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Improved two-level monitoring system for plant-wide processes

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ABSTRACT

In modern industries, the plant-wide process has become more and more popular, which always consists of various operation units, equipments, workshops and even factories. Therefore, it is more difficult to monitor those processes, and the monitoring complexity is also much higher. While the traditional multivariate statistical analysis provides satisfactory monitoring results within a single part, e.g. operation unit, it may fail to catch the detailed cross-information among different parts of the process. In this paper, an improved two-level monitoring system is formulated for plant-wide processes. In the first level, the latent variable information is extracted by the principal component analysis (PCA) model, based on which a global latent variable matrix is generated by combining latent variables from different parts of the process. In order to characterize the cross-data information of the plant-wide process, an efficient support vector data description (SVDD) method is employed for modeling the relationships among the global latent variable matrices. Based on the results of the Tennessee Eastman (TE) process, an enhanced performance is obtained by the improved two-level monitoring system. Compared to the traditional PCA based monitoring strategy, the new method is useful to describe the cross-data information of the plant-wide process, based on which more accurate monitoring results can be obtained.

1. Introduction

Recently, statistical monitoring approaches for plant-wide processes or large-scale processes have caught much research attention in the process system engineering and control areas. A typical plant-wide process always consists of several different operation units, workshops, manufacturing plants, or even has several factories that are located in different areas. Compared to the traditional process, monitoring of those plant-wide processes is much more difficult [1–3]. For example, a fault that happens in one part of the process may have great impacts in other parts, or a fault that happens in one unit may be smeared by another equipment. Therefore, even if the fault has been successfully detected, it is difficult to locate its root cause. Besides, the relationships among different parts of the plant-wide process are also difficult to characterize. As a result, how to develop efficient monitoring methods for plant-wide processes has been one of the significant challenges in this area.

While the traditional PCA method has been widely used for process monitoring, it may not function very well in the plant-wide process. One main disadvantage of PCA is the use of all variables to build a single model for the description of the whole process, which, however, may be not sufficient for the plant-wide process. Currently, several methods have already been developed for plant-wide process monitoring, such as hierarchical and multiblock statistical based approaches [1–8]. Particularly, by dividing the whole process into different sub-blocks, MacGregor et al. [1] developed both monitoring and diagnosis charts for each sub-block, as well as a global monitoring chart to improve the performance. Qin et al. [3] also proposed a multiblock PCA method, and defined block and variable contributions for decentralized process monitoring for plant-wide processes. Besides, a detailed analysis of several multiblock and hierarchical PCA and PLS algorithms has also been provided. However, most of the multiblock methods have not considered the cross-information between divided sub-blocks or different parts of the process. As a result, the deviation of the cross-information may not be observed within sub-blocks, which may cause poor monitoring performance. From the viewpoint of control performance assessment, some advances and new directions in plant-wide disturbance detection and diagnosis have been explored by Thornhill and Horch [9]. To analyze the root cause of the plant-wide disturbances, the nearest neighbor methods have been developed [10]. Detroja et al. [11] also proposed a fault detection and diagnosis for plant-wide processes, which is known as correspondence analysis. Recently, Ge and Song [12] proposed a two-level multiblock monitoring method for plant-wide process monitoring. Compared to the traditional multiblock method, this two-level monitoring method has gained more satisfactory monitoring performance, and the fault interpretation has also become much easier. Other recently published related works for plant-wide process monitoring include those of Ohran et al. [13], Jiang et al. [14], Lee et al. [15], Tessier et al. [16], Shardt et al. [17], Lindholm and Johnsson [18], Zheng et al. [19], Ge and Song [20], etc.

While the multivariate statistical modeling approach performs well in each single unit/sub-block of the plant-wide process, it may be difficult to capture the cross-relationships among different sub-blocks. In the second level of the monitoring system, the cross-block data

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information comes from different parts of the process [12]. Based on the traditional PCA method, the control limits of the corresponding monitoring statistics may be too conservative, which means that the fault detection sensitivity may be degraded. In this case, the number of type II errors of the monitoring system may increase dramatically. Particularly, some process faults might not be detected if they have small magnitudes or the abnormal relationships are not significantly explored in the measured process variables. Therefore, in order to model the cross-information among different sub-blocks, parts or locations of the plant-wide process, a more accurate data description and modeling approach should be employed, based on which the monitoring performance in the plant-wide scale could be improved.

The aim of this paper is to improve the two-level plant-wide process monitoring system, with the incorporation of the support vector data description (SVDD) method. By considering process monitoring as a one-class classification problem, SVDD has been successfully introduced for process monitoring. For example, Liu et al. [21] and Ge et al. [22,23] used SVDD to construct the control limit of traditional monitoring statistics such as I^2 and T^2. Compared to the conventional approach, the SVDD method has obtained a more accurate data description result for the latent variables, based on which the monitoring performance of the corresponding statistic has also been improved. In this paper, the SVDD method is employed for latent variable modeling in the second level of the plant-wide process monitoring system. Based on this efficient data description method, the normal operation region of the process can be captured more accurately, as well as the relationships among different parts of the process.

The remainder of this paper is organized as follows. First, the PCA and SVDD methods are briefly introduced in Section 2, which is followed by the detailed methodology of the improved two-level plant-wide process monitoring system in the next section. For performance evaluation of the proposed method, a case study of a typical plant-wide TE process is carried out in Section 4. Finally, conclusions are made.

2. Preliminaries

2.1. Principal component analysis

In the past years, PCA is one of the most popular multivariate statistical methods that have been used for process monitoring purposes [24,25]. The main idea of PCA is to find several latent variables form the process data which capture the largest amount of information in the dataset. To do this, the singular value decomposition algorithm is always employed for PCA modeling, based on which the eigenvalues of the covariance data matrix are arranged in descending order. Therefore, if the first k principal components (PCs) are selected, the PCA model is

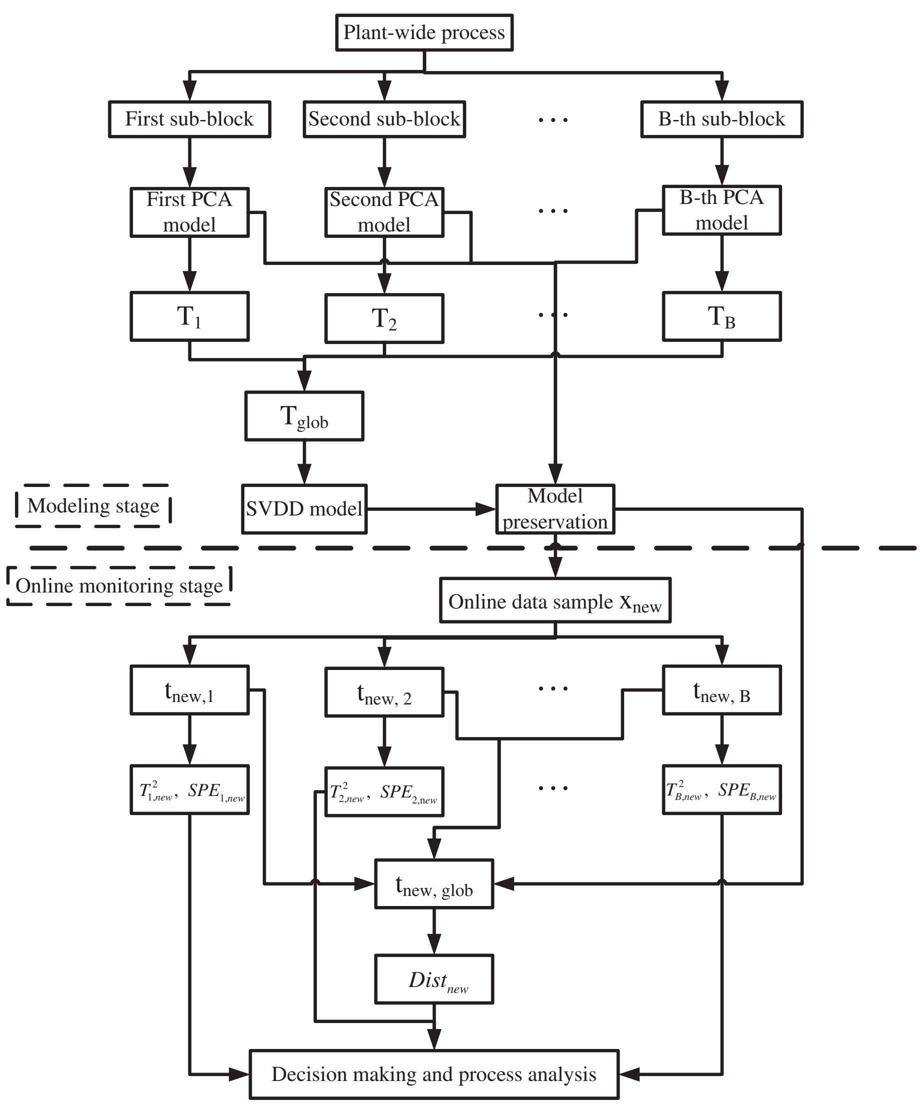

Fig. 1. Illustration of the improved two-level plant-wide process monitoring method.