Acta Automatica Sinica
Vol. 35, No. 6 June, 2009

Available online at www.sciencedirect.com
ScienceDirect

Data Driven Fault Diagnosis and Fault Tolerant Control: Some Advances and Possible New Directions

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Abstract This paper presents a selected survey covering the advances of fault diagnosis and fault tolerant control using data driven techniques. A brief summary of the general developments in fault detection and diagnosis for industrial processes is given, which is then followed by discussions on the widely used data driven and knowledge-based techniques. A successful application example is also given, which deals with faults caused by the misplacement of control loop set points and several areas of potential future directions are included in the paper.

Key words Fault detection, fault diagnosis, fault tolerant control, data driven techniques

Fault detection and diagnosis (FDD) and fault tolerant control (FTC) have been the subject of considerable interest in the control research community[1−39]. This is in response to the ever increasing requirements on the reliable operation of control systems, which are, in most cases, subject to a number of faults either in the internal closed loops or from environmental factors. Once system faults have occurred, they can cause unrecoverable losses and result in unacceptable environmental pollution, etc. Occasionally, the occurrence of a minor fault has resulted in disastrous effects. For example, it has been observed that faults have caused a 3 % ∼ 8 % reduction of the oil production in the United States, leading to $ 20 billion losses in the country′s economy per year. Also, in 1997, the faults in a chemical plant in Beijing caused heavy direct losses. Therefore, effective FDD is of vital importance to the safe operation of industrial plants. Indeed, FDD and FTC have now become an integral part of industrial process control.

In general, system faults can be grouped into several categories, namely, actuator faults, sensor faults, system faults and also abnormal operating faults caused by either the misplacement of control loop set points or unexpected variations in the raw materials to be processed. The purpose of FDD is to use available signals to detect, identify, and isolate possible sensor faults, actuator faults, and system faults. Conversely, FTC calculates the required actions (either controller modification or reconfiguration) so that the system can still continue to operate safely even under faulty conditions[2−3,40]. In terms of condition monitoring or FDD, the existing methods can also be grouped into the following two categories:

1) Model based FDD;
2) Data driven FDD including knowledge based FDD.

In the early days (1980′s onwards), model based FDD constituted the main stream of research, and a number of techniques were developed. Depending on whether the system model can be represented as either a state space model or an input-output model, FDD can be classified into two groups: observer based FDD[1] and system identification based FDD[4]. Also, to combine the best features of these two approaches, there is another group of FDD methods called adaptive observer based fault diagnosis, which uses parameter tuning principles from model reference adaptive control to directly estimate fault parameters online so that effective fault diagnosis can be achieved[5−6]. However, model based FDD uses mathematical system models to estimate the system state and parameters, and in general these methods can only be applied to low dimensional systems.

Alternatively, data driven based FDD can deal with high dimensional data, and data dimension reduction techniques are generally used to highlight important information in the data volume[7−14]. However, there are many important challenges in its use in FDD, when the system is time-varying and highly nonlinear. Knowledge based FDD uses a composition of a knowledge base (such as process input and output variables, abnormal process models, fault characteristics, operational constraints and assessment criteria) and a set of the qualitative models of the system to perform the required FDD[15−21]. Typical techniques are cause-effect analysis based FDD, fault feature tree analysis based FDD, rule based and case based reasoning for FDD[3].

After a fault has been detected and diagnosed, FTC can subsequently be used to guarantee the safe system operation and to prepare for an economical plant repair shutdown. FTC approaches can be generally classified as either passive or active FTC. The former uses the results of FDD to adjust some parameters of the controller in a similar manner as the well known adaptive controllers, such as self-tuning control, whilst the latter uses the FDD results to reconfigure the controller. A detailed survey on FTC was published in 2005[2].

1 Challenges as a result of growing system complexity

With the ever increasing complexity of industrial systems, distributed control systems (DCS) have been widely used to realize whole plant monitoring and control (see Fig. 1). Typical examples are the processes seen in steel making, car manufacturing, material processing, papermaking, chemical plant and mineral processes, etc, where these production processes are controlled via a multi-layer computer network. For the system infrastructure shown in Fig. 1, the lower levels of computers (microprocessors and PLCs) are used to directly control the individual process units on the production line, whilst the higher level computers are used to manage the overall system operation and to produce required control loop set points based on production planning and scheduling results. DCS can therefore provide a platform for the global management and optimization of the whole production line to achieve an optimal operation in terms of improved product quality, high

Received January 8, 2009; in revised form March 12, 2009
Supported by National Basic Research Program of China (973 Program) (2009CB320600), National Natural Science Foundation of China (60828007, 60534010, 60821063), the Leverhulme Trust (F/00 120/BC) in the United Kingdom, and the 111 Project (B08015)
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DOI: 10.1016/S1874-1029(08)60093-2

production efficiency, minimized effluent discharge, and reduced energy costs, etc.

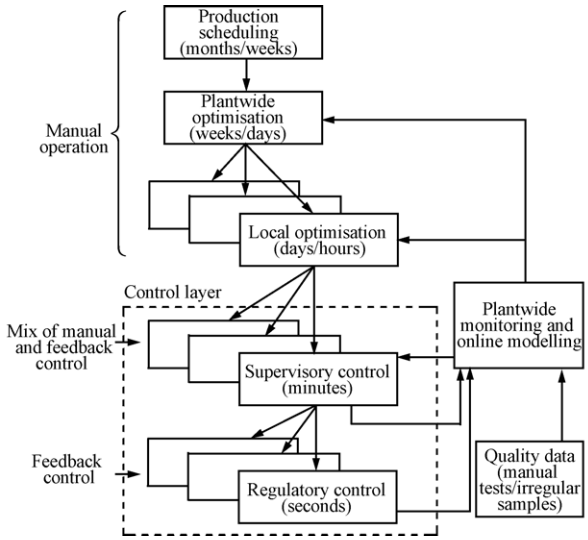

Fig. 1 DCS based plant-wide performance optimization

The advantage of using DSC systems is that a large number of process and product quality data is available for the reliable and optimal operation of the whole production line. As complex industrial processes cannot be easily represented using accurate or first principles mathematical models, data driven based FDD and FTC must be considered. This means that FDD and FTC of complex industrial systems must effectively use process data from the production line to identify faults and then use FTC techniques to realize safe operation of the whole plant until an economic shutdown can be achieved. It can therefore be expected that data driven based FDD and FTC techniques will play an increasingly important role in improving the reliable operation of complex industrial systems and data driven based FDD and FTC has already been applied in many processes[20−31]. In this paper, the following sections will give a brief survey on these techniques.

With ever increasing automation in complex industrial systems, there exists a greater chance of unstable system operation which presents new challenges for FDD. Specifically, as there are many uncertainties in the process and the complexity of the process includes nonlinearities, time-varying, and strong coupling effects amongst the variables, etc, it is generally difficult to establish a plant-wide system model and hence perform model based FDD. Moreover, in large scale industrial systems, network based sensors measure process variables and operational variables such as control loop set points. This data provides the required information for on-site operators to improve product quality, production safety, and process efficiency. However, such large data volumes present difficulties in building process models whilst they are very suited for data dimension reduction and the related FDD.

To perform effective FDD and FTC, in line with the DSC controlled system structure, Leung proposed to divide the production line into three layers: lower, middle, and high layers[15]. In the lower layers, tasks such as data acquisition, loop control, and signal processing is performed. In the middle layer, data analysis, process monitoring, and FDD takes place, whilst in the high layer planning and scheduling are carried out. As such, a fault can be defined as one or more parameter deviations from its, or their, nominal values. This constitutes a strict request on the middle and high level operations of the concerned production line.

At present, FDD units embedded in DCS and SCADA systems make use of single variable monitoring techniques. The FDD methods can be represented as classification based FDD, knowledge based system (KBS), contribution diagram, qualitative intelligent analysis such as fault tree analysis, as well as rule based, knowledge based FDD[15] and case based reasoning[3]. Following the FDD process, FTC can be realized using system redundancy in terms of control structure configuration[2].

Condition monitoring, in fact, performs the same task as FDD, albeit some papers use condition monitoring and others use FDD. In this paper, we will not deliberately draw a clear line between them as their purposes are similar — finding out faults in the system. Condition monitoring uses mean and variance statistics of important process variables, or their magnitude and frequencies as the basis. This includes multivariable statistics and signal processing based techniques etc. In terms of the data, nominal operation data form the basis of data driven FDD.

2 Data driven FDD – from signal based FDD to multi-variable statistics and knowledge based FDD

Data driven FDD has gone through three main phases in its development. These three phases are referred to as signal based FDD, multi-variable statistics based FDD, and knowledge based FDD. The common feature of these methods is that they all use raw system data and process knowledge to carry out the required FDD.

2.1 Signal based FDD

The first group of data driven FDD methods is signal based. Signal based FDD methods use signal processing methods consisting of correlation functions, signal model identification, signal parity checks, and spectral analysis using fast Fournier transformation and wavelet transformation. This is similar to the signal detection and trend detection for important variables using the available data. The key idea is that unexpected changes in the magnitude, phase shift and/or frequencies of the important signals can be regarded as the faults in the system. For example, in [7] wavelet transformations have been used for FDD in steel mills. In addition, statistical process control (SPC) has been applied to detect abnormal distribution changes of quality data in many production lines so that real-time alarms are produced when the data lies outside the upper and lower distribution limits. In SPC, Shewhart and Cusum charts have been widely applied to check whether important variables can be declared as normal or not. However, since SPC entirely relies on the data of the process quality, they cannot be used to detect the abnormal statistic distribution of the quality data. For example, if the quality data is not Gaussian, SPC does not produce a reliable test for FDD.

2.2 Multi-variable statistics based FDD

The key concept in principal component analysis (PCA) is to reduce a high dimensional data volume into a lower dimensional space, where the low dimensional data contains most of the useful information/variance contained in the original data set. The projection axes are referred to as principal components. As such, PCA has been widely used in industrial process control as a stan-