Sensor Failure Detection of FASSIP System using Principal Component Analysis

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Abstract. In the nuclear reactor accident of Fukushima Daiichi in Japan, the damages of core and pressure vessel were caused by the failure of its active cooling system (diesel generator was inundated by tsunami). Thus researches on passive cooling system for Nuclear Power Plant are performed to improve the safety aspects of nuclear reactors. The FASSIP system (Passive System Simulation Facility) is an installation used to study the characteristics of passive cooling systems at nuclear power plants. The accuracy of sensor measurement of FASSIP system is essential, because as the basis for determining the characteristics of a passive cooling system. In this research, a sensor failure detection method for FASSIP system is developed, so the indication of sensor failures can be detected early. The method used is Principal Component Analysis (PCA) to reduce the dimension of the sensor, with the Squared Prediction Error (SPE) and statistic Hotteling criteria for detecting sensor failure indication. The results shows that PCA method is capable to detect the occurrence of a failure at any sensor.

Keywords : Sensor, fault detection, FASSIP, Principal Component Analysis

1. Introduction

Safety is a condition that must always be achieved in the management of a nuclear reactor during the construction, the operation, until the completion of the decommissioning process. The operation reactor safety is closely linked to the reliability of structures, systems and components (SSC) of the nuclear reactor. All SSC will be affected by aging process and its functionality will be degraded, then the level of SSC reliability will be reduced.

The background of this research is the Fukushima Daiichi nuclear reactor accident in Japan in 2011, where the core damage was caused by failure of the active cooling system (diesel generator submerged in water). Then, passive cooling system researches (without pump driven force) at the nuclear power plant are performed in many countries in order to improve the safety aspects of nuclear reactors. An understanding of the passive cooling system is a cooling system that operates without the need of power supply, cooling flow occurs due to the phenomenon of natural circulation. Such phenomenon can be seen in the form of a closed loop thermosyphon heat, its water mass flow rate as an indicator of a natural circulation is obtained based on the difference in temperature, altitude and pressure between the hot section and the cold section of the loop [1, 2].

Sensor measurement accuracy at FASSIP system is essential, as the basis for determining the characteristics of a passive cooling system. In general, sensor failure can be very disadvantageous,
because it can affect the safety and quality of the output of the system. Failure of the sensors can be categorized into four types, namely: (1) signal output is constant, does not represent the value changes of the measured signal, (2) the output signal change in a short time, (3) the signal measurement contains noise, so that its values change randomly. Also with increasing operating time, (4) the sensor output signal may experience a drift [3].

Therefore, monitoring and analysis of sensor measurement should be done to detect if there are sensor failures. The purpose of this research is to develop a sensor fault detection of FASSIP system, so that an occurrence of sensor failure can be detected quickly. Many sensors have been installed at the FASSIP system for detecting the phenomena that occur in the passive cooling system. Thus in this research, the analytical data-driven method is appropriate for sensor failure detection. The method used is the Principal Component Analysis (PCA) to reduce the dimension of the sensor, and the criteria Squared Prediction Error (SPE) and statistics Hotteling value for detecting sensor failure indication. PCA is a multivariate statistical method that can be used to perform online monitoring [4, 5, 6, 7]. PCA method has advantages compared with other methods, such as PCA model transform high dimension original data into a representation of significantly reduced dimension. Therefore it will reduce the diagnosis time of sensor failure. The technology of online monitoring in a variety of industries has grown to the point where many cases of equipment failure and/or maintenance needs can be predicted quickly in a matter of days, weeks, or even months before the occurrence of equipment or system failures [8].

2. Theory

2.1. Sensor Fault Detection

Validation of the sensor is very important in safety-critical processes such as Nuclear Power Plant (NPP). The conventional method for sensor validation is to check and recalibrate the sensors at fixed time intervals [9]. Although this method has been widely applied in industry to detect a sensor failure, it is unable to detect a sensor failure when the system is being operated. In addition, because of the increasing number of sensors, it will be too expensive and even impossible to inspect all of the sensors regularly one by one. Therefore, efforts have been done to develop a more systematic method, which can generally be categorized into hardware redundancy and analytical redundancy approaches [10].

![Figure 1. Method classification of detection and identification of instrumentation failure [10].](image-url)

The concept of sensor failure detection method using hardware redundancy is by measuring each critical variable using two or more sensors. The faulty sensors are then detected and isolated by checking the consistency and voting logic. This approach has been widely used in safety-critical systems due to its simplicity and reliability.

The analytical redundancy approach does not use any additional sensor. It identifies the functional relationship between the measured variables by a mathematical model that can be
developed based on the relation of physical phenomena underlying the system, or is derived directly from the measured data. The residual difference between the sensor measurement and output model permits to detect and isolate the faulty sensor. As illustrated in Figure 1, the analytical redundancy approach can be further classified into model based methods, knowledge-based expert systems, and data-driven methods.

Increasing the number of sensors will provide data that can be collected from multiplying. It is very suitable for development of various methods of data-driven, for examples: multivariate statistics, Bayesian Belief Network and Principal Component Analysis (PCA).

2.2. Principal Component Analysis (PCA) Method
PCA is a linear transformation that is commonly used in data compression. PCA is also a common technique used to draw the features of the data on a high-dimensional scale. PCA can reduce the dimensionality of the data without losing important information from these data.

PCA model is constructed by changing the high dimensional data matrix into less dimensional representation. PCA model is built based on normal operating condition data, then it is used as the basis for process monitoring and fault sensor diagnostic. PCA-based failure detection focuses on a small number of PCs that represent a large number of process variables. Model PCA was established by the decomposition of eigenvalues of the covariance matrix of the original data. Here is the PCA algorithm used in this research [4,5]:

1. Collect data into a matrix. Suppose X is a data matrix where rows and columns represent data sample and variables consecutively.
2. Make a normal data by subtracting each data with the mean value.

\[ \hat{X} = X - \bar{X} \]  

where \( \hat{X} \) is the normalized vector, \( X \) is the column vector and is the average of \( X \).
3. Calculate the covariance matrix (C) from the normalized data.

\[ C = \frac{X^T \hat{X}}{m - 1} \]  

4. Calculate the eigen value and eigen vectors of the covariance matrix.
5. Construct principal components (PC).
The eigenvalues are arranged sequentially decreased, then the eigenvectors are arranged according to their eigenvalues. PCA model divides the monitoring data into two orthogonal parts, namely the principal component (PC) and the Residual Space (RS). Thus, the PCA model divides \( X \) into a number of products of \( n \) loading vectors (\( P_i \)) and score vectors (\( T_i \)), plus residual matrix (E), using the equation:

\[ X = \sum T_i P_i^T + E \]  

Fault detection
In the PCA, the latent variables (\( P_i \) and \( T_i \)) summarize the majority of the variation in the process. Therefore, monitoring of these two variables by using various statistical measures may provide significant information about the characteristics of the process. The new observations can be projected on a plane defined by the loading vector (\( P_i \)) to get a score value (\( T_i \)). Hotelling statistic \( \tau_2 \) is the sum of the squares of normalization, defined as follows:

\[ \tau_2^2 = T_i k^{-1} T_i^T \]  

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where $\lambda_k$ are eigenvalues associated to the principal components. In general, the higher the value of $\tau_2$, the further measurement distance from the mean. The matrix $\lambda^{-1}$ is a diagonal matrix containing the inverse of the eigenvalues associated to the $k^{th}$ eigenvector.

Squarred Prediction Error (SPE) is a part of the measurement that is not represented by the PCA model and is defined as the sum of squared errors.

$$SPE = e_i e_i^T$$ \hspace{1cm} (5)

where $e_i = (I - P_k P_k^T)$.

When a sensor error occurs, the faulty sensor will change the correlation with other sensors. If SPE value exceeds the limit value, then the variables with greater fault contribution is considered as a variable that is likely to fail.

2.3. FASSIP System

FASSIP system (Passive System Simulation Facility) is a passive cooling systems research facility. The design of FASSIP system is shown in Figure 2.

![FASSIP System](image)

**Figure 2.** Passive System Simulation Facility (FASSIP) [courtesy by M. Juarsa]

In order to validate models of the passive cooling system, the experiment data on FASSIP system are recorded using a Digital Data Acquisition System. It is important to ensure a valid value of sensor output signal, so that the generated parameter measurements are also accurate. There are three sensor types in FASSIP system:

- 68 Thermocouples,
- 1 Flowmeter,
- 2 Pressure Transducers (PTs).

The number of sensors and their placement are determined in order to acquire optimum information of the natural circulation phenomena in FASSIP system.

3. Methodology

The data used for PCA fault detection testing is obtained from FASSIP experimental data. The first experiment is conducted with all sensors to function normally, this data is used for data learning of PCA model. The next experiment is performed with failure simulation on one sensor with drift and noise error signals. This data is used to test the PCA sensor failure detection system. After that the failure is simulated on different sensors to test the overall system failure detection capabilities.
4. Results and Discussion

PCA model is constructed by transforming the high dimension data matrix into fewer dimension representation space. PCA models are based on the data of normal conditions of FASSIP operation, which is then used as the basis for process monitoring and sensors diagnostic. The data used for the PCA learning process are FASSIP commissioning, with the heater voltage of 180V, and the cooler pump is operated at frequencies of 10 to 50 Hz.

In this testing, the sampled sensor failure detection is a temperature sensor which is located below the cooler tube (see Fig. 2). It consists of four temperature sensors (four variables), the measurement result is shown in Figure 3.

![Figure 3. FASSIP temperature measurement in normal operation.](image)

After the process of data normalization for each variable, we calculate the eigenvalues (\(\lambda\)) and eigenvectors (\(\text{eigvec}\)) of the covarian matrix.

\[
\lambda = [3.9263, 0.0545, 0.0190, 0.0001]
\]

\[
\text{eigvec} = \begin{bmatrix}
0.4947 & 0.8364 & 0.2358 & -0.0085 \\
0.5029 & -0.1306 & -0.5688 & 0.6376 \\
0.5035 & -0.2043 & -0.3588 & -0.7590 \\
0.4990 & -0.4915 & 0.7015 & 0.1316
\end{bmatrix}
\]

According to the eigenvalues, if we choose one principal component, we will get a degree of certainty of 98.16%, while two principal components will result 99.5%. In this research we use the degree of certainty of 95%, with one principal component. The acceptance criteria are determined by the Hotteling method (T2) or Squared Prediction Error (SPE). If the value T2 or SPE is higher than the limit value, it is considered that the measurement data is not normal (fault occurrence). Based to the data test, the degree of certainty of 95% corresponded to:

\[
T2_{lim}(0.95) = 6.0353
\]

\[
SPE_{lim}(0.95) = 0.0715
\]

To test the ability of this method to detect a sensor failure, we simulated the erroneous input variable sensor. The fault sensor signal is generated following a mathematical equation:

\[
x(t) = \hat{x}(t) + w(t)
\]

where \(\hat{x}(t)\) is the target signal value and \(w(t)\) is the signal errors, a random value is used here. Figure 4 displays the input signals used to test the PCA, which is a continuation of the previous input signals (Fig. 3).
Figure 4. The input signal to the sensor failure detection.

The calculation result of Hotelling T2 value indicates a sensor error, if it exceeds the limit value (T2\_lim). The Hotelling T2 value is shown in Figure 5.

Figure 5. The value T^2

Figure 5 shows that the sensor error appears when t> 10 seconds, as the value T2 exceeds the fault limit value.

The identification of the faulty sensors is determined by its Fault Contribution value. Figure 6 shows the Contribution value, the higher the value indicates the higher probability of sensor error. In this test, the sensor error occurs at the temperature sensor number 3 (see Figure 4). From Figure 6 we can state that according to the PCA method developed in this research, the major fault contribution comes from sensor number 3.
Figure 6. Fault Contribution of each sensor.

From the above test result, the PCA method is capable to detect sensor faults. To determine whether the PCA method can detect any failure of the sensor, the test is done by simulating each sensor failure. Figure 7 shows a bar graph of each test.

Figure 7. Testing the detection of each sensor fault.

The failure of the first sensor (temperature 5) detected on the bar graph Figure 7(a) where the contribution of the first sensor failure is the highest value. Similarly, the test results in Figure 7(b) and 7(c) in accordance with each simulation used as an input sensor failure of PCA method.

5. Conclusion
In this research a detection method of FASSIP system sensor failure has been developed, using Principal Component Analysis (PCA). The learning process of PCA model is based on the data FASSIP operation under normal conditions. Testing of the sensor failure detection is done by simulating fault on one of the sensors. The results showed that PCA method is able to detect the occurrence of a failure in any sensor failure based on their fault contribution value.
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