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Artificial intelligence for monitoring and supervisory control of process systems

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Abstract

Complex processes involve many process variables, and operators faced with the tasks of monitoring, control, and diagnosis of these processes often find it difficult to effectively monitor the process data, analyse current states, detect and diagnose process anomalies, or take appropriate actions to control the processes. The complexity can be rendered more manageable provided important underlying trends or events can be identified based on the operational data (Rengaswamy and Venkatasubramanian, 1992. An Integrated Framework for Process Monitoring, Diagnosis, and Control Using Knowledge-based Systems and Neural Networks. IFAC, Delaware, USA, pp. 49–54.). To assist plant operators, decision support systems that incorporate artificial intelligence (AI) and non-AI technologies have been adopted for the tasks of monitoring, control, and diagnosis. The support systems can be implemented based on the data-driven, analytical, and knowledge-based approach (Chiang et al., 2001. Fault Detection and Diagnosis in Industrial Systems. Springer, London, Great Britain). This paper presents a literature survey on intelligent systems for monitoring, control, and diagnosis of process systems. The main objectives of the survey are first, to introduce the data-driven, analytical, and knowledge-based approaches for developing solutions in intelligent support systems, and secondly, to present research efforts of four research groups that have done extensive work in integrating the three solutions approaches in building intelligent systems for monitoring, control and diagnosis. The four main research groups include the Laboratory of Intelligent Systems in Process Engineering (LISPE) at Massachusetts Institute of Technology, the Laboratory for Intelligent Process Systems (LIPS) at Purdue University, the Intelligent Engineering Laboratory (IEL) at the University of Alberta, and the Department of Chemical Engineering at University of Leeds. The paper also gives some comparison of the integrated approaches, and suggests their strengths and weaknesses.

Keywords: Monitoring and control; Artificial intelligence techniques; Framework for intelligent system development; Process industry; Integrated systems

1. Introduction

Computerized control systems that monitor, control, and diagnose process variables such as pressure, flow, and temperature have been implemented for various processes. When these systems are for large-scale processes, they generate many process variable values, and operators often find it difficult to effectively monitor the process data, analyze current states, detect and diagnose process anomalies, and/or take appropriate actions to control the processes. To assist plant operators, process operational information must be analysed and presented in a manner that reflects the important underlying trends or events in the process (Rengaswamy and Venkatasubramanian, 1992). Intelligent decision support systems that incorporate a variety of AI and non-AI techniques can support this task. Our survey of some relevant literature reveals three general solution approaches for supporting the tasks of monitoring, control, and diagnosis can be identified. They include the data-driven, analytical, and knowledge based approaches (Chiang et al., 2001). Our review of the relevant literature also reveals extensive research effort has been devoted to enhancing robustness of the approaches by combining them so as to minimize their weaknesses and maximize their strengths. However, successful integration

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of the three approaches has not been realized. The task of integrating the solution approaches is rendered more complex due to the proliferation of software and databases, which makes it impossible to combine these approaches using the rigid structure of conventional integration methods. The objective of this paper is to explain characteristics of the three solution approaches and present efforts at integration conducted at some major research centers in both North America and Europe. The discussion also presents a summary of approaches from each of the four research groups as well as their advantages and disadvantages.

2. Solution approaches for developing intelligent support systems in process control engineering

For developing decision support systems in process control engineering, the three solution approaches of data driven, analytical, and knowledge-based have been identified; each approach will be discussed in detail as follows.

2.1. The data-driven approach

Early and accurate fault detection and diagnosis of industrial processes can minimise downtime, increase safety of plant operations, and reduce manufacturing costs. The process-monitoring techniques that have been most effective in practice are based on models constructed almost entirely from process data (Chiang et al., 2001). The most popular data-driven process monitoring approaches include principal component analysis (PCA), Fisher discriminant analysis, partial least-squares analysis (PLS), and canonical variate analysis. Among these, PCA and PLS have been increasingly adopted for feature extraction from historical databases developed from process operations (Yoon and MacGregor, 2004). Therefore, these two approaches are explained in greater detail in this section.

2.1.1. Principal component analysis

PCA can facilitate process monitoring by projecting data into a lower-dimensional space that characterizes the state of the process. PCA is a dimensionality reduction technique that produces a lower-dimensional representation while preserving the correlation structure between the process variables; it is thus optimal in terms of capturing variability in the data (Chiang et al., 2001). By adopting PCA to monitor industrial process data, variables can be captured in two or three dimensions and process variability can be visualized with a single plot (Piovoso et al., 1992). The visualization and structure abstracted from the multi-dimensional data can assist operators and engineers in interpreting the significant trends in the process (Kresta et al., 1997). In situations where the data variations cannot be captured in two or three dimensions, modified versions of the PCA method have been developed to automate the process monitoring procedures based on the following three considerations (MacGregor and Kourti, 1995; Raich and Cinar, 1996):

(1) PCA can produce lower-dimensional representations of the data, which are better for generalizing data independent of the training set than using the entire dimensionality of the observation space. This approach therefore improves proficiency of detecting and diagnosing faults.
(2) The structure abstracted by PCA can be useful for identifying either the variables responsible for the faults and/or the variables most affected by the faults.
(3) PCA can separate the observation space into subspaces capturing the systematic trends of the process, and subspaces containing the random noise.

Studies on applications of PCA to process industries can be found in Akbaryan and Bishnoi (2001), Amand et al. (2001), Kano et al. (2001, 2002), Kruger et al. (2001), McAvoy (2002), Ündey and Cinar (2002), Wong and Wang (2003), Lee et al. (2004), Miletic et al. (2004).

2.1.2. Partial least square

PLS, also known as projection to latent structures, is a dimensionality reduction technique for maximizing the covariance between the predictor (independent) matrix X and the predicted (dependent) matrix Y, for each component of the reduced space (MacGregor, 1994). A popular application of PLS is to include process variables in the predictor matrix and product quality data in the dependent matrix, which can include off-line measurement data (Kruger et al., 2001). Such inferential models (also known as soft sensors) can be used for on-line prediction of product quality data. PLS has also been incorporated into process monitoring and control algorithms (Zhang and Lennox, 2004). MacGregor et al. (1995) applied PLS for process monitoring and diagnosis of a low-density polyethylene tubular and auto clave reactor, which involves plotting variable contributions. In this case study, a database involving 55 observations on 44 process variables (i.e., a dimensionality of 55×44) was analysed using PCA and PLS. Both approaches can also be used for multivariate statistical monitoring, such that if the operating point is beyond the acceptable range of values, then the operation can be regarded as abnormal. (Kresta et al., 1991, 1997) discussed other examples using the same approach to design statistical monitoring systems for a fluidized bed reactor and a binary distillation column.

In addition to (Kruger et al., 2001), successful applications of PLS in process control industries include monitoring the multistages and multiphases of batch processes using both PCA and PLS (Ündey and Cinar, 2002), detecting faults in fed-batch fermentation process (Zhang and Lenox, 2004) and integrating knowledge-based systems and PLS for real-time batch process supervision (Ündey et al., 2003a, b, 2004).