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Fault detection and diagnosis in a cement rotary kiln using PCA with EWMA-based adaptive threshold monitoring scheme

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A B S T R A C T

This paper presents main results of fault detection and diagnosis in a cement manufacturing plant using a new monitoring scheme. The scheme is based on multivariate statistical analysis and an adaptive threshold strategy. The process is statistically modeled using Principle Component Analysis (PCA). Instead of the conventional fixed control limits, adaptive thresholds are used to evaluate the common T^2 and Q statistics as faults indicators. The adaptive thresholds are computed and updated using a modified Exponentially Weighted Moving Average (EWMA) chart. These techniques are merged together to construct a novel monitoring scheme whose effectiveness is demonstrated using involuntary real fault of a cement plant process and some simulated faulty cases.

1. Introduction

Data driven methods are complementary techniques that can be used in conjunction with classical and advanced control algorithms. Their main focus in complex processes is to ensure compliance of product quality (Pani & Mohanta, 2016) as well as holistic healthy mode of a system. These methods are exploited in early detection of faults and potential malfunctions, and diagnosis. Early fault detection gives invaluable warning time in order to implement the appropriate counter actions to avoid undesired failures or bad quality product in industrial processes. Like any chemical process plant, a cement rotary kiln, shown in (Fig. 1), presents interactions between its different variables, time-varying parameters of mass and heat transfer as presented by Stadler, Poland, and Gallestey (2011), nonlinearities dynamics, and large time delay due to the slow chemical reactions. These intrinsic features make the use of model-based techniques (Zhang, Rizzoni, Arenas, Amodio, & Guvenc, 2017) for fault detection and even for control purposes very difficult, if is not unrealistic. Furthermore many cement plants worldwide still use centralized manual control methods to ensure operation. Hence, it will be of great interest to integrate appropriate fault detection and diagnosis system able to monitor easily and accurately this type of processes.

Different fault detection methods in chemical processes, and mainly cement plants have been extensively investigated over the last decades to monitor a certain phenomenon or single unit operation. For instance, (Conesa, Ortuño, Abad, & Rivera-Austrui, 2016) used long-term monitoring system to assess the emission of different persistent organic pollutants from a cement plant that uses petroleum coke as primary fuel and other alternative fuels. Mahdavi, Shirazi, Ghorbani, and Sahebjamnia (2013) developed a model of multi-agent system by using artificial intelligence technique to control and monitor quality factors in cement production processes. Chen, Tran, Ao, and Huong (2016); Chen, Zhang, Hong, Hu, and Yin (2016) established image recognition system via dynamic features of blurry flame images for detection of the temperature condition inside the rotary kiln. Makaremi, Fatehi, Araabi, Azizi, and Cheloeian (2009) used an input–output locally linear neuro-fuzzy model-based technique for abnormal conditions detection in a cement rotary kiln. On the same way, Sadeghian & Fatehi (2011) developed three distinct models of normal and faulty situations to monitor a rotary kiln. Deng, Xie, and Zhou (2011) employed physical laws of mass conservation, composition balance, reaction kinetics, heat transfer, and energy in obtaining a mathematical model and designing a diagnostic system for holographic monitoring of a real-time simulated lime shaft kiln. However, for large scale systems including many complex units, data-driven methods (Beghi, Brignoli, Cecchinato, Menegazzo, Rampazzo, & Simmini, 2016; Chiang, Russell, & Braatz, 2001) make a superior alternative solution for fault detection and diagnosis systems. Generally, large size multivariate data with highly correlated variables present low

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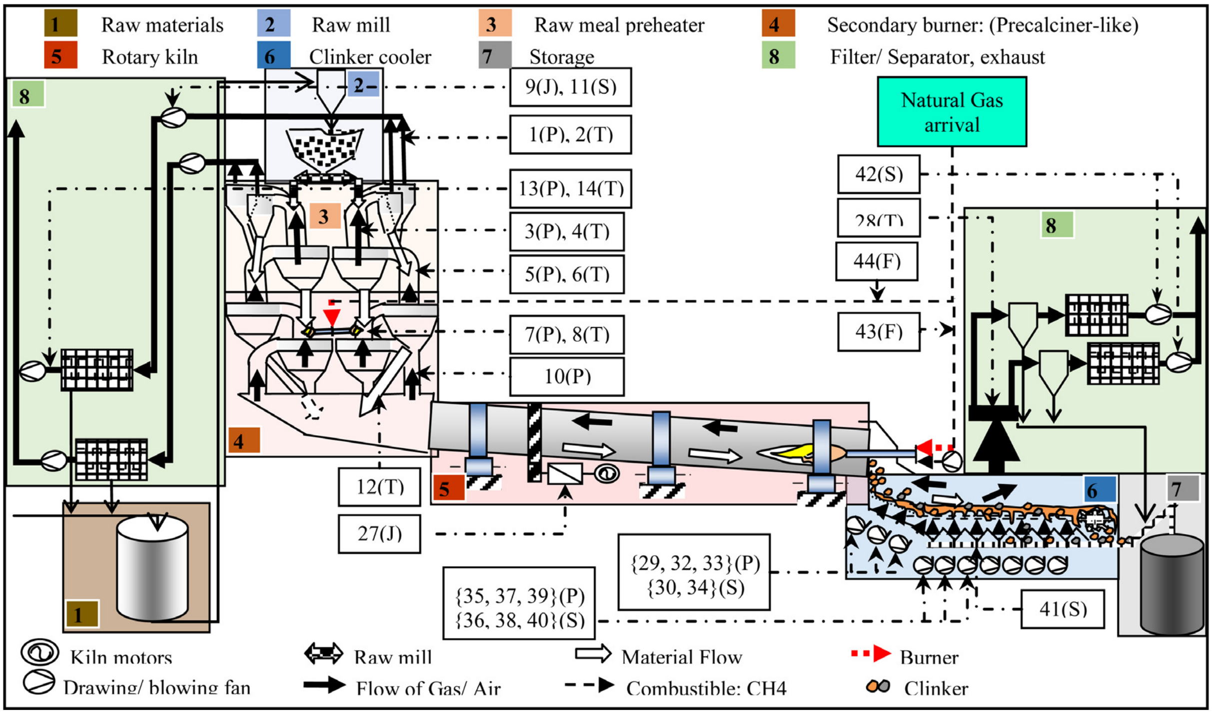

Fig. 1. An overview of the manufacturing process in the cement plant, depicting main unit operations (1–8) including the rotary kiln. The signals used for the application are indicated, including: temperature (T), pressure (P), speed (S), power (J), and feed (F). Signals of tower II are not indicated for simplicity.

statistical rank. Consequently, multivariate statistical methods (Chiang, Russell, & Braatz, 2000) use only few possible independent sources mostly causing the variation in the process and rendering these methods to be very efficient in monitoring large scale processes.

Most multivariate statistical methods used for fault detection and diagnosis systems include: Principal Component Analysis (PCA) (Zhou, Ye, Zhang, & Li, 2016) with main drawback of increased false and/or missed alarms due to slow process changes, weighted recursive PCA for adaptive fault detection is used to address this issue (Portnoy, Melendez, Pinzon, & Sanjuan, 2016), however it suffers from increased complexity due to updating PCA model (eigenstructure) and the possibility of missing (by involving in the updated model) slowly evolving drift faults as commented by Quiñones Grueiro and Verde (2016), Independent Component Analysis (ICA) (Ajami & Daneshvar, 2012; Tong, Lan, & Shi, 2017; Žvokelj, Zupan & Prebil, 2016), Partial Least Squares (PLS) (Godoy, Vega, & Marchetti, 2013; Luo, Bao, Mao, & Tang, 2016), Fisher Discriminant Analysis (FDA) (Gharavian, Almas Ganj, Ohadi, & Bafroui, 2013; Jiang, Zhu, Huang, Paulson, & Braatz, 2015), Canonical Variate Analysis (CVA) (Stubbs, Zhang, & Morris, 2012), and Higher-Order Cumulants Analysis (HCA) (Jia, Wang, & Huang, 2016; Wang, Fan, & Yao, 2014). The use of these conventional statistical methods suffer from the difficulty of extracting statistical properties of analyzed large size multivariate data of industrial process making it difficult to define the best random phenomena associated with established fault indicator. Therefore, fixed threshold based-techniques increase false faults and/or non-detected faults, which compromise the reliability of the fault detection scheme. In contrast to the fixed threshold technique, Kouadri, Bensmail, Kheldoun, & Refoufi (2014) have developed an adaptive thresholding technique by developing two-dimensional fault indicator with circular control limit. This adaptive threshold, that correctly detects faults, is established throughout multiple repeated experiments under healthy mode and same operating conditions of a cement rotary kiln. Dey et al (2016) designed an adaptive threshold generator to suppress the effects of modeling uncertainties based on its known bounds and nominal system dynamics. Other several extensions have been proposed to enhance the performance of the monitoring system. Fan, Qin, and Wang (2014) used xponentially Weighted Moving Average (EWMA) scheme to filter the monitoring indices of kernel ICA–PCA to improve monitoring performance. Similarly, Harrou, Nounou, Nounou, & Madakyaru (2015) combined the advantages of the (EWMA) control chart and PLS methods to enhance their performance for process monitoring. On quite same way, Harrou, Sun, & Khadraoui (2016) used EWMA with PCA indices to detect anomalies in the process mean. The direct integration of these statistical methods has obviously improved the monitoring performance. Furthermore, it may cause some false alarms, being based on a backward summation. Impact of alarming samples (false alarms and real faults) will affect the following samples corresponding to healthy process operation, which results in large fault clearance time delay between the real disappearance of process faults and the recovery of the fault indicator.

To overcome the drawbacks of these methods based on the conventional fixed control limits, and to improve fault detection performance of large-size processes using multivariate statistical methods, an adaptive thresholding technique is proposed for Q and T^2 statistics resulting through a PCA-based approach. The adaptive threshold is developed based on a limited window-length modified EWMA control chart. EWMA is a univariate statistical method (Roberts, 1959; Salsbury & Alcala, 2017), it is very effective but limited to univariate analysis such as quality control or monitoring the process mean, it can be extended to multivariate analysis but this requires variable selection or multiple testing (Lowry, Woodall, Champ, & Rigdon, 1992; Park & Jun, 2015), or combined with other data-based or model-based methods (Chen and Tran et al., 2016; Chen and Zhang et al., 2016; Raza, Prasad, & Li, 2015). The Q and T^2 statistics resulting from statistical PCA model are evaluated through the developed adaptive threshold which employs the most recent statistics values to eliminate the effects of corrupted data on the incomplete and inaccurate statistical model, and generates a wide range of dynamic values for the threshold above and below the conventional fixed limits to properly measure the deviation in the process operation and ensure a robust and reliable decision about the process safety.

In this paper, theoretical background to PCA method as a multivariate statistical tool for process monitoring is presented in Section 2. In