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A novel approach for fault detection and classification of the thermocouple sensor in Nuclear Power Plant using Singular Value Decomposition and Symbolic Dynamic Filter

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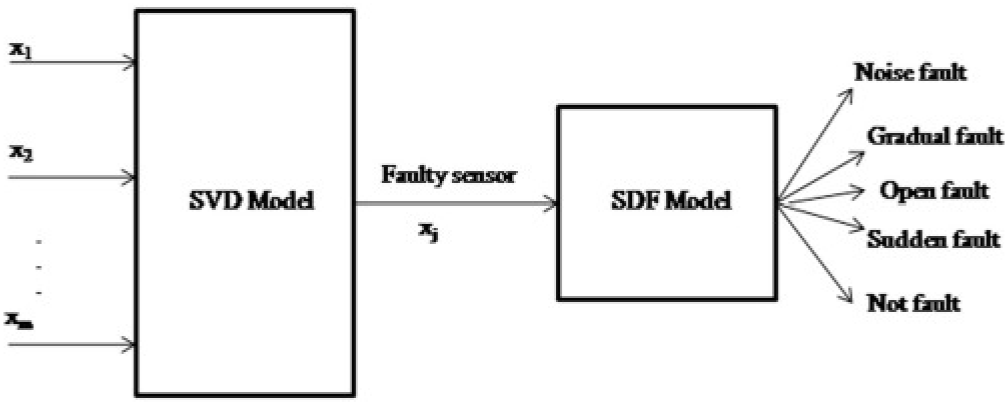
Highlights

- A novel approach to classify the fault pattern using data-driven methods.
- Application of robust reconstruction method (SVD) to identify the faulty sensor.
- Analysing fault pattern for plenty of sensors using SDF with less time complexity.
- An efficient data-driven model is designed to the false and missed alarms.

Abstract

A mathematical model with two layers is developed using data-driven methods for thermocouple sensor fault detection and classification in Nuclear Power Plants (NPP). The Singular Value Decomposition (SVD) based method is applied to detect the faulty sensor from a data set of all sensors, at the first layer. In the second layer, the Symbolic Dynamic Filter (SDF) is employed to classify the fault pattern. If SVD detects any false fault, it is also re-evaluated by the SDF, i.e., the model has two layers of checking to balance the false alarms. The proposed fault detection and classification method is compared with the Principal Component Analysis. Two case studies are taken from Fast Breeder Test Reactor (FBTR) to prove the efficiency of the proposed method.

Graphical abstract



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Introduction

For monitoring and controlling application of a complex production system, a large numbers of distributed sensor are used to provide chronological and spatial information. However, along with the benefit of using distributed sensors there are also presented some risk. Since, the system supervision and decisions making are fully depended on the data provided by the sensors, the severe consequences may arise if the signals provided by the sensors are out of calibration. Therefore, continuous monitoring of the performance of the sensor, i.e., sensor fault detection and localization are important issues in current research work.

Sensor fault detection and isolation are broadly classified into two categories: physical redundancy and analytical method. In physical (hardware) redundancy method, a single parameter or variable is measured by multiple (typically three) sensors (Park and Lee, 1993, Alag et al., 1995, Dorr et al., 1997). The value of the parameter is taken by voting scheme, which provided accurate result and detected the faulty sensor easily. However, the hardware redundancy is not realistic because of high installation cost and extra space. Therefore, analytical approaches are practical. One strategy in analytical method is a model based method (Shang and Liu, 2011, Huang et al., 2012, Saravanakumar et al., 2014, Tarantino et al., 2000, Alkaya and Eker, 2014, Youssef et al., 2013, Gertler, 1997). The model based method defines the physical representation of the variables of the system. The application of model based method depends on the availability of the physical representation of the model in the form of state space or input- output. In a complex system, it is very difficult to get an exact mathematical model.

The data-driven methods are more attractive because they need only a large amount of historical data, the knowledge of physical representation among the process variables is not necessary. In literature, a plenty of data-driven methods were introduced for fault detection and isolation. They include an Artificial Neural Network (ANN) (Upadhaya and Eryurek, 1992, Fast and Palme, 2010, Palme et al., 2011, Du et al., 2014, Hussain et al., 2015), Principal Component Analysis (PCA) (Wang and Chen, 2004, Harkat et al., 2007, Tharrault et al., 2008), Bayesian method (Mehranbod et al., 2005) and hybrid methods (Chen et al., 2015). These methods are not able to detect the fault pattern, and some methods also produce false alarms.

Ray (2004) developed a data-driven method, called Symbolic Dynamic Filter (SDF) for detection the sensor gradual fault from a quasi stationary time series data. Its performance is superior to Principal Component Analysis (PCA), Artificial Neural Network (ANN) and Bayesian techniques (Rao et al., 2008, Jin et al., 2012, Bahrampour et al., 2013). The limitation of SDF is that its analysis based on a single sensor time series data. But, the modern production system has a large number of sensors. To evaluate the performance of all sensors, one by one is a time consuming process.

In this paper, the SDF is applied to a system where uses a large number of sensors and the evaluation time complexity is minimum. The SDF technique is applied only on the faulty sensor data to classify its fault pattern, which is detected by another data-driven method. Singular Value Decomposition (SVD) is used to detect the faulty sensor from a data set of all sensors by reconstructing the data. Jha and Yadav (2011) reported that the SVD is more effective than PCA to reconstruct the signal by removing noise and outliers. The SVD reconstruction is not affected by the selection of principal components as in Principal Component Analysis, because in SVD, the first singular value is always very large (for sensor data) and others are very small if the singular values are sorted in decreasing order.

In this work, a two layer mathematical model is proposed to detect and classify the fault pattern along with balancing the false alarms. In the first layer, the SVD is used to identify the faulty sensor from the sensor data. The SDF is used to classify the fault pattern and prevent the false alarms. The contribution of this paper is given below:

(i) A novel approach to classify the fault pattern is proposed.

(ii) Applied a robust reconstruction method SVD to identify the faulty sensor.

(iii) Applying the SDF method to analyze the fault pattern in the system where exists a large number of sensors with a minimum time complexity.

(iv) An efficient data-driven model is designed to prevent the false alarms.

This paper is organized into seven sections including the present one. The next section presents a brief description about the First Breeder Test Reactor (FBTR) and the type of fault of thermocouple sensor signal. Section 3 represents the proposed mathematical model using the Singular Value Decomposition (SVD) and the Symbolic Dynamic Filter (SDF). Section 4 briefly describes, fault detection and feature extraction using PCA. Two case studies are described in Section 5. Result comparison of the proposed method with the PCA based method is explained in Section 6. Summary, conclusion of this paper and recommendations for future research work is given in Section 7.

Section snippets

Brief description of FBTR

The Fast Breeder Test Reactor (FBTR) uses plutonium-uranium mixed carbide as fuel and liquid sodium as a coolant. The entire system is broadly divided into three systems: primary sodium system, secondary sodium system, and steam and water circuit. The important components of the primary sodium system are the reactor assembly, two intermediate heat exchangers (IHX), two sodium pumps and interconnecting piping. The secondary system includes sodium pumps, re-heaters, surge tanks, steam generator

Proposed method

A layered mathematical model using data-driven method is proposed to detect and classify the fault of the thermocouple sensors, is depicted in Fig. 4. The first layer detects the faulty sensor from the data set of all sensors, and the second layer classifies its fault pattern. If the first layer detects any false fault, it is also rectified by the second layer. The SVD based method is applied to identify the faulty sensor signal and that faulty signal is analyzed by the SDF. Description of

Fault detection using PCA

The PCA is a widely used statistical tool for fault detection (Wang and Chen, 2004, Harkat et al., 2006, Tharrault et al., 2008). Let X be a data set matrix with dimension $M \times N$, where M is the number of observation and N is the number of variables (sensors). The PCA transforms the data matrix X into optimal vector space that captures the maximum variation of the data as follows:$\boldsymbol{S} = \boldsymbol{X}\widehat{\boldsymbol{V}}$

where $\boldsymbol{S} = [s_1, s_2, \ldots., s_l] \in \mathscr{R}^{M \times l}$ called the score vector or principal component vector and $\widehat{\boldsymbol{V}} = [\boldsymbol{v_1}, \boldsymbol{v_2}, \ldots, \boldsymbol{v_l}] \in \mathrm{R}^{\boldsymbol{N} \times \boldsymbol{l}}$ called the

Case studies

Two case studies are taken from the Fast Breeder Test Reactors thermocouple data to validate the efficiency of the proposed method. The first case study assumes that when the process is in isothermal condition, i.e. no power is generated and the second case study is taken when the process generated 40MW of thermal power.

Result and discussion

This section presents the results of the case studies using the SVD-SDF model for fault detection and classification. The proposed method results are compared with the PCA method. The proposed method consists of two layers to find out the faulty sensor and analyze the fault pattern. The next subsection gives the results of each layer.

Summary, conclusion and future work

This paper presents the combination of two data-driven methods for fault detection and classification. The algebraic method SVD is proposed to detect the faulty sensor in the first layer. In the second layer, the SDF is applied to classify the fault pattern which is detected by the first layer. The first layer efficiently provides the faulty sensor time series for further analysis. In the second layer, the features are extracted in compressed form, which is proficient to analyze. It has been

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Cited by (15)

Minor fault detection of thermocouple sensor in nuclear power plants using time series analysis

2019, Annals of Nuclear Energy

> *Citation Excerpt :*
>
> …The heat generated in the reactor core is transported to the steam generating system by circulating liquid sodium. The details of FBTR are provided in (Mandal et al., 2017a). Another three thermocouples are used to measure the sodium temperature in the inlet.…

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Sensor fault detection in nuclear power plants using symbolic dynamic filter

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> *Citation Excerpt :*
> …The fault free signal space is partitioned by MEP and faulty space is partitioned by UP. Training transformed signal space is partitioned by MEP (See Algorithm 2 author's previous paper, Mandal et al. (2017a) and a common partition is fixed. For UP, the width size is selected as 0.5.…

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