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Increment-based recursive transformed component statistical analysis for monitoring blast furnace iron-making processes: An index-switching scheme

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ABSTRACT

Detecting early abnormalities in blast furnaces is important for the smooth operation of the iron-making process. In this paper, recursive transformed component statistical analysis (RTCSA)-based algorithms are developed to monitor the iron-making process with the task of early abnormality detection. The increments of variables instead of the absolute measurements are used for RTCSA, in order to decrease the effect of the time-varying nature of the process. Owing to the peak-like disturbances caused by the switching of hot blast stoves, an online identification algorithm is designed to locate the disturbance intervals. Then an index-switching scheme is used for monitoring the process. The effectiveness of the proposed method is verified using the real data of two blast furnaces. Compared with the conventional methods such as the two-stage principal component analysis, the increment-based RTCSA can effectively detect early abnormalities in the iron-making process.

1. Introduction

Blast furnace iron-making refers to the continuous process of producing molten iron by smelting iron ore, fuel, solvent, and other raw materials (Chu, Yagi, & Shen, 2006). To ensure the continuity of the reduction reaction in blast furnace, the primary task of operation is to keep the furnace running smoothly and steadily (Geerdes, Chaigneau, & Kurunov, 2015). However, some improper operations, equipment failures, and fluctuations in the quality of raw materials may cause unexpected abnormalities, such as the slipping and hanging of the burden, the cooling and overheating of the thermal state, and gas channelling (Zhou, Ye, Zhang, & Li, 2016). These abnormalities will lead to a decline in iron quality and production efficiency, increases in energy consumption. Some severe abnormalities may cause the damage of equipment, and even damping down of the blast furnace. Hence, how to accurately detect the abnormalities in the early stage is critically important. However, in many iron works, detecting the abnormalities in blast furnaces still mainly relies on the personal experience of individual workers, which is highly dependent on the personal skills and sometimes it is insensitive. Consequently, an effective diagnosis method for early abnormalities in blast furnaces is required.

In the last several decades, many research efforts have been made to diagnose abnormalities in blast furnaces, including machine learning (Lian, Ning, Aiping, & Yaobin, 2010; Liu, Wang, Mo, & Zhao, 2011; Liu, Wang, Sha, Sun, & Li, 2011; Tian & Wang, 2010), expert system (Ladonkin, Zherebin, Chistov, & Paren'kov, 1997; Otsuka, Matoba, Kajiwara, Kojima, & Yoshida, 1990; Warren & Harvey, 2001), and multivariate statistical process monitoring (MSPM) (Zhang, Ye, Wang, & Zhang, 2014; Zhou et al., 2016). In the existing works, most of the machine learning based abnormality diagnosis approaches for blast furnaces are about support vector machine (SVM) and its extensions. Specifically, Tian and Wang (2010) proposed a diagnosis method for blast furnaces based on SVM ensemble. Liu, Wang, Mo et al. (2011) presented a multiclass classification approach base on least squares support vector machine (LS-SVM) for fault diagnosis of blast furnaces. For the imbalanced data, an optional SVM is proposed to diagnose faults of blast furnaces (Liu, Wang, Sha et al., 2011). These machine learning based approaches need not only the training data under normal

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conditions, but also those with different abnormalities. This limits its application when the abnormal data are unavailable or rare.

In the literature, the expert system is one of the most popular techniques for diagnosing abnormalities of the blast furnace iron-making process. Some mature diagnosis methods based on expert system have been developed and productized (Ganguly, Reddy, & Kumar, 2010; Le Goc, 2004; Le Goc & Frydman, 2004). These expert systems are effective with a prerequisite that the process variables, such as pressure, flow, ingredient, and temperature, are accurately measured. However, for some iron and steel enterprises, equipment levels and raw material qualities are difficult to satisfy this requirement. This leads to the inapplicability of expert systems.

As far as we know, the complexity of the blast furnace iron-making process makes it difficult to accurately obtain the structure, parameters, and states of the analytical model. Moreover, due to the lack of direct measurements of inner variables, it is difficult to characterize the complex reaction process inside the blast furnace based on the qualitative knowledge. Therefore, data-driven methods are relatively feasible for monitoring the blast furnace iron-making process. As a main branch of data-driven methods, MSPM utilizes multivariate statistical analysis to cope with data. Compared with machine learning, MSPM generally does not require data under abnormal conditions to train models. In the past decades, there have been extensive studies on MSPM (Ding, 2014; Ge, Song, & Gao, 2013; Ji, He, Shang, & Zhou, 2016, 2017; Kruger & Xie, 2012; Qin, 2003, 2012; Yin, Ding, Xie, & Luo, 2014). One of its representatives, principal component analysis (PCA), has been successfully applied in numerous industrial processes (Ge & Song, 2007; Jiang, Yan, & Huang, 2016; Kruger, Kumar, & Littler, 2007; Kruger, Zhou, & Irwin, 2004; Liu, Kruger, Littler, Xie, & Wang, 2009; Lu, Gao, & Wang, 2004; Mehran & Movahhedinia, 2018; Raveendran & Huang, 2017; Sedghi, Sadeghian, & Huang, 2017; Thornhill, Shah, Huang, & Vishnubhotla, 2002; Zhou, Ma, Li, Yang, Zhang, & Li, 2014). It has also been adopted to monitor abnormalities for blast furnace iron-making processes. Based on PCA, Zhang et al. (2014) proposed a two-stage PCA algorithm to handle the peak-like disturbances caused by the switching of hot blast stoves. Its application on real data from a blast furnace indicates its effectiveness in detecting abnormalities. Besides, Zhou et al. (2016) proposed a convex hull based PCA (CHPCA) approach by replacing T^2 statistic with the convex hull based detection logic. Its moving window version, called moving window convex hull based PCA (MWCHPCA), was also proposed for coping with the time-varying characteristics of process variables. Recently, Shang, Chen, Ji, and Zhou (2017) proposed an MSPM method called recursive transformed component statistical analysis (RTCSA), which can effectively detect incipient faults. In fact, the detection of incipient faults share many similarities with that of early abnormalities in blast furnaces. However, RTCSA can only cope with stationary process data, which limits its application in monitoring the blast furnace iron-making process.

In this paper, we propose an increment-based RTCSA with an index-switching scheme. It mainly uses the relative changes rather than absolute measurements. The difference technique is used to obtain the increments of the measured variables. Because the fluctuations of increments are less violent than those of absolute measurements when the process is under normal conditions, this technique decreases the effect of the time-varying nature of the process. Owing to the peak-like disturbances caused by the switching of hot blast stoves, an identification algorithm based on the variation of the hot blast pressure is designed to locate the disturbance intervals. During online process monitoring, once the disturbance interval is determined, the index-switching scheme is used for monitoring the process. This effectively decreases false alarms when the blast furnace is affected by the switching of hot blast stoves.

The remainder of this paper is organized as follows. The detailed description of the blast furnace iron-making process and the problem formulation are given in Section 2. RTCSA is briefly reviewed in Section 3. The main content of the proposed method is elaborated in Section 4, including the identification of disturbance intervals and the increment-based RTCSA. In Section 5, the practical data collected from two blast furnaces of Guangxi Liuzhou Iron and Steel (Group) Company of China are used to verify the effectiveness of the proposed method. Conclusions are given in Section 6.

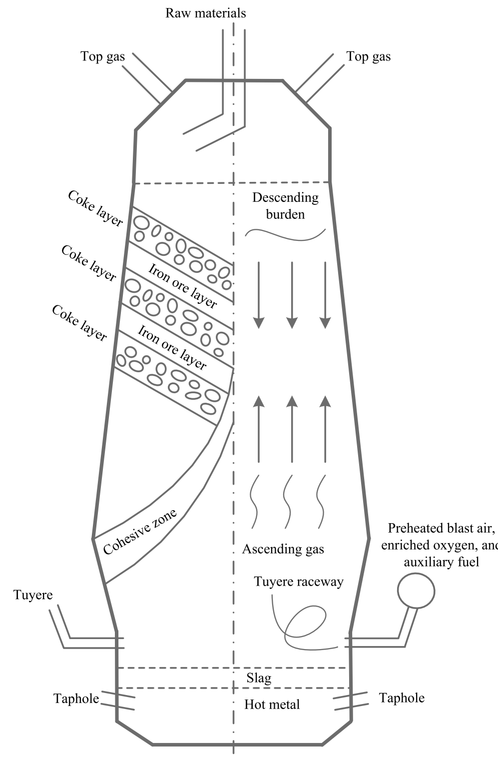

Fig. 1. A schematic diagram of blast furnace (Shang, Chen, Ji, Zhou, Zhang, & Li, 2017).

2. Process description and problem formulation

In the area of iron-making industry, blast furnaces are the major reactors used for reducing molten iron from oxide ores (Chu et al., 2006). They are large and vertical metallurgical furnaces with complex structures. The principal function of a blast furnace is to continuously produce liquid metal (Radhakrishnan & Mohamed, 2000).

The schematic diagram of a blast furnace is illustrated in Fig. 1. The furnace charges including raw materials, iron ore, coke, and flux are loaded into the blast furnace from the top, and move from the top to the bottom. High-pressure hot blast is blown into the tuyere at the lower part of the blast furnace. The fuel burns in front of the tuyere to form hot gas, which constantly moves upward and interacts with the descending charge. The descending burden is heated by the ascending hot gas stream, and a series of physicochemical reactions occur during the process. Finally, liquid metal and solid-state slag are formed, and released from the taphole regularly (Chu et al., 2006).

As discussed in Section 1, the unexpected abnormal conditions may occur in the process, owing to the variations of raw material qualities, inappropriate operation, and equipment failures. In blast furnace iron-making processes, one of the most common abnormalities is hanging, which probably leads to economic losses due to the reduction of production efficiency. Hanging in a blast furnace means that the furnace charge stops descending. Then, a space filled with high-pressure gas and void of charge will be formed. If the hanging is not relieved by some manual operations, it may trigger the slipping of the burden, which means that unprepared furnace charge falls uncontrollably and it may cool off the blast furnace. Therefore, it is necessary to detect hanging in

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