An Automatic Process Monitoring Method Using Recurrence Plot in Progressive Stamping Processes

Cheng Zhou, Kaibo Liu, *Member, IEEE*, Xi Zhang, *Member, IEEE*, Weidong Zhang, and Jianjun Shi

***Abstract*—In progressive stamping processes, condition monitoring based on tonnage signals is of great practical significance. One typical fault in progressive stamping processes is a missing part in one of the die stations due to malfunction of part transfer in the press. One challenging question is how to detect the fault due to the missing part in certain die stations as such a fault often results in die or press damage, but only provides a small change in the tonnage signals. To address this issue, this article proposes a novel automatic process monitoring method using the recurrence plot (RP) method. Along with the developed method, we also provide a detailed interpretation of the representative patterns in the recurrence plot. Then, the corresponding relationship between the RPs and the tonnage signals under different process conditions is fully investigated. To differentiate the tonnage signals under normal and faulty conditions, we adopt the recurrence quantification analysis (RQA) to characterize the critical patterns in the RPs. A parameter learning algorithm is developed to set up the appropriate parameter of the RP method for progressive stamping processes. A real case study is provided to validate our approach, and the results are compared with the existing literature to demonstrate the outperformance of this proposed monitoring method.**

***Note to Practitioners*—This paper is motivated by the challenge of monitoring tonnage signals in progressive stamping processes. By using the proposed monitoring approach, the missing part problem, which is one of the critical faults in progressive stamping processes, could be successfully addressed. To fully make use of this approach, it is necessary: 1) to automatically adjust and determine the appropriate parameters of the RP method for particular applications; 2) to understand the relationship between the tonnage signals and the recurrence plots under both normal and faulty conditions; and 3) to choose appropriate features to characterize the patterns in the recurrence plots for detection of condition change. A real case study shows that the proposed process monitoring scheme delivers a better performance than other methods in literature when detecting the process fault due to missing part. It is worth mentioning that this proposed approach is not limited to progressive stamping processes, but also has a great potential for other fault detection problem by using repetitive and cyclic signals, especially when the fault only exhibits small-signal changes.**

***Index Terms*—Process monitoring, progressive stamping processes, recurrence plot (RP), tonnage signals.**

I. Introduction

PROGRESSIVE stamping processes have been widely used to produce parts and components in forming industries due to their high productivity and high precision. In this process, a work piece is transferred from one die station to the next die station sequentially with an automatic feeding system. Multiple forming operations are simultaneously performed in the corresponding die stations by one stamping stroke [1]. Fig. 1 shows a progressive stamping process with five die stations including preforming, blanking, initial forming, forming, and trimming. When a work piece passes through these five stations, each die station should have an intermediate work piece during each stroke. However, a missing part problem, which means that the work piece is not settled in the right die station but is conveyed to the downstream stations, may occur in this process [2]. Such a fault often leads to unfinished or nonconforming products and/or severe die damage. In general, this process can produce over 800 parts per minute, and it is nearly impossible and unrealistic to directly observe the machine for process monitoring. Hence, seeking an efficient fault detection method is of great significance for production control and quality assurance in progressive stamping processes.

A few sensors have been used for process monitoring and diagnosis in literature. For example, research work has been reported to use the acceleration transducer for online monitoring of the stamping process [3]. However, the acceleration signals are usually affected by the noise disturbances and are very sensitive to many other factors, such as sensor mounting location, die geometric, work-piece material, and punch speed [4]. In addition to the acceleration transducer, the press tonnage sensors, which are the strain gages mounted on the press uprights or linkages, have also been widely installed in many stamping machines. The setup and maintenance costs for the tonnage sensors are generally affordable, which promotes its wide adoption in practice. Moreover, the tonnage signal measured by the press tonnage sensor is the summation of the stamping forces, which contains rich process information of stamping operations. As a result, tonnage signals have been one of the most commonly used measures for monitoring and diagnosis of stamping

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C. Zhou and W. Zhang are with the National Center for Materials Service Safety, University of Science and Technology Beijing, Beijing 100083, China (e-mail: czhou88@gmail.com; zwd@ustb.edu.cn).

K. Liu is with the Department of Industrial and Systems Engineering, University of Wisconsin-Madison, Madison, WI 53706 USA (e-mail: kliu8@wisc.edu).

X. Zhang is with the Department of Industrial Engineering and Management, Peking University, Beijing 100871, China (e-mail: xi.zhang@pku.edu.cn).

J. Shi is with the H. Milton Stewart School of Industrial and Systems Engineering, Georgia Institute of Technology, Atlanta, GA 30332 USA (e-mail: jianjun.shi@isye.gatech.edu).

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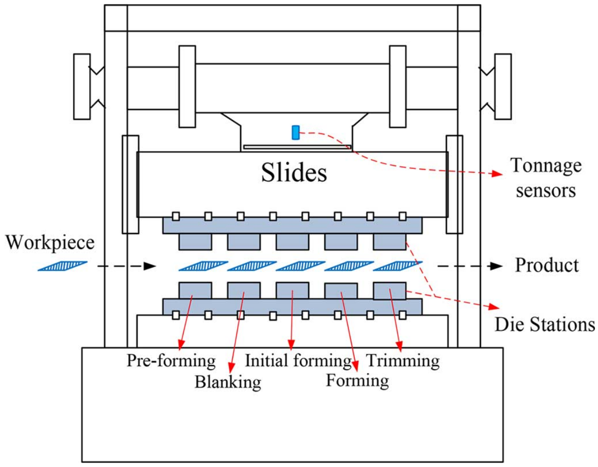

Fig. 1. Schematic procedure of a progressive stamping process.

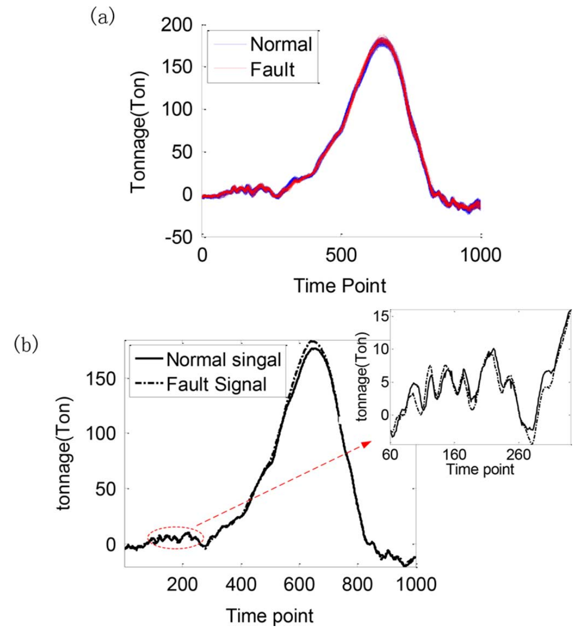

Fig. 2. Tonnage signals under the normal and abnormal (missing part fault occurs in the forming operation) conditions: (a) a group of tonnage signals under these conditions and (b) one normal and one faulty tonnage signals under these conditions.

processes [5]–[7]. For example, the local magnitude and frequency of the tonnage signal correspond to different forming operations in each die station. When this process is in control, the tonnage signal should be repeatable between strokes, though some inherent and random variation may exist due to material heterogeneities, machine tolerances, and system dynamics. If some fault occurs in certain die stations, the tonnage signal will change, and some segments of the tonnage signal will deviate from their repeated patterns that are collected under the normal condition. Thus, studying the tonnage signal provides an opportunity for effective monitoring of stamping processes.

Various efforts have been made in process monitoring and diagnosis for stamping processes. Examples include detecting abnormal conditions caused by shut height change [8], in-die mismatch [9], thermal energy of the work piece [10], and dimension changes of feeding sheet metal [11]. Although these problems have been well studied, all of these researches only focused on the stamping process with a single die station. However, for progressive stamping processes, the missing part problem poses a much more challenging issue for fault detection due to the following two reasons.

1) In progressive stamping processes, the tonnage signal is generally characterized by the stamping force in one stroke operated simultaneously at all die stations. Thus, unlike the conventional stamping process with a single die station, it is almost impossible for us to clearly partition the tonnage signal into separated segments by studying the physics of the processes, which only correspond to the specific operation condition at each die station.
2) The fault due to missing part may occur in any die station. In some station, the fault due to missing part may only cause a small change in the tonnage signal, while others may not. For example, Fig. 2(a) shows two groups of tonnage signals collected under the normal condition and the faulty condition in which the fault due to missing part occurs in the forming station. Fig. 2(b) shows one normal tonnage signal present with a quite similar pattern that could not be easily distinguished from each other.

To detect the fault due to missing part in progressive stamping processes, much research work has been reported in the literature. For example, Jin and Shi [1] combined experiment design techniques and engineering domain knowledge to decompose the original total tonnage signals to obtain tonnage signals corresponding to individual stations without using in-die sensors. However, this study requires carefully designed experiments to acquire large amounts of data, and it is not convenient to be implemented in practice. Lei *et al.* [2] proposed a feature selection method through principle component analysis (PCA) and integrated selected features into a hierarchical method for classification of missing part problems at different operational die stations. This method successfully classified the faults due to missing part occurring in four out of five individual die stations. However, one limitation of this method is that it fails to identify the tonnage signals if the fault occurs in the forming station (see Fig. 2).

In order to address this issue, this paper proposes a profile monitoring approach via the recurrence plot (RP) method to detect the changes in tonnage signals caused by the fault due to the missing part in the progressive stamping processes. The RP method has been recognized as one of the pervasive tools for analysis of dynamic systems [12] and applied in many fields including physics and physiology [13], [14]. However, to the best of our knowledge, few studies have been reported for process monitoring in advanced manufacturing systems.

It should be noticed that, though the stamping process is nonstationary at one stroke operation and no clear recurrence exists within a single piece of tonnage signal, signals collected from a number of repeated cycles of operations under the same process condition would have similar patterns. In this way, the stamping process can be considered as a stationary system with repeated cycles of stroke operations and thus the RP method can be effectively employed here to characterize the unique signal patterns collected under a certain operation condition.

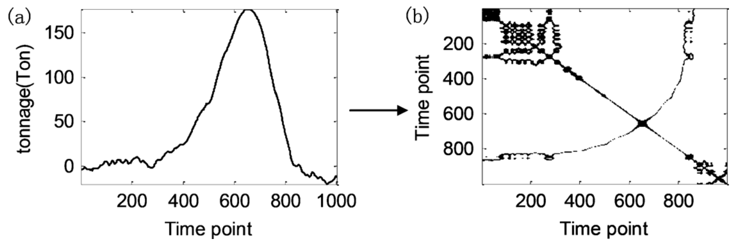

Fig. 3. Example of the transformation from an original tonnage signal into a RP plot. (a) Sample of tonnage signal. (b) RP plot of the tonnage signal.

The motivation for studying the RP method for monitoring of progressive stamping processes in this paper is summarized here.

1) The RP method does not require assumptions of data distribution, signal length and signal stationarity [12]. As the profiles of the tonnage signals do not satisfy the stationary assumption, as shown in Fig. 2, this unique property of the RP method provides an advantage for analysis and monitoring of progressive stamping processes.
2) The original signal can be transferred into a two-dimensional recurrence plot which provides a clear visualization for physical interpretation.
3) The RP method provides a one-to-one relationship between recurrence plots and profile patterns of original tonnage signals. Any details of changes in original signals will be reflected at particular regions in recurrence plots. Such unique feature provides distinct interpretations and time positioning of process faults.

The contribution of this paper can be summarized into three aspects: 1) this is the first paper that leverages the RP method to monitor progressive stamping processes, which provides a better understanding of the relationship between the changes in original signals and in recurrence plots; 2) this paper advances the state-of-the-art in detecting the small changes in progressive stamping processes, especially for the missing part problem; and 3) in order to maximize the detection capability governed by the underlying faulty condition, a self-learning parameter selection algorithm (SLPS) is developed to determine the appropriate parameter values involved in the RP method.

This paper is organized as follows. An introduction of the RP method and interpretations of basic recurrence plot patterns are given in Section II. In Section III, a systematic monitoring procedure using the RP method for change detection is proposed. The relationship between recurrence plots and original tonnage signals is investigated and the SLPS algorithm is developed. Section IV provides a real case study of progressive stamping processes to demonstrate the efficacy of the RP method and the efficiency of our proposed method, and further compares the results with existing literature. Finally, Section V provides a conclusion and a discussion of future research directions.

II. Review of the RP Method

A. A Brief Introduction of Recurrence Plot

Generally, the RP method, first proposed by Eckmann *et al.* [15], is an approach for characterization of the nonlinear profiles collected from dynamic systems by transforming these profiles into two-dimensional (2-D) matrices. To define the RP method, let $u_t, t = 1, 2, \ldots, N$ be a one-dimensional (1-D) signal observed in a dynamic system with a time index t. A series of d-dimensional vectors $\vec{X}_i$ can be constructed from this signal u_t as

$$\vec{X}_i = [u_i, u_{i+\tau}, \ldots, u_{i+(d-1)\cdot\tau}], \qquad i \in [1, N'] \tag{1}$$

where d and τ are called the embedding dimension and the time delay, respectively, and $N' = N-(d-1)\cdot\tau$. The vector $\vec{X}_i, i = 1, 2, \ldots, N'$ represents the signal trajectories in a d-dimensional space. A 2-D matrix can be formed by differencing all vectors $\vec{X}_i$ with each other as represented in the following equation:

$$R_{i,j} = \Psi(\xi - \|\vec{X}_i - \vec{X}_j\|), \quad \vec{X}_i, \vec{X}_j \in R^d, \quad i, j \in [1, N'] \tag{2}$$

where ξ is a threshold parameter and $\Psi(\cdot)$ is an indicator function that $\Psi(x) = 1$ when $x \geq 0$ and $\Psi(x) = 0$ when $x < 0$. $R_{i,j}$ is defined as the element on the ith row and the jth column of the matrix $\boldsymbol{R}$. Here, the matrix $\boldsymbol{R}$ is called the RP matrix. If the distance between $\vec{X}_i$ and $\vec{X}_j$ is equal or shorter than the threshold ξ, then $R_{i,j} = 1$; otherwise $R_{i,j} = 0$. Hence, the RP matrix can be visualized as a binary image only coded in 0 and 1. In order to avoid ambiguity between the RP method and the image formed by the RP matrix, we call this image the "RP plot" in this paper. Fig. 3 shows an example using the RP method. The tonnage signal in Fig. 3(a) can be considered as u_t in (1), and the RP matrix can be derived from the tonnage signal with parameters $d = 3, \tau = 1$ and $\xi = 4$. The RP plot in Fig. 3(b) is a binary image of the RP matrix.

B. Interpretations of RP Plot Patterns

In this subsection, we focus on interpreting the patterns in the RP plot and then introducing some critical features to quantify these patterns. Generally, the texture of the RP plot could be classified into single points, diagonal lines, vertical lines and horizontal lines [12]. In a recurrence plot matrix, since $R_{i,j} = R_{j,i} = \Psi(\xi - \|\vec{X}_i - \vec{X}_j\|)$, the patterns in the RP plot are symmetric across the main diagonal line. Thus, the horizontal lines carry the same message as the vertical lines. The texture of the RP plot could be interpreted as follows.

1) A single point in a RP plot can be expressed as $R_{i,j} = \Psi(\xi - \|\vec{X}_i - \vec{X}_j\|) = 1$ and all neighboring points are $R_{i,j\pm1} = R_{i\pm1,j} = R_{i\pm1,j\pm1} = 0$. This indicates that the distance between vectors $\vec{X}_i$ and $\vec{X}_j$ is less than ξ whereas the distance between vectors $\vec{X}_i$ and $\vec{X}_{j\pm1}$, or $\vec{X}_{i\pm1}$ and $\vec{X}_j$, or $\vec{X}_{i\pm1}$ and $\vec{X}_{j\pm1}$ is larger than ξ. In other words, the original signal u_t at time index i or j starts with a sudden jump which causes a single dot in the RP. In practice, a RP

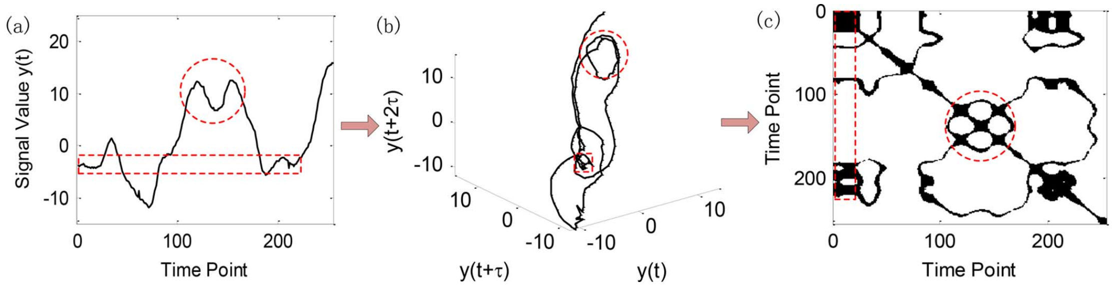

Fig. 4. Diagram interpreting the relationship between the original signal and the RP plot.

TABLE I
FEATURES EXTRACTED FROM THE RP PLOT BY THE RQA

Features	Formulae	Features	Formulae
Recurrence Rate (RR)	$RR = \frac{1}{N^2} \cdot \sum_{i,j=1}^{N} R_{i,j}$	Laminarity (LAM)	$LAM = \frac{\sum_{v=v_{min}}^{N} v \cdot P(v)}{\sum_{v=1}^{N} v \cdot P(v)}$
Determinism (DET)	$DET = \frac{\sum_{l=l_{min}}^{N} l \cdot P(l)}{\sum_{i,j}^{N} R_{i,j}}$	Trapping time (TT)	$TT = \frac{\sum_{v=v_{min}}^{N} v \cdot P(v)}{\sum_{v=v_{min}}^{N} P(v)}$
Entropy (ENT)	$ENT = -\sum_{l=l_{min}}^{N} P(l) \cdot \ln P(l)$		
$P(l)$ is the frequency with respect to all diagonal lines with the length l; l_{min} is the interested minimal length with respect to all diagonal lines for detection; $P(v)$ is the frequency with respect to all vertical lines with the lengths v; v_{min} is the interested minimal length with respect to all vertical lines for detection.			

plot will contain many individual points if there is a large amount of process noise existing in the original signal.

2) The diagonal lines are the ones in a RP plot which are parallel to the main diagonal line. We denote an original signal as u_t and two signal segments within this signal as u_{t_1} and u_{t_2}. Then, the diagonal line can be expressed as $R_{t_1,t_2} = \Psi(\xi - \|\vec{X}_{i+\Delta} - \vec{X}_{j+\Delta}\|) = 1$, where $\vec{X}_{i+\Delta}$ and $\vec{X}_{j+\Delta}$ are d-dimensional vectors constructed from u_{t_1} and u_{t_2}, Δ represents the length of the diagonal line. Therefore, a diagonal line exists if the distance between vectors $\vec{X}_{i+\Delta}$ and $\vec{X}_{j+\Delta}$ is always shorter than ξ, i.e., the vectors $\vec{X}_{i+\Delta}$ and $\vec{X}_{j+\Delta}$ are nearly parallel in the d-dimensional space. In such case, we can conclude that the original signal segments u_{t_1} and u_{t_2} exhibit similar dynamical evolution and thus considered as recurrent patterns. Fig. 4 shows a segment of a tonnage signal to explain the relationship between the tonnage signal and the corresponding RP plot with $d = 3, \tau = 1$ and $\xi = 2.5$. The sub-segment highlighted by a dashed circle in the original signal [Fig. 4(a)]exhibits a recurrent pattern, which reflects as diagonal lines highlighted by a dashed circle in the RP plot [Fig. 4(c)].

3) The horizontal lines (or the vertical lines as they are symmetric) in a RP plot can be expressed as $R_{t_1,t_2} = \Psi(\xi - \|\vec{X}_{t_1} - \vec{X}_{t_2}\|) = 1$, where $t_1 = i, t_2 \in [j, j + \Delta]$, and Δ represents the length of the horizontal line. Therefore, a horizontal line exists if the distance between vectors $\vec{X}_{t_1}$ and $\vec{X}_{t_2}$ is always shorter than ξ, i.e., the vectors $\vec{X}_{t_2}$ stays close to the vector $\vec{X}_{t_1}$ in the d-dimensional space. This means that the signal within the segment $[j, j + \Delta]$ displays a small change from the signal value at time i. As shown in Fig. 4, the subsegments highlighted in a dashed rectangle in the original signal [Fig. 4(a)] change slowly. Consequently, we can observe that the RP plot in the corresponding areas contain a lot of horizontal lines or vertical lines [Fig. 4(c)].

According to the above discussions, the RP plot can be considered as a combination of four different features: the single point, the diagonal line, the vertical line, and the horizontal line. In the light of the explanation of the RP plot's texture, recurrence quantification analysis (RQA) has been developed to quantify RP plot patterns. Webber and Zbilut [16] proposed a set of quantitative features such as recurrence rate (RR), determinism (DET), and entropy (ENT) based on the single points and the diagonal lines. Marwan *et al.* [17] further proposed analytic features such as laminarity (LAM) and trapping time (TT) based on the vertical lines. Table I summarizes the definitions of these features.

It can be seen that the feature RR refers to the density of the black dots in the RP plot. The feature DET measures the frequency distributions of diagonal lines with different lengths in the RP plot. Processes with stochastic behavior cause none or very short diagonal lines, while deterministic processes cause longer diagonal lines in the RP plot [12]. ENT is referred to the Shannon entropy of the diagonal lines with the probability $P(l)$, and it reflects the complexity of the RP plot in respect of the diagonal lines. The feature LAM measures the amount of vertical structures and the occurrence of vertical lines in the RP plot. The vertical lines have the same interpretation as the horizontal lines which are caused by the slow changes from a certain signal

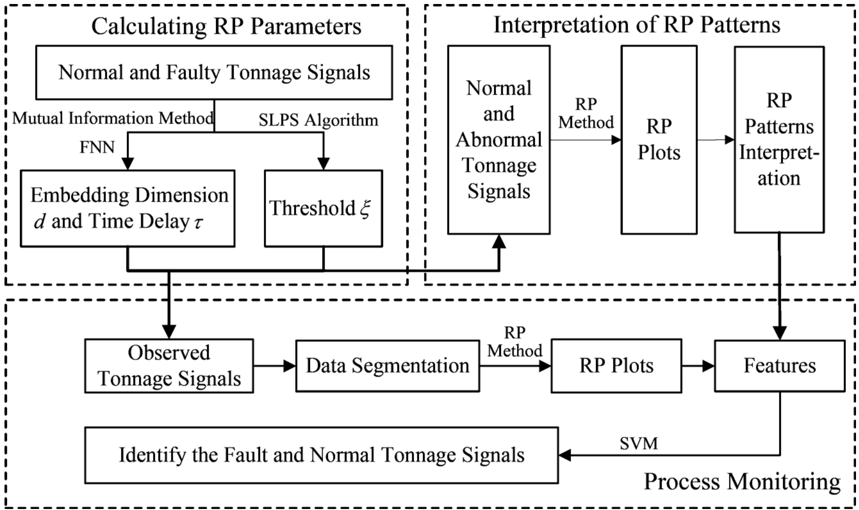

Fig. 5. Framework of the monitoring scheme for progressive stamping processes.

value in the original signal. The feature TT calculates the average length of the vertical lines which are longer than $v_{\min}$, and it represents the average length of the vertical lines in RP plots [12]. The progressive stamping process can be considered as a dynamic system and the tonnage signals contain non-stationary behaviors of the physical processes. Fig. 4(b) shows a trajectory of the tonnage signal segment of Fig. 4(a) in a three-dimensional (3-D) space. According to the interpretations of dynamic system characteristics in [18], the trajectories should be invariant under normal condition and will vary if the physical process has been changed. Therefore, these above-mentioned RP features of normal tonnage signals are consistent and would be changed under faulty conditions.

III. Monitoring Scheme of Progressive Stamping Processes

Here, we develop an automatic process monitoring scheme via the RP method in progressive stamping processes. Fig. 5 shows the framework of the process monitoring scheme. First, we determine the appropriate parameter settings in the RP method. An SLPS algorithm is proposed to derive the key parameter ξ based on the observed tonnage signals. Second, informative features that differentiate RP plots of normal and abnormal tonnage signals are selected. Interpretations of the one-to-one relationship between the original tonnage signal and the corresponding RP plot will be provided. Finally, we implement the support vector machine (SVM) classification technique based on the extracted features to identify critical faulty conditions due to missing part. Since SVM techniques have been reported in much literature, we will specifically focus on the discussions of parameter settings and the interpretations between RP plots and original tonnage signals in this section.

A. *Strategy for Determining RP Parameters*

To implement the RP method, three parameters need to be determined which are embedding dimension d, time delay τ and threshold ξ. Existing research studies have well explored how to set the parameters d and τ. Specifically, one common approach is to use the false nearest neighbor (FNN) algorithm [19] and mutual information method [20] to obtain these two parameters, respectively. Many studies have shown that such approaches achieved good results [12]–[14]. Hence, for these two parameters, we generally followed the existing well-known methods to estimate their values. The parameter threshold ξ is a crucial tuning parameter here, whose value determines the texture of the RP plot. Generally speaking, if the threshold ξ is set to be a large value, there will be a mass of black dots shown in the RP plot which may mask critical information in original signals and thus deteriorate the process monitoring performance. On the contrary, if the threshold ξ is chosen to be a small value, less useful information will be preserved in the RP plot and thus the effectiveness of fault detection can be potentially degraded. Several attempts have been reported in the literature to determine the threshold ξ. For example, Zbilut and Webber suggested that this threshold should be less than 10% of the maximum phase space trajectories diameter [21]. Later, Zbilut *et al.* [22] advised to calculate the threshold ξ to keep the RR value approximately to be 1%. Thiel *et al.* [23] proposed that the threshold ξ should be larger than the standard variation of the observational noise by five times. However, those problem specific methods are based on the *ad hoc* rules, and fail for analysis of the signals with very low signal-to-noise ratio (SNR). Eroglu *et al.* [24] developed a novel method to choose a critical point ξ_c as the value for the threshold ξ to ensure that the components of recurrence network are connected. However, this approach only finds the smallest possible threshold in a conservative way and thus it may not be effectively used here to satisfy the detection requirement in progressive stamping applications. Schinkel *et al.* [25] explored the relationship between the threshold ξ and each RQA measure, and compared the area under the curve (AUC) in receiver operating characteristic (ROC) curve of each RQA measure. However, this method focuses on separating the noises from a deterministic signal. Thus, it is not suitable to be used here for process monitoring and fault detection.

In this paper, the SLPS is proposed to appropriately determine the threshold ξ based on the observed data collected in progressive stamping processes. The main idea of the SLPS algorithm is to choose the threshold ξ to maximize the differences between normal and faulty tonnage signals. The detailed procedures of the SLPS algorithm are as follows.

1) Determine the appropriate range of the threshold ξ. First, we obtain a group of M in-control signals and denote the mth in-control signal as $u_{m,i}, i = 1, 2, \ldots, N$. According to the definition in (1), the d-dimensional vectors for the mth sample are $\vec{X}_{m,i} = [u_{m,i}, u_{m,(i+\tau)}, \ldots, u_{m,(i+(d-1)\cdot\tau)}]$. Likewise, from (2), the element on the ith row and the jth column of the recurrence matrix for the mth sample is $R^m_{i,j} = \Psi(\xi - \|\vec{X}_{m,i} - \vec{X}_{m,j}\|)$, where $m = 1, 2, \ldots, M$. Thus, if $\xi \geq \max(\|\vec{X}_{m,i} - \vec{X}_{m,j}\|)$ for any i and any j, then all elements in $R^m_{i,j}$ will be equal to "1". Similarly, if $\xi < min(\|\vec{X}_{m,i} - \vec{X}_{m,j}\|)$, then all elements in $R^m_{i,j}$ will be "0". Thus, we can set the range Ω_ξ of the parameter ξ to be $\Omega_\xi = [\xi_{\min}, \xi_{\max}]$, in which $\xi_{\min} = \min_{m,i,j}(\|\vec{X}_{m,i} - \vec{X}_{m,j}\|)$ and $\xi_{\max} = \max_{m,i,j}(\|\vec{X}_{m,i} - \vec{X}_{m,j}\|)$.
2) Discretize the range Ω_ξ by introducing an incremental parameter $\Delta_\xi : \Omega'_\xi = \{\xi_{\min}, \xi_{\min} + \Delta_\xi, \ldots\}$. Two issues here need to be solved: determination of the values of: 1) the increment Δ_ξ and 2) the upper boundary of Ω'_ξ. Specifically, we choose the increment Δ_ξ as the nonzero smallest distance between $\vec{X}_{m,i}$ and $\vec{X}_{m,j}$, i.e., $\Delta_\xi = \min_{m,i,j}(\|\vec{X}_{m,i} - \vec{X}_{m,j}\| \neq 0)$. For the upper boundary of Ω'_ξ, we can set its value as $\xi_{\max}$ and $\Omega'_\xi = \{\xi_{\min}, \xi_{\min} + \Delta_\xi, \ldots, \xi_{\min} + \Delta_\xi \cdot \Gamma((\xi_{\max} - \xi_{\min})/\Delta_\xi), \xi_{\max}\}$. Here, $\Gamma(a)$ is defined to be the largest integer that is strictly smaller than a
3) Obtain a group of historical sample data that include both normal and faulty signals. Assume these data have been correctly labeled off-line (i.e., normal or faulty sample). Let ξ_i equal the ith element of the set Ω'_ξ. We will implement the K-fold cross-validation method, in which the original dataset is randomly partitioned into K equal size subgroups, to determine the appropriate setting of the parameter ξ. Specifically, in the kth fold, we first extract features from the RP plots based on the $K-1$ subgroup data. Then, an SVM classifier is trained and the detection rate η^k_i is calculated based on the remaining subgroup (also referred as the validation data) in the current fold: $\eta^k_i = (\text{Number of correct classifed samples})/\text{Total number ofsamples})$. The final detection performance corresponding to the current value of ξ_i is expressed as $\eta_i = \sum_{k=1}^{K} \eta^k_i / K$.
4) Determine the minimum detection rate η^* based on the detection requirement in the real application. Then, search the appropriate value ξ^* of parameter ξ, starting from $\xi_i = \xi_{\min}$. If $\eta_i \geq \eta^*$, then the parameter ξ is set to be equal to ξ_i, i.e., $\xi^* = \xi_i$. Otherwise, we try the next element in the set Ω'_ξ and calculate the new detection rate η_i. The process will not be terminated until $\eta_i \geq \eta^*$. If $\eta_i < \eta^*$ for all i, we simply choose $\xi^* = arg\,\underset{\xi_i}{max}\{\eta_i\}$ as the value of the parameter ξ.

Fig. 6 shows the flow chart of the SLPS algorithm. This method can be used to determine the threshold ξ in other applications as well.

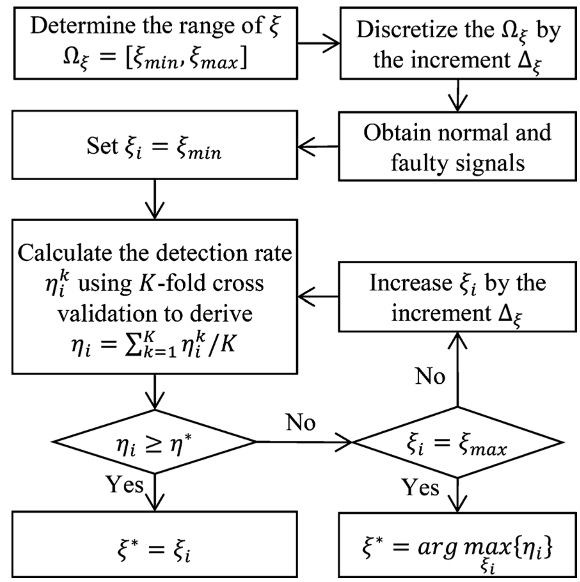

Fig. 6. Flowchart of the SLPS algorithm.

B. Relationship Between RP Plots and Faulty Tonnage Signals

A progressive stamping process that consists of five die stations is studied in this paper. These five stations correspond to five individual operations: pre-forming, blanking, initial forming, forming, and trimming. The fault due to missing part may occur in any die station. As a demonstration, we will focus on the faults that occur in the die stations pre-forming and forming in this section. According to the literature, the faults that occur in the die stations preforming, blanking, initial forming and trimming can be well detected [2]; however, the fault that occurs in the forming station poses critical challenges for detection. Thus, in this subsection, we consider one of the faulty conditions (e.g., pre-forming) that have been well studied in the literature and also the faulty condition that occurs in the forming station which has not been well solved. In the progressive stamping process as shown in Fig. 1, the operation time periods of the die station corresponding to pre-forming and forming are segments $S_1 = [50, 510]$ and $S_2 = [200, 360]$. According to the signal segmentation method in Jin and Shi [1], the relationship between the tonnage signal and the operations in each die station was well studied and the signal segmentation method has been validated by using a real industry example. Thus, the errors from the signal segmentation are negligible and can be ignored here. We will provide our interpretations based on these two segments, respectively.

1) Die Station "Pre-forming" With the Missing Part Problem: Fig. 7(a) and (b) shows examples of the normal tonnage signal and the faulty tonnage signal on segment S_1 when the fault due to missing part occurs in the pre-forming station. The corresponding RP plots are presented in Fig. 7(c) and (d), respectively. For better illustration of the relationships between original signals and RP plots, we define the subregion $[X_1, X_2; Y_1, Y_2]$ in RP plots, where $[X_1, X_2]$ and $[Y_1, Y_2]$ denote the ranges of this sub-region on the horizontal and the vertical axes, respectively. Recall that the RP plot is symmetric to its main diagonal line, and thus the patterns of the subregions $[X_1, X_2; Y_1, Y_2]$ and $[Y_1, Y_2; X_1, X_2]$ are exactly same. As

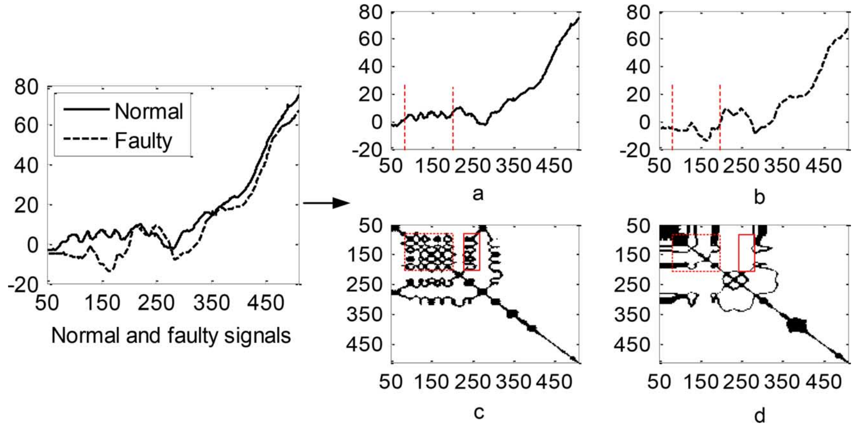

Fig. 7. Tonnage signals and corresponding RP plots under the normal and faulty conditions in the pre-forming station. (a) Normal signal. (b) Faulty signal. (c) RP of normal signal. (d) RP of faulty signal.

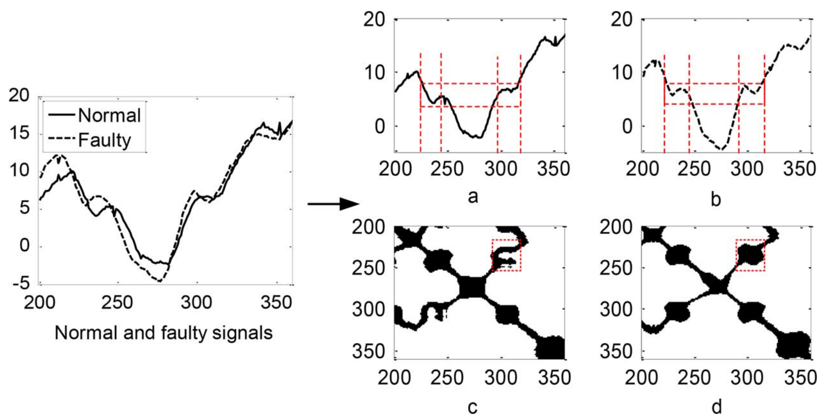

Fig. 8. Tonnage signals and corresponding RP plots under the normal and faulty conditions in the forming station. (a) Normal signal, (b) Faulty signal, (c) RP of normal signal, (d) RP of faulty signal.

a result, we only focus on the former one in the following discussion.

It is apparent to see that the largest differences between RP plots in Fig. 7(c) and (d) appear in the subregion [70, 200; 70, 200] (the area highlighted by the dashed rectangle). The RP plot under the normal condition [Fig. 7(c)]in this subregion [70, 200; 70, 200] contains a large number of diagonal lines. According to the interpretation of the diagonal line in Section II-B, it indicates that the normal tonnage signal contains several cyclic patterns. This is confirmed in Fig. 7(a) that the normal tonnage signal in the segment [70, 200] does exhibit several cyclic sinusoidal patterns with a similar oscillation amplitude and frequency. On the contrary, in Fig. 7(d), the RP plot of the faulty condition in the sub-region [70, 200; 70, 200] is mainly composed of horizontal lines and vertical lines. This means that the faulty tonnage signal contains a slowly increasing or decreasing trend in the corresponding time period according to the interpretations in Section II-B. As shown in Fig. 7(b), the faulty tonnage signal has a slow decreasing trend in the segment [50,120] and has no repeated patterns in the segment [70, 200].

There are some other differences in Fig. 7(c) and (d), such as the patterns in the subregion [240, 260; 70, 200] (the area highlighted by the solid line rectangle). The RP plot in the faulty condition in this subregion does not contain any dot as shown in Fig. 7(d). The reason here is that the amplitudes and frequencies of the faulty tonnage signal in the segments [240, 260] and [70, 200] are quite different in Fig. 7(b). On the contrary, the RP plot in normal condition contains many horizontal lines and diagonal lines in this sub-region as shown in Fig. 7(c). This is because that the tonnage signal in the segment [240, 260] does show a similar pattern (i.e., slowly oscillating pattern) as the tonnage signal in the segment [70, 200] in Fig. 7(a).

In general, the RP plot under the normal condition contains more diagonal lines than the faulty condition, while the latter contains much more vertical lines and horizontal lines than the former one. Based on the above illustrations and interpretations, we can see that critical features including diagonal lines and horizontal lines can be used to differentiate the normal and faulty tonnage signals. Thus, RQA method is adopted here to extract these useful features. Particularly, the recurrence rate (RR) measures the density of the points. The determinism (DET) and the entropy (ENT) measure the discrepancies of the diagonal lines between different RP plots while DET specifically measures the occurrence of the diagonal lines and the ENT measures the variability in the lengths of the diagonal lines. Similarly to DET, the laminarity (LAM) and the trapping time (TT) measure the discrepancies of the vertical lines and the horizontal lines between different RP plots while LAM specifically measures the occurrence of the vertical lines and TT measures the difference of the length of vertical lines. (see the detailed interpretation in Section II-B).

2) Die Station "Forming" With the Missing Part Problem: Fig. 8(a) and (b) shows examples of normal tonnage signal versus faulty tonnage signal on the segment S_2 when the fault due to missing part occurs in the forming station. The corresponding RP plots are presented in Fig. 8(c) and (d), respectively. Though the normal tonnage signal and the faulty tonnage signal are almost same, the RP plot in the normal condition [see Fig. 8(c)]in the subregion [245, 260; 210, 220] (highlighted by the dashed rectangle) only contains few dots while the RP plot in the faulty condition [see Fig. 8(d)] in this subregion contains a lot of diagonal lines. This is because the normal tonnage signal in Fig. 8(a) has no recurrent pattern [see the area highlighted by the rectangle in Fig. 8(a)] while the faulty tonnage signal contains an oscillation pattern in the segment [245, 260], which has an approximate frequency and amplitude as the segment [210, 220] [see the area highlighted by the rectangle in Fig. 8(b)]. Similarly, we can use the RQA method to extract these useful features to differentiate the normal and faulty tonnage signals.

IV. Case Study

As introduced in Section I, the progressive stamping process in our real industrial case study contains five individual die stations, which are preforming, blanking, initial forming, forming and trimming, respectively. It should be noted that the fault due to missing part may occur in any die station. In this case, we compare the performance of our proposed method with Lei's method [2] when detecting the faults due to missing part occurring in all five die stations, and discuss more on the forming station which could not be well solved by Lei's method.

A. Description of the Dataset

Six groups of tonnage signals are collected under the normal condition and the faulty condition and used in this case study. Five groups under faulty condition are referred as Type 1, Type 2, Type 3, Type 4, and Type 5, respectively. Each group contains 69 samples which are collected under the faults due to missing part occurring in these five operations respectively. The group under normal condition is referred to as "Good" and contains 157 samples. The tonnage signals are collected with a high-precision encoder and each tonnage signal recorded at each cycle has the same starting state.

B. RP Analysis and Feature Extraction

According to the analysis in Jin and Shi [1], segments $S_1 = [50, 510]$, $S_2 = [200, 720]$, $S_3 = [430, 720]$, $S_4 = [200, 360]$ and $S_5 = [120, 360]$ for Type 1, Type 2, Type 3, Type 4, and Type 5 are acquired, respectively. Hence, the RQA features $\mathcal{F}$ of all groups are derived from each signal segment and the feature sets $\mathcal{F}_{S_1}, \mathcal{F}_{S_2}, \mathcal{F}_{S_3}, \mathcal{F}_{S_4}, \mathcal{F}_{S_5}$ can then be obtained. In each feature set $\mathcal{F}_{S_i}, i = 1, 2, \ldots, 5$, it involves the RQA measures calculated from all types of faulty and normal tonnage signals.

Here, we adopt the FNN algorithm and the mutual information method to determine the embedding dimension $d = 3$ and the time delay $\tau = 1$ based on the normal signals. The threshold ξ is trained by using our proposed SLPS algorithm based on both the normal signals and the faulty signals that belong to each specific faulty type. As a result, the RP plot effectively characterizes the various signal patterns with different parameter ξ settings. In this case study, the threshold parameter are $\xi = 2$, $\xi = 3$, $\xi = 12$, $\xi = 7$ and $\xi = 3$ for Type 1, Type 2, Type 3, Type 4, and Type 5 faulty groups, respectively.

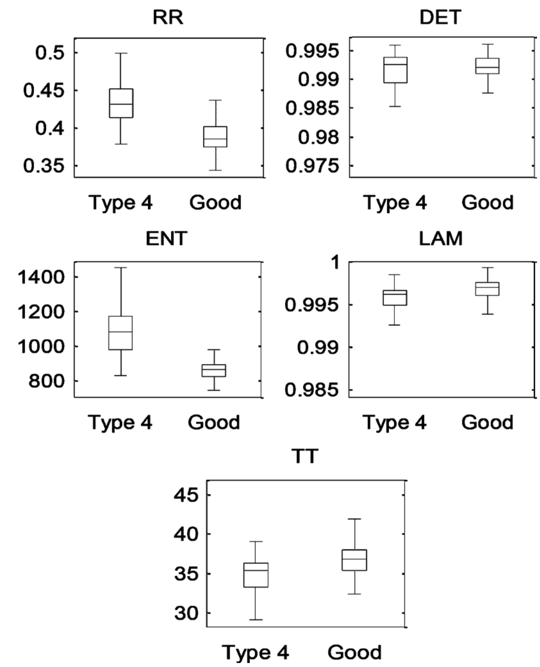

Fig. 9. Boxplot of the RQA features of tonnage signals in 'Type 4' and 'Good' groups.

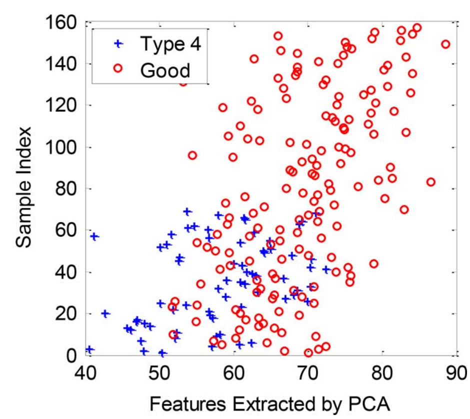

Fig. 10. PC features of tonnage signals in Type 4 and Good groups extracted by Lei's method [2].

According to the studies in Lei *et al.* [2], the fault due to missing part occurring in forming station is difficult to detect because it generates the similar tonnage profile as that in the normal condition shown in Fig. 2. This is one of the most challenging tasks for process monitoring and fault detection, which could not be well solved in the existing literature. Hence, we provide more details on detecting this fault of classifying the Type 4 and Good group to highlight the outperformance of our proposed method.

Fig. 9 shows the boxplots of the RQA features extracted from the Type 4 and Good groups, and Fig. 10 shows principal component (PC) features of the tonnage signals extracted from the same signal sets with the minimum probability of misclassification in Lei's method [2]. We can see that several features such as RR, ENT and TT, are more informative to distinguish the tonnage signals of the Type 4 group from the tonnage signals of the Good group, whereas the features in Fig. 10 fail to characterize the tonnage signals in Type 4 and Good groups.

TABLE II
(A) CONFUSION MATRIX (%) OF OUR PROPOSED METHOD. (B) CONFUSION MATRIX (%) OF LEI'S METHOD [2]

A

Actual \ Predicted	Type 1	Type 2	Type 3	Type 4	Type 5	**Good**
Type 1	100	0	0	0	0	0
Type 2	0	100	0	0	0	0
Type 3	0	0	100	0	0	0
Type 4	0	0	0	91	0	9
Type 5	0	0	0	0	100	0
Good	0	0	0	7	0	93

B

Actual \ Predicted	Type 1	Type 2	Type 3	Type 4	Type 5	**Good**
Type 1	100	0	0	0	0	0
Type 2	0	100	0	0	0	0
Type 3	0	0	100	0	0	0
Type 4	0	0	0	79	0	21
Type 5	0	0	0	0	99	1
Good	0	0	0	22	0	78

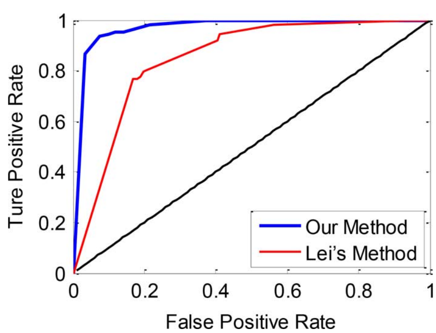

Fig. 11. ROC curves of our method and Lei's method on classifying the Type 4 and Good groups.

C. Results

An SVM is used as the multi-class classifier to identify the faulty tonnage signals in this study. A 5-fold cross-validation is used to evaluate the proposed method and Lei's method [2]. Tables II-A and II-B provide the confusion matrices of our proposed method and Lei's method when both methods are used to classify the normal condition and all types of faults due to missing part. The classification performance of the Type 1, Type 2, Type 3, and Type 5 groups using our proposed method and Lei's method are almost the same and the accuracies are around 100%. However, the sensitivity of Type 4 group by using our proposed method is 91%, whereas the sensitivity of Lei's method is only 79%. Fig. 11 further shows the receiver operating characteristic (ROC) curves of the Type 4 and the Good group using our proposed method and Lei's method. We can conclude that the detection power of our method is much stronger than Lei's method.

V. CONCLUSION

In progressive stamping processes, process monitoring based on tonnage signals is an important research topic to study for quality assurance. The fault due to a missing part is one of the critical process faults in progressive stamping processes, as it may lead to unfinished or nonconforming products and/or severe die damage. However, such fault could not be effectively detected by existing methods in literature because of the small signal changes caused by the missing part problem that occurs in certain die station. To address this limitation, we developed a process monitoring method to detect the fault due to missing part based on the tonnage signals in progressive stamping processes. In addition, we provided a detailed interpretation of the representative patterns in the recurrence plot. Then, the corresponding relationship between the recurrence plots and the tonnage signals under different process conditions was fully investigated. Based on this analysis, the RQA was adopted to extract features to differentiate the tonnage signals under normal and faulty conditions. We further developed an SLPS algorithm to obtain an appropriate setting of the threshold parameter ξ when using the RP method. In our case study, our proposed method showed a better performance for detection of the missing part problem that occurs in the forming operation, and meanwhile it was comparable to the existing method for fault detection due to missing part that occurs in other die stations.

The proposed RP-based process monitoring method is the first of its kind to use the RP method to monitor progressive stamping processes and provides a better understanding of the relationship between the changes in original tonnage signals and in recurrence plots, and it provides an alternative tool for abnormal condition detection. This method is particularly effective when only a small change exists in the tonnage signals under abnormal conditions. There are several important topics for future research that are related to this work. First, further studies can be conducted to investigate how to distinguish the fault due to missing part occurring on multiple die stations in progressive stamping processes. Second, further studies can be conducted to investigate how to localize the faulty condition segment in progressive stamping processes. Since the RP plot is able to characterize the one-to-one relationship from its original signal, any details of the changes in the original signal will be reflected at the particular regions in the RP plot. At last, it is worth to investigate how to combine this monitoring scheme with engineering domain knowledge and extend it to other applications, in which repetitive and cyclic signals are collected for process condition monitoring and fault detection.

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Cheng Zhou received the B.S. degree in automatic control from the University of Science and Technology Beijing, Beijing, China, in 2009, where he is currently working toward the Ph.D. degree at the National Center for Materials Service Safety.

His research interests are focused on process monitoring, diagnosis and nonlinear profile analysis.

Kaibo Liu (M’14) received the B.S. degree in industrial engineering from the Hong Kong University of Science and Technology, Hong Kong, in 2009, and the M.S. degree in statistics and Ph.D. degree in industrial engineering from the Georgia Institute of Technology, Atlanta, GA, USA, in 2011 and 2013, respectively.

Currently, he is an Assistant Professor with the Department of Industrial and Systems Engineering, University of Wisconsin-Madison, Madison, WI, USA. His research interests are data fusion for process modeling, monitoring, diagnosis and prognostics.

Dr. Liu is a member of INFORMS, IIE, and ASQ.

Xi Zhang (M’15) received the B.S. degree in mechanical engineering and automation from Shanghai Jiaotong University, Shanghai, China, in 2006, and the Ph.D. degree in industrial engineering from the University of South Florida, Tampa, FL, USA, 2010.

Currently, he is an Assistant Professor with the Department of Industrial Engineering and Management, Peking University, Beijing, China. His research interests are focused on physical-statistical modeling and analysis for monitoring and diagnosis in complex dynamic systems.

Dr. Zhang is a member of INFORMS, IIE, and ASQ.

Weidong Zhang received the B.S. degree in industrial electric automation specialty and Ph.D. degree in control science and engineering from the University of Science and Technology Beijing, Beijing, China, in 1996 and 2002, respectively.

Currently, he is a Professor with the National Center for Materials Service Safety, University of Science and Technology Beijing, Beijing, China. His research interests are focused on complex manufacturing system modeling and analysis, design of electric vehicle, data fusion and system evaluation.

Dr. Zhang is a member of INFORMS and TMS.

Jianjun Shi received the B.S. and M.S. degrees in electrical engineering from the Beijing Institute of Technology, Beijing, China, in 1984 and 1987, respectively, and the Ph.D. degree in mechanical engineering from the University of Michigan, Ann Arbor, MI, USA, in 1992.

Currently, he is the Carolyn J. Stewart Chair Professor with the H. Milton Stewart School of Industrial and Systems Engineering, Georgia Institute of Technology, Atlanta, GA, USA. His research interests include the fusion of advanced statistical and domain knowledge to develop methodologies for modeling, monitoring, diagnosis, and control for complex manufacturing systems.

Dr. Shi is a Fellow of the IIE , ASME, and INFORMS, an academician of the International Academy for Quality, an elected member of the ISI, and a Life Member of ASA.