Available online at www.sciencedirect.com
ScienceDirect
Engineering Applications of Artificial Intelligence 20 (2007) 115–131
Engineering Applications of
ARTIFICIAL INTELLIGENCE
www.elsevier.com/locate/engappai

Artificial intelligence for monitoring and supervisory control of process systems

Varanon Uraikul, Christine W. Chan*, Paitoon Tontiwachwuthikul

Faculty of Engineering, University of Regina, Regina, Saskatchewan, Canada S4S 0A2

Received 25 May 2006; received in revised form 6 June 2006; accepted 8 July 2006
Available online 2 October 2006

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

*Corresponding author. Tel.: +1 306 585 5225; fax: +1 306 585 4855.
E-mail address: christine.chan@uregina.ca (C.W. Chan).

0952-1976/$ - see front matter © 2006 Elsevier Ltd. All rights reserved.
doi:10.1016/j.engappai.2006.07.002

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).

In summary, data-driven methods such as PCA and PLS are applicable in domains in which the assumption that the first few principal components can capture most of the variations in a multivariate database is valid. However, when the assumption is not applicable, especially when the dimension of the original variables is high, unsupervised learning approaches are more appropriate. Despite weaknesses of the data-driven approaches, PCA and PLS techniques are useful for pre-processing data and eliminating linear dependencies among variables. They are also powerful tools for dimension reduction in neural networks, see for example (González-García et al., 1998; Lin et al., 2000; Adebiyi and Corripio, 2003). PCA and PLS have been successfully applied for solving problems in process engineering; for example, Neogi and Schlags (1998) analysed the data of emulsion batch process using PLS, Zhang et al. (1996) adopted PLS for fault detection and diagnosis, and Chen et al. (1996) described the application of PCA for identifying normal regions in monitoring of multivariate statistical processes.

2.2. The analytical approach

The analytical approach generally involves detailed mathematical models that use some measured input u and output y, and generate features such as residuals r, parameter estimation p, and state estimation x. Then, based on these values, fault detection and diagnosis can be performed by comparing the observed feature values with those associated with normal operating conditions either directly or after some transformations. Analytical methods can be categorized into the two common methods of parameter estimation and observer-based method (Garcia and Frank, 1996). In the parameter estimation method, a residual is defined as the difference between the nominal and the estimated model parameters, and deviations in the model parameters serve as the basis for detecting and isolating faults (Isermann, 1994a, b). In the observer-based method, the output of the system is reconstructed using the measured value or a subset of the measurements with the aid of observers. The difference between the measured and the estimated outputs is used as the vector of residuals (Ding and Guo, 1996). When accurate first principles or other mathematical models are available, the analytical methods can improve process monitoring systems when they are coupled with data-driven or knowledge-based approaches. The two analytical methods of parameter estimation and observers are discussed in detail as follows.

2.2.1. Parameter estimation method

When appropriate mathematical models of the process can be obtained, the parameter estimation method addresses process faults which are associated with changes in model parameters. The model parameters are generally not measured, but can be estimated using standard parameter estimation techniques (Beck and Arnold, 1977). The parameter estimation method consists of five basic steps (Chiang et al., 2001):

(1) Identify the process equations that relate the measurable input variables $u(t)$ and the physical model parameters p_j to the output variables $y(t)$. These equations can make use of conservation equations and phenomenological relationships such as phase equilibria, and fluid constitutive equations.
(2) Gather physical model parameter p_j so that new parameters θ_j is observable and, later, can be uniquely determined. During this step, it is also useful to redefine variables so that the new variables θ_j can be entered linearly in the process equations, as this will simplify the parameter estimation problem.
(3) Estimate the model parameters θ_j from the current and recently measured input variables $u(t)$ and output variables $y(t)$ (Young, 1981). If θ_j appears linearly in the process equations, then it is possible to stack the equations so that
$$z = \Psi\theta + e, \tag{1}$$
where z is a vector that contains known functions of the measured variables, Ψ is a matrix of measured variables, θ is the vector of parameters to be estimated, and e is the vector of the equation errors.
(4) Calculate estimates of the physical parameter $\hat{p}_j$ from the estimated model parameters $\hat{\theta}_j$. If lumping was used, then in some cases only combinations of the physical parameter $\hat{p}_j$ can be determined.
(5) If changes in the physical parameters are larger than those observed in the training data and observations, faults can be detected.

For fault detection and isolation, Step 5 compares the estimated parameter to their nominal values by computing the differences using
$$\Delta p_j = p_j - \hat{p}j, \tag{2}$$
where p_j is the nominal value for the physical parameter. Even if no fault has occurred in the plant, Δp_j will not be equal to zero due to process disturbance and noise. That is, Δp_j will be stochastic variables, and a threshold is needed to indicate whether a fault has occurred. If a single Δp_j or a combination of Δp_j is greater than some predefined thresholds, then a fault has occurred; the parameters responsible for the threshold violation are those associated with the fault.

2.2.2. Observer-based method

The observer-based method for detecting and isolating additive faults is appropriate if the faults are associated with changes in actuators, sensors, or unmeasurable state variables. A detailed mathematical model of the process, preferably a first-principled process model, is required to physically interpret the state-space equations. The first principled model provides significant structure to state-space equations, which are essential for modeling the effect of faults on the states and process outputs. The meaning of the states helps to isolate and diagnose the faults when the thresholds on the residuals have been violated. The unmeasured states are reconstructed from the measurable input and output variables using a Luenberger observer or Kalman filter method (Burrell and Inman, 1998).

On the one hand, a residual from the measured states can be determined from the difference between the estimated and the measured state. On the other, a residual from the unmeasured states can be determined by the difference in the estimated and the measured process outputs, or by some linear transformation of this difference.

Research work that adopted the observer-based method for process monitoring has been reported in Frank (1992), Isermann (1984), and applications of these methods can be found in Isermann (1994a, b), Kesavan and Lee (1997), and Ku et al. (1994).

In comparing the two analytical methods for generating residuals, namely the parameter estimation and observer-based methods, the former is often adopted for handling multiplicative faults, while the latter is useful for addressing additive faults (Stephanopoulos and Han, 1996). A residual from the measured states can be determined from the difference between the estimated and the measured state, whereas a residual from the unmeasured states can be determined by the difference in the estimated and the measured process outputs, or by some linear transformation of this difference.

2.3. *The knowledge-based approach*

Knowledge-based approaches as implemented in automated reasoning systems incorporate heuristics and reasoning, which involve uncertain, conflicting, and non-quantifiable information (Luo et al., 2002). The artificial intelligence technologies that are associated with knowledge-based approaches and adopted for monitoring, control, and diagnosis in the process industries include expert systems, fuzzy logic, machine learning and pattern recognition.

2.3.1. *Expert systems*

An expert system is a software system that captures human expertise for supporting decision-making; this is useful for dealing with problems involving incomplete information or large amounts of complex knowledge. Expert systems are particularly useful for on-line operations in the control field because they incorporate symbolic and rule-based knowledge that relate situation and action(s), and they also have the ability to explain and justify a line of reasoning (Chiang et al., 2001).

A common application of expert system technology in process control is for fault diagnosis. Typically, the basic components of an expert system include a knowledge base, an inference engine and user interface. The knowledge base contains either shallow knowledge based on heuristics, or deep knowledge based on structural, behavioral or mathematical models (Chiang et al., 2001). Various types of knowledge representation schemes can be used, including production rules, frames, and semantic networks (Xia and Rao, 1999b). Since performance of the expert system is highly dependent on the correctness and completeness of the information stored in the knowledge base, updates to the knowledge base is necessary should the industrial process changes. The inference engine provides inference mechanisms to direct use of the knowledge, and the mechanisms typically include backward and forward chaining, hypothesis testing, heuristic search methods, and meta-rules (Prasad et al., 1998; Norvilas et al., 2000; Rao et al., 2000). Finally, the user interface translates user input into a computer understandable language and presents conclusions and explanations to the user.

Early applications of expert systems primarily focused on medical diagnosis (Clancey and Shortliffe, 1984). Currently, expert systems have been adopted in many industrial applications, including equipment maintenance, diagnosis and control, plant safety, and other areas in engineering. For example, Srihari (1989) discussed a framework of knowledge-based system in industrial applications, using it for the tasks of diagnosis, supervision, and control; Xia and Rao (1999a, b) built an expert system for operation support of pulp and paper manufacturing industries; Sun et al. (2000) and Uraikul et al. (2000) developed an expert system for optimizing natural gas pipeline network operations; Kritpiphat et al. (1998) implemented an expert system for intelligent monitoring and control of municipal water supply and distribution; Norvilas et al. (2000) developed an intelligent process monitoring and fault diagnosis environment by interfacing knowledge-based systems with multivariate statistical process monitoring techniques; Rao et al. (2000) developed an intelligent system for operation support for a boiler system and a chemical pulping process; Viharos and Monostori (2001) developed a hybrid system combining expert system and simulation for optimizing process chains and production planning; Wang et al. (1998, 2000) described the combination of expert system with neural networks for fault diagnosis of a transformer; and Prasad et al. (1998) applied the technology for constructing an operations support system for diagnosis and maintenance of a fluidized catalytic cracking unit and a paraxylene production unit. Fig. 1 is a schematic of a typical expert system architecture in process system applications (Tzafestas and Verbruggen, 1995).

Although expert systems have been widely adopted for process control, some well-known limitations include the following (Power and Bahri, 2004a, b):

(i) Control over inference application is implicit in the structure of the knowledge base, e.g. in the ordering of rules for a rule-based system.
(ii) As the size of the knowledge base increases, the inference engine may be unable to identify the solutions in a timely fashion.

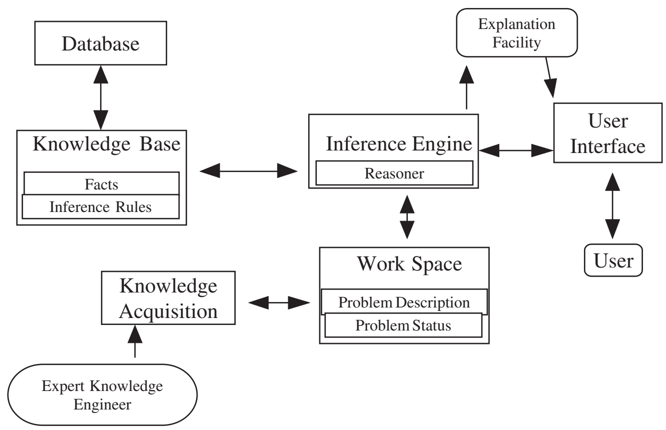

Fig. 1. Typical expert system architecture (Tzafestas and Verbruggen, 1995).

(iii) Most expert systems are domain specific and typically, an expert system is only developed for an individual application.
(iv) Knowledge from experts is difficult to acquire and represent, and most often involves uncertainties.

To overcome the above limitations, a promising approach is the integration of expert systems with other solution approaches such as fuzzy logic, machine learning, and pattern recognition techniques, see for example (Rengaswamy and Venkatasubramanian, 1992; Venkatasubramanian, 1994; Power and Bahri, 2004a, b). The uncertain knowledge can be handled by incorporating fuzzy logic into the knowledge representation.

2.3.2. Fuzzy logic

Fuzzy logic as a mechanism for representing uncertain knowledge has been widely adopted in many engineering applications in recent years (Aggarwal et al., 1999; Jain et al., 1999; Kasabov, 1996). A brief introduction to fuzzy logic and its applications are given below.

Fuzzy logic provides a mechanism for approximation using graded statements instead of ones that are strictly Boolean. It is useful for representing process descriptions such as "high or low", which are inherently fuzzy and involve qualitative conceptualizations of numerical values meaningful to operators. A process descriptor can be translated to fuzzy concepts using a membership function $\mu_A(x)$, which maps every element x of the set X to the interval [0,1]. Mathematically, it can be defined as

$$\mu_A(x) : X \to [0, 1], \quad (3)$$

where A is a fuzzy subset of X. Each value of the membership function is called a membership degree. A membership degree of 0 indicates no membership, while a membership degree of 1 indicates full membership in the set A. A set defined in classical logic (commonly referred to as a crisp set) is a special case of fuzzy set in which only two membership degrees of 0 and 1 are allowed (Zadeh, 1964).

Fuzzy logic supports representation of variables and relationships in linguistic terms. A linguistic variable is a variable with linguistic meaning which takes fuzzy values, and it is often based on a quantitative variable in the process. For example, the linguistic variable of pipe temperature can take the fuzzy values of "Low", "Normal", and "High", and each fuzzy value can be modeled. In this case, the temperature of a pipe at 60 °C takes a fuzzy value of "Normal" and a membership degree of 0.95 represented as μNormal (T), or takes a fuzzy value of "High" and a membership degree of 0.08 represented as μHigh (T). A linguistic variable can also be qualitative. The linguistic variable of "certainty" can take fuzzy values such as "Highly Certain" or "Not Very Certain". The process of representing a linguistic variable as a set of fuzzy variables is called fuzzy quantification.

Fuzzy logic systems handle the imprecision of input and output variables directly by defining them with fuzzy memberships and sets that can be expressed in linguistic terms. Complex process behaviour can be described in general terms without precisely defining the complex phenomena involved. However, it is difficult and time consuming to determine the correct set of rules and membership functions for a reasonably complex system; and fine-tuning a fuzzy solution can be time-consuming. To resolve some of these weaknesses, neural networks are often adopted to learn the best membership functions through its training algorithms. There are a number of successful control applications that combined fuzzy logic and neural networks technologies in the process industries. For example, Koiranen et al. (1998) described a hybrid adaptation system which combined fuzzy logic and neural networks algorithms for developing a cased-based reasoning system for process equipment selection. Chen and Peng (1999) combined the advantages of fuzzy logic and neural network techniques to develop an intelligent system to control a continuous stirred tank reactor (CSTR) that involved an open-loop unstable non-linear process. Belarbi et al. (2000) developed a fuzzy inference system that involved a connectionist network with logical neurons connected to binary and numerical weights; and the resulting fuzzy neural network system was used in a simulation study for estimation and control of a pulp batch digester. Linkens et al. (2000) used a blackboard-based framework for developing an integrated intelligent control system (BIICS) for a cryogenic plant used for superconductor testing at temperatures below 100 °K; the system was designed to simultaneously support multiple heterogeneous intelligent technologies, such as neural networks, expert systems, fuzzy logic, and genetic algorithms. Ruiz et al. (2001, 2002) described a process fault detection and diagnosis system (PFD&D), which combined an artificial neural network and a fuzzy system in a block-oriented configuration; the system was applied to a fluidized bed coal gasifier plant. Alexandridis et al. (2002) proposed a new systematic methodology that combined neural networks, fuzzy logic and truncated Chebyshev series for modelling a nonlinear dynamic process. The methodology was tested in the identification of certain operating regions in a CSTR, which exhibited various types of nonlinear behaviour, such as limit cycles and multiple steady states.

2.3.3. Machine learning and patterns recognition techniques

Machine learning techniques are often adopted for addressing the knowledge acquisition (KA) bottleneck in implementing expert systems. The KA bottleneck arises due to the fact that experts are better at collecting and archiving cases than in expressing their experience and encountered cases explicitly into production rules (Wong and Wang, 2003). In using machine intelligence techniques to tackle this bottleneck, knowledge is automatically extracted from data (Bakshi and Stephanopoulos, 1994a, b). Symbolic information can be integrated into an artificial neural network learning algorithm (Kasabov, 1996), and the learning system supports knowledge modeling and extraction. For example, Wang et al. (1998) developed a fuzzy network method for generating production rules from data for process operational decision support.

Pattern recognition approaches are applicable to process monitoring because of the assumed relationship between the data patterns and fault classes while ignoring the internal process states or structures; a widely adopted pattern recognition approach is that of the artificial neural networks (ANN). The ANN approach involves a nonlinear mapping between input and outputs, which consist of interconnected neurons arranged in layers. The layers are connected so that the signals at the input layers of the neural network are propagated throughout the network. The overall nonlinear behaviour of the neural network is determined by the choice of network topology and the weight of connections between neurons. In the process industries, ANNs have been applied for fault detection and diagnosis. For example, Cubillos and Lima (1998) described an adaptive hybrid system built upon prior knowledge and neural networks to model process control strategies and uncertain parameters in a highly non-linear CSTR and a four-stage floatation unit. Lennox et al. (1998) applied neural networks to model a vitrification process which encapsulates highly active liquid waste in glass to provide a safe and convenient method of storage, and capture non-linear characteristics of the process. The ANN model could also detect imminent fault of a vessel used in the same vitrification process. Kavchak and Budman (1999) adopted neural networks for non-linear process estimation and control of an exothermic. Ho et al. (2001) suggested that using neural networks with confidence bounds could provide more quality information on the performance of the deposition process for better decision-making and continuous improvement of a solder paste deposition process. Tsai et al. (2002) developed a robust model predictive control architecture using artificial neural networks. The regional knowledge analysis method was proposed and incorporated in the analysis of dynamic artificial neural network models in process control. The resulting analysis method and the modified model predictive architecture have been applied to a neutralization process. Wong and Wang (2003) used neural networks for sensitivity identification to enhance a set of control strategies for non-linear process systems; as well, he described a decomposed neural networks (DNN) model for an adaptive control system and applied it to benchmarking a chemical process. Power and Bahri (2004b) described a two-step supervisory fault diagnosis framework using neural networks. Based on this framework, a fault detection system was implemented to identify the exact location of faults and diagnose them in a pilot plant case study.

3. A survey of four integrated approaches for monitoring, diagnosis and control of industrial processes

Our survey on literature about development of intelligent systems for monitoring, diagnosis and control in process industries reveals that the three solution approaches described in Section 2 are often combined in system construction. Due to growing complexity of current systems, the integration of the three solution approaches into an intelligent system requires a framework which coordinates communication among the different solution modules. Tzafestas and Verbruggen (1995) stated that an integrated framework can facilitate the development process and help overcome the constraints of expense, time, and limited availability of human expertise. Intelligent systems that are built upon an integration of solution approaches can enhance plant performance, reduce plant operating costs, facilitate labor intensive tasks, and enable the operator to make more frequent and better informed decisions for improved environmental safety of the plant (Power and Bahri, 2004a). This section reviews some of the state-of-the-art integrated frameworks that combine the three solution approaches in process control industries.

From our survey, nine research groups were identified to be conducting research on issues related to automation of process control; these include efforts at Ohio State University, University of Texas at Austin, University of Maryland, Carnegie Mellon University, Massachusetts Institute of Technology, and Purdue University in the United States, University of Leeds in the United Kingdom, and University of Alberta and McMaster University in Canada. We focused on four groups because they are involved extensively in the fundamental development and applications of modern control methods, they include: (1) the Laboratory of Intelligent Systems in Process Engineering (LISPE) at the Massachusetts Institute of Technology, (2) the Laboratory for Intelligent Process Systems (LIPS) at Purdue University, (3) the Intelligent Engineering Laboratory (IEL) at the University of Alberta, and (4) the Department of Chemical Engineering at University of Leeds. The four research groups are distinctive in that they propose integrated and comprehensive frameworks that support developing intelligent systems to address multiple tasks related to monitoring and supervisory control of process systems. This is in contrast to other groups which either adopt particular approaches or focus on specific tasks related to monitoring and supervisory control. Each of the four research groups has their own unique features which are discussed as follows. The MIT group developed the language MODELLA, which was specifically designed for process control systems. To develop a process control language is a significant undertaking which no other research group attempted and which could potentially have substantial impact on the entire field of automated process control systems. The MIT group also proposed a hierarchical structure for developing automated process control systems which consists of high level control actions and an archive of process data. Similar to the Purdue University group, the University of Alberta group emphasized using a scheduler or meta-system. But contrary to the Purdue University group's adoption of a predefined and global data structure in its implementation of intelligent systems, the University of Alberta group proposed a framework which relies on an integration of multiple knowledge representation techniques and multimedia. The Leeds University research group's proposed framework demonstrates a clear separation among the three types of data-driven, information-driven, versus knowledge-based driven approaches. The other three groups' approaches did not show this clear separation of the three solution methods. The following gives a brief synopsis on features of the four integrated approaches.

3.1. *Laboratory of intelligent systems in process engineering (LISPE), MIT*

The research work of LISPE focuses on developing intelligent systems for monitoring, analysis and interpretation of process trends for diagnosis and operational support in process industries. They emphasized developing new problem formulations, formal theoretical frameworks, and methodologies for the solution of important process systems engineering problems. Under the direction of Dr. George Stephanopoulos, this group has studied diverse issues including artificial intelligence in process engineering (Stephanopoulos, 1990a, b); modeling language in process engineering (Stephanopoulos et al., 1990a, b); process trend representation for diagnosis and control (Cheung and Stephanopoulos, 1990a, b; Bakshi and Stephanopoulos, 1994a, b); integrating information, management and control in process industries (Han and Stephanopoulos, 1995); intelligent systems in process engineering (Stephanopoulos and Han, 1996); and multi-scale modeling, estimation and control of processing systems (Stephanopoulos et al., 1997). Their approach aims at integration of classical approaches in control and estimation theories, mathematical programming, statistical and stochastic processes with modern developments in computer science and artificial intelligence.

The LISPE group developed a first prototype called "Integrated Real-Time Workstation" (IRTW), which integrated Distributed Control System (DCS), supervisory control computer, and a series of external programs and databases for conducting engineering tasks. The IRTW was designed to have four fundamental components in an integrated environment: (1) a hierarchy of data models to describe various types of controllers; (2) hierarchies of data models to describe classes of actuators, sensors, logical constraints, process models, and faults; (3) rule-based expert systems to provide logical support to for example, PID controllers, and cascade controllers and; (4) hierarchies of data models to describe processes at various abstractions of plant, plant-section and unit operation, and signals at various scales and levels of detail.

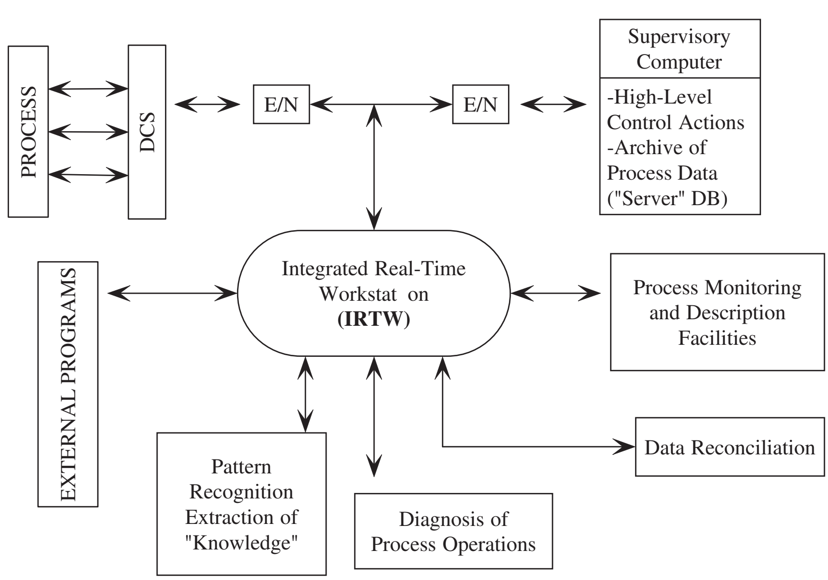

Fig. 2. The framework of IRTW (Han and Stephanopoulos, 1995).

The IRTW was developed to accommodate the needs of diverse users in different units of an organization, such as operators, process engineers, plant managers, and corporate planners through a distributed, client-server architecture of computing resources (Han and Stephanopoulos, 1995). The framework of IRTW is depicted in Fig. 2.

Although IRTW provides a sound example of a generic integrated framework for combining different functionalities in process operations, a rigidly structured organization with many levels functions best when the environment is relatively stable. For dynamic environments, a rigid structure is no longer appropriate and a more flexible organization that can adapt to changes quickly is needed (Kreitner, 1998). Generally, tasks in process industries are commonly designed to be isolated from each other and executed in a hierarchical manner where upper level decisions are imposed on lower levels with limited feedback up the chain. In this environment, any uncertainty associated with process data can upset the hierarchy because the framework cannot account for possible changes to the flow of information (Power and Bahri, 2005). The IRTW framework has this weakness as it cannot accommodate any change in information flow. An adaptive framework is desired, but this research group has not tackled the issue of building a flexible and adaptive framework.

3.2. Laboratory for intelligent process systems (LIPS) at Purdue University

The research objective of the LIPS group is diagnosis of process systems, and their approach focuses primarily on the development, integration and application of concepts and techniques drawn from fundamental sciences, engineering principles, computer science, artificial intelligence, mathematical programming, statistics, and information technology to address challenging engineering problems. Venkatasubramanian et al. (2003a, b, c) identified the challenge in process control industries as the creation of next generation prognostic and diagnostic systems which can monitor complex equipment and processes in real time, identify degradation in performance, predict potential failure scenarios, diagnose actual failures, and recommend and/or take corrective maintenance or control actions. However, the design of such systems is difficult due to constraints such as process complexity and equipment dynamics, lack of sensing techniques, sensor problems, lack of adequate models, incomplete and uncertain data, multiple sources of knowledge, and the significant amount of effort and expertise required to develop and maintain the systems.

Over the past 20 years, the LIPS group has developed diagnostic systems that employ different technologies, including knowledge-based systems, neural networks, statistical methods, analytical models and hybrid systems. Some of their contributions include an intelligent decision support system for abnormal situation management (ASM). This system can identify and mitigate any significant deviation of the process from an acceptable normal range of operations in a timely manner (Shin and Venkatasubramanian, 1996; Vedam et al., 1999). They also built an intelligent system called Op-Aide, which was developed based on an open, modular, blackboard-based architecture, and implemented using the expert system shell G2 (trademark of Gensym Corporation, USA), MATLAB (trademark of MathWorks, Inc, USA) and the C programming language. The modular architecture of Op-Aide is shown in Fig. 3.

As illustrated in Fig. 3, Op-Aide consists of six modules (or knowledge sources), which include: (1) a data acquisition module for data retrieval; (2) a module for monitoring the process abnormalities using PCA; (3) a diagnosis module for identifying the root causes for the abnormalities using multiple diagnosis methods, including signed directed graph, B-Spline, an adaptive system for trend analysis (ASTRA), and a knowledge based system containing knowledge about process diagnosis; (4) a Fault paRAmeter Magnitude Estimation (FRAME) module used for estimating the magnitude and rate of change of the root causes; (5) a simulation module used for predicting the values of process outputs or estimating consequences of an abnormal situation and; (6) an operator interface module to enable the operator to access the process knowledge and query the modules for explanations. In addition, Op-Aide consists of an Op-Scheduler which coordinates the six modules (Fig. 4).

Another contribution made by the LIPS group is a hybrid, distributed, multi-expert based blackboard framework, called Dkit, which was developed and was part of Honeywell's abnormal situation management consortium (1995–2000) (Mylaraswamy and Venkatasubramanian, 1997). This was the first hybrid diagnostic system that

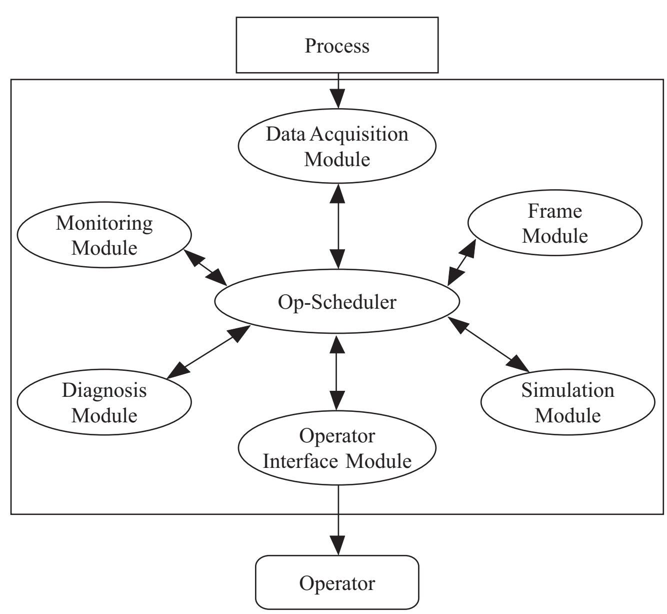

Fig. 3. Architecture of Op-Aide.

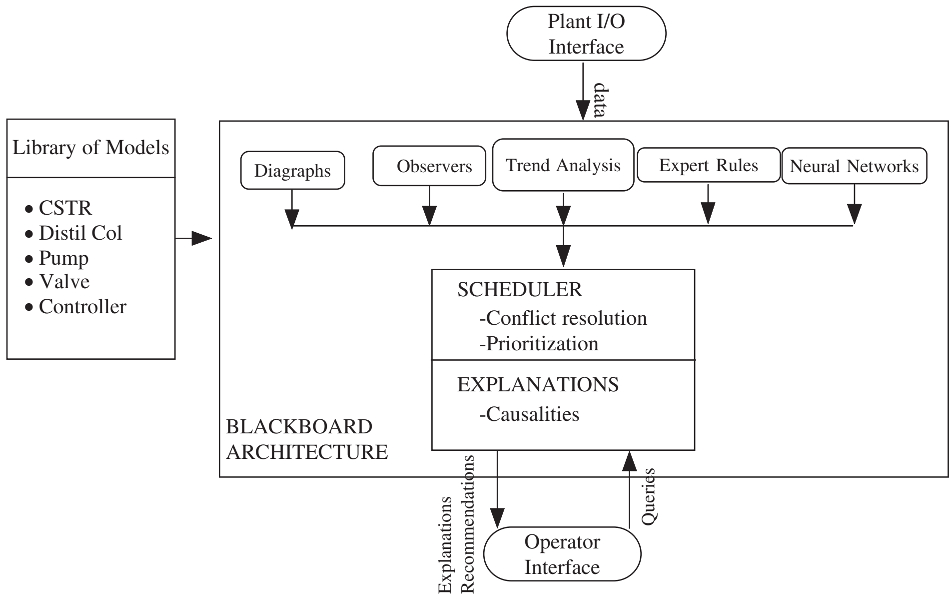

Fig. 4. Dkit hybrid framework (Mylaraswamy and Venkatasubramanian, 1997).

has been tested successfully on large-scale industrial processes. The DKit framework has been adopted for the design and implementation of the abnormal events guidance and information system (AEGIS) prototypes, funded in part by National Institute of Standards and Technology (NIST). In 1999, Honeywell licensed the DKit-based technology from Purdue University. This is the first time a university-developed technology was licensed by a control system vendor for ASM applications.

The Dkit framework consists of six major components including: (1) a diagnostic expert system, which is a component that contains a collection of one or more diagnostic methods such as signed diagraph, residue generation and parameter estimation, qualitative trend analysis, and statistical classifiers; (2) a blackboard, which was designed as pigeon holes, with each hole serving as a placeholder for a well-defined process state; (3) a scheduler that consists of a monitoring component for keeping track of new events and states, a switchboard for directing information to relevant subscribers, and a component for conflict resolution; (4) a plant input–output interface which receives all monitored process measurements and functions as a central repository for all diagnostic methods; (5) an operator interface that presents diagnostic results to the operator and; (6) a process equipment library used for developing DKit.

The resulting diagnostic system was implemented and applied to a fluidized catalytic cracking unit (FCCU) process. The hybrid DKit framework provides the environment for integrating the methods of qualitative trend analysis, probability density function-based statistical classifier, model-based diagnostic methods and process history-based methods. The integrated approach enhanced the chance of generating a more comprehensive solution.

In summary, the blackboard architecture has the advantage that the problem-solving state is made available in the form of a global data structure while each module can be kept isolated (Albayrak and Krallmann, 1995). However, the blackboard model only outlines the organization principle, it does not specify the computational procedures involved for realizing the system. Also, applications of the blackboard model often requires extensions to the framework (Engelmore et al., 1988).

3.3. *Intelligence engineering laboratory (IEL) at the University of Alberta*

The integrated framework advanced by the IEL relies on a meta-system for coordinating diverse solution approaches, knowledge representation schemes, and process control tasks. The main research focus of the IEL are: (1) to develop integrated distributed intelligent systems and intelligent multimedia systems for on-line real-time applications; (2) to develop technology that provides better integration of theoretical investigations and practical applications; (3) to provide researchers with an interdisciplinary training and research environment; (4) to better support industry and government R&D partnerships and; (5) to provide an active framework for international collaborative research and education programs (Rao, 1995).

Rao (1991) proposed a framework called the Integrated Distributed Intelligent System (IDIS) for on-line monitoring and control of processes. Based on this framework, a platform for developing an INTElligent Multimedia system for On-line Real-time applications (INTERMOR) was constructed. The platform consists of functions and tools needed for automating an entire process of on-line monitoring, fault diagnosis and information management.

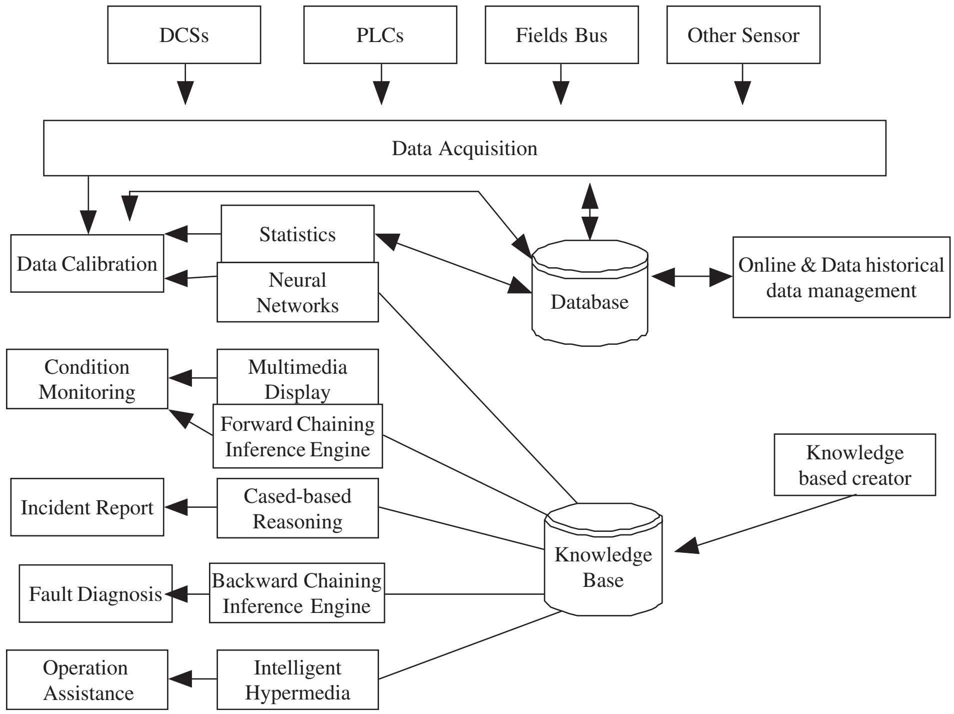

Fig. 5. INTEMOR's platform (Rao et al., 2000).

It includes modules for data acquisition, data calibration, condition monitoring, fault diagnosis, maintenance, on-line help, operation manual, historical data management and knowledge-base creation. Fig. 5 illustrates the information flow in the INTEMOR platform (Rao et al., 2000).

The acquired data is initially processed at the data calibration module, which uses neural networks and statistics to perform data pre-processing, data compression and data format transfer. The condition monitoring module, coupled with forward chaining inference, alerts the user to abnormal process conditions. Then, the incident report module uses the case-based reasoning (CBR) technique to determine whether the current conditions had previously occurred. If they had, the fault diagnosis module will generate a solution. Otherwise backward chaining will be invoked to detect faults. Finally, the multimedia system displays operational assistance for the users to correct the faults. INTEMOR was developed with the objective of integrating various methods so as to compensate for limitations of each (Rao et al., 2000). Other objectives of INTEMOR include: (1) to integrate various problem solving methods, such as rule-based, model-based and CBR methods, as well as neural networks; (2) to integrate various types and levels of knowledge representation, such as integrating rules sets, past solutions, process models and real time data in an object-oriented system and; (3) to integrate multiple problem solving tasks and application systems, such as for condition monitoring, fault diagnosis and maintenance support.

The INTEMOR system had been used to develop many intelligent systems, including an expert process monitoring system which was applied to a pulp bleaching process (Xia and Rao, 1999b), a prototype intelligent operation support system (IOSS) that was implemented on a bleached chemi-thermo-mechanical pulp plant (Xia and Rao 1999c), an intelligent maintenance support system for monitoring and troubleshooting of mining truck conditions (Ursenbach et al., 1994), an integrated distributed intelligent system for on-line monitoring and control of pulp processes (Rao and Xia, 1994, 1997), an expert system for on-line incident detection and reporting (Erlenbach et al., 1994), an expert system for real-time process condition monitoring and incident prevention of a chemical pulp mill process (Feng et al., 1998), and a knowledge integration system for pulp and paper process operations (Farzadeh et al., 1995). The major weakness of this framework is its lack of scalability. When the size of the problem increases and more knowledge or analysis modules are needed to solve a problem, a knowledge co-ordinator module is needed to perform meta-level inferencing and control, but the INTEMOR framework does not support this capability. Hence, when the number of plausible solutions increases, this scalability issue becomes a serious limitation. The framework lacks a knowledge management module for coordinating problem solving when multiple solutions are involved.

3.4. Department of Chemical Engineering at University of Leeds

The research objective of the group at Department of Chemical Engineering of University of Leeds is to investigate advanced mathematical, knowledge-based as well as data-driven techniques for building integrated and on-line measurement, control, and information systems for improved process performance. The research work include studies on applications of data mining techniques for operational data analysis and interpretation for process systems (Wang et al, 1999a, b; Chen and Wang, 1999, 2000; Sebzalli et al., 2001); wavelets, fuzzy logic and independent and principal component analysis for on-line data pre-processing (Chen and Wang, 1999; Wang et al., 1999a, b; Sebzalli and Wang, 2001; Li and Wang, 2002; Al-Bazzaz and Wang, 2004); unsupervised neural networks for temporal clustering and analysis of industrial process data (Chen et al., 1998; Yang et al., 2000); and intelligent, multi-objective, multi-variable and predictive control (Yang et al., 1998; Al-Bazzaz and Wang, 2004). Other research projects undertaken include studies on data mining for batch process monitoring and control, data mining for prediction of eco-toxicity of chemicals and their mixtures, on-line measurement and control of the sizes and growth rates of organic particulate solid products using on-line acoustic spectroscopy, near infrared spectroscopy techniques and on-line imaging.

Wang (1999) proposed a software system architecture for developing a state-space based monitoring and control environment which conducts data mining and knowledge discovery from the process operations database. The system has the following functions: (1) identification of operational states; (2) projection of the operation to a single point of the operational plane; (3) providing explanations on the major variables that are responsible for the projection to unacceptable operational states; and (4) providing guidance for adjusting the variables to bring the system back within the acceptable operational states. Fig. 6 shows a conceptual diagram of the system architecture and its associated components.

Wang (1999) suggested that an integrated data mining and knowledge discovery from database (KDD) system for process monitoring and control requires the following functions:

(1) *Pattern recognition*: The system should be able to group data into clusters and then analyse similarities between the clusters. This function is useful for identifying abnormal conditions.
(2) *Trend analysis of the process data*: This function is implemented as various techniques for trend analysis including statistics and calculation of mean and standard deviations.
(3) *Link and dependency analysis*: This function provides plant operators with understanding of process behavior and performance. Some existing data mining methods such as inductive learning approaches are unable to deal with real-valued dynamic trends and interactions between variables. Therefore, the ideal system must provide the tool for link and dependency analysis.
(4) *Summarizing*: This function uses summary of rules, multivariate visualization techniques, and functional relationship between variables to provide compact descriptions of a subset of data, such as mean and standard deviation of all fields.
(5) *Sequence analysis*: This function aims at generating the sequence or extracting report deviations and trends over time. It models sequential patterns in data with time dependencies, such as time series analysis.
(6) *Regression*: This is required for predictive model development.

Implementing data mining and knowledge discovery techniques typically involve the following procedures: (1) developing an understanding of the application domain; (2) creating a target data set; (3) data pre-processing and

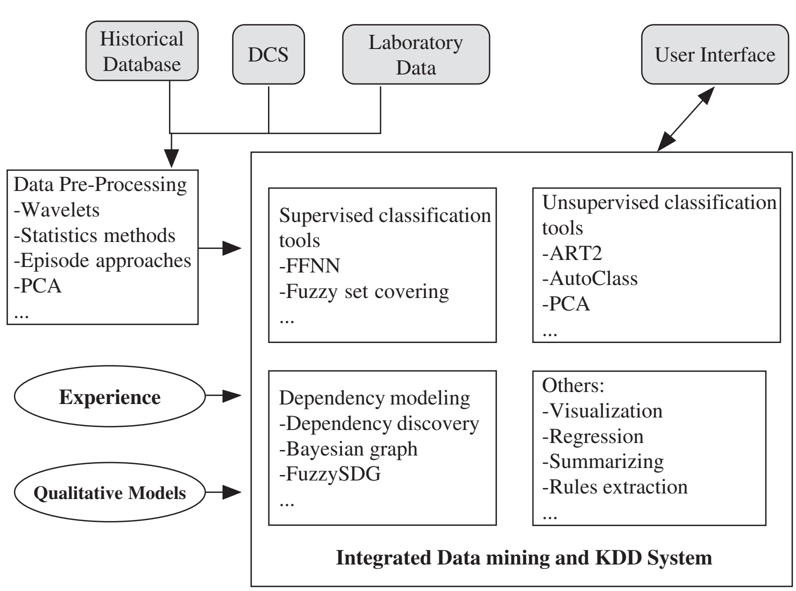

Fig. 6. The conceptual architecture of an integrated data mining and KDD system (Wang, 1999).

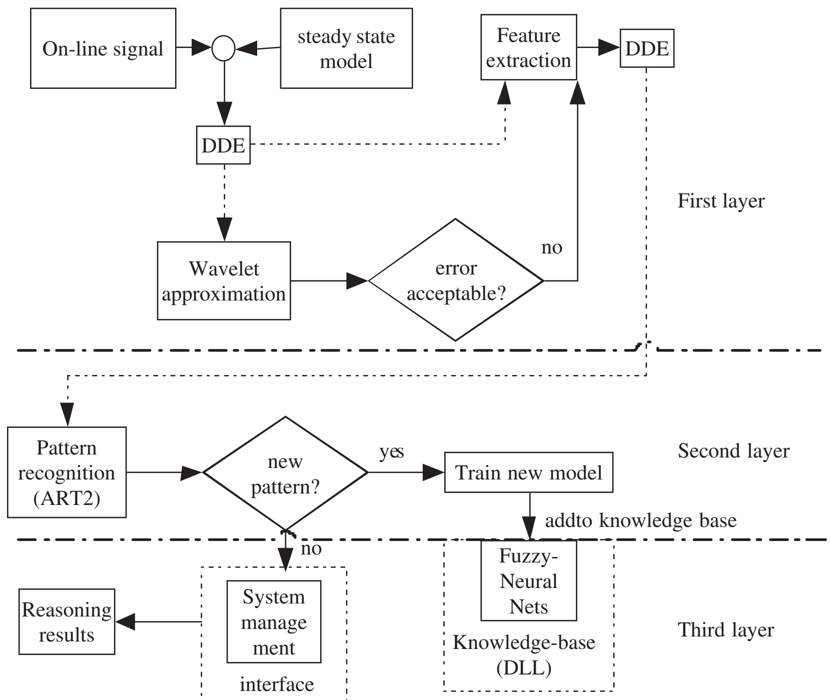

Fig. 7. Framework of the operation support system (Chen and Wang, 1999).

cleaning; (4) data reduction and projection; (5) choosing the data mining tasks; (6) choosing the data analysis algorithm (s); (7) data mining; (8) interpreting mined patterns and; (9) consolidating the discovered knowledge. Wang (1999) categorized data mining methods and tools according to their functions and application purposes into the following groupings: clustering, classification, summarization, dependency modeling, link analysis and sequence analysis. He also proposed a general framework for data mining and knowledge discovery from process data (Wang et al., 2000).

The conceptual architecture of an integrated knowledge discovery and data mining system has guided the development of various intelligent systems. For example, Chen and Wang (1999) proposed a framework for an on-line operational support system (OOSS) for fault diagnosis in process plants. The system supports rapid interpretation of dynamic signals, knowledge representation for reasoning on continuous evolution, display of transparent results, and reliable corrective responses. The framework can perform three major tasks: (1) transient determination and residual generation; (2) interpretation of transients including feature extraction and pattern recognition; and (3) creation of a model base consisting of a group of fuzzy feed forward neural networks (FFNNs). The resulting system is integrated into an overall management facility that displays results of the reasoning process. Fig. 7 illustrates the framework for the operational support system for fault diagnosis in process plants advanced in Chen and Wang (1999).

In the first layer of Fig. 7, the system implements an on-line residual acquisition and data processing system using FFNN and wavelet transform. The output of the Distributed Control System (DCS) will be compared with the output of FFNN to generate the residual. The wavelet transform works as a smoother or low-pass filter of output using inverse transform. In the second layer, the pattern recognition algorithm of ART 2 is chosen for pattern identification purposes. In the third layer, the knowledge base consists of a group of trained fuzzy FFNN. The system management module in the middle of this layer matches a pattern by finding a suitable network. When a new pattern is discovered, the data is collected to train a new fuzzy FFNN and added to the knowledge base. Wang et al. (1999a, b) applied this framework for analysis of data from a refinery residual fluid catalytic cracking process (RFCC).

This framework provides a clear overview of information flow and applicable techniques useful for process control operations. Within this context, the authors identified the wavelet approximation module for data preprocessing to be one of the most desirable tools for dealing with incomplete information. However, while this framework can be used to integrate operational tasks for continuous operations, it is not clear how coordination of those tasks can be achieved.

4. Discussion

On comparing the four integrated frameworks of IRTW, INTEMOR, OOSE, and DKIT in terms of their approaches and tasks addressed, a number of similarities and differences can be observed. The four integrated frameworks for development of intelligent systems for process systems combine the three solution approaches, but the priority they assign to the approaches are different. INTEMOR, DKIT and IRTW give the highest priority to the knowledge-based system (KBS) solution approach whereas OOSS assign the highest priority to the data-driven solution approach. DKIT and IRTW adopt the same priority assignment scheme, which gives first priority to the KBS approach, then analytical and data-driven approaches, while INTEMOR ranks KBS approach first, then data-driven and analytical approaches. The ranking of solution approaches in OOSS is data-driven, analytical, then KBS approach. While all four integrated frameworks address the broad group of tasks involved in process systems, their emphasis also differs. INTEMOR mainly focuses on system condition monitoring, fault diagnosis, and maintenance support, while OOSS' emphasis is on fault diagnosis. Both DKIT and IRTW tackle process monitoring, supervisory control, and diagnosis of process operations. The four integrated frameworks all adopt the three solution approaches but each has its own method of integrating them. INTEMOR uses a meta-system to coordinate the different approaches and integrate different knowledge representation mechanisms, and DKIT includes a scheduler for coordinating the different approaches and for conflict resolution. The meta-system includes a database, rule-base and inference engine that can be used for managing and coordinating the symbolic reasoning and numeric computation within the system during various phases of information gathering and processing. The scheduler in DKIT on the other hand, analyzes recommendations generated by the different solution approaches, assesses their strengths and weaknesses and produces a final result after applying conflict-resolution algorithms based on a weighted voting scheme derived from probability theory. The OOSS framework includes three layers with the specific functionalities of (1) determination and residual generation, (2) feature extraction and pattern recognition, and (3) model creation, whereas IRTW includes a hierarchy of data models, which describe different types of controllers, actuators, sensors, logical constraints, process models, faults, and processes at various abstraction levels.

In terms of strengths and weaknesses of the integrated frameworks, the primary strength is that all the frameworks support integration of the three solution approaches. The INTEMOR framework not only integrates

Table 1
Table of comparison of the four integrated frameworks

	INTEMOR	OOSS	DKIT	IRTW
Approach	Combines data-driven, analytical, and knowledge-based approaches; the priority among the three approaches is: KBS, data-driven, and analytical	Combines data-driven, analytical, and knowledge-based approaches; the priority among the three approaches is: data-driven, analytical, and KBS	Combines data-driven, analytical, and knowledge-based approaches; the priority among the three approaches is: KBS, analytical and data driven	Combines data-driven, analytical, and knowledge-based approaches; the priority among the three approaches is: KBS, analytical, and data driven
Task	Condition monitoring, fault diagnosis, and maintenance support	Fault diagnosis	Process monitoring, diagnosis, and supervisory control	Supervisory control, and diagnosis of process operations, and process monitoring and description facility
Features	It uses a meta-system to coordinate different approaches and integrates knowledge representation techniques	It features three- layers of functionalities: (1) determination and residual generation, (2) feature extraction and pattern recognition, and (3) model creation	The scheduler module conducts conflict resolution and coordinates different approaches	It includes a hierarchy of data models on types of controllers, actuators, sensors, logical constraints, process models, faults, and processes at various abstractions
Strength	It integrates solution approaches, knowledge representation techniques, and process control tasks.	It provides good understanding of information flow throughout the process control operations	The blackboard structure has the advantage that the problem-solving state is made available in the form of a global data structure while each module can be kept isolated	It provides a generic integrated framework for combining different functionalities in process operations
Weakness	The meta-system would have a scalability problem when the knowledge base keeps growing in size. The meta-level's inference engine needs to handle a large number of plausible solutions	It lacks coordination among process control tasks	The blackboard model only outlines its organization principle, and not its computational procedure	The hierarchical structure does not accommodate any change in information flow

the solution approaches, but also different knowledge representation schemes and process control tasks. OOSS clearly defines the information flow among the process control operations, while DKIT has a blackboard structure, which ensures the problem-solving state is shared among different modules by means of a global data structure. IRWT on the other hand, provides a generic integrated framework for combining different functionalities in process operations.

The frameworks also suffer from some weaknesses. Since INTEMOR was designed to coordinate diverse solution approaches, knowledge representation schemes, and process control tasks, if the problem domain tackled is complex and involves a large knowledge base that can grow in size, then the meta-level inference engine needs to handle a large and possibly growing number of plausible solutions. Scalability would become an issue. By contrast, OOSS aims to integrate the functions of determination and generation of residuals, feature extraction, pattern recognition, and model creation, and coordinates the three solution approaches using a three-layered structure. However, while the three-layered structure provides good support in terms of information flow among the process control operations, it is unclear how coordination of the different tasks involved in process control can be achieved. By comparison, the DKIT framework has defined the mechanisms for coordinating the process control tasks of monitoring, diagnosis, and supervisory control. While the blackboard structure in DKIT can adequately support organization of the diverse modules, it cannot specify the computational procedures involved. The IRTW framework can integrate the process control tasks of supervisory control, diagnosis of process operations, and process monitoring, and the hierarchical data structure in IRTW provides a generic integrated framework for combining different functionalities in process operations. However, its weakness is that the hierarchical data structure cannot accommodate any change in the information flow. In other words, it is not flexible and adaptive. The characteristics of the four integrated frameworks discussed have been summarized in Table 1.

5. Conclusion

This paper has presented an overview of research work on development of intelligent systems for monitoring, supervisory control, and diagnosis of operations in process systems engineering. We have discussed the three solution approaches often adopted for building automated systems in process control engineering, namely the data-driven, analytical and knowledge-based approaches. Some popular algorithms and applications of each approach have also been discussed. We have also presented what we consider to be the four most comprehensive integrated intelligent system frameworks, namely IRTW, INTEMOR, OOSE, and DKIT, and their advantages and disadvantages. Based on our review, we believe desirable properties of integrated intelligent frameworks to include (Venkatasubramanian et al., 2003c):

(1) the ability to coordinate various process control tasks such as monitoring, diagnosis and supervisory control,
(2) the ability to integrate the solution approaches of data-driven, analytical and knowledge-based systems,
(3) the ability to coordinate different knowledge representations schemes such as rules, frames, models, and cases,
(4) the ability to maintain a global database and global management of process knowledge,
(5) a hierarchical structure of data models on types of controllers, actuators, sensors, logical constraints, process models, faults, and processes at various abstraction levels,
(6) the ability to adapt to a changing environment.

The four integrated frameworks reflect consideration of the first five but not the last consideration. We believe future research on developing integrated intelligent systems for monitoring, diagnosis, and control of industrial processes should consider including all of the desirable properties. A further direction in future research is to tailor the framework for developing intelligent systems for process systems in the energy and environment sector. We hypothesize that particular problem domains have specific characteristics, which need to be reflected in the design of an intelligent system framework for monitoring, control and diagnosis of process systems. This hypothesis will be tested as we propose a framework for intelligent system development and apply it for automating specific processes in energy and environmental engineering systems.

Acknowledgement

We would like to acknowledge the generous financial support of a Strategic Grant from Natural Sciences and Engineering Research Council (NSERC) of Canada.

References

Adebiyi, A.O., Corripio, B.A., 2003. Dynamic neural networks partial least squares (DNNPLS) identification of multivariable processes. Computers & Chemical Engineering 27, 143–155.

Aggarwal, K.R., Xuan, Y.Q., Johns, T.A., Li, F., Bennett, A., 1999. Novel approach to fault diagnosis in multicircuit transmission lines using fuzzy ARTmap neural network. IEEE Transactions on Neural Networks 10, 1214–1221.

Albayrak, S., Krallmann, H., 1995. Distributed artificial intelligence in manufacturing control. In: Tzafesta, G.S., Verbruggen, B.H. (Eds.), Artificial Intelligence in Industrial Decision Making, Control and Automation. Kluwer., The Natherlands, pp. 247–294.

Al-Bazzaz, H., Wang, X.Z., 2004. Statistical process control charts for batch operations based on independent component analysis. Industrial Engineering and Chemistry Research 43, 6731–6741.

Alexandridis, P.A., Siettos, I.C., Sarimveis, K.H., Boudouvis, G.A., Bafas, V.G., 2002. Modelling of Nonlinear Process dynamics using

kohonen's neural networks, fuzzy systems and chebyshev series. Computers & Chemical Engineering 26, 479–486.
Akbaryan, F., Bishnoi, R.P., 2001. Fault diagnosis of multivariate systems using pattern recognition and multisensor data analysis technique. Computers & Chemical Engineering 25, 1313–1339.
Amand, T.H., Heyen, G., Kalitventzeff, B., 2001. Plant monitoring and fault detection synergy between data reconciliation and principal component analysis. Computers & Chemical Engineering 25, 501–507.
Bakshi, R.B., Stephanopoulos, G., 1994a. Representation of process trends—III multiscale extraction of trends from process data. Computers & Chemical Engineering 18 (4), 267–302.
Bakshi, R.B., Stephanopoulos, G., 1994b. Representation of process trends—IV induction of real-time patterns from operating data for diagnosis and supervisory control. Computers & Chemical Engineering 18 (4), 267–302.
Belarbi, K., Bettou, K., Mezaache, A., 2000. Fuzzy neural networks for estimation and fuzzy controller design: simulation study for a pulp batch digester. Journal of Process Control 10, 35–41.
Beck, V.J., Arnold, J.K., 1977. Parameter Estimation in Engineering and Science. Wiley, New York.
Burrell, P., Inman, D., 1998. Expert system for the analysis of faults in an electricity supply network: problems and achievements. Computers in Industry 37, 113–123.
Chen, J.G., Bandoni, J.A., Romagnoli, J.A., 1996. Robust PCA and normal region in multivariate statistical process monitoring. AIChE Journal 42, 3563–3566.
Chen, T.C., Peng, T.S., 1999. Intelligent process control using neural fuzzy techniques. Journal of Process Control 9, 493–503.
Chen, Z.F., Wang, Z.X., 1999. An integrated data mining system and its application to process operational data analysis. Computers & Chemical Engineering 23, s777–s780.
Chen, Z.F., Wang, Z.X., 2000. Discovery of operational spaces from process data for production of multiple grades of products. Industrial Engineering and Chemistry Research 39, 2378–2383.
Chen, H.B., Wang, Z.X., McGraavy, C., 1998. On-line operational support system for faults diagnosis in process plants. Computers & Chemical Engineering 22 (suppl.), s973–s976.
Cheung, Y.J.T., Stephanopoulos, G., 1990a. Representation of process trends—Part I. A formal representation framework. Computers & Chemical Engineering 14 (4-5), 495–510.
Cheung, Y.J.T., Stephanopoulos, G., 1990b. Representation of process trends—Part II. The problem of scale and qualitative scaling. Computers & Chemical Engineering 14 (4–5), 511–539.
Chiang, H.L., Russell, L.E., Braatz, D.R., 2001. Fault Detection and Diagnosis in Industrial Systems. Springer, London, Great Britain.
Clancey, J.W., Shortliffe, H.E. (Eds.), 1984. Readings in Medical Artificial Intelligence: The First Decease. Addison-Wesley, Reading, MA.
Cubillos, A.F., Lima, L.E., 1998. Adaptive hybrid neural models for process control. Computers & Chemical Engineering 22 (Suppl.), s989–s992.
Ding, X., Guo, L., 1996. Observer-based fault detection optimized in the frequency domain. In: Proceedings of the 13th IFAC World Congress, Vol. N. IEEE Press, Piscataway., New Jersey, pp. 157–162.
Engelmore, S.R., Morgan, J.A., Nii, P.H., 1988. Introduction (chapter 1). In: Engelmore, R., Morgan, T. (Eds.), Blackboard System. Addison-Wesley, England, pp. 1–22.
Erlenbach, S., Ying, Y., Rao, M., Danielson, K., 1994. An expert system for on-line incident detection and reporting. In: Proceedings of the 1994 CPPA Western Branch Fall Conference, October 25–27, Grande Prairie, Canada.
Farzadeh, H., Xia, Q., Ying, Y., Rao, M., Henriksson, C., Danielson, K., Olofsson, J., 1995. Knowledge integration system for slave lake pulp corporation and DMI Peace River Division. Pulp & Paper Canada 96, 25–28.
Feng, E., Yang, H., Rao, M., 1998. Fuzzy expert system for real-time process condition monitoring and incident prevention. Expert Systems with Applications 15 (3–4), 383–390.
Frank, P.M., 1992. "Robust Model-based Fault Detection in Dynamic Systems," IFAC Symp. on On-line Fault Detection and Supervision in the Chemical Process Industries, p.1. Newark, Del.
Garcia, A.E., Frank, M.P., 1996. On the relationship between observer and parameter identification based approaches to fault detection. In: Proceedings of the 13th IFAC World Congress, vol. N. Piscataway., New Jersey, pp. 25–29.
González-García, R., Rico-Martínez, R., Kevrekidis, G.I., 1998. Identification of distributed parameter systems: a neural net based approach. Computers & Chemical Engineering 22 (Suppl.), s965–s968.
Han, C., Stephanopoulos, G., 1995. Integrating information, management and control in process industries. In: Berber, R. (Ed.), Methods of Model Based Process Control. Kluwer Academic Publishers, Netherlands, pp. 715–751.
Ho, L.S., Xie, M., Tang, C.L., Xu, K., Goh, N.T., 2001. Neural network modeling with confidence bounds: a case study on the solder paste deposition process. IEEE Transactions on Electronics Packing Manufacturing 24 (4), 323–332.
Isermann, R., 1984. Fault diagnosis of machines via parameter estimation and knowledge processing—tutorial paper. Automatica 20, 387–404.
Isermann, R., 1994a. Integration of fault detection and diagnosis methods. In: Fault Detection, Supervision, and Safety for Technical Processes. IFAC Symposium. Pergamon Press, Oxford.
Isermann, R., 1994b. Model based fault detection and diagnosis methods. In: Fault Detection, Supervision, and Safety for Technical Processes. IFAC Symposium. Pergamon Press, Oxford.
Jain, C.L., Johnson, P.R., Takefuji, Y., Zadeh, A.L. (Eds.), 1999. Knowledge-Based Intelligent Techniques in Industry. CRC Press, New York.
Kano, M., Hasebe, S., Hashimoto, I., Ohno, H., 2001. A new multivariate statistical process monitoring method using principal component analysis. Computers & Chemical Engineering 25, 1103–1113.
Kano, M., Nagao, K., Hasebe, S., Hashimoto, I., Ohno, H., Strauss, R., Bakshi, R.B., 2002. Comparison of multivariate statistical process monitoring methods with applications to the Eastman challenge problem. Computers & Chemical Engineering 26, 161–174.
Kasabov, K.N., 1996. Foundation of Neural Networks, Fuzzy Systems, and Knowledge Engineering. MIT Press., Cambridge, MA.
Kavchak, M., Budman, H., 1999. Adaptive neural network structures for non-linear process estimation and control. Computers & Chemical Engineering 23, 1209–1228.
Kesavan, P., Lee, H.L., 1997. Diagnostic tools for multivariable model-based control systems. Industrial Engineering and Chemistry Research 36, 2725–2738.
Koiranen, T., Virkki-Hatakka, T., Kraslawski, A., Nyström, L., 1998. Hybrid, fuzzy and neural adaptation in case-based reasoning system for process equipment selection. Computers & Chemical Engineering 22, s997–s1000.
Kreitner, R., 1998. Management, 7th Ed. Houghton Mifflin Company, USA.
Kresta, V.J., Marlin, E.T., MacGregor, F.J., 1991. Multivariable statistical monitoring of process operating performance. Canadian Journal of Chemical Engineering 69, 34–47.
Kresta, V.J., Marlin, E.T., MacGregor, F.J., 1997. Development of inferential process models using PLS. Computers & Chemical Engineering 21 (Suppl.), s1123–s1129.
Kritpiphat, W., Tontiwachwuthikul, P., Chan, W.C., 1998. Pipeline network modeling and simulation for intelligent monitoring and control: a case study of a municipal water supply. Industrial Engineering and Chemistry Research 37, 1033–1044.
Kruger, U., Chen, Q., Sandoz, J.D., McFarlane, C.R., 2001. Extended PLS approach for enhanced condition monitoring of industrial processes. AIChE Journal 47 (9), 2076–2091.
Ku, W., Storer, H.R., Geogakis, C., 1994. Uses of state estimation for statistical process control. Computers & Chemical Engineering 18, s571–s575.
Lee, M.J., Yoo, K.C., Lee, B.I., 2004. Fault detection of batch processes using multiway kernel principal component analysis. Computers & Chemical Engineering 28, 1837–1847.

Lennox, B., Rutherford, P., Montague, A.G., Haughin, C., 1998. Case study investigating the application of neural networks for process modelling and condition monitoring. Computers & Chemical Engineering 22 (21), 1573–1579.

Li, F.R., Wang, Z.X., 2002. Dimension reduction of process dynamic trends using independent component analysis. Computers & Chemical Engineering 26, 467–473.

Lin, W., Qian, Y., Li, X., 2000. Nonlinear dynamic principal component analysis for on-line process monitoring and diagnosis. Computers & Chemical Engineering 24, 423–429.

Linkens, A.D., Abbod, F.M., Browne, A., Cade, N., 2000. Intelligent control of a cryogenic cooling plant based on blackboard system architecture. ISA Transactions 39, 327–343.

Luo, X., Zhang, C., Jennings, R.N., 2002. A hybrid model for sharing information between fuzzy, uncertain and default reasoning models in multi-agent systems. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems 10 (4), 401–450.

MacGregor, F.J., 1994. Statistical Process Control of Multivariate Proceses. In: Proceedings of the IFAC International Symposium on Advanced Control of Chemical Processes. Pergamon Press, New York, pp. 427–435.

MacGregor, F.J., Kourti, T., 1995. Statistical process control of multivariate processes. Control Engineering Practice 3, 403–414.

McAvoy, T., 2002. Model predictive statistical process control of chemical plants. Industrial Engineering and Chemistry Research 41, 6337–6344.

Miletic, I., Quinn, S., Dudzic, M., Vaculik, V., Champagne, M., 2004. An industrial perspective on implementing on-line applications of multivariate statistics. Journal of Process Control 14, 821–836.

Mylaraswamy, D., Venkatasubramanian, V., 1997. A hybrid framework for large-scale process fault diagnosis. Computers & Chemical Engineering 21, S935–S940.

Neogi, D., Schlags, C.E., 1998. Multivariate statistical analysis of an emulsion batch process. Industrial Engineering and Chemistry Research 44, 1596–1610.

Norvilas, A., Negiz, A., DeCicco, J., Cinar, A., 2000. Intelligent process monitoring by interfacing knowledge-based system and multivariate statistical monitoring. Journal of Process Control 10, 341–350.

Piovoso, J.M., Kasonovich, A.K., Pearson, K.R., 1992. Monitoring process performance in real time. In: Proceedings of the American Control Conference. IEEE Press, Piscataway, New Jersey, pp. 2359–2363.

Power, Y., Bahri, A.P., 2004a. Integration techniques in intelligent operational management: a review. Knowledge-Based Systems 20, 1–9.

Power, Y., Bahri, A.P., 2004b. A two-step supervisory fault diagnosis framework. Computers & Chemical Engineering 28, 2131–2140.

Power, Y., Bahri, A.P., 2005. Integration techniques in intelligent operational management: a review. Knowledge-Based Systems 18 (2–3), 89–97.

Prasad, R.P., Davis, F.J., Jirapinyo, Y., Josephson, R.J., Bhalodia, M., 1998. Structuring diagnostic knowledge for large-scale process systems. Computers & Chemical Engineering 22 (12), 1897–1905.

Raich, C.A., Cinar, A., 1996. Statistical process monitoring and disturbance diagnosis in multivariable continuous processes. AIChE Journal 42, 995–1009.

Rao, M., 1991. Integrated System for Intelligent Control. Springer, Berlin.

Rao, M., 1995. Turning dreams into reality through technology diffusion. IEL Proceeding of the Second Research Review Conference, August 24–25, Edmonton, Canada, pp. 1–22.

Rao, M., Xia, Q., 1994. Integrated distributed intelligent system for on-line monitoring and control of pulp process. Canadian Artificial Intelligence 33, 5–10.

Rao, M., Xia, Q., 1997. IOMCS project—a university/industry/government R&D partnership program. International Journal of Engineering Education 13 (4), 275–284.

Rao, M., Sun, X., Feng, J., 2000. Intelligent system architecture for process operation support. Expert Systems with Applications 19, 279–288.

Rengaswamy, R., Venkatasubramanian, V., 1992. An Integrated Framework for Process Monitoring, Diagnosis, and Control using Knowledge-based Systems and Neural Networks. IFAC, Delaware, USA, pp. 49–54.

Ruiz, D., Cantón, J., Nougués, M.J., Espuña, A., Puigjaner, L., 2001. On-line fault diagnosis system support for reactive scheduling in multipurpose batch chemical plants. Computers & Chemical Engineering 25, 829–837.

Ruiz, D., Benqlilou, C., Nougués, M.J., Puigjaner, L., 2002. Proposal to speed up the implementation of an abnormal situation management in the chemical process industry. Industrial Engineering and Chemistry Research 41, 817–824.

Sebzalli, M.Y., Wang, Z.X., 2001. Knowledge discovery from process operational data using PCA and fuzzy clustering. Engineering Applications Artificial Intelligence 14, 607–616.

Sebzalli, M.Y., Li, F.R., Wang, Z.X., 2001. Knowledge discovery from process operational data for assessment and monitoring of operator's performance. Computers & Chemical Engineering 24, 409–414.

Shin, D., Venkatasubramanian, V., 1996. Intelligent tutoring system framework for operator training for diagnostic problem solving. Computers & Chemical Engineering 20 (Suppl.), s1365–s1370.

Srihari, N.S., 1989. Application of expert systems in engineering: an introduction. In: S.G. Tzafestas, G.S. (Eds.), Knowledge-based System Diagnosis, Supervision, and Control. Plenum Press, New York, pp. 1–10.

Stephanopoulos, G., 1990a. Artificial intelligence … what will its contributions be to process control? In: David, M., Prett, Others (Eds.), The Second Shell Process Control Workshop. Butterworth Publishers, Stoneham, Massachusetts.

Stephanopoulos, G., 1990b. Artificial intelligence in process engineering—current state and future trends. Computers & Chemical Engineering 14 (11), 1259–1270.

Stephanopoulos, G., Han, C., 1996. Intelligent systems in process engineering: a review. Computers & Chemical Engineering 20 (6/7), 743–791.

Stephanopoulos, G., Henning, G., Leone, H., 1990a. MODEL.LA. a modeling language for process engineering—I. the formal framework. Computers & Chemical Engineering 14 (8), 813–846.

Stephanopoulos, G., Henning, G., Leone, H., 1990b. MODEL.LA. a modeling language for process engineering—II. multifaceted modeling of processing systems. Computers & Chemical Engineering 14 (8), 847–869.

Stephanopoulos, G., Dyer, M., Karsligil, O., 1997. Multi-scale modeling, estimation and control of processing systems. Computers & Chemical Engineering 21 (Suppl.1), s797–s803.

Sun, C.L., Uraikul, V., Chan, W.C., Tontiwachwuthikul, P., 2000. An integrated expert system/operation research approach for automation of natural gas pipeline operations. Engineering Applications Artificial Intelligence 13 (4), 465–475.

Tsai, F.P., Chu, Z.J., Jang, S.S., Shieh, S.S., 2002. Developing a robust model predictive control architecture through regional knowledge analysis of artificial neural networks. Journal of Process Control 13, 423–435.

Tzafestas, G.S., Verbruggen, H.B., 1995. Artificial intelligence in industrial decision making control, and automation: an introduction. In: Tzafestas, G.S., Verbruggen, B.H. (Eds.), Kluwer, The Netherlands, pp. 159–188.

Ündey, C., Cinar, A., 2002. Statistical monitoring of multistage, multiphase batch processes. IEEE Control Systems Magazine, 40–52.

Ündey, C., Ertunc, S., Cinar, A., 2003a. Online batch/fed-batch process performance monitoring, quality prediction, and variable-contribution analysis for diagnosis. Industrial Engineering and Chemistry Research 42, 4646–4658.

Ündey, C., Tatara, E., Cinar, A., 2003b. Real-time batch process supervision by integrated knowledge-based systems and multivariate statistical methods. Engineering Applications Artificial Intelligence 16, 555–566.

Ündey, C., Tatara, E., Cinar, A., 2004. Intelligent real-time performance monitoring and quality prediction for batch/fed-batch cultivations. Journal of Biotechnology 108, 61–77.

Uraikul, V., Chan, W.C., Tontiwachwuthikul, P., 2000. Development of an expert system for optimizing natural gas pipeline operations. Expert System with Applications 18, 271–282.

Ursenbach, A., Wang, Q., Rao, M., 1994. Intelligent maintenance support system for mining truck condition monitoring and troubleshooting. International Journal of Surface Mining, Reclamation and Environment 8, 73–81.

Vedam, H., Dash, S., Venkatasubramanian, V., 1999. An intelligent operator decision support system for abnormal situation management. Computational Chemical Engineering 23, S577–S580 (in the Proceedings of ESCAPE 9).

Venkatasubramanian, V., 1994. Towards integrated process supervision: current status and future directions. IFAC Computer Software Structures Integrating AI/KBS Systems in Process Control, Lund, Sweden, 1–13.

Venkatasubramanian, V., Rengaswamy, R., Kavuri, N.S., 2003a. A review of process fault detection and diagnosis part II: qualitative models and search strategies. Computers & Chemical Engineering 27, 313–326.

Venkatasubramanian, V., Rengaswamy, R., Kavuri, N.S., Yin, K., 2003b. A review of process fault detection and diagnosis part III: process history based methods. Computers & Chemical Engineering 27, 313–326.

Venkatasubramanian, V., Rengaswamy, R., Yin, K., Kavuri, N.S., 2003c. A review of process fault detection and diagnosis part I: quantitative model-based methods. Computers & Chemical Engineering 27, 293–311.

Viharos, Z.J., Monostori, L., 2001. Optimisation of process chains and production plant using hybrid, AI- and simulation based general process models. The Fourteen International Conference on Industrial & Engineering Applications of Artificial Intelligence & Expert Systems, Budapest, Hungary, June, 4–7.

Wang, J., 2003. Sensitivity identification enhanced control strategy for nonlinear process systems. Computers & Chemical Engineering 27, 1631–1640.

Wang, Z.X., 1999. Data Mining and Knowledge Discovery for Process Monitoring and Control. Springer, Great Britain.

Wang, Z.X., Liu, Y., Griffin, J.P., 1998. A combined ANN and expert system tool for transformer fault diagnosis. IEEE Transactions on Power Delivery 13, 1224–1229.

Wang, Z.X., Chen, H.B., Yang, H.S., McGreavy, C., 1999a. Application of wavelets and neural networks to diagnostic system development, 1, feature extraction. Computers & Chemical Engineering 23, 899–906.

Wang, Z.X., Chen, H.B., Yang, H.S., McGreavy, C., 1999b. Application of wavelets and neural networks to diagnostic system development, 2, an integrated framework and its application. Computers & Chemical Engineering 23, 945–954.

Wang, Z.X., Liu, Y., Griffin, J.P., 2000. Neural net and expert system diagnose transformer faults. IEEE Computer Applications in Power 13, 50–55.

Wong, K.C.A., Wang, Y., 2003. Pattern discovery: a data driven approach to decision support. IEEE Transactions on Systems, Man, and Cybernetics-Part C: Applications and Reviews 33 (1), 114–124.

Xia, Q., Rao, M., 1999a. Dynamic case-based reasoning for process operation support systems. Engineering Applications of Artifical Intelligence 12 (3), 343–361.

Xia, Q., Rao, M., 1999b. Knowledge architecture and system design for intelligent operation support systems. Expert Systems with Applications 17, 115–127.

Xia, Q., Rao, M., 1999c. Actuator and sensor design for operation support systems. Computers in Industry 39, 79–95.

Yang, H.S., Chen, H.B., Wang, Z.X., 2000. Neural network based fault diagnosis using unmeasurable inputs. Engineering Applications of Artifical Intelligence 13 (3), 345–356.

Yang, H.S., Chung, H.W.P., Wang, Z.X., McGreavy, C., 1998. Multi-objective constraint control for FCC reactor-regenerator system. Computers & Chemical Engineering 22, s831–s834.

Yoon, S., MacGregor, F.J., 2004. Principle-component analysis of multiscale data for process monitoring and fault diagnosis. AIChE Journal 50 (11), 2891–2903.

Young, C.P., 1981. Parameter estimation for continuous-time models—a survey. Automatica 17, 23–29.

Zadeh, A.L., 1964. Fuzzy sets. Information and Control 8, 338–353.

Zhang, J., Martin, E.B., Morris, A.J., 1996. Fault detection and diagnosis using multivariate statistical techniques. Transactions of IChemE 74A, 89–96.

Zhang, H., Lennox, B., 2004. Integrated condition monitoring and control of fed-batch fermentation processes. Journal of Process Control 14, 40–50.