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Integration techniques in intelligent operational management: a review

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Abstract

Until recently the concept of an integrated framework for coordinating operational tasks in industrial plants has not been possible due to technological limitations. Integration of functions within an intelligent system architecture would result in improved plant performance, safety and an increase in production. As a result of increased computing power and powerful memory systems, a fully computer integrated system is now possible, however, achieving an integrated framework for operational tasks is quite complex. Problems of task integration include not only the consideration of information flow and timing for a continuously changing environment, but the integration of various problem-solving methodologies. Integration frameworks proposed in the past fail to provide for a fully integrated system. A new approach to accommodate the changing dynamics of a plant's operation is now possible with the Coordinated Knowledge Management method.

This paper reviews the components that need to be integrated to encompass intelligent process operation. It also reviews various integration frameworks outlining limitations and presents a proposed method of integration based on knowledge management.

Keywords: Intelligent operation; Knowledge-based expert system; Integrated framework; Data acquisition; Regulatory control; Process monitoring; Fault detection and diagnosis; Supervisory control

1. Introduction

Modern industrial plants are expected to perform complex tasks with high accuracy under uncertain conditions. Task integration needs to include techniques that are capable of effectively dealing with incomplete information concerning the plant and its environment within unexpected or unfamiliar conditions. In addition to conventional control techniques using numeric algorithms and process models, task integration should include methods capable of self-learning (neural nets), methods of organizing knowledge (Petri nets), techniques dealing with incomplete or inexact information (fuzzy logic strategies) and non-numeric techniques such as knowledge-based methods. When these techniques are combined through object-oriented programming, they form a powerful strategy for integration of tasks.

Intelligent operation has evolved through the integration of aspects of artificial intelligence, operations research and automotive control systems, computer science and control theory [23]. Intelligent operation is utilized in a wide variety of applications in disciplines such as engineering, medicine and business. Some engineering applications using intelligent operational strategies include control of advanced robots, intelligent scheduling and planning, expert control systems, voice control, intellectualized instruments, household appliances, flight vehicles, manufacturing systems and mining applications [7]. The processing industry can benefit from the use of intelligent system methodologies to improve plant performance.

This paper begins with a description of the components, which need to be integrated in the process industry. These include data reconciliation, regulatory control, fault detection, fault diagnosis, supervisory control, planning and scheduling. Next a discussion on expert systems is presented and different integration frameworks are then reviewed drawing from the areas of process industries and management. Finally, a coordinated method of task integration is presented, which eliminates some of the shortcomings of previous methods.

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2. Operational tasks

The functional tasks which computer aided process operations encompass can be partitioned into seven plant operational tasks. The components that need to be integrated include (i) data acquisition, (ii) data reconciliation, (iii) regulatory control, (iv) fault detection and diagnosis, (v) supervisory control, (vi) planning, and (vii) scheduling. These tasks are categorized as low-, mid- and high-level tasks. In the following sections these tasks will be outlined starting from the low-level tasks followed by the mid- and high-level tasks.

2.1. Low-level tasks

2.1.1. Data acquisition

The basic component is *data acquisition*. Process data is acquired from the plant through sensors attached to the plant. Transducers convert the data to a form recognizable by a computer. The data is then used as a foundation either directly or indirectly for every other task. Typical process variable measurements include temperature, pressure, flow, density, liquid level, viscosity, composition, electrical heating, flow adjustment and alarms [40].

2.1.2. Data reconciliation

On-line process measurements are corrupted by errors during measurement and transmission of data. These errors are unavoidable and are caused by power supply fluctuations, networks transmission, signal conversion noise and changes in ambient temperature to name a few [34]. Two types of errors are usually present: random and gross errors. Random errors are small and are due to normal process fluctuations. Gross errors, on the other hand are large and are due to incorrect calibration or malfunction of instruments, process leaks, etc. [53]. Before plant data can be usefully used, it is therefore necessary to reconcile this data into meaningful values. This is the objective of the data reconciliation module. Techniques such as the Measurement Test, Generalized Likelihood Ratio can be used in conjunction with data reconciliation in order to identify the presence and location of gross errors such as sensor drift or bias [34].

Much research has been conducted into data reconciliation of steady state plant measurements in both linear and nonlinear systems [6,8,9,11,12,26,31,57]. Generally this involves finding the solution to a constrained least-squares optimization problem minimizing the difference between the measured values and the reconciled estimates. Given this problem, one must also have a method in order to detect when the process is at steady state [32,33].

Current research is tending towards dynamic data reconciliation of nonlinear systems. This requires the use of nonlinear state estimation techniques such as Kalman filtering. Several references can be sited on the treatment of the nonlinear and dynamic data reconciliation problem [2,4,9,13,27,34,48,53].

Companies such as OSIsoft and Invensys have developed packages such as Sigmafine and DATACON, respectively, for industrial data reconciliation applications [41,58]. Industrial applications of data reconciliation are also discussed in [8,14,44].

2.1.3. Regulatory control

Regulatory control occurs when the control system functions to counteract the effect of disturbances in order to maintain the output at its desired set point [40]. Output variables may deviate from their set points due to disturbance effects or set point changes. These deviations can result in instability and poor plant performance. The most common regulatory controller used in industry is the PID controller.

2.2. Mid-level tasks

2.2.1. Fault detection and diagnosis

Fault detection and diagnosis involves the tracking of process execution, detection of departures from normal operation and identification of cause [52]. Fault detection uses data in order to detect abnormal situations and isolate faults. Faults include gross parameter changes in a model, structural changes, malfunctioning sensors and actuators, external obstacles such as clogging or outflows and defects in construction such as cracks [66].

Many methods have been proposed in order to solve the fault detection and diagnosis problem. The most commonly employed solution methods of fault diagnosis systems include (i) knowledge-based, (ii) model-based, and (iii) pattern recognition-based methods [66].

Generally knowledge-based methods are used when there is a lot of experience but not enough details to develop accurate quantitative models. Analytic model-based methods can be designed in order to minimize the effects of unknown disturbances and perform consistent sensitivity analysis. Pattern recognition approaches are applicable to a wide variety of systems and exhibit real-time characteristics [66].

Pattern recognition approaches include artificial neural networks, which are massively connected networks that can be trained to represent nonlinear functions at a high level of accuracy [25]. In an artificial neural network, data are presented to the network via the input layer, hidden layers are used for storing information and the output layer is used to present the output of the network. An example of a typical multi-layered neural network is shown in Fig. 1. A well-trained neural network can be viewed as a means of knowledge representation and can provide both qualitative and quantitative knowledge [30]. Knowledge is stored through the structure of the neural networks through its connection weights and local processing units. Neural networks acquire knowledge from samples that are trained