Sensors Response Time validation using Dimensionality Reduction Techniques

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***Abstract* -The temperature and Pressure sensors play a vital role in Nuclear Power Plants (NPP). The Rosemount temperature sensor helps to produce the exact temperature and pressure measurement of the nuclear power plant. The sensors that supply real data must respond quickly to the safety systems of NPP. In this paper, first the Dimensionality of the Original dataset is reduced by using Principal Component Analysis (PCA), Independent Component Analysis (ICA) and Singular Value Decomposition (SVD). Finally the sensors Response Time is computed and compared with original response time.**

Keywords - Principal Component Analysis (PCA), Independent Component Analysis (ICA), Singular Value Decomposition (SVD), Nuclear Power Plant (NPP), Dynamic Response Time.

I. Introduction

In NPP, Instrumentation and control (IC) systems should sense and communicate the process variables in appropriate manner and should have a quick response time. Dynamic measurement helps to ensure better precision in response time of sensors in NPP. Steady state measurement and fast dynamic response time are the first requirements in a NPP operation. Process to sensor interface is the second requirement. For example, the temperatures of the fluid in plants are measured by using sensors which are installed securely in thermowells to the process piping.

Thermowell must be designed and installed in a good manner to give proper support to protect the temperature sensors and also to set better accuracy in response time. Rosemount Nuclear Pressure Transmitters are designed for exact pressure measurement in plant operation. The transmitters were qualified as per a KTA3505, which is a type of testing the measuring sensors of the safety systems. Rosemount Pressure Transmitters have similar construction and performance. Absolute (AP), Gauge (GP) and differential (DP) configurations are the Rosemount pressure range option units.

Through an isolating diaphragm (valves) the process pressure and silicon oil are transmitted to a sensing valves in NPP. Similarly, the reference pressure is transmitted to the other side of the sensing valves in NPP. Capacitance plates are placed on both sides of the sensing diaphragm which helps to detect the position of the sensing diaphragm. The response time of Rosemount Pressure Transmitters is 63.2% at 37.8^0C (100^0F). Rosemount Pressure Transmitters has various applications such as Pressurized Water Reactors (PWR), valve chambers, annulus and auxiliaries. Based on the performance of process instrumentation the plant power level is set among all other factors.

The plant is allowed to produce more power based on the performance of the process instrumentation on measurement assurance basis. For example, the in-active temperature sensors were found in one U.S Nuclear Power Plant was informed by the regulators. The regulators could operate only at 100% power level, and the response time of its safety system was 6.0 seconds or less. However, if the response time is degraded to above 6.0 seconds, the temperature instrumentation is ordered to decrease the power production level.

Principal Component Analysis (PCA) is a tool for classifying the patterns in data and representing the data to emphasize their similarities and differences. Since in high-dimension data, it is hard to find out the patterns, PCA is an effective tool for analysing the data. PCA finds the directions of maximum variance of the data. Main advantage of PCA is, to find out the patterns in the data and compress it, (i.e.) reducing the dimension of the data without any loss of information. It approximates a high-dimensional dataset with a lower-dimensional subspace. It's also used for analysing the multivariate data.

Independent Component Analysis (ICA) is another dimensionality reduction technique. While applying the ICA on large dataset it reduces the number of dimension and separates the featured data from the original dataset. ICA results in performance improvement and flexibility. ICA finds the maximum independence of the data. Its applications are sound source separation, image processing, under water communications, sonar target identification, wireless communications, brain wave analysis (EEG) and brain imaging (FMRI).

Singular Value Decomposition (SVD) is a tool for dimensionality reduction technique. It provides the simplified data from the original dataset. It is a technique for managing matrices that do not have an inverse.

This includes square matrices which determinant is zero and all rectangular matrices. SVD is used for computing the least-squares solutions, rank, range, null space and pseudo inverse of a matrix. It is used to represent the data in smaller number of variables and identifies the pattern from noisy data. Applications of PCA, ICA and SVD are feature extraction, signal processing, dimensionality reduction, de-noising and visualization.

II. Related Works

H.M.Hashemian [4] proposed the advances in sensor system monitoring techniques. It would seem to follow that nuclear utilities around the world would be applying the true techniques to optimize up time and to provide additional condense in the output of processing sensors Warshawsky I et.al [2] proposed an Instrumentation and control (IC) technology which focus on digital upgrades in Power Plant. Korsah et.al [5] suggested a modified IC architectures in Power plants. They focused on Sensor and measurement systems.

David Roverso [1] proposed a dynamic empirical modelling technique for the process diagnostics. Eric Blocher et.al [3] proposed the methods for effective detection and mitigation of aging mechanism in Nuclear Power Plant. R.M.Shepard [7][8] proposed an LCSR test (Loop Current Step Response) for calculating response time of temperature and pressure sensors. T.W.Kerlin [9][10] proposed an analytical basis approach for response time calculation. Thie and Joseph [11][12] proposed a noise analysis for dynamic response time of pressure transmitters.

Joe applied the noise analysis to various applications on nuclear reactors, manufacturing industries and fossil power plants. Upadhyaya [13] applied the noise analysis technique on process condition monitoring in numerous industrial applications. Wong. C et.al [14] used the similar noise analysis in medical field for monitoring the heart functionality. Keith Holbert [15] proposed an efficient application of the noise analysis technique for the diagnostics of sensing line problems in power plants.

H.M.Hashemian proposed [16] an In-Situ response time testing of RTDs and a method for validating the noise analysis technique for pressure transmitters in Nuclear Power Plant. Xiangyu Kong et.al [17] proposed a Unified Self- Stabilizing algorithm for PCA. This is for monitoring the Principal subspace (PS) and minor subspace (MS). Urs Böniger and Jens Tronicke [18] proposed that PCA is an efficient tool for extracting the polarization from dual-configuration GPR data. Paul Honeine [19] proposed an Online Kernel PCA (KPCA) for a reduced order model.

Tipping and Bishop proposed a Probabilistic PCA (PPCA) from classical linear model. Sangwoo Moon and Hairong Qi [22] proposed a hybrid dimensionally reduction algorithm, Support Vector Machine (SVM) and Independent Component Analysis (ICA). In a supervised manner it reduces the SVM-based structural risk and in an unsupervised manner it increases the ICA-based data independence. Majid Mahrooghy [23] proposed a methodology for enhancing Satellite Precipitation Estimation through an Unsupervised Dimensionality Reduction (UDR) technique as ICA which works well among all other UDR methods.

Mahdi Hasanlou [24] used the PCA and ICA in a hyper spectral dimension reduction. Both PCA and ICA gives better performance in feature extraction and image classification. L.N. Sharma et.al [25] proposed a multichannel principal component analysis for multichannel electrocardiogram (MECG) data reduction. Xiaolei Zou et.al [26] applied PCA in the Microwave Humidity Sounder (MWHS) in order to characterizing the noise in the data. Michael E. Wall et. al [27] has applied SVD and PCA in gene expression for visualizing the gene data.

III. Proposed Work

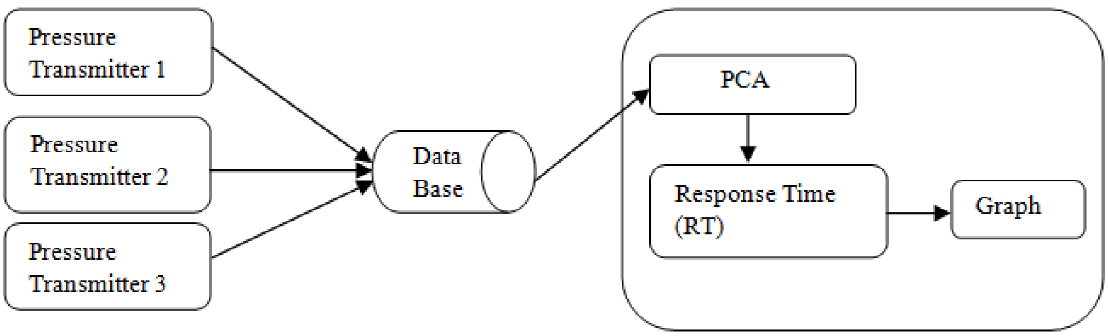

Fig. 1. System Design

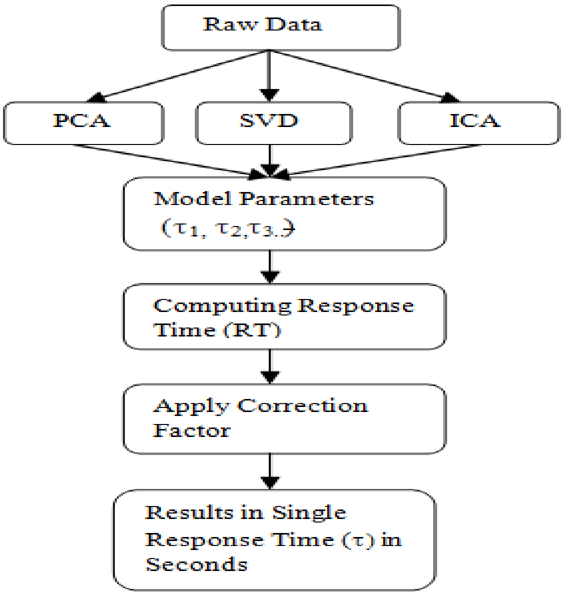

Fig. 2. Flow Chart

IV. Principal Component Analysis (PCA)

The Principal Component Analysis is the most commonly used tool for dimensionality reduction. It makes the data easier to use and reduce noises in the data. This can be applied to high-dimensional dataset for retrieving effective dimensionally reduced dataset. And it's a useful tool for pattern recognition and time series production. Hardware implementation cost and complexity also reduced by PCA. In PCA, the original dataset is transformed from its original coordinate system to a new coordinate system.

In this paper the PCA is applied on process variables of sensors, in order to get a reduced dataset. Covariance of matrix and Eigen values are computed and correlated values also removed. The relationship between the principal components and the percentage of variance is given in fig 3.

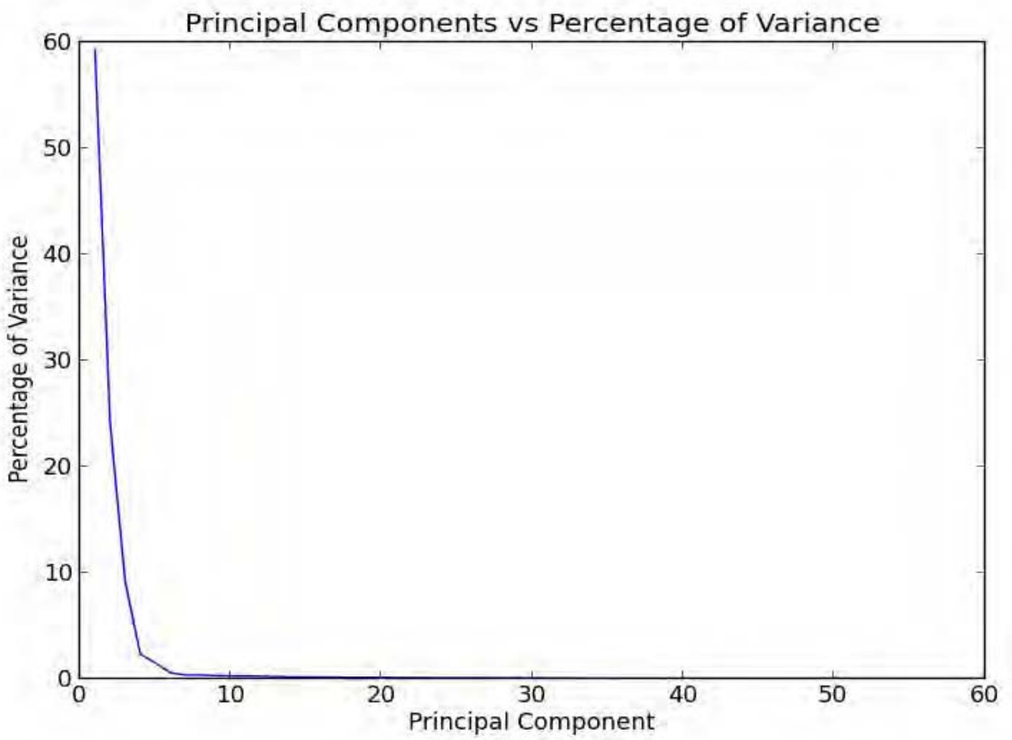

Fig. 3. Principal Component Analysis Vs Percentage of Variance.

TABLE 1
Principal Components and the Percentage of Variance from the original dataset.

Principal Components No.	Percentage of Variance
1	59.2540
2	24.1238
3	9.1500
4	2.3005
5	1.4591

V. Independent Component Analysis

Independent Component Analysis is an unsupervised dimensionality reduction method to provide better data representation. And ICA is a multivariate data analysis process for high-dimensional dataset. More essential information is provided by ICA, that resulting in performance improvement and flexibility. Based on non-Gaussianity ICA provides fast independence measure on dimensionally large dataset.

Unlike Principal Component Analysis, even in non-gaussian data it shows interesting features over datasets. For example, Cocktail-party problem, where two people are speaking simultaneously. And the two microphones are located in different places. The microphones give two different recorded signals. It leads to the complexity of separate the different sound sources by the human.

Independent Component Analysis easily separates the sound sources without any anxiety about the positions of the microphones. In this project ICA separates the featured data from the original dataset in order to reduce the dimension.

Fast ICA is an algorithm for independent component analysis which is based on fixed-point iteration. It minimizes the statistical dependence of the data and maximizes the non-Gaussianity. It provides the exact representation of the data. It helps in subsequent analysis for suitable representation of the data.

Resultant Matrix from ICA is as follows,

```
[[ 3.03093000e+03   2.56400000e+03   2.18773330e+03 ...,   1.64749042e-02
   5.28333333e-03   9.96700663e+01]
 [ 3.09578000e+03   2.46514000e+03   2.23042220e+03 ...,   2.01000000e-02
   6.00000000e-03   2.08204500e+02]
 [ 2.93261000e+03   2.55994000e+03   2.18641110e+03 ...,   4.84000000e-02
   1.48000000e-02   8.28602000e+01]]
```

VI. Singular Value Decomposition

Singular Value Decomposition is a tool used for dimensionality reduction of high-dimensional dataset. It provides the simplified data from the largest dataset. SVD removes noise and redundancy data. SVD is used for retrieving the important features of the data. SVD is based on taking the high dimensional dataset and reducing it to a lower dimensional dataset that exhibits the substructure of the original dataset. If there is a variation below any threshold value, SVD simply ignores it and greatly reduces the data.

SVD is commonly used for decomposing a matrix into many component matrices, and revealing many of the useful and interesting properties of the original matrix.

This is called as factorization. It is used to determine the dimension of the matrix range or rank. This rank of a matrix is equal to the number of independent rows and columns. This is called as a minimum spanning set or a basis. It provides solutions for least-squares problems.

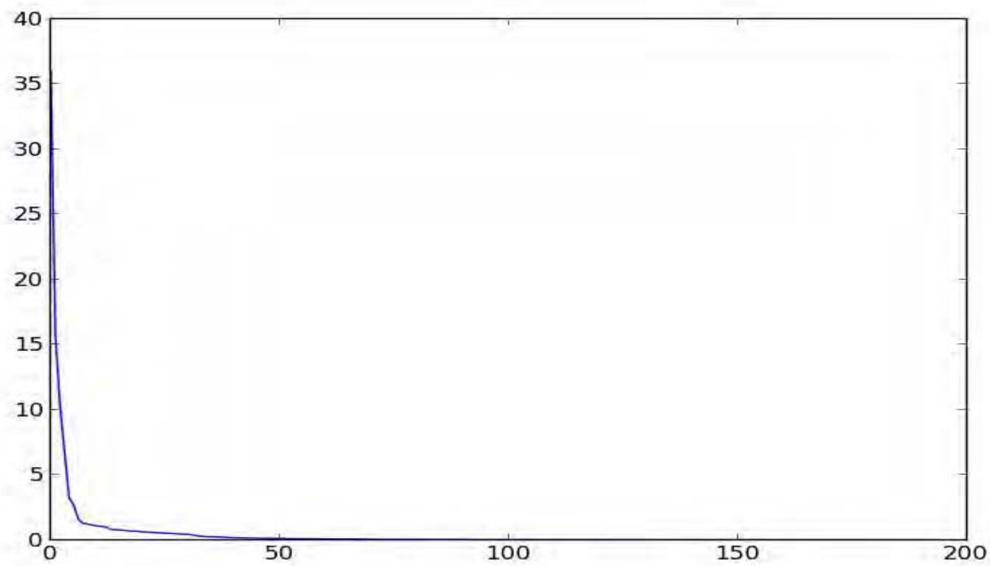

Fig. 5. Result of Singular Value Decomposition.

This graph is plotted by using Eigen values which is obtained from the original dataset. Principal component values and percentage of variance are taken in X and Y axis respectively. When compared with the PCA result, SVD provides the reduced data from the original dataset.

TABLE 2
Principal Components and the Percentage of Variance from the original dataset

Principal Components No.	**Percentage of Variance**
1	35.9704
2	15.7667
3	10.3804
4	6.7433
5	3.2131

VII. Computing the Response Time

Based on the processed values from Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Single Value Decomposition (SVD) sensors response time is computed. Pressure Transmitter dynamic response time is essential for power production in power plants. Sensors over all response time can be computed by the following formula.

$$\tau = \tau_1 \left[1 - Ln\left(1 - \frac{\tau_2}{\tau_1}\right) - Ln\left(1 - \frac{\tau_3}{\tau_1}\right) - \cdots Ln\left(1 - \frac{\tau_n}{\tau_1}\right)\right] \quad (1)$$

τ= Over all time constant.

τ_i= ith modal time constant.

L_{n} = natural logarithm operator.

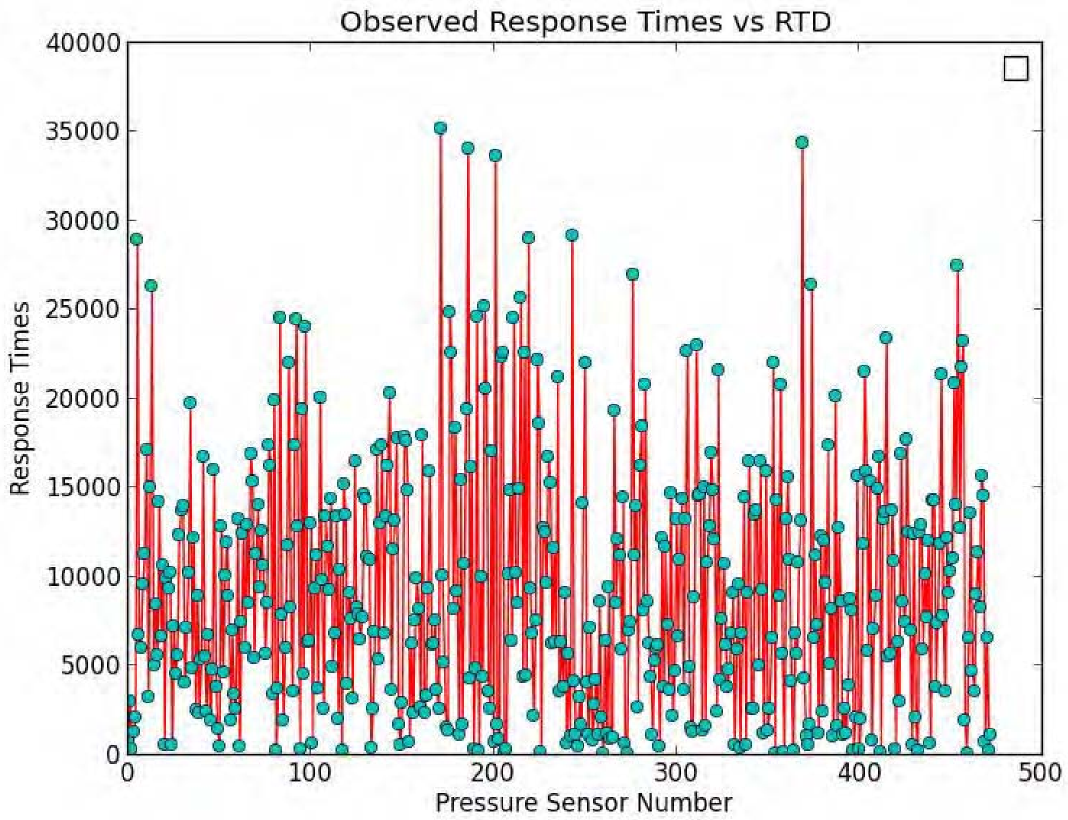

Fig. 4. Observed Response Time Vs RTDs

Above graph shows the result of Observed Response Time Vs RTDs. This graph is plotted from the Eigen values and the Covariance which is obtained from the data. The ‘r’ values are plotted as a line and the ‘co’ values are plotted as circles.

VIII. Results and Discussions

In NPP, the temperature and pressure sensors response time should be dynamic in order to avoid plant accidents. By Using PCA the correlated values are removed from the original coordinate system and redundancy also reduced. ICA used here for separates the featured data from the original data. SVD used for reducing the high dimensional data. Finally sensors response time is computed.

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