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# A FAULT DETECTION METHOD BASED ON STACKING THE SAE–SRBM FOR NONSTATIONARY AND STATIONARY HYBRID PROCESSES

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This paper proposes a fault detection method by extracting nonlinear features for nonstationary and stationary hybrid industrial processes. The method is mainly built on the basis of a sparse auto-encoder and a sparse restricted Boltzmann machine (SAE-SRBM), so as to take advantages of their adaptive extraction and fusion on strong nonlinear symptoms. In the present work, SAEs are employed to reconstruct inputs and accomplish feature extraction by unsupervised mode, and their outputs present a knotty problem of an unknown probability distribution. In order to solve it, SRBMs are naturally used to fuse these unknown probability distribution features by transforming them into energy characteristics. The contribution of this method is the capability of further mining and learning of nonlinear features without considering the nonstationary problem. Also, this paper introduces a method of constructing labeled and unlabeled training samples while maintaining time series features. Unlabeled samples can be adopted to train the part for feature extraction and fusion, while labeled samples can be used to train the classification part. Finally, a simulation on the Tennessee Eastman process is carried out to demonstrate the effectiveness and excellent performance on fault detection for nonstationary and stationary hybrid industrial processes.

**Keywords:** fault detection, sparse auto-encoder, sparse restricted Boltzmann machine, hybrid industrial processes.

## 1. Introduction

Currently, complex and larger industrial systems are being extensively developed and integrated to satisfy the demands on quality and safety. Numerous industrial systems consider fault detection an extremely important issue to obtain high performance, and this can help their owners become or remain market leaders (Montmain *et al.*, 2015). As far as current research indicates, the fault in industrial system is regarded as some unexpected deviation in at least one feature or variable (Montmain *et al.*, 2015; Adil *et al.*, 2016). Fault detection is therefore designed to determine whether these faults happened, by monitoring the system operation status.

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Generally, traditional process monitoring systems are often constructed with three paradigms: model-based, knowledge-based and data-driven methods (Severson *et al.*, 2016). Because rich monitoring data extensively yield out, multivariate statistical process control (MSPC), belonging to data-driven methods, is gaining more and more attention of researchers around the world. However, one drawback of MSPC is always unavoidable, and it can be summarized as follows (Lin *et al.*, 2019a): the system always operates in a stationary condition, whose mean and covariance are time-invariant; process variables are independent of each other, i.e., there is no serial correlation between them. Obviously, this defect seriously masks its application and development in practical industrial systems. In fact, the operation condition of an industrial process is not constant, but switching frequently. Therefore, a practical industrial system shows extremely nonstationary characteristics not only due to the above reasons, but also due to the changes in marker demands, external disturbances, or equipment defects in sensors.

In practical industrial systems, fault symptoms are often overwhelmed by these nonstationary characteristics, resulting in the fact that the usage of the above MSPC-based techniques brings about a large number of false and missed alarms. In particular, due to the rapid development of distributed control systems (DCSs), precision instrumentation systems, and industrial Internet, three new changes have appeared in recent years: (i) in order to avoid safety accidents, more measurement points are installed for each device to monitor modern industrial systems; (ii) furthermore, the sampling frequency of monitoring data becomes higher and higher, so as to prevent any clues from being missed; (iii) from the beginning of service to the end of its life, data collection has been getting longer and longer, which gains a larger amount of monitoring data (Ren *et al.*, 2017).

The conventional methods become extensively difficult to build a monitoring system for practical industrial processes. The main reasons can be the problem of extracting and fusing high-dimensional nonlinear features of process monitoring variables in nonstationary and stationary hybrid industrial processes, which makes estimation of the probability distribution of fault symptoms difficult (Lin *et al.*, 2019b). Therefore, this paper proposed a fault detection method based on stacking the SAE-SRBM to meet formidable challenges of fault detection for industrial processes, and its contribution can be described as follows:

- A fault detection method is proposed by extracting nonlinear features for nonstationary and stationary hybrid industrial processes, which is very difficult for conventional methods to deal with.

- Input reconstruction and feature extraction are accomplished in an unsupervised manner by SAEs, and the attendant problem of the unknown probability distribution is solved by SRBMs via transforming them into energy characteristics. The unsupervised mode of combining SAEs and SRBMs takes full advantages of their adaptive extraction and fusion on strong nonlinear symptoms.

- A novel method is proposed to construct labeled and unlabeled training samples while maintaining the time series features, these labeled and unlabeled samples can be used to train the part for feature extraction and fusion as well as train the classification part, respectively.

The paper is organized as follows. Section 2 is focused mainly on motivation and concerns. Section 3 details the feature extraction and fault detection method, such as a framework, a sparse stacked auto-encoder and a restricted Boltzmann machine, etc. Section 4 reports the simulation results and discussion to prove the effectiveness of this method. Lastly, conclusions and future research works are presented.

## 2. Related work and motivation

The stationary process refers to the fact that the operation states cannot change with time, which is reflected by its monitoring variables. This means that the mean, the variance and the covariance of monitoring variables are not changed with time, and it provides the prerequisite of a constant probability distribution for numerous machine learning methods. However, most modern industrial systems do not satisfy this condition, and their operation processes are always mixed nonstationary and nonlinear, which always masks fault symptoms and makes fault detection difficult (Liu and Qin, 2016).

**2.1. Related work.** Independence and identical distributions of monitoring variables is a premise for machine learning to make data-driven fault diagnosis available, and this requires constant statistical characteristics of the monitoring variables in the time and frequency domain. In fact, most often studies on data-driven fault diagnosis describe the monitoring variables as weakly stationary, whose means, variances and covariances are slightly changing with time. The purpose of setting monitoring variables is to estimate the operation state of every subprocess, whose common trouble are the nonlinear and dynamic changes. These changes can be regarded as classical characteristics in modern industrial processes. A practical situation can be considered where the mean, variance and covariance of some variables are not changed with time. Industrial processes with these characteristics are as nonstationary and stationary hybrid processes.

For nonstationary industrial processes, the mainstream method is co-integration theory, which was proposed by Engle and Ganger (1987). The core idea of this method is reflected in the co-integration relationship between nonstationary variables, which is manifested in their random fluctuations around the common trend, and this common trend is independent of their nonstationarity. Chen *et al*. (2009) proposed an anomaly detection method based on co-integration theory, whose idea can be summarized as follows: when an abnormality exists in monitored processes, the system parameters and structures would change and affect the co-integration relationship between monitoring variables, i.e., the original common trend between various variables will also change.

Recently, some prospective research on system reliability and safety has attracted much attention of academic and industrial circles, since its fault symptoms may be hidden in nonstationary monitoring signals (Lin *et al.*, 2019b). For fault detection and diagnosis based on nonstationary and stationary monitoring signals for industrial processes, Lin *et al.* (2019a; 2019b) as well as Zhao and Huang (2018b; 2018a) introduced a revised common trend framework to estimate nonstationary and dynamic trends in complex industrial processes, and their framework mainly relies on the following ideas: the common stationary and nonstationary factors should be identified and separated; these factors should be modeled by multivariate time-series models; a compensation scheme should be incorporated to directly monitor these factors without being compromised by the forecast recovery effect.

Similarly, Zhao and Huang (2018b; 2018a) as well as Zhao and Sun (2019) also focus their recent studies on complex industrial processes with both stationary and nonstationary characteristics. They first proposed a novel full-condition monitoring strategy based on co-integration and process features analysis, and focused on two aspects: certain equilibrium relations extend beyond current time although the operation conditions may vary over time; certain dynamic relations may exist invariant under normal process operation despite different conditions. Furthermore, a triple subspace decomposition based on dissimilarity analysis was developed by them to detect incipient abnormal behaviors. Earlier they reported their study of closed-loop control, and proposed a dynamic distributed monitoring strategy to separate dynamic variations from steady states and to employ it to distinguish changes in normal operation conditions and real faults.

In addition, some other researchers leverage co-integration analysis to online isolation or diagnosis of faulty variables, such as a sparse reconstruction strategy to reduce the requirements on historical fault data (Sun *et al*., 2017), a meticulous model for feature extraction to assess the operation performance of nonstationary processes (Zou and Zhao, 2019). Li *et al*. (2014) adopted a nonstationary test to distinguish nonstationary series form stationary ones, and used co-integration analysis to construct monitoring indices by describing the stochastic common trends and equilibrium errors. Similar research also includes the time-varying auto-regressive (TVAR) model aiming to characterize nonstationary behaviors (Souza *et al*., 2019), dominant trend based logistic regression for monitoring nonstationary processes (Shang *et al*., 2017), a mathematical model for calculation of nonstationary hydraulic and separation processes in a gas centrifuge cascade for separation of multi-component isotope mixtures (Orlov *et al*., 2017).

In summary, the nonstationary characteristics of practical industrial processes are caused by numerous factors, such as equipment aging, unknown disturbances (Lin *et al*., 2019a; 2019b; Engle and Granger, 1987; Chen *et al.*, 2009; 2020a; 2020b; Zhao and Huang, 2018b; 2018a; Souza *et al.*, 2019; He *et al.*, 2015; Firouzi *et al.*, 2018). Previous studies pointed out that some monitoring variables have nonstationary characteristics, while others do not. All of these reasons make modern processes stationary and nonstationary hybrid. In the study of nonstationary process monitoring, co-integration analysis can be regarded as an effective method to extract correlations between nonstationary variables (Shang *et al*., 2017; Zou and Zhao, 2019; Orlov *et al*., 2017; Lin *et al*., 2017; Worden *et al*., 2016; Ma *et al*., 2018), i.e., fault detection for nonstationary and stationary hybrid industrial processes can be built on the common trend model.

**2.2. Motivation.** The common trend idea stimulates us to meet formidable challenges of fault diagnosis for nonlinear and nonstationary in practical processes, and it can be considered an equilibrium relationship formed by the interaction of many process monitoring variables. This relationships are often employed to achieve fault detection, e.g., using the auto-regressive moving average model (ARMA) or canonical correlation analysis (Chen *et al.*, 2020a; 2020b), etc. Fault monitoring signals, generated in practical industrial systems, tend to pose some new challenges, such as nonlinearity, dynamics, variability, and limited labels in nonstationary and stationary hybrid processes, which leads to the fact that the traditional, linear, and stationary common trend analysis methods are difficult to implement in fault detection (Zhirabok and Shumsky, 2018; Byrski *et al*., 2019). Therefore, considering the diversity of nonstationary and stationary industrial process faults and the fact that most of them are nonlinear or even strongly nonlinear, it is necessary to combine multiple variable analysis to explore relationships between many monitored variables, and then to describe the dynamic system behaviors (Worden *et al*., 2016; Ma *et al*., 2018; Zhang and Zhao, 2017; Zhang *et al*., 2018; Yan *et al*., 2016).

For the detection of nonlinear or even strongly nonlinear faults for nonstationary and stationary hybrid industrial processes, some researchers have studied this problem and achieved interesting results in some fields (Ma *et al.*, 2018; Zhang and Zhao, 2017; Zhang *et al.*, 2018; Yan *et al.*, 2016). Auto-encoders (SAE) and the restricted Boltzmann machine (RBM) can be considered typical methods, and can be used to realize a super-high-dimensional feature representation of input data by stacking multiple-layer auto-encoders and the layer-by-layer pre-training method. This method can be employed to construct nonlinear relationships between complex multiple dimensional monitoring variables and abnormal modes to describe strongly nonlinear behaviors of industrial processes (Pröll *et al.*, 2018; Zhang *et al.*, 2016).

The capability of SAE-based or RBM-based fault detection mainly relies on hierarchical features or representations of the observational data to find the internal structure exploring the essential relationships between different variables (Utkin *et al.*, 2016; Leng and Jiang, 2016; Sun *et al.*, 2016; 2017; Wang *et al.*, 2016; Li *et al.*, 2014; Lu *et al.*, 2017; Xiong and Zuo, 2016; Sadough Vanini *et al.*, 2014; Jiang *et al.*, 2016). In our previous research (Ren *et al.*, 2017; 2018), the SAE or RBM was used to achieve unsupervised learning to automatically extract features to detect a fault, while in this paper, the SAE and RBM are leveraged to build up a specific architecture to describe industrial processes. The aim of this paper in using the SAE and RBM is to meet the requirement of processing a large amount of data. However, this work takes the monitoring signals of nonstationary and stationary hybrid processes as the research object, and the dynamic correlation features, contained in the nonlinear industrial process monitoring variables, can be calculated by the stacked SAE-RBM. The complex mapping between multiple dimensional monitoring signals and abnormal modes can be finally constructed to realize feature extraction and fault detection for industrial processes.

The difficulties of fault detection for modern industrial processes, especially for nonstationary and stationary hybrid industrial processes, are observed in the following issues: the amount of data becomes larger, and it requires the monitoring system to possess the ability of processing a large amount of data; time-variant behaviors and variables become more mainstream, and this means the nonstationary and nonlinear behanions become a common problem in modern industrial processes. Motivated by the above difficulties of fault detection, a fault detection method by extracting nonlinear features for nonstationary and stationary hybrid industrial processes has been proposed, and it is mainly built on the basis of the sparse auto-encoder (SAE) and the sparse restricted Boltzmann machine (SRBM) to take advantages of their adaptive extraction and fusion of strongly nonlinear symptoms. In this method, SAEs are employed to reconstruct inputs and accomplish feature extraction by unsupervised mode, while SRBMs are naturally used to transform features into energy characteristics. The main contribution of this method is the capability of further mining and learning of the nonlinear features without considering the nonstationary problem.

## 3. Methodology

This study on feature extraction and fault detection based on stacking the SAE-SRBM for nonstationary and stationary hybrid industrial processes is still in the initial exploration stages (Jiang *et al.*, 2016; Ren *et al.*, 2017; 2018). The strategy of deep neural network learning can be regarded as simulating the learning and reasoning process of human thinking, which can be employed to realize fault detection by effective nonlinear features, transmission and classification.

**3.1. Nonstationary and stationary hybrid processes.** For practical industrial processes, the linear or nonlinear variable correlations between process variables may be presented in typical nonstationary characteristics. Therefore, whether the monitoring variables are stationary or not becomes a necessary and important issue. Typical characteristics of nonstationary and stationary hybrid processes can be considered to include the mean, variance and covariances of their monitoring variables constant with time. Generally, the augmented Dickey–Fuller (ADF) test is employed to detect whether or not the industrial process is nonstationary, while the Largrange multiplier principle (LMP) statistic is leveraged to confirm the stationary of industrial processes.

The *augmented Dickey–Fuller test* can be regarded as an effective method to recognize the nonstationary variables, and it is extended from the Dickey–Fuller (DF) statistic or the unit root test (Dickey, 1981). The goal of the DF test is to determine whether a series is consistent with the unit root process, and the unit root process refers to the data-generating process with its first difference stationary. This paper exactly employs this method to realize the identification of nonstationary monitoring variables.

The null hypothesis of the DF statistic test ($p = 0$) or the ADF test ($p > 0$) is nonstationary, while the stationary tests can be implied by the *Lagrange multiplier principle*, which can be used to test the null hypothesis of a trend stationary. The critical values can be computed by numerical simulation or set when giving a significance level. The null hypothesis can be regarded as the accepted one when the critical value is greater than the LMP test statistic. Similarly, this method is also employed to find stationary monitoring variables.

The high level of complexity and nonlinearity makes it difficult to build an integrated precise mathematical model for the purpose of fault detection. Due to the unknown property regarding whether or not the monitoring variables are nonstationary, which often masks the faults, resulting in serious accidents. Therefore, the challenge of fault detection for practical industrial processes is how to describe the operational dynamics in nonstationary and stationary hybrid processes.

**3.2. Framework of fault detection.** According to previous research, the character of a time series is likely to be nonstationary. However, a stationary relationship between two or more time series can be established through co-integration theory, and then the properties of stationarity can be fully applied (Engle and Granger, 1987). According to this theory, if there exist nonstationary variables and co-integration relationships, the system nonstationary characteristics can be regarded as the sum of nonstationary and stationary random trends. The random trends between the monitoring variables are consistent and can eliminate each other. Therefore, although the variables themselves are nonstationary, their common trend is stationary, which means that the monitored variables exhibit a long-term dynamic equilibrium relationship on the common trend (Utkin *et al.*, 2016; Leng and Jiang, 2016; Sun *et al.*, 2016; 2017; Wang *et al.*, 2016; Li *et al.*, 2014; Lu *et al.*, 2017; Xiong and Zuo, 2016; Sadough Vanini *et al.*, 2014; Jiang *et al.*, 2016).

When this theory is analogous to industrial process state monitoring, if the nonstationary process monitoring signal is first-order monotonous and there exists a co-integration relationship between monitoring variables, the linear joint model can be employed to generate a stationary information variable to describe the system operational states. When a system fault occurs, the system model parameters or structure will change, and finally reflect in the dynamic relationship between monitoring variables, i.e., the final common trend between the monitoring variables will change (Utkin *et al.*, 2016; Leng and Jiang, 2016; Sun *et al.*, 2016; 2017; Wang *et al.*, 2016; Li *et al.*, 2014; Lu *et al.*, 2017; Xiong and Zuo, 2016; Sadough Vanini *et al.*, 2014; Jiang *et al.*, 2016).

The new common trend between monitoring variables no longer confirms the past co-integration relationship, and may even have no common trend. If the faulty monitoring variables are brought into a normal co-integration relationship, the common trend change part will not be eliminated by the model and will remain in the new information variable. The nonstationary and stationary monitoring variables in the process layer can be regarded as a group of variables related to each other, and then information contained in a single signal is limited. In order to realize feature extraction and fault detection based on nonstationary monitoring variables, it is necessary to make a joint analysis of multiple variables, to explore the dynamic and nonlinear characteristics, and to describe the operational state and system behaviours (Utkin *et al.*, 2016; Leng and Jiang, 2016; Sun *et al.*, 2016; 2017; Wang *et al.*, 2016; Li *et al.*, 2014; Lu *et al.*, 2017; Xiong and Zuo, 2016; Sadough Vanini *et al.*, 2014; Jiang *et al.*, 2016).

Because the statistical characteristics of nonstationary monitoring variables are all dynamically changing, such as the mean, the variance, covariances, etc., the change and distribution characteristics are investigated. The most important part is to investigate the time series variation characteristics, i.e., it should be necessary to design some related methods to describe the transient time of nonstationary monitoring variables. Therefore, a deep neural network with stacking an SAE-SRBM has been constructed to exploit the clear advantages of the SAE on extracting nonlinear features and then fusing the unknown probability distribution features by the SRBM, as shown in Figs. 1(a) and (b). The reconstruction of input is accomplished by the SAE to extract nonlinear features with an unknown probability distribution, which can be solved by the SRBM to transform the distribution into energy-based features.

As shown in Fig. 1(b), a unique unsupervised method for extracting nonlinear features, named the SAE, has been considered a suitable approach to handle the varied inputs in this architecture. Then, the SRBM is used to further learn and fuse the output features of SAE, to mine the nonlinear features of the original monitoring signal on a deeper level, and to be employed for final classification and identification. Finally, the stacked SAE-SRBM can be employed to describe the system dynamic behaviors from input to output, as shown in Fig. 1(c).

From the above analysis, this proposed method can be used to learn the system dynamic behaviors by the input monitoring variables, and to describe the change law of the whole system by the relationships between related variables without considering whether or not they are stationary. According to the core idea of co-integration theory, this SAE-RBM can be used to mine the correlations between many monitoring variables to build a common change trend of industrial processes. In other words, the common change trend can be constructed by the correlations between monitoring variables, and in this way, this trend can be employed to described the behaviors of the industrial processes and will not be affected by the nonstationarity and stationarity of many monitored variables. Therefore, if the SAE-SRBM has been trained, then a change rule describing all the monitored variables can be constructed; while a fault occurs, the monitoring variable information is transformed into the model, and a different trend from the original state can be obtained. Fault detection can be performed by analyzing the trend.

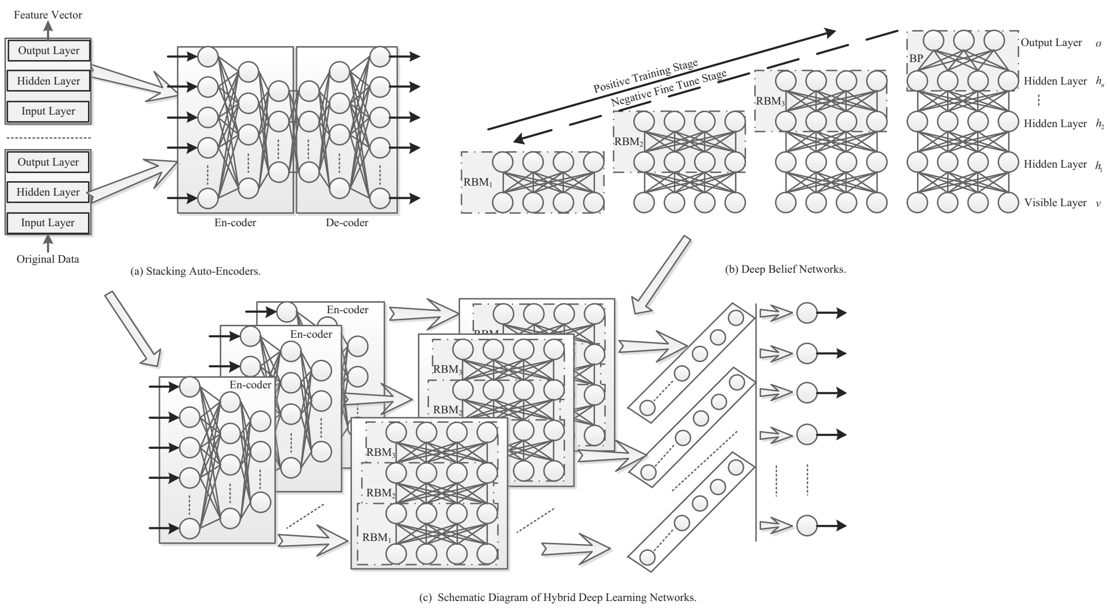


Fig. 1. Schematic diagram of hybrid deep learning networks.

**3.3. Sparse auto-encoder.** The auto-encoder was proposed by Rumelhart *et al*. (1986) and applied to handle high-dimensional complex data, which greatly promoted the development of neural networks. As an unsupervised learning method, its outputs are trained to equal its inputs, and to capture the important information of input data, while the network weights can be used to represent relationships between network variables.

Generally, the auto-encoder mainly consists of an input layer, a hidden layer and an output layer. The number of neurons in the input layer is equal to that in the output layer, while the number of neurons in the hidden layer is smaller than that in the input layer. Based on this idea, a learning model can be constructed, where the output is equal to its input, as shown in Fig. 1(a):

$$\textbf{Encoder:} \qquad y = s(Wx + b), \tag{1}$$

$$\textbf{Decoder:} \qquad \hat{x} = s(W'y + b_o), \tag{2}$$

where $x = (x_1, x_2, \ldots, x_n)^T \in \mathbb{R}^n$ is input data and $\hat{x} = (\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_n)^T \in \mathbb{R}^n$ presents output data, which refers to the reconstruction of input data. Moreover, $y$ is the output of the encoder; $W, b$ are the weights and the bias between the input the bias and hidden layers; $W'$ and $b_o$ are the weights and the bias between the hidden and output layers, and they can be regarded as the transposition of $W$ presented as $W' = W^T$. Here $s(\cdot)$ is a nonlinear function, such as a sigmoid.

The auto-encoder is often used in feature learning and dimension reduction. The encoder process mainly occurs in the input layer to the hidden layer, which can be used to realize compression representation of the input data, while the decoder process can be employed to reconstruct and restore the output signal from the hidden layer to the output layer. Auto-encoder training can be considered to adjust network parameters, which can be employed to make the final output $\hat{x}$ close to the input data $x$ as much as possible. This process can be evaluated by the typical square error, and the cross-entropy can be used as follows:

$$L_H(x, \hat{x}) = -\sum_{k=1}^{n} [x_k \log \hat{x}_k + (1 - x_k) \log(1 - \hat{x}_k)], \tag{3}$$

where $x = (x_1, x_2, \ldots, x_n)^T \in \mathbb{R}^n$ is input data and $\hat{x} = (\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_n)^T \in \mathbb{R}^n$ signifies the output data.

The sparse auto-encoder can be regarded as the fusion of sparse representation theory and the auto-encoder, and the sparse representation is used to realize the simplest sparse representation of input data features; the core idea of sparse representation theory is to construct a linear mapping transforming the domain and to reconstruct the original signal with sparse atoms or mapping bases as sparse as possible. This means that the reconstruction error should be as small as possible under the requirement of sparsity, and this can be described as follows:

$$\hat{D} = \arg\min_{D, \alpha_i} \sum_{i=1}^{n} \|y_i - D\alpha_i\| + \lambda \|\alpha_i\|_1, \tag{4}$$

where $y$ is the output of the encoder. $D = [d_1, d_2, \ldots, d_n]$ signifies a dictionary, $\alpha = [\alpha_1, \alpha_2, \ldots, \alpha_n]^T$ is the sparse coding vector.

Obviously, if all the input data samples are regarded as the dictionary $D = [d_1, d_2, \ldots, d_n]$, the over-completeness and adaptability of the dictionary can be guaranteed, while all the input data can be regarded as the reconstruction dictionary in each calculation of auto-encoder, and this dictionary has the property of dynamic updating. As in the above analysis, the auto-encoder and sparse representation also have some similarities, and their difference focuses on the dictionary construction method. As shown in (4), the key of the sparse auto-coder is to introduce a sparse penalty term and to employ sparse constraints to learn features. All of these can be used to simulate the unsupervised calculation of human perceptual learning and to optimize the performance of auto-encoders on representing the characteristics of input data. Generally, the KL (Kullback–Leibler) divergence method can be used when the distance between the average activation and an other activation is too large. When adding the coefficient penalty, the sparse auto-encoder loss can be described as follows:

$$\mathrm{SL}(W, b) = L(W, b) + \beta \sum_{j=1}^{S_2} \mathrm{KL}(\rho \| \hat{\rho}_j), \tag{5}$$

where $\beta$ is the adjustment coefficient of controlling the sparse penalty term, $\hat{\rho}_j = (1/m)[h_j(x_i)]$ presents the average activation of the $j$-th neuron in the hidden layer with training data-set $x = \{x_i\}_{i=1}^m$. $\mathrm{KL}(\rho\|\hat{\rho}_j) = \rho \log \rho/\hat{\rho}_j + (1-\rho) \log 1 - \rho/1 - \hat{\rho}_j$ is the KL divergence.

From (5), it is necessary to optimize weights $W$ and bias $b$ during the whole coding process. The cost function $\mathrm{SL}(W, b)$ takes the weights $W$ and the bias $b$ as the variables, which can be optimized. Therefore, the optimal weights $W$ and bias $b$ can be obtained by minimizing the cost function.

**3.4. Sparse restricted Boltzmann machine.** As a stochastic neural network, the RBM is built on a probability graph model, i.e., it can be considered a special case of the energy generation model. It can be employed to learn the inherent intrinsic representation of the input data and to provide a learning method for the input data with an unknown probability distribution. The restricted Boltzmann machine is a bipartite graph containing a visible layer and hidden layer. The neuron nodes of both the layers are not connected, while the neuron nodes between the layers are fully connected, as shown in Fig. 1(b).

Generally, visible layer units can be used to observe the characteristics of a certain aspect of the input data, while hidden layer units can be used to obtain the dependency between the corresponding variables of the visible layer unit, which is often called the feature extraction layer. The RBM can be constructed based on the law of energy distribution, which can be defined as an energy function, and a series of related probability distribution function sets can be constructed by using this energy function. Almost any inputs can be reconstructed based on this energy function, and this can be used to realize feature extraction and fusion. For a given set of unit states $(v, h)$, the energy function can be described as

$$E_\theta(v, h) = -\sum_{i=1}^{n_v} a_i v_i - \sum_{j=1}^{n_h} b_j h_j - \sum_{i=1}^{n_v} \sum_{j=1}^{n_h} h_j w_{ji} v_i, \tag{6}$$

where $n_v$ and $n_h$ are the numbers of neuron nodes in the visible layer and the hidden layer, respectively, $v, h$ are the nodes of the visible and hidden layers, $v = (v_1, v_2, \ldots, v_n)^T \in \mathbb{R}^{n_v}, h = (h_1, h_2, \ldots, h_n)^T \in \mathbb{R}^{n_h}$ represent the state vectors of the visible and the hidden layers. Similarly, $a = (a_1, a_2, \ldots, a_n)^T \in \mathbb{R}^{n_v}, b = (b_1, b_2, \ldots, b_n)^T \in \mathbb{R}^{n_h}$ represent the bias vectors of the visible and hidden layers; $a_i, b_j$ signify the biases of the $i$-th and the $j$-th neuron in visible and hidden layers, $v_i$ represents the state of the $i$-th neuron in the visible layer. $w = (w_{ij}) \in \mathbb{R}^{n_h \times n_v}$ are the weights between the visible layer and the hidden layer, and $w_{ij}$ is the weight between the $i$-th neuron in the visible layer and the $j$-th neuron in the hidden layer, $\theta = (w, a, b)$ are parameter vectors of the RBM.

When considering the state of all neurons in a given visible layer or a hidden layer, a neuron in the hidden layer or the visible layer is activated (the value is 1), and its probability can be expressed as follows:

$$\begin{cases} P_\theta(h_k = 1|v) = f(b_k + \sum\limits_{i=1}^{n_v} w_{k,i} v_i), \\ P_\theta(v_k = 1|h) = f(a_k + \sum\limits_{j=1}^{n_h} w_{j,k} h_j), \end{cases} \tag{7}$$

where $f(\cdot)$ is a sigmoid function. The probability distributions $P_\theta(v)$ and $P_\theta(h)$ correspond to the input data in the visible layer, and the hidden layer data, respectively. From (7) and the following function can be obtained:

$$\begin{aligned} P_\theta(h|v) &= \prod_{j=1}^{n_h} P_\theta(h_j|v), \; P_\theta(v|h) \\ &= \prod_{i=1}^{n_v} P_\theta(v_i|h). \end{aligned} \tag{8}$$

As shown in (8), when the neuron states in the visible layer are noticeable, the activation conditions of the hidden layer are independent of each other. On the contrary, the activation conditions of visible layer neurons are independent when the neurons are given.

The training of the restricted Boltzmann machine is actually adjusting the model parameters so that it can be used to fit the given input training sample. Generally, training the restricted Boltzmann machine is to maximize the following likelihood function:

$$\ln L_{\theta,S} = \ln \prod_{i=1}^{n_S} P_\theta(v^i) = \prod_{i=1}^{n_S} \ln P(v^i), \tag{9}$$

where $S = \{v^1, v^2, \dots, v^{n_S}\}$ is a given set of training samples, $v^i = (v_1^i, v_2^i, \dots, v_n^i)^T$ is a unit state in the visible layer, $n_S$ is the number of training samples. The numerical method commonly used in the maximization of (9) is the gradient ascent method, whose gradient calculation can be described as follows:

$$\begin{aligned}\frac{\partial \ln L_{\theta,S}}{\partial \theta} &= -\sum_h P(h|v^m)\frac{\partial E_\theta(v^m,h)}{\partial \theta}\\ &\quad + \sum_{v^m,h} P(v^m|h)\frac{\partial E_\theta(v^m,h)}{\partial \theta}.\end{aligned} \tag{10}$$

From (10), the computed gradient $\partial \ln L_{\theta,S}/\partial\theta$ can be interpreted as follows. The first term $\sum_h P(h|v^m)\partial E_\theta(v^m,h)/\partial\theta$ is the expectation of the corresponding energy gradient function $\partial E_\theta(v^m,h)/\partial\theta$ under conditional distribution $P(h|v^m)$. The second term $\sum_{v^m,h} P(v^m|h)\partial E_\theta(v^m,h)/\partial\theta$ is the expectation of the corresponding energy gradient function $\partial E_\theta(v^m,h)/\partial\theta$ under conditional distribution $P(v^m|h)$. Therefore, after further derivation of the related calculation, the following formula can be obtained:

$$\begin{cases}\dfrac{\partial \ln L_{\theta,S}}{\partial w_{ij}} = \sum\limits_{m=1}^{n_S} [P(h_i=1|v^m)v_j^m \\ \qquad\qquad - \sum\limits_v P(v)P(h_i=1|v)v_j],\\ \dfrac{\partial \ln L_{\theta,S}}{\partial a_i} = \sum\limits_{m=1}^{n_S} [v^m - \sum\limits_v P(v)v_j],\\ \dfrac{\partial \ln L_{\theta,S}}{\partial b_j} = \sum\limits_{m=1}^{n_S} [P(h_i=1|v^m)v_j^m \\ \qquad\qquad - \sum\limits_v P(v)P(h_i=1|v)].\end{cases} \tag{11}$$

Generally, the solution of (11) based on the conventional method is still a very slow process, and the most important reason can be the fact that it needs to go through complex state transition to make the restricted Boltzmann machine fit the training sample distribution. Lee *et al.* (2008) and Yan *et al.* (2016) proposed an important method to improve the efficiency of network computations by combining a sparse representation and the restricted Boltzmann machine. This method is to sparsely optimize the activation process of hidden layer units in the restricted Boltzmann machine. In this way, the feature learning can be considered a certain level of sparsity, and the essential features of the input data can be abstracted better.

The core idea of this method is to add a sparse penalty term on the basis of likelihood function maximization, so as to control the activation of hidden layer units in the restricted Boltzmann machine. The optimization problem can be described as follows:

$$\begin{aligned}\min_{W,a,b} &= -\sum_{l=1}^{n_v} \ln P_\theta(v)\\ &\quad + \lambda \sum_{j=1}^{n_h}\Big[p - \frac{1}{n_v}\sum_{l=1}^{n_v} E(h|v)\Big]^2,\end{aligned} \tag{12}$$

where $E(\cdot|v)$ means the conditional expectation for a given sample, $\lambda$ is the regularization parameter, $p$ can be regarded as the parameter for controlling the average activation of neurons in the hidden layer.

In practical industrial processes, a large amount of monitoring signals are generated with normal operational conditions. Furthermore, uncertainty factors occupy the main components when some faults occur in industrial processes, which are characterized by unknown probability distributions and the lack of prior information.

**3.5. Construction of training samples.** Fault detection based on hybrid deep learning networks can be implemented by stacking the sparse auto-encoder and the sparse restricted Boltzmann machine, and it can be used to realize nonlinear feature extraction and recognition with nonstationary and stationary hybrid processes. The key of neuron networks is the super large amount and super high dimensional weights, which can be obtained by using gradient descent with a large amount of high-quality samples. Therefore, the proposed fault detection method can be only regarded as a static model with effective architecture, and does not have any influence on fault detection. In order to give it life, the time dynamic characteristics of monitoring data should be taken into consideration, and it is necessary to add the time variation law into the training samples.

On the one hand, time variation is not only contained in a single sequence signal in practical industrial processes, but also in correlations between monitoring variables. The time-varying characteristics mentioned in this article refer to the correlation between monitoring variables that are strongly correlated with time. On the other hand, not all monitoring variables in the process layer are labeled, but the labeled and unlabeled variables are mixed. The unsupervised training samples, i.e., the unlabeled monitoring variables, are reconstructed from monitoring signals maintaining time characteristics.

As shown in Fig. 2, $\tau$ refers to the time scale factor and $X$ are the initial data or feature sets, which contain labeled and unlabeled data. The first step is to build the unlabeled training samples $X^{\tau u}$, which can be regarded as labeled and unlabeled data, i.e., the initial features $X$.

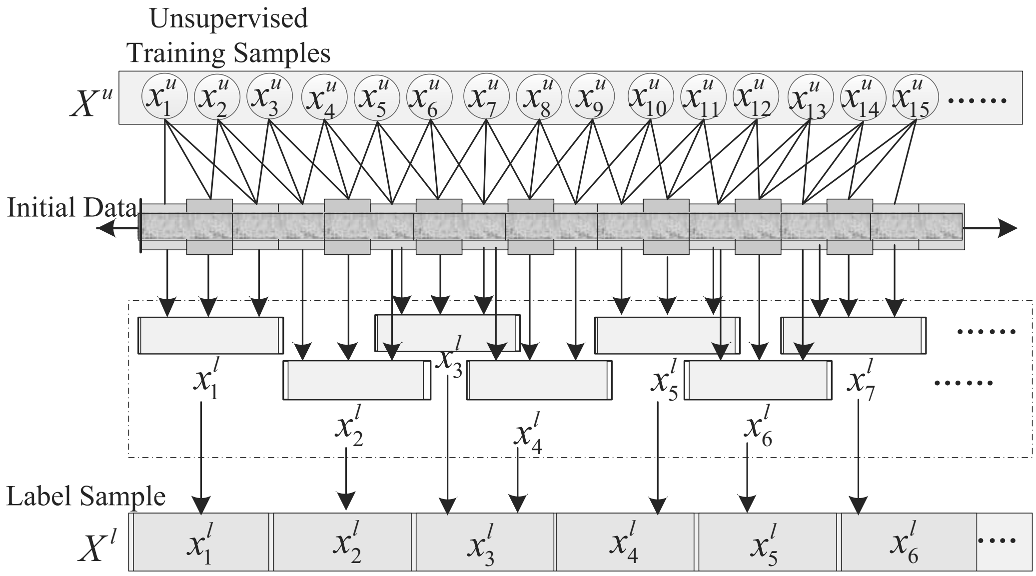


Fig. 2. Construction of training samples with dynamic time.

All of these unlabeled training samples can be briefly represented as

$$X^{\tau u} = \{X_1^{\tau u}, X_2^{\tau u}, \dots, X_N^{\tau u}\}. \tag{13}$$

Equation (13) means that unlabeled training samples $X^{\tau u}$ can be regarded as the spread of the initial sample with the scale factor $\tau$. In this way, every element $x_i^{\tau u}$ can maintain the time dynamics of monitoring variables, and ensure the time law of nonstationary processes. Similarly, the labeled training samples $X^{\tau l}$ should also contain the time dynamics of monitoring variables, and these can be constructed as

$$X^{\tau l} = \{X_1^{\tau l}, X_2^{\tau l}, \dots, X_M^{\tau l}\}. \tag{14}$$

Unlabeled training samples can be yielded out by (13), while labeled training samples can be constructed by (14). This training sample generation mode can not only save human resources, but also make full use of valuable data resources. More importantly, the training samples with time dynamic characteristics can be used to describe system characteristics through training the SAE-SRBM.

**3.6. Training steps.** Nonlinear feature extraction can be achieved by the stacked sparse auto-encoder, while the SRBM can be regarded as the method for feature fusion. The classification can be accomplished by a BP neural network. Currently nonlinear feature extraction and fusion can be achieved without considering the property of stationarity and nonstationarity, and fault detection by stacking the SAE-SRBM can be realized naturally. Finally, the last step is to give life to this neural network, i.e., the training network, and these steps can be summarized as follows.

**Step 1:** *Training samples.* Monitoring variables should first be normalized. The unlabeled samples $X^{\tau u}$ can be constructed by (12), while the labeled samples $X^{\tau l}$ can be calculated by (13).

**Step 2:** *Pre-training SAE (unsupervised).* Unlabeled training samples $X^{\tau u}$ are used to train SSAE, and the characteristics of these samples can be learned in an unsupervised manner. The output of the SSAE can be expressed as $F_{SSAE}^{\tau ul}$, and these features can be regarded as an unknown probability distribution.

**Step 3:** *Pre-training SRBM (unsupervised).* The unknown probability distribution of features $F_{SSAE}^{\tau ul}$ is used to train SRBMs, and these characteristics of features $F_{SSAE}^{\tau ul}$ can be learned in an unsupervised manner.

**Step 4:** *Fine-tune SAE (unsupervised).* Similarly, the labeled samples $X^{\tau l}$ are used to train SAE again; however, the label of each sample is not used in this step. The sample features, i.e., the output of SAE, can be learned in an unsupervised manner. The extracted features $F_{SSAE}^{\tau l}$ can be obtained in an unsupervised manner.

**Step 5:** *Fine-tune SRBM (unsupervised).* Supervised training sample features $F_{SSAE}^{\tau l}$, i.e., the output of the SAE, can be used to train SRBMs again, and sample features $F_{SSAE}^{\tau l}$ can be learned in an unsupervised manner.

**Step 6:** *Joint fine-tune SAE-SRBMs.* The labeled samples $X^{\tau l}$ are used again to train SAE-SRBMs with their labels, which contained considerable human knowledge. The BP neural network can be trained with these labeled samples

$X^{\tau l}$, and then this classification network can be combined with SAE-SRBMs.

From Step 1 to Step 6, every step is independent of one another. Labeled and unlabeled samples are first constructed (Step 1). Unlabeled samples are employed to train the SAE (Step 2), and a similar training stage is also accomplished by labeled samples (Step 4). Correspondingly, the SRBM is trained by the output of the SAE, which is trained by unlabeled and labeled samples (Steps 3 and 5). Finally, labeled samples are used to train the whole network, and this step gives life to the SAE-SRBM for fault detection.

**3.7. Performance evaluation index.** Generally, all performance parameters are calculated for each testing, and finally the average of the performance parameters for all testing instances gives the final average performance parameters. Confusion matrix metrics are often employed to report the performance of fault detection. The criteria of performance evaluation are usually employed in fault detection, which consists of three parts: classification accuracy (AC), false positive rate (FP), or false alarm rate, and missed alarm rate (FN), or missed alarm rate.

## 4. Simulation and results

The Tennessee Eastman (TE) benchmark process can be regarded as a typical industrial simulation based on a practical industrial process, which is often used as the data source to compare and verify the effectiveness of various methods. It has been widely applied in control design, multivariate statistical process monitoring and fault detection (Yin *et al.*, 2012; Geng *et al.*, 2018; Dong *et al.*, 2015; Xi *et al.*, 2018; Zhang *et al.*, 2019). The TE processes are used to verify the effectiveness of the proposed method on extracting and fusing nonlinear features to achieve fault detection for nonstationary and stationary processes.

**4.1. TE benchmark processes.** The TE process generally covers five major operation units: a reactor, a product condenser, a vapor-liquid separator, a recycle compressor, and a product stripper. Raw materials, labeled as A, C, D and E, can be used to produce two liquid products, G, H. These exothermic reactions can be simply described as follows:

$$\begin{cases} A(g)+C(g)+D(g)\rightarrow G(lip), \\ A(g)+C(g)+E(g)\rightarrow H(lip), \\ A(g)+E(g)\rightarrow F(lip), \\ 3D(g)\rightarrow 2F(lip). \end{cases} \tag{15}$$

The TE process has been widely accepted as a benchmark for control and monitoring studies, and its 33 variables (22 process measurements, 11 manipulated variables) have always been used to monitor processes. Similarly, 21 faults can be simulated, where Faults 1–7 are regarded as step changes in related variables, while Faults 8–12 are considered random variations of some variables. Besides, Faults 14, 15 and 21 are the sticky valves, while Faults 16 and 20 are unknown faults.

**4.2. Nonstationary and stationary variables.** 480 original normal samples from the training data-sets can be selected to test the nonstationarity of all variables. According to the calculation methods of the ADF test and MLP statistics, the monitoring variables of TE processes can be identified as nonstationary series by setting lags $p = 2$ without a linear time trend.

The result of the ADF test and MLP statistics is listed in Table 1, in which '0' refers to accepting the hypothesis of unit root nonstationarity and '1' refers to accepting the hypothesis of a stationary trend. As shown in Table 1, seven nonstationary variables can be seen as the result of MLP statistics; however, there are only four nonstationary series that can be tested by the ADF test. All the results are consistent with the nonstationary and co-integration tests of Li *et al*. (2014).

From the related test results, it should be noted that the TE process can be regarded as a nonstationary and stationary hybrid process, which is very suitable to verify the effectiveness of the proposed method.

**4.3. Discussion and results.** In this part, a number of 3014 fault detection samples are used, each fault of which happened in its 91st sample data, and of which only 30 percent of random samples can be regarded as labeled samples. In order to effectively test the influence of nonstationary monitoring signals on the simulation results, all fault detection results and only fault labeled as 4, 5, 7, 9–12 were used in this simulation, as shown in Fig. 3.

In this fault detection simulation, the model parameters of the hybrid neural network are shown in Table 2, while the fault detection results are given in Table 3. In order to effectively describe the influence of nonstationary variables on the final fault detection results, random removal of variables labeled 7, 11, 13, 16, 18, 19, 31, 38, 46 is carried out to obtain the influence on detection results, as shown in Table 4.

As seen in Table 3, most of the seven normal versus faulty state detection cases in the TE process achieved the expected results. From the accuracy results of fault detection labeled as AC, the highest detection rate is 100.0%, while the lowest is 59.28%. The related simulation results show that the hybrid deep neural network can effectively realize feature extraction and

Table 1. Monitoring variables of the TE process system and nonstationary tests.

| Label. | Measured variable | Base | Unit | ADF tests | LMP statistic |
|---|---|---|---|---|---|
| XMEAS1 | A feed (stream 1) | 0.25052 | kscmh | 1 | 1 |
| XMEAS2 | D feed (stream2) | 3664.0 | kg/h | 1 | 1 |
| XMEAS3 | E feed (stream 3) | 4509.3 | kg/h | 1 | 1 |
| XMEAS4 | A,C feed (stream 4) | 9.3477 | kscmh | 1 | 1 |
| XMEAS5 | Recycle flow (stream 8) | 26.902 | kscmh | 1 | 1 |
| XMEAS6 | Reactor feed rate (stream 6) | 42.339 | kscmh | 1 | 1 |
| XMEAS7 | Reactor pressure | 2705.0 | kPa gauge | 1 | 1 |
| XMEAS8 | Reactor level | 75.000 | % | 1 | 1 |
| XMEAS9 | Reactor temperature | 120.40 | $^o$C | 1 | 1 |
| XMEAS10 | Purge rate (stream 9) | 0.3372 | kscmh | 1 | 1 |
| XMEAS11 | Product separator temperature | 80.109 | $^o$C | 1 | 1 |
| XMEAS12 | Product separator level | 50.000 | % | 1 | 1 |
| XMEAS13 | Product separator pressure | 2633.7 | kPa gauge | 1 | 1 |
| XMEAS14 | Product separator under flow | 25.160 | $m^3h^{-1}$ | 1 | 1 |
| XMEAS15 | Stripper level | 50.000 | % | 1 | 1 |
| XMEAS16 | Stripper pressure | 3102.2 | kPa gauge | 1 | 1 |
| XMEAS17 | Stripper under flow (stream 11) | 22.949 | $m^3h^{-1}$ | 1 | 0 |
| XMEAS18 | Stripper temperature | 65.731 | $^o$C | 0 | 0 |
| XMEAS19 | Stripper steam flow | 230.31 | kg/h | 0 | 0 |
| XMEAS20 | Compressor work | 341.43 | kw | 0 | 0 |
| XMEAS21 | Reactor cooling water outlet temperature | 94.599 | $^o$C | 1 | 1 |
| XMEAS22 | Separator cooling water outlet temperature | 77.297 | $^o$C | 1 | 1 |
| XMV1 | D feed flow (stream 2) | 63.053 | kg/h | 1 | 1 |
| XMV2 | E feed flow (stream 3) | 53.980 | kg/h | 1 | 1 |
| XMV3 | A feed flow (stream 1) | 24.644 | kscmh | 1 | 1 |
| XMV4 | A,C feed flow (stream 4) | 61.302 | kscmh | 1 | 1 |
| XMV5 | Compressor recycle valve | 22.210 | % | 1 | 0 |
| XMV6 | Purge valve (stream 9) | 40.064 | % | 1 | 1 |
| XMV7 | Separator pot liquid flow (stream 10) | 38.100 | $m^3h^{-1}$ | 1 | 1 |
| XMV8 | Stripper liquid product flow (stream 11) | 46.534 | $m^3h^{-1}$ | 1 | 1 |
| XMV9 | Stripper steam valve | 47.446 | % | 0 | 0 |
| XMV10 | Reactor cooling water flow | 41.106 | $m^3h^{-1}$ | 1 | 1 |
| XMV11 | Condenser cooling water flow | 18.114 | $m^3h^{-1}$ | 1 | 0 |

fault detection in nonstationary and stationary hybrid processes.

As shown in Table 4, when randomly removing some nonstationary variables, the accuracy AC is significantly decreased. In this case the false and missed alarm rates increased significantly. This result means that the nonstationary monitored variables in the process layer significantly affect the operational states of the entire system.

## 5. Conclusions and future work

Aiming at the diversity, nonlinearity, or even strong nonlinearity of faults in nonstationary and stationary hybrid processes, a feature extraction and fault detection method for nonstationary and stationary hybrid processes has been proposed, with the contribution as follows:

(i) Dynamic and nonlinear characteristics in nonstationary and stationary hybrid industrial processes can be considered.

(ii) A stacked sparse auto-encoder is used to realize nonlinear features extraction, while the restricted Boltzmann machine is used to learn the feature characteristics to construct the nonlinear mapping between complex multi-dimensional monitoring signals and heterogeneous modes.

(iii) Process monitoring signals can be used to reconstruct the training samples and to retain the time series. Simulation on nonlinear feature extraction and fault detection for a nonstationary and a stationary hybrid nonlinear TE process was carried out to verify the effectiveness of this proposed method.

Table 2. Parameter set of the SSAE-SRBM for fault detection.

| Parameters | SAE1 | SAE2 | SAE3 | SAE1 | SRBM2 |
|---|---|---|---|---|---|
| Neur. num. | 180 | 700 | 300 | 800 | 300 |
| Learn. rate | 8e-4 | 8e-3 | 8e-3 | 5e-3 | 5e-3 |
| Iter. num. | 2000 | 1500 | 1500 | 2000 | 1000 |
| Mini-batch | 20 | 20 | 20 | 15 | 15 |

Table 3. TE industrial process fault detection results.

| Normal vs. Fault | AC | False alarm | Missed alarm |
|---|---|---|---|
| Normal vs. 4 | 99.49 | 0.89 | 0.11 |
| Normal vs. 5 | 98.83 | 0.79 | 0.56 |
| Normal vs. 7 | 88.00 | 0.00 | 26.00 |
| Normal vs. 9 | 58.07 | 35.42 | 48.44 |
| Normal vs. 10 | 68.75 | 17.71 | 44.79 |
| Normal vs. 11 | 84.29 | 13.65 | 17.77 |
| Normal vs. 12 | 88.39 | 5.25 | 17.97 |

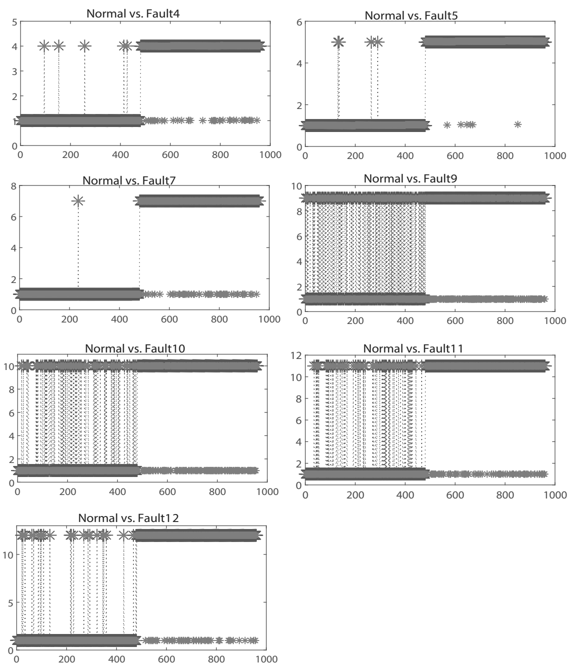


Fig. 3. Confusion matrix metrics of a stationary and a nonstationary hybrid process (TE).

However, this paper only considers the characteristics of a large number of variables and strong nonlinearity in studying fault detection for nonstationary and stationary hybrid industrial processes. Furthermore, this proposed model is mainly constructed on joint analysis of multiple variables to mine the association relationships of many variables and to describe the system dynamic behaviors. Furthermore, an in-depth study on nonstationary and stationary monitoring variables should also be carried out, and the influence of nonstationary and stationary variables was not discussed in detail. The study of nonstationary and stationary hybrid industrial processes has just attracted attention of some researchers. Therefore, some studies trying to solve these problems will be carried out, and fault diagnosis of the nonstationary and stationary hybrid industrial process will be further realized.

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Table 4. TE industrial process fault detection results.

| Normal vs. fault | AC | False alarm | Missed alarm | Removed variable |
|---|---|---|---|---|
| Normal vs. 4 | 68.75 | 17.71 | 44.79 | 7, 11, 18, 19, 38 |
| Normal vs. 5 | 74.83 | 20.76 | 39.58 | 11, 13, 18, 16, 46 |
| Normal vs. 7 | 60.32 | 11.27 | 68.08 | 11, 16, 19, 38, 46 |
| Normal vs. 9 | 45.83 | 53.39 | 51.56 | 7, 13, 19, 38, 46 |
| Normal vs. 10 | 57.29 | 25.78 | 59.63 | 11, 16, 18, 31, 38 |
| Normal vs. 11 | 61.33 | 50.11 | 27.23 | 11, 18, 19, 31, 46 |
| Normal vs. 12 | 68.75 | 17.71 | 44.79 | 7, 13, 19, 38, 46 |

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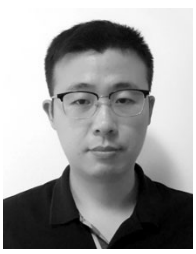

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