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Data driven approach for fault detection and diagnosis of turbine in thermal power plant using Independent Component Analysis (ICA)

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ABSTRACT

In this paper, a statistical signal processing technique, known as Independent Component Analysis (ICA) for fault detection and diagnosis in the real Turbine system (V94.2 model) is suggested. The information of one of MAPNA's power plants turbine system is utilized at first. In order to reduce the dimensionality of the data set, to identify the essential variables and to choose the most useful variables, PCA approach is applied. Then, the fault sources are diagnosed by ICA technique. The results indicate that suggested approach can distinguish main factors of abnormality, among many diverse parts of a typical turbine system. The presented results will show that suggested approach can avoid false alarms and fault misdiagnosis due to changes in operation conditions and model uncertainty. The presented results show the validity and effectiveness of ICA approach for faults detection and diagnosis in noisy states.

1. Introduction

The process of power generation involves a large amount of energy and materials. The thermal power plant components are subjected to very high temperatures and pressures, consequently a system failure can result in a significant loss life and property. Therefore, it is essential for a power plant controller to incorporate some forms of system alarms to inform system operators of the abnormal operating conditions [1]. Four procedures associated with process monitoring are: fault detection, fault identification, fault diagnosis and process recovery. There appears to be no standard terminology for these procedures. The terminology given by Chiang, Russel and Braatz is adopted here [2].

Fault detection involves determining whether a fault has occurred. Fault identification identifies the observed variables relevant to the fault. Fault diagnosis determines which fault occurred. Process recovery, also called intervention, removes the effect of the fault, and it is the required procedure for closing the process monitoring loop. Whenever a fault is detected, the fault identification, fault diagnosis, and process recovery procedures are employed as shown in Fig. 1 sequence [3].

In another point of view, all fault diagnosis approaches can be classified as on-line fault detection and off-line fault detection schemes. In the on-line schemes the fault diagnosis algorithm operates simultaneously with the plant. In the off-line schemes the fault diagnosis algorithm determines the presence or absence of a fault by analyzing the historical data of plant or operating process characteristics [4].

On the other hand, fault diagnosis schemes can also be classified as model-free or model-based schemes. The model-free schemes do not use a mathematical model of the system for fault diagnosis, while model-based schemes utilize a mathematical model of the system for fault diagnosis [5]. The present paper by acquiring data from a real power plant steam turbine, focuses on the black-box approach for fault detection and diagnosis because it can give satisfactory results in complex industrial modeling applications, with reasonable computational and time efforts. This eliminate need to access too many parameters for detailed modeling and simulating of a power plant.

2. Literature review

Classical model-based methods of fault detection use dynamic models of the process. The basic idea is: states or variables of the model and real system are compared to generate residual signals, which in the presence of faults, take non-zero values and often monitored using estimation techniques [6–8] or parity equations

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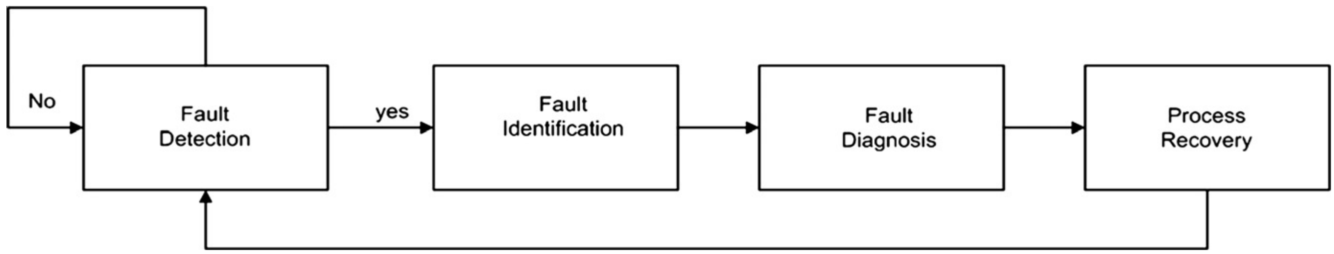

Fig. 1. A schema of the process monitoring loop [2].

[9]. However, application of model-based approach is not reasonable in industrial systems such as power plant components because the large amount of variables and parameters is an obstacle to achieve precise models.

Rule-based expert systems have been investigated very intensively for fault detection and diagnosis problems such as [10–12]. Nevertheless, these systems need an extensive database of rules and the accuracy of diagnosis is dependent on the rules.

Limit checking is the most frequently used method for fault detection. This is usually applied to measurable absolute values and their trends. Basic method is the real time estimation of the mean and variance of observed stochastic variables. Also statistical test like hypothesis testing, *T*-test, *F*-test is developed in this approach. Doyle et al. [13] showed that limit sensing, lacks sensitivity to some process faults, because it ignores interactions between the process variables for the various sensors [13,14].

Principal Component Analysis (PCA) is another method for fault detection, analysis the fluctuation of input and output variables of large scale processes. PCA can reduce the number of variables to those being uncorrelated while preserving most of the information. Jackson, A showed that PCA is an optimal method for dimension reduction by capturing the variance of the data [14]. Daneshvar and Farhangi Rad apply Principal Component Analysis approach for fault detection and identification of the boiler of a coal fired power plant [15]. In this reference, fault detection based on PCA uses two statistics, Hotelling's T^2 and SPE.

3. Basic Principal Component Analysis (PCA) algorithm

Principal Component Analysis [16] transforms a set of correlated random variables with zero mean value into a small number of de-correlated variables called principal components while saving as much information as possible from the original variables. The training set data, consists of "*m*" observable variables and "*n*" samples for each variable, is stacked into a matrix $X \in \Re^{n\times m}$ as below:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{1}$$

The mean value of each variable can be obtained as:

$$\bar{x}_{\substack{i \\ i\le m}} = \frac{1}{n}\sum_{k=1}^{n} x_{ki} \tag{2}$$

And the covariance of two variables is calculated as:

$$Q_{ij\,\substack{i \\ i,j\le m}} = \frac{1}{n-1}\sum_{k=1}^{n}(x_{ki}-\bar{x}_i)(x_{kj}-\bar{x}_j) \tag{3}$$

The mean value and the covariance matrix are unbiased estimates for the mean and the covariance matrix of the random variables. The reason why the sample covariance matrix has $n-1$ in the denominator rather than n is essentially that the populations mean $E(X)$ is not known and is replaced by the sample mean $X_{i,\ i\le m}$. Assume that the observations follow Gaussian distribution and the data vector *X* is centered about its mean and is properly scaled. Thus the obtained matrix is called the "sample covariance matrix" (or "empirical covariance matrix").

$$S = \frac{1}{n-1}X^T X \tag{4}$$

PCA serves as a model reduction tool to preserve the dominant linear relationships among the variables. In fact PCA decomposes a measurement vector *X* into two components, *X* and X', which determines two orthogonal subspaces defined by the columns of the matrix P^{prime} with the following condition [17]:

$$\begin{aligned} &\min_{P,P^{prime}} E[X'^T X'] \\ &\text{Subject to :} \\ &X = X' + E \\ &X' = XP'P' \end{aligned} \tag{5}$$

The two subspaces given by the columns of the matrix $V = [P' | \quad \tilde{P}]$ are called the Principal Component (PC) subspace and the Residual Component (RC) subspace, respectively. Given a data matrix *X* with '*m*' measured variables, the solution of the minimization problem given in (5) is that the columns of P' are the eigenvectors corresponding to 'a' largest eigenvalues of the covariance matrix of data matrix *X*, and the columns of $\tilde{P}$ are the eigenvectors corresponding to the smallest "*m–a*" eigenvalues. Singular value decomposition of data matrix can be calculated through following equations:

$$\frac{1}{\sqrt{n-1}}X = U\Sigma V^T \tag{6}$$

$$U^T U = UU^T = I \tag{7}$$

$$V^T V = VV^T = I \tag{8}$$

where $U \in \Re^{n\times n}$ and $V \in \Re^{m\times m}$ are unitary matrices, and the matrix $\Sigma \in \Re^{n\times m}$ contains the non-negative real singular values decreasing along its main diagonal ($\sigma_1 \geqslant \cdots \geqslant \sigma_{\min(m,n)} \geqslant 0$) and zero off diagonal elements. Solving (6) is equal to solving an eigenvalues decomposition of the sample covariance matrix *S*.

$$S = (1/n-1)X^T X = (U\Sigma V^T)^T \times (U\Sigma V^T) \tag{9}$$

$$S = \frac{1}{n-1}X^T X = V\Lambda V^T \tag{10}$$

$$\Lambda = \Sigma^T \Sigma \tag{11}$$

where $\Lambda \in \Re^{m\times m}$ is a diagonal matrix and the elements of its main diagonal are the non-negative real eigenvalues as decreasing ($\gamma_1 \geqslant \gamma_2 \geqslant \cdots \geqslant \gamma_m \geqslant 0$) and the *i*th Eigen value is equal with the square of the *i*th singular value.

$$\gamma_i = \sigma_i^2 \tag{12}$$