Fault Diagnosis in a Heat Exchanger using Process History Based-Methods

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Abstract

A comparison of fault diagnosis systems based on Dynamic Principal Component Analysis (DPCA) method and Artificial Neural Networks (ANN) under the same experimental data is presented. Both approaches are process history based methods which do not assume any form of model structure, and rely only on process historical data. The comparative analysis shows the online performance of both approaches when sensors and/or actuators fail. Robustness, quick detection, isolability capacity, false alarm rates and multiple faults identifiability are considered for this experimental comparison. An industrial heat exchanger was the experimental system. ANN showed instantaneous detection for actuator faults; however, with greater (22%) false alarm rate. ANN can isolate multiple faults; whereas, DPCA did not show this property, but required a minor training effort.

Keywords: DPCA, ANN, Fault Detection, Fault Diagnosis

1. Introduction

Early detection and diagnosis of abnormal events in industrial processes can represent economic, social and environmental profits. Generally, the measuring and actuating elements of a control system fail causing abnormal events. When the process has a great quantity of sensors or actuators such as chemical processes, the Fault Detection and Diagnosis (FDD) task is very difficult. Advanced methods of FDD can be classified into two major groups (Venkatasubramanian, et al., 2003), process history-based methods and model-based methods.


A comparative analysis between two FDI systems is proposed in this paper. One of them is based on the Dynamic Principal Component Analysis (DPCA) and another one on Artificial Neural Networks (ANN). Both methods are designed to online detect and isolate faults related to sensor or actuators in an industrial HE.

Recently, DPCA and Correspondence Analysis (CA) have been compared (Detroja, et al., 2005). CA shows shorter detection delay and lower false alarm rates; however, CA needs greater computational effort. Mina and Verde (2007) proposed an adaptive standardization for DPCA which allows detecting faults and avoiding normal variations. Many approaches based on ANN have been proposed to diagnosis faults in nonlinear systems (Korbicz et al., 2004). Tan et al. (2009) used an ANN to model a HE including detection and fault classification.
The aforementioned works are tested under different faults and non-uniform process conditions, i.e. it is impossible a comparative analysis. This paper shows a comparison between DPCA and ANN under the same experimental data provided from a HE.

This paper is organized as follows: in the next section, DPCA formulation is presented. Section 3 describes the ANN design procedure. Section 4 shows the experimentation. Section 5 presents the results. Final conclusions of this work are presented in section 6.

2. DPCA Formulation

Process data in the normal operating point must be acquired. Process variables can have different ranges of values, thus the data matrix $X$ must be normalized. In chemical processes, serial and cross-correlations among the variables are very common. To overcome the limitations of normality and statistical independence of the samples, the column space of the data matrix $X$ must be augmented with a few past observations for generating a static context of dynamic relations.

$$X_D(t) = [X_1(t), X_1(t-1), \ldots, X_1(t-w), \ldots, X_n(t), X_n(t-1), \ldots, X_n(t-w)]$$

where $w$ represents the quantity of time delays to include in $n$ process variables. The main objective of DPCA is to get a set of a smaller number ($r < n$) of variables by solving an optimization problem which involves the maximization of the explained variance in the data matrix. $r$ must preserve most of the information given in these variances. DPCA formulation can be reviewed in detail in (Tudón, et al., 2009). Once the scaled data matrix $\overline{X}$ is projected by a set of orthogonal vectors, called loading vectors $(P)$, a new and smaller data matrix $T$ is obtained: $T = \overline{X}P$. $P$ contains the eigenvectors with the largest eigenvalues. Matrix $T$ can be back-transformed into the original data coordination system as, $X^* = TP^T$. Fig. 1 shows the block diagram for getting the characterization of the normal operating point using DPCA.

2.1. FDD using DPCA

Normal operating conditions can be characterized by $T^2$ statistic (Hotelling, 1993) based on the first $r$ Principal Components (PC), or by $Q$ statistic (Jackson, et al., 1979) based on the residual space. Left plot in Fig. 2 shows the block diagram for applying DPCA in the online fault detection task. New measurements are projected in both spaces. A fault is correctly detected when both statistics overshoot their respective thresholds, see details in (Tudón, et al., 2009). Once a fault is detected, contribution plots are used to isolate the most relevant cause of fault (Miller, et al., 1998). Fig. 2 (right) shows a block diagram for achieving the fault diagnosis using contribution plots. Since the residual space is more sensible to the faults than the PC space (Isermann, 2006), residual space is used to generate the residue which is used to compute the error contributions.
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3. Design of the ANN

An ANN is a computational model inspired on biological neural networks, it is composed by several basic elements named neurons which are clustered in layers and highly interconnected. These connections are used to store knowledge. The ANN architecture determines the neurons distribution into three types of layers: input layer, hidden layers and output layer. Based on the flow of signals, the ANN architecture can be classified into two major groups: feedforward and recurrent networks. Feedforward networks project the flow of information only in one way, i.e. the output of a neuron feeds to all neurons of the following layer (Hagan, et al., 1996). The ANN training is defined as the adaptation process of the synaptic connections under external stimulations. The backpropagation algorithm is the most used training method since it allows to solve problems with complex net connections; its formulation can be reviewed in detail in (Freeman and Skapura, 1991). Korbicz et al. (2004) established that the ANN can be used to model nonlinear, complex and unknown dynamic systems, as well as to take decisions (e.g. in faulty scenarios). A Multilayer Perceptron (MLP) has been proposed for diagnosis sensor and actuator faults. The main objective of the MLP is to classify the inputs into a specific class of faults (binary values) using a nonlinear transformation function. For the HE data, the MLP is designed to classify the set of the inputs in normal or faulty operating conditions. ANN inputs correspond directly to the process measurements. ANN outputs generate a fault signature which must be codified into pre-defined operation states. When the ANN output is zero the sensor or actuator is free of faults; otherwise it is faulty. All neurons of the input and hidden layers have an activation function of hyperbolic tangent; while the neurons of the output layer have sigmoid function. The trained network can be subsequently validated by using unseen process data. Crossed validation is used to assess the ability of the ANN to generalize the process it has been trained to represent.

4. Experimental System

4.1. Industrial Heat Exchanger

An industrial shell-tube HE was the test bed. Fig. 3 (left side) shows a photo of the HE; while right picture shows a diagram of the main instrumentation: 2 temperature sensor/transmitters ($TT_1, TT_2$), 2 flow sensor/transmitters ($FT_1, FT_2$) and their control valves ($FV_1, FV_2$). Instrumentation is connected to a data acquisition system (NI USB-6215).

4.2. Design of Experiments

Abrupt faults in sensors and actuators (soft faults) have been implemented in additive form. Also, the process always was free of disturbances. Multiple faults identifiability is
analyzed under sensor faults, which simulate transmitter biases. The fault magnitude for each sensor is: $FT_1 \rightarrow 6\% (5\sigma)$, $FT_2 \rightarrow 8\% (5\sigma)$, $TT_1 \rightarrow 2^\circ C (8\sigma)$, $TT_2 \rightarrow 2^\circ C (8\sigma)$. Four types of faults have been implemented in the steam (cases 1 and 2) and water (cases 3 and 4) control valves. The faults are considered like low or high pressure in the valves ($\pm 10\%$). The case 0 corresponds to the normal operating point: steam valve in 70\% and water valve 38\%.

4.3. Implementations

DPCA uses 1 second as time delay in the training stage, and 1900 experimental data for each sensor. Thus, the measurement vector is: $x(t) = [FT_2(t) FT_1(t) TT_1(t) TT_2(t)]$. In the DPCA training, all data vectors are considered in the normal operating point. While, a $MLP$ (4-10-4) is used to detect sensor faults, i.e. an ANN with 1 hidden layer of 10 neurons. 3000 experimental data for each sensor are used to train the ANN. For actuator faults, a $MLP$ (4-10-10-3) is used, i.e. the ANN has 1 more hidden layer in order to increase the network expressivity. 1000 measurements of each sensor were taken from the normal and faulty process conditions for training the ANN.

5. Results

For comparison, same metrics have been monitored in both approaches: quick detection, isolability capacity, false alarm rates and multiple faults identifiability.

5.1. DPCA approach

Taking one time delay of each measurement, it is possible to explain a high quantity of variance including the possible auto and cross correlations. The normal operating conditions can be explained with 5 principal components (99.95\%). When a fault is implemented in $FT_1$ at time 10, both statistics clearly overshoot their thresholds (left plot in Fig. 4). Contribution plot shows correct fault isolation, 59\% of total error corresponds to water flow signal. When the remainder faults are introduced, the statistics belong still upon their control limits; however, they move more away from them. After the 1st fault,
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contribution plots can not associate the error to a specific variable (right plot in Fig. 4). A similar result to Fig. 4 is obtained for actuator faults. No matter if the bias is positive or negative, both statistics overshoot their control limits when a fault is detected. For the cases 1 and 2, the steam flow signal has the greatest error contribution because these faults are associated to changes in the pressure of steam valve. Similarly, the water flow has the greatest error contribution when the water valve fails (cases 3 and 4).

5.2. ANN approach

*Fresh* data are used in the ANN testing. Fig. 5 shows the ANN performance for sensor faults. After $t = 1750$, multiple faults are considered. The output layer of the MLP has 4 neurons, one for each sensor signal. When the signal is equal to 1, a fault has occurred.

![Figure 5. FDD analysis for sensor faults using ANN](image)

Fig. 6 shows the ANN targets and outputs under faulty actuators. 3 neurons are considered in the output layer. A codifier is used to translate the 5 different operating points to a set of binary fault signature, e.g. the case 3 in the binary signature is: $(3)_B = (011)_2$. The binary numbers 110 and 111 are considered as false alarms.

![Figure 6. FDD analysis for actuator faults using ANN](image)

5.3. Comparison of the methods

The false alarm rate is the index of false events which occurs when: (1) the FDI system does not detect an occurred fault or (2) the FDI system detects a fault which did not happen. For actuator faults, the false alarm rate is greater 22% in ANN because the isolation decision is ON/OFF; while in DPCA, the false alarm is caused by the time delay of both statistics. Furthermore, the detection time is greater in DPCA even when these faults are abrupt; whereas, ANN shows an instantaneous detection (Table 1). Both methods can detect multiple faults; however, DPCA can not isolate correctly two or more sequential faults.

<table>
<thead>
<tr>
<th>Approach</th>
<th>Location</th>
<th>Detection (s)</th>
<th>Isolability</th>
<th>False alarm (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>DPCA</em></td>
<td>Actuators</td>
<td>9 – 18</td>
<td>✓</td>
<td>14.13</td>
</tr>
<tr>
<td></td>
<td>Multiple sensors</td>
<td>Instantaneous</td>
<td>—</td>
<td>0</td>
</tr>
<tr>
<td><em>ANN</em></td>
<td>Actuators</td>
<td>Instantaneous</td>
<td>✓</td>
<td>18.30</td>
</tr>
<tr>
<td></td>
<td>Multiple sensors</td>
<td>Instantaneous</td>
<td>✓</td>
<td>2.01</td>
</tr>
</tbody>
</table>

According to computational requirements, the ANN training needs greater resources (memory) since historical data of the normal and faulty conditions must be known. While, the DPCA training is quickly executed; it only requires historical data of the normal operating point. Although both methods are based on historical data, they have
different frameworks: DPCA is a multivariate statistical method; whereas, ANN is based on pattern recognition. When unknown soft faults are presented, the performance of ANN can be deteriorated; whereas, the DPCA method does not suffer this limitation. Although, the ANN has the extrapolation property in nonlinear systems as well as the capacity to interpolate unknown results, a new ANN training can be necessary under these new malfunctions. On the other hand, DPCA does not require more training effort because only deviations from the normal operating point are considered. Both methods are deteriorated when the process is time-variant; however, the training stage of both methods (retraining) can be easily applied every specific time window.

6. Conclusions
A comparison between DPCA and ANN under the same experimental data provided from an industrial heat exchanger is presented. DPCA, which do very well on fast detection of abnormal situations, is easier to implement in industrial applications. A process model is not required; however, a broad acquisition of the historical process measurements under only normal conditions is necessary; whereas, the ANN training requires a priori knowledge of normal and faulty conditions. Under new and unknown faults, the training stage of the ANN must be computed again including all faulty behaviours; while, DPCA does not need more training effort because only deviations from the normal operating point are considered. Therefore, unknown soft faults can be detected and isolated using DPCA; while, ANN can diverge.

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