Applied Thermal Engineering 109 (2016) 65–74

Contents lists available at ScienceDirect

Applied Thermal Engineering

journal homepage: www.elsevier.com/locate/apthermeng

Research Paper

Improved detection of incipient anomalies via multivariate memory monitoring charts: Application to an air flow heating system

Fouzi Harrou [a,*], Muddu Madakyaru [b], Ying Sun [a], Sofiane Khadraoui [c]

[a] King Abdullah University of Science and Technology (KAUST), Computer, Electrical and Mathematical Sciences and Engineering (CEMSE) Division, Thuwal 23955-6900, Saudi Arabia
[b] Department of Chemical Engineering, Manipal Institute of Technology, Manipal University, Manipal, India
[c] University of Sharjah, Department of Electrical and Computer Engineering, Sharjah, United Arab Emirates

HIGHLIGHTS

- An improved monitoring approaches using memory control chart developed.
- The proposed approaches are designed for detecting incipient anomalies.
- One case study on a heating air-flow system is performed.
- The detection results show effectiveness of the proposed approaches.

ARTICLE INFO

Article history:
Received 7 June 2016
Accepted 7 August 2016
Available online 10 August 2016

Keywords:
Incipient anomaly
Multivariate control chart
Anomaly detection
Memory monitoring charts

ABSTRACT

Detecting anomalies is important for reliable operation of several engineering systems. Multivariate statistical monitoring charts are an efficient tool for checking the quality of a process by identifying abnormalities. Principal component analysis (PCA) was shown effective in monitoring processes with highly correlated data. Traditional PCA-based methods, nevertheless, often are relatively inefficient at detecting incipient anomalies. Here, we propose a statistical approach that exploits the advantages of PCA and those of multivariate memory monitoring schemes, like the multivariate cumulative sum (MCUSUM) and multivariate exponentially weighted moving average (MEWMA) monitoring schemes to better detect incipient anomalies. Memory monitoring charts are sensitive to incipient anomalies in process mean, which significantly improve the performance of PCA method and enlarge its profitability, and to utilize these improvements in various applications. The performance of PCA-based MEWMA and MCUSUM control techniques are demonstrated and compared with traditional PCA-based monitoring methods. Using practical data gathered from a heating air-flow system, we demonstrate the greater sensitivity and efficiency of the developed method over the traditional PCA-based methods. Results indicate that the proposed techniques have potential for detecting incipient anomalies in multivariate data.

© 2016 Elsevier Ltd. All rights reserved.

1. Introduction

Process safety and product quality are major challenges for automatic production systems. Process monitoring is employed by various process industries for improving the quality of products and enhancing process safety. Monitoring is required to ensure that both product quality and safe operation are maintained. Generally, anomalies in modern automatic processes are difficult to avoid and may generate catastrophic process degradations. The problem of process monitoring is prevalent within diverse domains such as chemical process, environmental protection and industrial system monitoring [16,20]. Proper operation of complex chemical processes, such as those in the oil and gas industries, requires careful monitoring of certain key process variables to enhance the productivity of these processes and more importantly to avoid disasters in the cases of failure [19]. Also, monitoring the atmospheric air pollution levels is extremely important for the safety of humans and the marine life, especially in areas with large fuel productions or consumptions and large climate fluctuations [11]. Anomaly detection and diagnosis represent two vital components of process monitoring, during which anomalies are firstly identified and then isolated to ensure that they can be appropriately handled. In other words, anomaly detection is essential for checking the conformance of the inspected process to its desired requirements, and it is the focus of this paper.

* Corresponding author.
E-mail address: fouzi.harrou@kaust.edu.sa (F. Harrou).

http://dx.doi.org/10.1016/j.applthermaleng.2016.08.047
1359-4311/© 2016 Elsevier Ltd. All rights reserved.

Process monitoring is central for ensuring proper and safe operation of several chemical and environmental processes. Along past several decades, researchers and engineers have developed several anomaly detection techniques that generally could be split into two main families: model-based and data-based monitoring techniques [3,16,2]. Techniques using an explicit model, compare the process gathered data with estimation obtained from an analytical model, which is generally computed using some fundamental knowledge of the process under healthy conditions [16]. The model-based monitoring approaches comprise the observer-based approaches [34,31], parity space approaches [26,23], and interval methods [4]. Of course, the efficiency of these model-based anomaly detection approaches relies on the quality of the models utilized. Unfortunately, sometimes it is very difficult to derive precise models of the inspected systems, notably for large-scale processes. Then data driven analysis methods offer an alternative way. Data-based methods provide efficient tools for extracting pertinent information for designing monitoring systems through the available process data. More specifically, data-based monitoring methods depend on the availability of historical data obtained from the monitored fault-free process [30]. These methods are capable to extract useful information from available data, computing the relationship between the variables in the absence of an analytical model. These data are first employed to construct an empirical model, which is then utilized to detect anomalies in new data. In a wide variety of industrial and on-board applications, the detection of anomalies are considered primordial to guarantee high performance level of the plant operation, to reduce economic losses and to enhance the security of a plant operating in a controllable region. Several data-based monitoring methods have been developed including partial least square regression methods, independent component analysis [6], Fuzzy systems [21], and pattern recognition methods [9]. Data-based anomaly detection techniques, particularly those that use PCA or its extended versions, were widely used in many applications in a large spectrum of industries, such as in the chemical industry [7,32], air quality monitoring [11], water treatment [18], hospitals management [10], biology and biotechnology [29], and semiconductors [35].

The multivariate data-based techniques attempt to analyze high dimensional data in order to capture the underlying structure formed with some latent variables (unmeasurable variables) that reveal some characteristics [33]. PCA is a major statistical tool in multivariate techniques and is widely used in various disciplines [13,28] (e.g., data compression, estimation, pattern recognition, classification, filtering, and in anomaly detection). PCA is a linear dimensionality reduction approach that determine the optimal number of principal components (PCs) that explain most of the variability in multivariate data while removing data redundancy. Towards this end, PCA projects large-dimensional data onto a lower dimensional space by maximizing the variance of the projections [1]. The goal of PCA is to model the correlation structure existing among the process variables. It is especially useful when the number of variables is large enough so that their variation is likely due to a small number of underlying relevant variables.

Handling incipient anomalies is a key challenges in building safe and reliable processes. The detection of incipient anomalies is central in maintaining the normal operation of a system by providing an early warning which helps in avoiding serious damage and subsequent economic loss. Indeed, incipient anomalies is characterized by a weak signature that requires detection indicators that have high sensitivity to small changes. However, PCA-based monitoring metrics such as T^2 and Q statistics utilize information solely from the actual observation and they are relatively insensitive at detecting incipient or small anomalies in process mean. Therefore, this potentially makes conventional PCA-based monitoring less efficient in this case. To cope with such limitation, alternative charts like the multivariate cumulative sum (MCUSUM) and multivariate exponentially weighted moving average (MEWMA) monitoring schemes, which are rested on a decision statistic that takes into account information from past observations with that of current observations, can be used [25,22]. The objective is to exploit the advantage of the PCA modeling and those of memory control charts MEWMA and MCUSUM by developing PCA-based MEWMA and MCUSUM monitoring methods to achieve enhanced detection performance compared with the traditional PCA monitoring techniques.

The application of memory control chart, as an informational index, to detect small anomalies in multivariate processes, is investigated in this paper. The sensitivity of memory control chart with respect to small changes will be compared to other commonly used statistics for fault detection, namely T^2 and SPE. Combining the advantages of PCA modeling with those of the MEWMA and MCUSUM monitoring scheme should result in an improved anomaly detection system. To achieve this coupled approach, we developed the PCA-based MEWMA and MCUSUM anomaly detection scheme. This paper is structured as follows. In the following section, the PCA approach is briefly reviewed. In Section 3, some backgrounds of the MCUSUM and MEWMA charts, are briefly described. Section 4 describes the proposed PCA-based MCUSUM and MEWMA anomaly detection approaches. Next, in Section 5, we assess the proposed scheme and present some simulation results. Finally, some conclusions are given in Section 6.

2. Review of PCA based anomaly detection

PCA is basically a modeling technique to study relationships which exists between variables of multivariate process without considering any a priori explicit structure. In other words, the purpose of PCA is to model the dependency structure of multivariate data in order to obtain a compact representation of the original data and eliminate insignificant data. It can be very helpful when dealing with highly cross-correlated data [27,24]. More specifically, PCA intends to transform high-dimensional cross-correlated variables into a lower dimension, where the transformed variables or components are uncorrelated in the new space [24]. This section is dedicated for a brief introduction about PCA ad its used for anomaly detection.

2.1. Feature extraction based on PCA

Assume that there is an $n \times m$ data matrix $\mathbf{X} = \left[\mathbf{x}_1^T, \ldots, \mathbf{x}_n^T\right]^T \in R^{n\times m}$ with n measurements and m process variables. First, the data collected from the monitored production process have been scaled to zero mean and variance one. It can then be split by PCA as two complementary orthogonal parts: a modeled data $\widehat{\mathbf{X}}$ which contains the most significant variations present in the data and a residual data $\mathbf{E}$ which represents noises, i.e.,

$$\mathbf{X}_s = \mathbf{T}\mathbf{P}^T = \sum_{i=1}^{l} t_i p_i^T + \sum_{i=l+1}^{m} t_i p_i^T = \widehat{\mathbf{X}} + \mathbf{E} \tag{1}$$

with $\mathbf{T} = [t_1\ t_2 \cdots t_m] \in R^{n\times m}$ represents a matrix of the transformed uncorrelated variables, $t_i \in R^n$ termed principal components, which are defined to be uncorrelated linear combinations of the original variables that successively maximize the total variance of data projection. The column vectors $p_i \in R^m$, termed the loading vectors, arranged in the matrix $\mathbf{P} \in R^{m\times m}$ are obtained by the eigenvectors related to the covariance matrix of $\mathbf{X}_s$, i.e., Σ. The eigenvector decomposition of Σ is:

Download English Version:

https://daneshyari.com/en/article/644443

Download Persian Version:

https://daneshyari.com/article/644443

Daneshyari.com