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Online fault prognosis with relative deviation analysis and vector autoregressive modeling

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HIGHLIGHTS

- An fault prognosis strategy is developed for proactive abnormality management.
- Combined relative analysis is developed to extract critical fault effects.
- A vector auto-regression model is developed to predict future fault effects.
- A new statistical index is defined to integrate the critical fault effects.
- A reality check index is defined to reveal whether the prediction is reliable.

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ABSTRACT

The conventional fault detection in general focuses on reactively detecting the abnormal changes and failure of the plant state as indicated by confidence limit violation, which, however, is not indicative of a developing fault. In the present work, an online fault prognosis strategy is developed for proactive abnormality management. The modeling procedure includes three components, including fault direction extraction based on combined relative analysis, vector autoregressive modeling based on the associated fault magnitudes and definition of a new statistical index for fault prognosis. First, a combined version of relative analysis algorithm is proposed to extract critical fault directions along which changes of process variations reflect critical fault effects. These critical variations are deemed to be evolving with time and thus responsible to the future process failure. Then, based on the decomposition results, the combined fault magnitudes along these critical directions are calculated from which a vector auto-regression model is developed to capture the time-series correlation and track the fault evolution process. A new statistical index is defined to integrate the critical fault effects and it then works with a reality check index to reveal how soon the process failure will happen. By the above modeling strategy, uninformative fault effects that do not present time-wise autocorrelations are excluded so that the true fault degradation process can be focused on for online fault prognosis. The proposed method is verified by both numerical and experimental data.

1. Introduction

As stated by Juricek et al. (2001), the current status of an industrial process can be classified as one of three possible operating modes: normal, abnormal and emergency. To identify the process status, real-time fault detection and diagnosis (Juricek et al., 2001; Chun-Chin and Chao-Ton, 2011; Zhao and Sun, 2014; He et al., 2013; Subrahmanya and Shin, 2013; den Kerkhof et al., 2013; Bin et al., 2011; Joe Qin, 2003; Qian and Kruger, 2005; Kruger et al., 2007; Alcala and Qin, 2009a; Muradore and Fiorini, 2012; Li et al., 2010a) of industrial processes, as a challenging and yet interesting problem, has drawn increasing attention recently. The task of fault detection and diagnosis involves detection of abnormal process behavior and identification of fault root cause. For fault detection and diagnosis, it is hoped that abnormality can be detected as early as possible so as to enable prevention of major accidents and reduce the maintenance downtime. In the last few

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decades, multivariate statistical analysis techniques, such as principal component analysis (PCA) (Wold et al., 1987) and partial least squares (PLS) (Burnham et al., 1996; Dayal and MacGregor, 1997), have been used widely for process analysis, monitoring and fault diagnosis. Some specific monitoring models and statistics are defined based on analysis of measurement data to evaluate whether the concerned process remains in a "state of statistical control" where the monitoring statistics should stay in the normal regions.

However, the fault effects may have become significant when the failure of operation process is indicated by out-of-control monitoring statistics. That is, they in general answer the question of "has a failure occurred" instead of "whether a failure will occur and how soon", called reactive fault detection here. For some faults, a limit violation may be a very serious matter that can have catastrophic consequences. Therefore, it may be late for the engineer to make any corrective actions based on the reactive detection results. Online fault prognosis is drawing significant incentives, which tries to signal future emergency limit violation in advance or as early as possible, saving time to take effective corrective action before an "incident". Instead of online fault detection, some data-driven statistical analysis methods have been developed in combination with prediction technologies for fault prognosis which has been playing an important role in maintenance and repair of complex dynamic processes. A predictive monitoring strategy is proposed for continuous processes by using multiway PCA(MPCA) algorithm developed for batch processes (Chen and MaAvoy, 1998). In their method, data windows were constructed by cutting along the time dimension of data series where some predicted future data were included. The method was reported to be able to provide an early detection of process faults. However, the future predictions were obtained by remaining constant at their current values and may be different from the real measurement which thus may deteriorate the performance. Jurícek et al. (2001) proposed a predictive process monitoring method by initiating future predictions after a fault or abnormal situation has been detected. The predictions were made based on kalman filter and disturbance estimation to indicate whether process variables will violate an emergency limit in the future and the reliability of future predictions was checked by evaluation of a T^2 statistic. However, predictions are made for each separate process variable where the correlations between process variables are not considered. In general, fault prognosis covers two important issues: (1) evaluate whether a failure is impending and (2) predict how soon the fault effects can be significant. For those complex industrial processes which experience a slow-varying evolution process, some corrective actions can be taken before the process fails and breaks if the degradation process can be predicted ahead of time. Therefore, online fault prognosis plays an important role in safety security and process maintenance.

One major component of fault prognosis strategy is that how to evaluate the fault effects which can thus correctly indicate degradation trend of fault process. Li et al. (2010b) developed a multivariate fault prognosis approach for continuous processes. The fault magnitudes were estimated based on the fault reconstruction technique (Dunia and Qin, 1998; Yue and Qin, 2001; Alcala and Qin, 2009b; Gang et al., 2011) and then modeled by a vector autoregressive (AR) model (Lewis and Reinsel, 1985; Lutkepohl, 1991) to estimate the remaining useful life after the fault was detected by some monitoring index. Vector autoregression (VAR) was introduced by Sims (Sims and Christopher, 1980) as a technique that could characterize the joint dynamic behavior of a collection of variables to identify underlying structural parameters. It has become a prevalent method of time-series modeling. Although the data-driven fault prognosis algorithm is reported promising, the fault effects are not evaluated well. In their work, the fault effects are checked by extracting some fault directions and calculating fault magnitudes associated along these directions. The fault directions are in general obtained by directly performing multivariate statistical analysis, such as PCA, on the fault measurement data. However, the conventional PCA based modeling methods model all general variations from measurement variables by following the size of their distribution variances. Large distribution variations in fault data may not necessarily represent critical fault information which thus may not well reveal fault evolution process. In fact, the process variations at fault status that are different from those at normal status can more clearly reveal the fault effects. To improve reconstruction-based fault diagnosis performance, Zhao and Sun (2013), and Zhao (2014) have proposed the idea of relative analysis to extract the significant fault variations in two different monitoring subspaces respectively and thus remove out-of-control monitoring statistics more efficiently. Instead of directly modeling the fault data, the relative changes from normal to each fault case were analyzed which in fact revealed those critical fault effects. The relative analysis method can effectively improve the reconstruction model and thus fault diagnosis performance, which, however, is isolated to the work of fault diagnosis. If the time-series correlations of critical fault deviations are analyzed, they can provide more meaningful information, e.g., revealing the fault degradation process and predicting future fault status.

In the present work, a novel fault prognosis strategy is developed for proactive abnormality management. The current work is different from our previous work (Zhao and Sun, 2013) where the specific purpose here is fault prognosis instead of fault diagnosis. A major component of the proposed methodology is that critical fault deviations are extracted for regression modeling to predict the fault degradation process and one new statistical index in combination with reality check is defined as an indicator to predict how soon the fault deviation will violate the emergency limit in the future. First, reconstruction-based relative analysis is performed to decompose the underlying fault effects where a combined relative analysis (CRA) algorithm is proposed, which can integrate the changes of process variations in two PCA monitoring subspaces under the influences of fault. Critical fault deviation directions are extracted and the associated fault magnitudes are estimated. Online fault prognosis is then made by developing vector autoregressive (AR) model on multivariate fault magnitudes where a new statistical index is defined based on the predictions to reveal the fault degradation process. Also, the online prediction performance is evaluated with a reality check index. Its feasibility is illustrated with both numerical and experimental data.

2. Methodology

In this section, the proposed method is described. Several important issues will be addressed, including how to evaluate the changes of process variations under the influences of disturbances (i.e., fault effects), how to extract those critical fault effects and how to capture their time-series correlations in order to predict how soon they will violate a confidence limit in the future. By separating and modeling different types of relative variations, the proposed method can efficiently explore critical fault changes and predict the fault evolution process. The specific implementation procedure is presented in the following subsections.

2.1. Combined relative analysis (CRA)

For fault detection, it is clear that alarm monitoring statistics are majorly contributed by larger fault deviations in comparison with those in the normal case. Along different monitoring directions, the