FAULT DETECTION AND IDENTIFICATION USING BAYESIAN RECURRENT NEURAL NETWORKS

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Abstract Overview

Chemical manufacturing processes operate under a number of disturbances. Automatic control systems are usually able to counter these disturbances. Process faults are large changes that result when control system compensation is inadequate to mitigate the disturbance. It is therefore important to develop process monitoring systems to ensure process safety, reliability and product quality by effectively detecting and identifying the faults. In this paper, a novel probabilistic fault detection and identification approach is proposed which adopts a recently developed Bayesian recurrent neural network (BRNN) model using dropout. Compared to traditional statistic-based data-driven fault detection and identification methods, the BRNN-based method can model nonlinear system dynamics and, most importantly, yields uncertainty estimates which allows simultaneous fault detection, direct fault identification, and fault propagation analysis of chemical processes. The performance of BRNN for fault detection and identification is demonstrated and compared to the industry-wide applied (dynamic) principal component analysis in the benchmark Tennessee Eastman (TE) process and a real chemical manufacturing dataset.

Keywords

Process monitoring and diagnostics, Bayesian recurrent neural networks, Tennessee Eastman process

Introduction

In industrial chemical manufacturing process, a fault is defined as any abnormal deviation from the normal operating condition (NOC). Effective fault detection and identification are important steps for making appropriate maintenance decisions and significantly reduce the time to recover to the NOC. Toward that end, data-driven methods for fault detection and identification have dominated the literature for the past decade and have been widely applied in practice (Chiang et al., 2000).

For fault detection, statistical multivariate data-driven methods, such as principal component analysis (PCA), have been shown to have good detection accuracy (Chiang et al., 2000; Qin, 2012). However, PCA has an implicit assumption that the measurements are independent in time and that the system variables are linearly correlated. To characterize the temporal correlations from the system's dynamics, dynamic principal component analysis (DPCA) has been developed (Ku et al., 1995). A limitation of this approach is the linearity of the ARX model for the description of dynamic processes. For systems with nonlinear NOC dynamics, different nonlinear PCA extensions have been proposed (Dong, 1996; Lee, 2004) but those methods assume independent measurements.

For fault identification, PCA-based contribution plots (Westerhuis et al., 2000) are one of the most popular techniques for determining the variables that are most strongly associated with the faults. However, the above-mentioned limitations with PCA-based approaches will also

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be reflected in the identification procedure. Moreover, those methods provide only indirect information on the severity to each affected variable.

Apart from traditional statistical methods, data-driven methods based on neural networks (NNs) have recently received significant attention due to their capability and flexibility for modeling complex and nonlinear systems. Two fault detection schemes are generally proposed within the NN framework: (1) NNs are used as a classification tool when prior knowledge about the normal and faulty conditions are available (Chine et al., 2016; Zarei et al., 2014; Zhang and Zhao, 2017; Wu and Zhao, 2018); This approach, however, is only effective when there is extensive training data of the faulty conditions; (2) NNs are used to model input-output relationships during normal operating condition (Nie et al., 2018; Wang et al., 2017). However, it is often difficult to figure out the exact input and output variables due to the closed-loop controllers and this approach only focuses on the residual of the output variables, whereas deviations in input variables induced by faults are also crucial to the process. Fault identification occur naturally in the first scheme, but it is limited by the fault conditions and data available during training, and it has not been properly addressed in the second scheme. In addition, NN-based models must be properly regularized to prevent overfitting and ensure good generalization.

In this paper, we propose a fault detection and identification method which adopts recently developed Bayesian recurrent neural networks (BRNNs) by dropout (Gal and Ghahramani, 2016). BRNNs are principled models to obtain uncertainty estimation for complex models with nonlinear dynamics. In particular, the BRNN with dropout is utilized due to its simplicity, regularization capability, strong generalization ability, and scalability. To the best of our knowledge, this is the first time the BRNN has been successfully applied to fault detection and identification. The proposed probabilistic approach enables sensitive and robust fault detection and identification with easily interpretable visualizations to the plant operators, which enables quick fault type categorization, and analysis of the possible fault propagation path and root cause using engineering judgement.

Results and Discussion

The proposed BRNN based monitoring framework was applied to the Tennessee Eastman (TE) process (Downs and Vogel, 1993). As an example, two BRNN model output variables (XMEAS 1 and XMEAS 16) for Fault 1 are shown in Figure 1. The dark blue lines are the real data and the light blue lines are predictive distribution by BRNN model with 400 repetitions via dropout. The fault alarm is triggered when the real measurements are outside the light blue band and Fault 1 is accurately detected by the proposed BRNN system.

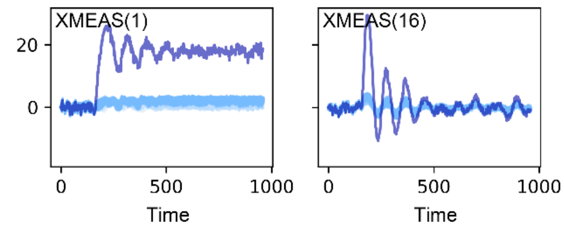

Figure 1. Scaled *BRNN model outputs for TE process Fault 1 XMEAS(1) & (16). Dark blue lines are real measurements and light blue lines are BRNN predictive distributions under NOC.*

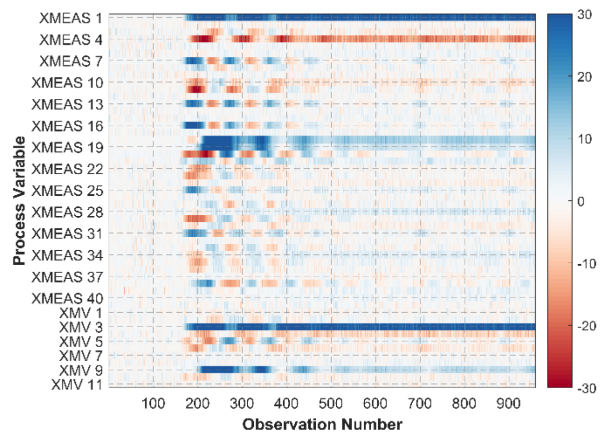

Figure 2. Fault identification plot by BRNN for TE process Fault 1.

The identification plot by BRNN is shown in Figure 2, which shows the number of standard deviation of a variable from its normal predictive distribution (Zhu and Braatz, 2014). The variables that are affected by the disturbance can be clearly identified from the plot. At first a large number of variables are affected by the fault but, after the 400th time point, variables with oscillation behavior are either back to normal or move to a new steady state.

Useful insights can be obtained from the identification plot: variables that are most significantly affected by Fault 1 are XMEAS(1) and XMV(3), which are the sensor measurements of A feed flow and the manipulate variable of A feed flow, respectively. Both variables are positively deviated from the NOC region. XMEAS(4), which is the total feed flow rate of Stream 4, is negatively deviated from the NOC region. Therefore, the possible root cause can be analyzed as the A component decrease in Stream 4 and A feed in Stream 1 is increased by the controller to compensate that disturbance, which agrees with the truth of the process.

Conclusion

A novel BRNN-based fault detection and identification system for manufacturing processes is proposed in this paper. The proposed method simultaneously tackles two key challenges in real process data: (1) concurrent spatial and temporal correlations and (2) nonlinearity. These challenging features are emblematic in the chemical manufacturing industry due to reaction chemistry and complex control systems. The BRNN framework is demonstrated to enable:

(1) fault detection of chemical process with nonlinear dynamics, and

(2) direct fault identification with easy visual interpretability and fault propagation analysis

The proposed BRNN-based fault detection and identification framework can be directly applied to any manufacturing process with historical NOC measurements. The BRNN model with dropout technique yields uncertainty estimates, which provide an adaptive confidence interval. The concurrent online calculation capability and easy implementation of dropout to any model architecture make the BRNN ideally suitable for fault-detection in large-scale industrial processes.

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