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Chemical Engineering Research and Design

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

IChemE

Using improved self-organizing map for fault diagnosis in chemical industry process

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ABSTRACT

There are numerous fault diagnosis methods studied for complex chemical process, in which the effective methods for visualization of fault diagnosis are more challenging. In order to visualize the occurrence of the fault clearly, a novel fault diagnosis method which combines self-organizing map (SOM) with correlative component analysis (CCA) is proposed. Based on the sample data, CCA can extract fault classification information as much as possible, and then based on the identified correlative components, SOM can distinguish the various types of states on the output map. Further, the output map can be employed to monitor abnormal states by visualization method of SOM. A case study of the Tennessee Eastman (TE) process is employed to illustrate the fault diagnosis and monitoring performance of the proposed method. The results show that the SOM integrated with CCA method is efficient and capable for real-time monitoring and fault diagnosis in complex chemical process.

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Keywords: Self-organizing maps; Correlative component analysis; Fault diagnosis; Monitoring; TE process

1. Introduction

Nowadays, with the development of science and technology, modern chemical process becomes more and more automatic and complex. The connection of all components in a chemical process is much closer than before. On the one hand, all these progress can increase production capacity as well as reduce production cost. On the other hand, a slight error in the process may cause a huge loss in the end because of the compact connection. So it is very important to find an effective method to monitor the whole process and detect the fault in time. Over the past decades, different approaches have been pursued in order to achieve this goal. An abundance of literature on process fault diagnosis ranging from analytical methods to artificial intelligence and statistical approaches are discussed (Venkatasubramanian et al., 2003a,b,c).

Generally speaking, fault diagnosis and monitoring methods can be broadly categorized into two classes, namely, “model-based methods” and “data-based methods.” Model-based methods, as the name implies, need to construct an accurate model of the process to detect and diagnose

deviations, such as expert systems (Muthuswamy and Srinivasan, 2003), Kalman filters (Bhagwat et al., 2003), multi-linear models (Azimzadeh et al., 2001) and so on. However, it is seldom available and difficult to construct an accurate model for some highly complex processes (Venkatasubramanian et al., 2003a,b). Thus this shortcoming restricts its practical applicability, especially for complex industrial-scale process. To overcome the difficulty in developing precise model, the data-based approaches have been employed. These methods do not assume any form of model and rely on historical data of operation to characterize the process. So the data-based methods have attracted more attention and been well developed. Statistical models and neural networks are widely used as data-based methods in fault diagnosis. Statistical models include Principal Components Analysis (PCA) (Chiang et al., 2000), Partial Least Squares (PLS) (Lee et al., 2003), Canonical Variate Analysis (CVA) (Russell et al., 2000) and so on. Chiang et al. (2001) reviewed the above-mentioned statistical methods and made a comparison of them in an industrial process. The result shows that every method has both advantage and disadvantage. Kernel independent component analysis

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Received 20 February 2012; Received in revised form 17 May 2012; Accepted 8 June 2012

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<http://dx.doi.org/10.1016/j.cherd.2012.06.004>