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FAULT DETECTION AND DIAGNOSIS IN BIOCHEMICAL PROCESSES

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ABSTRACT

Biochemical processes are gaining industrial importance because of their inherent advantages like mild operating conditions and versatility of the processes which mean lower operating costs in terms of lesser energy requirements and a number of industrially important products that could be made from a general process setup. These features have made the biochemical processes the target of intense research in pharmaceutical, fine chemical and bioactive component fields. The literature is rich with information on the fault detection and diagnosis (FDD) techniques for conventional chemical processing plants. This article reviews the applicability of FDD techniques to biochemical processes.

Key words: Biochemical process, Diagnosis, Fault detection.

INTRODUCTION

Quick and correct detection and identification of process faults are extremely important for efficient and economic operation of biochemical processes. Successful detection and identification of process faults at an early stage can increase the success rate of fault recovery during operations and prevent huge losses and unnecessary shutdowns. Detection and diagnosis of process faults in chemical processes has been an active area of research. In the literature, several methodologies have been proposed for fault detection and identification (FDI) in chemical processes[1-5] including principal components analysis (PCA), artificial neural-networks (ANN), self-organizing maps (SOM), qualitative trend analysis (QTA), signal processing methods or first principles models. Each of these methods has its advantage and weakness in practical application.

Fault detection (FD) is a well studied area in many disciplines by the very nature that FD is essential to safe operations. While a fault is exhibited as non-normal behavior in contrast, a failure is when a process is unable to perform its required functions within pre-specified performance requirements. Generally, a fault is minor when compared to failure, but most failures tend to stem from ignored or undetected faults. During the past twenty years, research activities in several sub-areas related to fault detection include: determining what kind of prior-

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knowledge is better to represent the process for FD applications to achieve accuracy in real-time, (e.g. first-principles model and historical data, etc.); which approach (quantitative or qualitative methods) will result in effective FD; and the more focused areas of sensor faults[6]; actuator faults, and process faults[7]. Excellent reviews on FDI can be found.[1-3,8-10]

Fault-detection and diagnosis methods

Processes are usually continuous with discrete time measurements. Faults can be considered either multiplicative (function of the states and inputs) or additive (dependent on the process and fault dynamics). The latter faults are usually detected by filtering techniques, while the former are found using parameter estimation techniques. The most frequent method to determine a fault is to apply a quantitative model-based approach[8]. In the area of FD, the inconsistency between the actual and expected behavior which is a non-normal event indicating a potential fault is expressed as a residual. Confirming a residual involves some form of comparison and redundancy. There are two types of redundancies, hardware redundancy and analytical redundancy. The former requires redundant sensors which is limited by physical constraints and economical costs. While analytical redundancy can be achieved by analyzing the functional dependency among process variables and are usually expressed as a set of equations with the states, inputs and outputs of the process.

The essence of analytical redundancy is to compare the actual system behavior against the model for consistency check. Any inconsistency is used for detection and isolation purposes. Considering process and measurement noises, the residuals should be near zero when no fault occurs but show significant deviation when a fault is present. The generation of a residual requires an explicit, quantitative model. A first-principles model becomes more useful in the diagnostic procedures because of the physical meanings of its parameters. Although nonlinearity is inherent in most chemical processes, the application of FDI to a nonlinear system uses a linearization around the operating point since the fault is about a fixed operating condition. With a linear, approximate model various algorithms have been proposed to obtain analytical redundancies, such as parity relations[11,12]. Kalman filters[13,14] and parameter estimation[9,15]. Most of the model-based FDI methods suffer from model uncertainty for obvious reasons - no model is perfect. Some researchers have suggested a robust FDI approach[16,17] in which the model uncertainty effect is suppressed. However, in some cases the suppression of the model uncertainty effect cannot be done without influencing the fault-residual effect. To cope with this problem, some researchers propose not to suppress all the uncertainty effect but to formulate a mini-max optimization problem in which the model uncertainty is minimized while the sensitivity to the fault is maximized[18]. For online real-time applications, the optimization approach may not be practical.

In real processes, measurements are considered to be statistical time series, which is a combination of deterministic system dynamics and stochastic dynamics arising from random influences. Therefore, it is not unreasonable to formulate the system states in a probabilistic setting. That, when the process is at its nominal state, the observations have expected probability distributions. If the expected distributions are statistically violated, the process is declared to be out of the nominal state. Typically, a parametric approach is used to characterize the probability distribution; e.g, the mean and the standard deviation. Thus, under faulty conditions, either the mean or the standard deviation would deviate from an acceptable range. Accordingly, fault detection is transformed into a procedure of checking the values of these statistic parameters.

As the complexity of processes keeps increasing, multivariate statistical techniques are necessary to focus the correlated data so that the essential information is retained. The main function of multivariate statistical techniques such as principle component analysis (PCA)/ partial least squares (PLS) is to convert a set of process measurements correlated by internal dynamics and noise into a smaller set of uncorrelated variables.

Another promising statistical approach is statistical classifiers that cast a classification problem into a classical statistical pattern recognition framework. The FDI is realized by combining over time the instantaneous estimates of the classifier using knowledge about the statistical properties of the failure modes of the system.

Also, the application of artificial neural networks for FDI have generated considerable research. In general, artificial neural networks for fault diagnosis can be classified along two dimensions[1-3], the architecture of the network and the learning strategy (e.g. supervised and unsupervised).

Fault detection and isolation functions are often implemented as a part of a process supervisory/management system. Comparable to process control design, FDI requires computational efficiency to obtain real-time performance. The logic of fault detection is to provide either an affirmative or a negative as to the existence of a fault(s). While the aim is straightforward, the approach is not easy. There are two types of error that are challenging when designing the FD module, false alarms (type I) and the inability to detect faults (type II).[6] If the FD design is too sensitive to the deviations from nominal operations a type I error is triggered. On the other hand, if the threshold of the FD design is set too high it is possible that a fault is masked which leads to a type II error. Also, for closed-loop processes, as time progresses, compensating effects such as dynamic feedback may begin to mask the effects of faults, thus capturing the faulty behavior at or very close to the initial time the fault occurred is important to avoid masking or compounding effects which may result in catastrophic failures.

Once a fault(s) is detected fault isolation follows. If the assumption of a single fault is valid either brute force or smart analysis can be applied to isolate the root cause. The former relies on a scheme that checks exhaustively all potential faulty components, however such an approach is time consuming. The latter may include approaches such as knowledge-based reasoning, cluster analysis, pattern recognition and signature analysis, qualitative reasoning, statistical analysis, or any number of parametric and nonparametric models.[1-3]

The FDI process essentially consists of two stages: residual generation and decision making. For a particular set of hypothesized failures, an FDI system has the structure shown in Fig. 1. Outputs from sensors are initially processed to enhance the effect of a failure (if present) so that it can be recognized. The processed measurements are called the *residuals*, and the enhanced failure effect on the residuals is called the *signature* of the failure. Intuitively, the residuals represent the difference between various functions of the observed sensor outputs and the expected values of these functions in the normal (no-fail) mode. In the absence of a failure residuals should be unbiased, showing agreement between observed and expected normal behavior of the system; a failure signature typically takes the form of residual biases that are characteristic of the failure. Thus, residual generation is based on knowledge of the normal behavior of the system. The actual process of residual generation can vary in complexity.

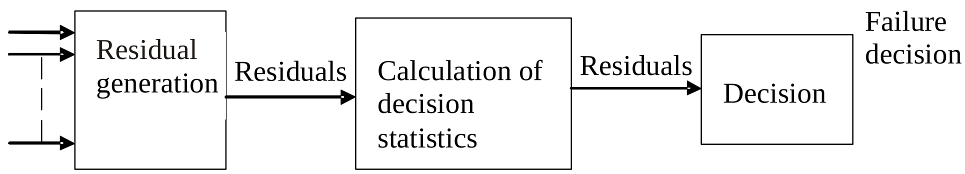

Fig. 1: Two stage structure of FDI process

Model-based fault-detection methods[19]. The task consists of the detection of faults of the technical process including actuators and sensors by measuring the available input U(t) and output Y(t) variables. Basic process-model-based methods are:

1. State and output observers (or estimators)
2. Parity equations
3. Identification and parameter estimation.

They generate residuals for state variables or output variables with fixed parametric models for (1), fixed parametric or nonparametric models for (2) and adaptive nonparametric or parametric models for (3).

An important aspect of these methods is the kind of fault to be detected. One can distinguish between additive faults which influence the variables of the process by a summation, or multiplicative faults which are products with the process variables. The basic methods show different results, depending on these types of faults.

If only output signals Y(t) can be measured, signal model-based methods can be applied. In particular, vibrations can be detected, which are related to rotating machinery or electrical circuits. Examples of typical signal-model-based methods of fault detection are:

4. Band pass filters
5. Spectral analysis (FFT)
6. Maximum-entropy estimation.

The characteristic quantities or features from fault detection methods show stochastic behaviour with mean values and variances. Deviations from the normal behaviour have then to be detected by methods of change detection, like

7. Mean and variance estimation

8. Likelihood-ratio-test, Baye’s decision

9. Run-sum test, two-probe t-test.

Fault-diagnosis methods If several symptoms change differently for certain faults a first way of determining a fault is to use classification methods which indicate changes of symptom vectors. Some classification methods are:

10. Geometrical distance and methods

11. Artificial neural networks

12. Fuzzy clustering.

If more information about the relations between symptoms and faults is available in form of diagnostic models, methods of reasoning can be applied. Diagnostic models then exist in the form of symptom-fault causalities, e.g. in the form of symptom-fault trees. The causalities can then be expressed as IF-THEN rules. Then analytical as well as heuristic symptoms (from operators) can be processed. By considering them as vague facts, probabilistic or fuzzy-set descriptions lead to a unified symptom representation (Fig. 1). By forward and backward reasoning, probabilities or possibilities of faults are obtained as a result of diagnosis. Typical approximate reasoning methods are:

13. Probabilistic reasoning

14. Possibilistic reasoning with fuzzy logic

15. Reasoning with artificial neural networks.

This very short consideration shows that many different methods have been developed during the last 20 years. It is obvious that many combinations of them are possible. Frequency response methods are not widely used due to their inherent complexity in application.

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