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Research Article

Process fault isolation based on transfer entropy algorithm

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ABSTRACT

Complexity of industrial plants and their stringent environmental and safety regulations have necessitated early detection and isolation of process faults. All the existing fault isolation methods can be categorized into two general groups: model-based and data-based. Transfer entropy is a data-based method for measuring propagation direction of disturbance and finding its root cause. In this paper, a new transfer entropy-based method is proposed to isolate different process faults. The novelty of this paper lies in using the transfer entropy idea to generate distinct patterns of information flow among process variables, recognize their correlations in the context of the transferred information in any abnormal condition, and finally isolate different process faults. The experimental results clearly demonstrate the superiority of the proposed method to the conventional methods.

1. Introduction

An industrial chemical process plant is often subjected to low productivity caused by abnormal operating conditions as a result of faulty operations, equipment degradation, and external disturbances. The ever-increasing demands on safety and environmental protection, and the economic concerns have forced the industries to search for newer and more effective techniques to diagnose process malfunctions [1]. Fault diagnosis in large-scale and complex industrial plants is particularly difficult because of the high degree of interconnection among various plant components. A simple fault in such plants may easily propagate throughout the plant and spread to a wider domain along the material or information paths. In such a case, the use of conventional methods or human operators to pin-point the source of such a fault, with many possible origins, becomes time-consuming, difficult and expensive. Thus, it is necessary to use an exact and automatic monitoring system to satisfy the process stringent performance measures [2].

A fault, by definition, is an unanticipated alteration in the process operation, which can be caused by a damaged mechanical part, sensor or actuator, the failure of a pump, poisoning of a catalyst, the sudden change in the composition of a feed stream and the like. Soft faults in the form of bias or drift in sensors and actuators are known to be the most common instrument faults in industrial processes [3]. The actuators working in process plants are prone to fault because of their continuous movements. In fact, most of the reported actuator faults are due to the stickiness and corrosiveness of the materials that circulate in the chemical processes [4]. Early Fault Detection and Isolation (FDI) in industrial plants is crucially required to prevent product damage, severe machine failure, production deterioration, quality degradation, profit loss, environmental pollution and threats to human health [1].

This vital necessity has greatly motivated the research communities to conduct diverse research activities on FDI subjects. By detecting the faults and pointing to probable sources, the automated FDI schemes practically alert and guide the process operators and maintenance personnel so that they can coordinate their efforts for the improvement of process abnormalities [2].

On the other hand, a common form of process malfunction occurs through process disturbances. Plant-wide persistent disturbances in both the oscillatory and nonperiodic manners are common in industrial processes [5]. A disturbance often proceeds throughout the production path of a continuous process and affects its downstream production performance. While disturbance propagates in a process, different process variables are prone to change. This is due to the time delays, noise and the

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other disturbances existing in the process. The main purpose for using a diagnosis measure is to determine direction path of disturbance propagation in order to discover root cause of the disturbance.

The main sources of process disturbances include nonlinear effects like saturation, dead zone or hysteresis in the control valves, sensors or the process, local instability due to control loops interactions, structural disturbances arising from mass or energy transfer between different process units especially with recycle streams, disturbances in the process boundaries and weakly-tuned controllers. A major part of these disturbances is oscillatory in nature [1].

Plant-wide disturbance diagnosis is a method which aims to investigate disturbance distribution in a plant to properly determine location, kind and root cause of disturbance with high accuracy [6]. Many fault diagnosis methods have been addressed in the literature for FDI purposes [6,7]. Each method has its own merits, depending on the process and the type of fault. Generally, Fault Detection and Diagnosis (FDD) methods can be categorized into two general model-based and data-based groups, where each group includes both qualitative and quantitative methods. A diagram differentiating the available methods with different samples has been shown in [7]. Moreover, descriptive comparisons of the FDD methods have been fully explained in [7,8].

Generally speaking, a model-based fault diagnosis operation is based on a residue, i.e. the difference between the real response of a process and that obtained through a mathematical model. The residue can be generated in different ways. The most common residue generation schemes are parity equation, observers and the parameter estimation. Neural networks and fuzzy systems are the other kinds of model-based methods. However, it is practically difficult to develop a complete and robust mathematical model for a real industrial process due to its inherent complexity and high dimensionality, unavailability of the prior process knowledge and extra modeling costs [9,10]. Thus, the model-based methods are often limited to processes with a small number of variables [11].

Data-based fault diagnosis methods can be used to overcome the above problems. These methods do not rely on the system model to infer the presence of a fault occurrence. As a consequence, data-based methods are suitable for systems that simply cannot be modeled due to their nonlinearity and complexity features. These methods, however, require huge volumes of historical process data which can be acquired in most practical applications by installing real-time monitoring instruments [11]. It should be noted that the qualitative data-based methods often rely on the exact knowledge of process behavior in different abnormal conditions which is not generally available in complex processes. Moreover, the conventional quantitative data-based methods rely on the use of different classifiers. In this regard, the Bayes, Radial Basis Function Neural Network (RBF-NN) and the Support Vector Machine (SVM) are known as the most often used classifiers in isolating the predefined process faults. It is possible to have several complex faults in each process which may be difficult for a classifier to correctly identify. These faults may be incorrectly identified mainly because of the controllers' reactions. According to our observations, these methods are not often capable of isolating all the process faults and hence most of the complex faults may be misclassified. This represents the main disadvantage of the classifier-based methods. Therefore, the FDD algorithms for process plants have often been implemented by using the quantitative data-based methods due to their complexity and large dimensionalities. In this study, the transfer entropy concept has been chosen as an efficient data-based approach to isolate the known process faults.

The use of the proposed method can be justified by the fact that the transfer entropy concept is an information-theory-based measure which has been introduced by Schreiber [12]. In fact, it is a data-based method which can extract a qualitative model on the basis of historical process data in the form of a directed graph to describe the cause and effect relationships. It is often used as a tool in chemical process plants to determine the direction of disturbance propagation, and consequently, to find root cause of process disturbance [13]. To the best of our knowledge, no research study has been conducted so far to isolate the process faults by using the transfer entropy method. Therefore, the main and distinct contributions of this paper are as follows.

A new transfer entropy-based algorithm has been proposed for the first time to isolate different faults in a process plant. The proposed method applies the transfer entropy idea to recognize the set of information-transfer correlations among process variables in different abnormal conditions. Since information-flow patterns among process variables are distinct in different abnormal conditions, the developed patterns can be used to isolate the process faults. In other words, there are some cause and effect relationships among process variables which are fault-specific. These causal relationships can be exploited to isolate the different faults that may occur. The confidence level with which the causal relationships are accepted, in fact, represents the fault diagnosis accuracy. This methodology makes it possible to isolate both the easy and complex process faults. On the other hand, it is possible to simultaneously experience several faults in the process. New faults may originate from totally independent sources or they may be caused by the other faults. It is noted that the causal relationships do not change along the whole length of faulty data. However, if several faults occur simultaneously, the causal relationships among the process variables will change. Thus, the whole faulty data set should be investigated in order to find out if only one or more faults have occurred in a specific duration.

A set of similar fault isolation scenarios has been organized to be conducted on the TE benchmark process plant using a number of conventional methods so that their results can be compared to those obtained by the proposed method.

It should be noted that the normal operation data is not used in the conducted studies mainly due to the fact that the research is focused on fault isolation aspect. The assumption is that a fault detection algorithm is already there to identify the abnormal status of the process, and thus, the proposed fault isolation method is triggered following the fault detection task. As an example, a PCA-based fault detection method can be used to detect the fault occurrence and alert the onset of abnormal status for the process fault isolation.

The remainder of this paper is organized as follows. Detailed descriptions of the proposed method are developed in Section 2. The conventional methods that are used to isolate the process faults in an intended comparative study are described in Section 3. The Tennessee Eastman (TE) process is introduced as a benchmark process plant in Section 4. A set of experimental results is presented in Section 5 to comparatively evaluate performance of the proposed method with those of the conventional approaches. Finally, the concluding remarks are summarized in Section 6.

2. Proposed method

The transfer entropy concept is first introduced in the next section. Then, the kernel method is presented for the estimation of Probability Density Functions (PDFs).

2.1. Transfer entropy algorithm

The interdependency of two variables can be determined by using the correlation coefficient, mutual correlation and mutual