is not the ultimate goal. The ultimate goal is to prevent the occurrence of faults or automatically eliminate the influence of the fault, and promote the system to operate in an optimal state, i.e., process recovery. It is termed closed-loop FDD in the present work. As shown in Fig. 1, engineers often control some equipment based on their own experience through relevant detection indicators and monitoring results of operating conditions. In practice, due to the difference of experience and knowledge, human intervention and adjustment are subject and different, which cannot guarantee the optimal treatment of faults. Moreover, the industrial process conditions are complex with multiple scales, strong nonlinearity, strong coupling and other issues. It is impossible to accurately, timely and frequently regulate each equipment object. Improper handling may cause serious catastrophic consequences or passive shutdown accidents. In addition, human intervention is only limited to eliminating faults, but it does not consider whether the operating state of the industrial system is in the optimal range. The original process monitoring is still a relatively rough judgment. Even in normal state, it is often not in the optimal operating range which may be affected by external disturbance factors such as different production settings, changes in production plans, fluctuations in raw material quality, and changes in ambient temperature and humidity, resulting in poor performance. Therefore, for the research on recovery of nonstationary industrial processes, indicators such as unit energy consumption, product quality, and operating costs should also be considered to further analyze the pros and cons of the current normal operating state so as to guide the adjustment of operating conditions and obtain higher benefits.

At present, the research on operation self-healing and self-optimization of industrial processes is still in its infancy, and there are few related research work. Although some scholars have made some attempts on some simple industrial objects [187,188], they have not considered the frequent switching of operating conditions of industrial processes and the nonstationary nature, which also brings problems and challenges to process recovery research. Digital twin technology provides a new means for realizing self-healing regulation of industrial production operating conditions. A digital twin [6,189,190] is a virtual entity that digitally creates a physical entity. With the help of historical data, real-time data, and algorithm models, it is a technical means to simulate, verify, predict, and control the entire life cycle process of a physical entity. It is the focus of follow-up research to study the digital twin technology for specific industrial scenarios, and to verify, guide and feedback the implementation effect of self-healing regulation through the interactive mapping between the digital model constructed in the virtual space and the physical entity.

6. Conclusion

The scope of this paper is to provide an overview of existing nonstationary process monitoring methods and prospects the future research work. Since no review literature on nonstationary monitoring has not been introduced in the monitoring field, this article opens up an opportunity to improve major theoretical advances in using popular data-driven methods on nonstationary monitoring problem. By summarizing the complex characteristics of its operation, we reveal the problems that need to be solved in process monitoring. Progress in nonstationary process monitoring systems would benefit from the identification of specific problems to focus on the most promising directions in algorithm development. By reviewing 200 data-driven methods in the past 30 years and summarizing the representative methods in each development stage, it highlights their impacts and scopes of application with analysis of both advantages and disadvantages. This paper also may be used a guide for statistical process monitoring practitioners who want to introduce data-driven methods in their work. In this regard, this paper allows to easily search for a particular process monitoring topic in order to identify the nonstationary methods suitable of being used within it.

Concerning potential future research, it pointed out that a very promising line is the design of closed-loop FDD, that is, how to prevent the occurrence of faults or automatically eliminate the influence of the fault, and promote the system to operate in an optimal state. The authors encourage practitioners to follow this research line, since it will allow users to construct very flexible and problem-dependent nonstationary analysis methods.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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