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SENSOR VALIDATION USING NONLINEAR MINOR COMPONENT ANALYSIS (PREPRINT)

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14. ABSTRACT
In this paper, we present a unified framework for sensor validation, which is an extremely important module in the engine health management system. Our approach consists of several key ideas. First, we applied nonlinear minor component analysis (NLMCA) to capture the analytical redundancy between sensors. The obtained NLMCA model is data driven, does not require faulty data, and only utilizes sensor measurements during normal operations. Second, practical fault detection and isolation indices based on Squared Weighted Residuals (SWR) are employed to detect and classify the sensor failures. The SWR yields more accurate and robust detection and isolation results as compared to the conventional Squared Prediction Error (SPE). Third, an accurate fault size estimation method based on reverse scanning of the residuals is proposed. Extensive simulations based on a nonlinear prototype non-augmented turbofan engine model have been performed to validate the excellent performance of our approach.

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Sensor Validation Using Nonlinear Minor Component Analysis

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Abstract. In this paper, we present a unified framework for sensor validation, which is an extremely important module in the engine health management system. Our approach consists of several key ideas. First, we applied nonlinear minor component analysis (NLMCA) to capture the analytical redundancy between sensors. The obtained NLMCA model is data driven, does not require faulty data, and only utilizes sensor measurements during normal operations. Second, practical fault detection and isolation indices based on Squared Weighted Residuals (SWR) are employed to detect and classify the sensor failures. The SWR yields more accurate and robust detection and isolation results as compared to the conventional Squared Prediction Error (SPE). Third, an accurate fault size estimation method based on reverse scanning of the residuals is proposed. Extensive simulations based on a nonlinear prototype non-augmented turbofan engine model have been performed to validate the excellent performance of our approach.

1. Introduction

A real-time fault diagnosis and accommodation scheme for jet engines can significantly improve flight safety by enabling automated fault tolerance and by providing important engine health information for the pilot. A Fault Tolerant Control (FTC) system is capable of automatically compensating for the effects of faults and maintaining the performance of the control system at an acceptable level, even in the presence of faults. A traditional approach to fault tolerant control is to use robust control design for anticipated faults, which is, in general, a conservative approach and may sacrifice potential performance under normal operating conditions. In contrast, an active fault tolerant control system that automatically detects and identifies component failures and adapts to such failures as they occur has the potential to achieve superior performance through the full range of flight operations. The key to successful fault tolerant control consists of early detection of faults of small magnitude, identification of the fault location, accurate assessment of current fault or defect size, and reconfigure the control system.

In the past decade, considerable research efforts have been devoted to fault diagnosis and accommodation[1, 2, 3, 4, 5, 6, 7, and 9]. Fault Detection and Identification (FDI) has laid a foundation for FTC. To perform fault tolerant control, a fault needs to be first detected and identified accurately. Also, the fault degradation status has to be justified.

While FDI provides significant potential in improving safety and performance of future advanced jet engines, clearly the success of this method is highly dependent upon the accuracy of the sensor signals used to drive FDI approaches. If these signals do not match the real signals of the physical engine, then the FDI approaches will be corrupted and consequently the engine health monitoring and control will fail. Therefore, the integration of the FDI concept with a fault diagnosis and accommodation scheme for the signals is particularly important to realize the full potential of FDI and FTC technologies.

The approaches to sensor fault detection/isolation are usually categorized into two types: model-based and data-driven. Model-driven approaches are preferable when a physical model of the system is available [4,5, and 7]. However, in many applications, physical models may not be available or may be inaccurate, especially for systems with complex nonlinear dynamics. In the absence of a physical model. or if the accuracy of a model can not meet the fault detection/isolation requirements, design of the model based FDI and FTC system will be extremely difficult, if not impossible. Even if a physical model is available, the effectiveness and robustness of the model-based fault detection/isolation approaches will deteriorate more or less due to the model mismatch or external disturbances.

On the other hand, data driven approaches do not require physical models and therefore do not have the limits aroused form the model based approach. Recent research advances in data driven FDI and fault accommodation methods, for example, Fuzzy Logic inference, Neural Networks (NN), Case-Base Reasoning (CBR) [9]. However, all these methods require thorough information about system behaviors in different fault modes for fault diagnostics. In practice, such data are not always available. Therefore, data-driven approaches are usually criticized due to this strict requirement.

In this paper, a data-driven sensor fault detection and isolation (FDI) scheme is presented. Once a fault is detected and isolated, the control system automatically reconfigures to compensate for the effect of faults and maintain acceptable control performance even in the presence of faults. For instance in the case of a sensor failure, the analytical redundancy among all the sensor signals is used to provide an estimate of the actual value of the faulty sensor and this value is then used for feedback control. This novel data-driven approach is based on Nonlinear Minor Component Analysis (NLMCA) and is designed for nonlinear system FDI. Compared with other sensor FDI methods, the proposed approach does not require a physical model and only needs training data in normal conditions that is usually easily accessible. This property distinguishes our approach from many other data-driven approaches that require faulty data in training. Meanwhile, a reverse scan method is used to reconstruct the faulty signal. Finally, extensive simulations were performed to illustrate the effectiveness of the proposed scheme with a nonlinear engine model from NASA.

In the following, a framework is developed and aimed at detecting and isolating sensor faults and estimating the fault size and the sensor FDI approach based on the NLMCA technique is described in detail to solve the sensor validation problem. The NLMCA is trained to be able to detect and isolate a sensor fault when the sensor corresponding to that variable is faulty. With the sensor fault identified, a reverse scan method is used to reconstruct the faulty sensor signal. Finally, extensive simulations were performed and some selected simulation results are presented to illustrate the effectiveness of the proposed nonlinear FDI scheme with a nonlinear engine model from NASA.

2. FDI Based on Nonlinear Minor Component Analysis Architecture

The Nonlinear Minor Component Analysis (NLMCA) based Fault Detection and Isolation (FDI) approach is developed for the sensor validation of nonlinear dynamic systems. The architecture of NLMCA for sensor validation is shown in Figure 1. This architecture contains three main modules: detection, isolation, and size estimation.

The fault detection module is used for detecting sensor faults and it is based on the NLMCA method and Squared Weighted Residual (SWR) generation. After a fault is detected, the fault isolation estimator is activated. The fault isolation estimator contains a bank of m NLMCA structure, where m is the number of sensors. With the fault isolated, a reverse scan method is used to estimate the degradation status, i.e., the fault size of the faulty sensor.

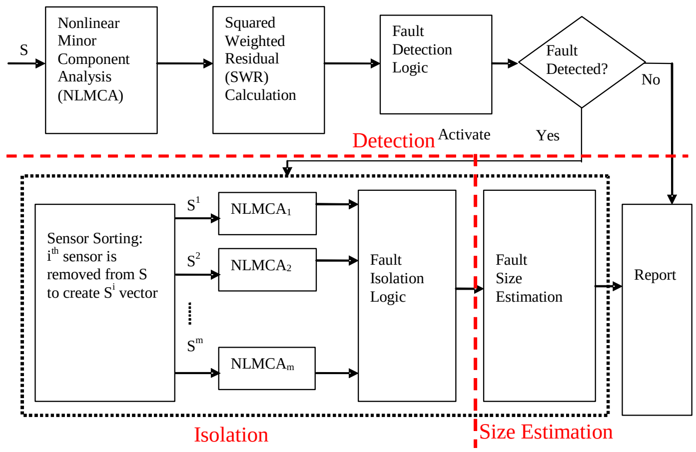

Fig. 1. NLMCA for sensor fault detection/isolation architecture

2.1 Fault Detection Scheme

The fault detection scheme is based on Minor Component Analysis (NLMCA) technique, which is built upon two current popular signal processing techniques: Principal Component Analysis (PCA) and Minor Component Analysis (MCA).

2.1.1 Nonlinear Minor Component Analysis

For a nonlinear system, linear methods, such as PCA and MCA, imply a potential oversimplification of the data being analyzed. Therefore, nonlinear methods are suggested for nonlinear dynamics, such as Nonlinear PCA (NLPCA) and Nonlinear Minor Component Analysis (NLMCA). Various Neural Network (NN)methods have been developed for performing the NLPCA [10, 11, and 12]. Nonlinear Minor Component Analysis (NLMCA) can be performed using the same structure as NLPCA. The i-th principal component is defined as the projection of the input vector to the i-th eigenvector of the input data covariance matrix, corresponding to the i-th largest eigenvalue. The projection to the eigenvectors corresponding to the j-th smallest eigenvalues is defined as a minor component.

The first principal component can be extracted using a NN structure.

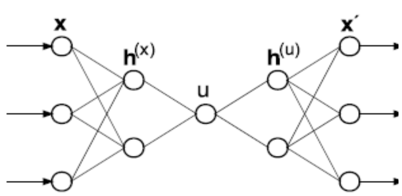

Fig. 2. NLPCA structure [8]

The cost function is defined in the following equation.

$$J^1 = \| e^1 \|^2 = \| X - X^{'} \|^2$$

If the cost function is minimized, then u can be regarded as the first principal component. To obtain the second principal component and other principal components for nonlinear systems, we can feed the residual e^1 into the same NLPCA structure. Also, the nonlinear minor components can be extracted based on the nonlinear principal components: $MC^1 = PC^{n-k+1}$, $MC^2 = PC^{n-k+2}$, …, $MC^k = PC^n$. The overall structure of NLMCA is shown in fig 3.

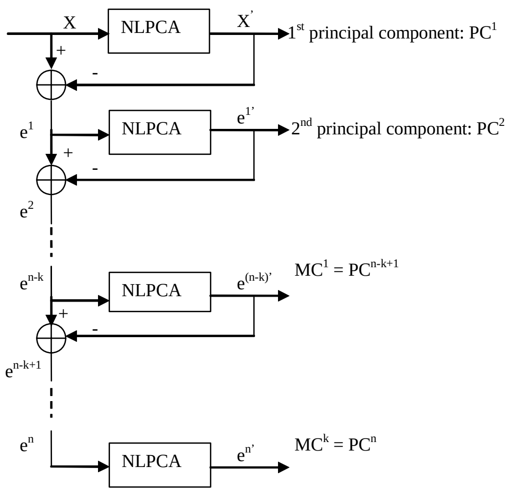

Fig. 3. NLMCA Architecture

Once the minor components are available, a sensor fault detection/isolation structure can be built.

2.1.2 NLMCA for Sensor Fault Detection

In normal conditions, the minor components are usually around zero. If not, an abnormal is usually indicted. Usually, a so-called Square Predicted Error (SPE) is used to indicate the presence of a fault. The SPE is defined as:

$$d_{SPE} = e^T e$$

where *e* is extracted from the minor components. In our approach, instead of using SPE, Squared Weighted Residual (SWR) [13], is used as the fault detection index in our approach. The SWR is given by:

$$d_{SWR} = e^T R_s^{-1} e$$

where R_s is derived from training data, $R_s = E(e*e^T)$. It has been proved that the revised index is more sensitive to faults and more robust to noise. The SWR in normal conditions follows a Chi-square distribution, which can easily determine the threshold for a given confidence level. The decision on the occurrence of a fault (detection) is made when the SWR exceeds this predefined threshold. Based on this feature, the approach of NLMCA to sensor fault detection is accordingly developed.

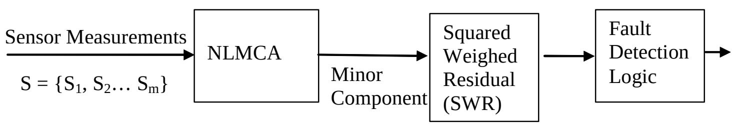

Fig 4 NLMCA for fault detection architecture

The normal dynamics are captured in the minor component space, an therefore any abnormal increase in the SWR indicates an abnormal situation. This feature is also employed for the isolation of the fault.

2.2 Fault Isolation Scheme

After a fault is detected, the fault isolation estimator is activated. Similarly, to isolate each sensor fault, a bank of NLMCA structures are built, each NLMCA structure is used to monitor one sensor only and uses training data from all the other sensors, as shown in figure 5.

Assuming that the original NLMA structure (NLMCAS) is modeling the sensors $S=\{S_1, S_2, \ldots, S_m\}$ and a fault, bias or drift, occurs on sensor S_i, then the minor components will be detected to be larger than predefined thresholds. If we use a subset of sensors S, $S_i=\{S_1, \ldots, S_{i-1}, S_{i+1}, \ldots, S_m\}$ to build NLMCAS, it is easy to see that the residual will remain small. Meanwhile, all the other isolation NLMCAS will most likely produce a high SWR since the NLMCA structures, MCA_1……, MCA_{i-1}……MCA_m are affected by sensor S_i.

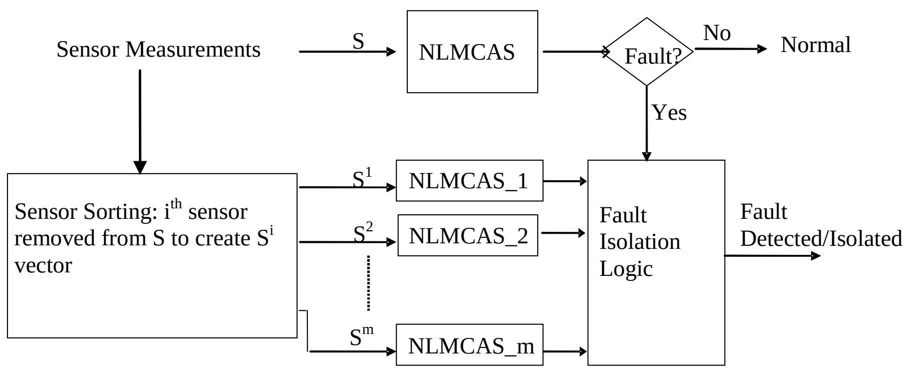

Fig. 5 . Fault isolation logic

Therefore, each NLMCA structure captures the normal dynamics of sub-set of sensors with the sensor being monitored removed. If a fault is indicted, by comparing the fault detection index form each size reduced NLMCAS, the smallest one is an indication of the sensor that is most likely to be failed.

2.3 Fault Size Estimation

After a fault is detected and isolated, it is critical to estimate the fault size and reconstruct the faulty sensor outputs. The fault size estimation can not be expressed in simple mathematical form and therefore, we used a reverse scan method to reconstruct the faulty sensor signals. A reverse scan method is based on the fault detection index (SWR) calculation. We can substitute the faulty sensor measurement with a value selected from a certain range, for example, ±p% of the measurement value of the faulty sensor, and calculate the SWR for each substituted sensor measurements. The sensor value with the minimum SWR is assumed to be the "true" value of the faulty sensor.

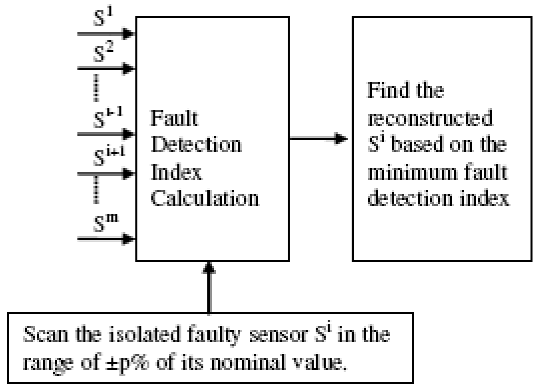

Fig. 6. Fault Size Estimation Logic Using Reverse Scan Method

3. Simulation Results

This sensor validation approach was validated and verified using a nonlinear generic engine model. The nonlinear engine model is a prototype non-augmented turbofan engine model [14]. The Table 2 shows the sensors in the engine model.

Table 1 Engine modules ([14])

	Parent Module	Instantiated Component Model
1	Compressor	Fan Hub, Fan Tip, HPC, LPC
2	Turbine	HPT, LPT
3	Combustor	Combustor and Afterburner
4	Nozzle	Exhaust Nozzle
5	Inlet	Inlet conditions
6	Mixer	Mixer/ By Pass ratio calculator
7	Shaft	Fan shaft, Core shaft
8	Cooling	Combustor cooling, HPT cooling, LPT cooling
9	FADEC	Control Scheduled N1 through WF

Table 2 Sensor List ([14])

ID	1	2	3	4	5	6	7	8	9	10
Sensor Name	T2	P2	NL	NH	T27	P27	PS3	T3	PS5	T5

To generate baseline training data, a thorough simulation is run by varying the four set-point inputs:

- Altitude: an ambient input (from sea level to 70,000 feet).
- Mach number: from 0 to 0.65.
- DTamb: difference in ambient temperature from that of a standard day. (in deg F)
- PLA: N1 demand. It is compared to the feedback N1 and this error is used to adjust the fuel demand.

For the non-linear data driven approach, two different types of faults are tested: bias faults and drift faults.

3.1 Bias Faults

To illustrate our approach, a bias fault is first initiated on sensor T2 and the fault size is 3% of its nominal value. A white noise with a variance of 2% of the nominal value of each sensor is added in this model. The bias fault is initiated at time t = 90 sec. The fault detection result is shown in figure 7. Clearly, by examining the fault detection index, we can detect the fault soon after it is initiated. Following the detection of a fault, the isolation logic is activated, and the fault on sensor T2 is isolated according to the fault isolation indices.

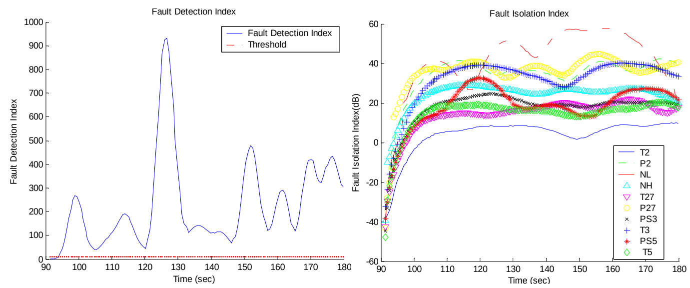

Fig. 7. Fault detection/isolation results.

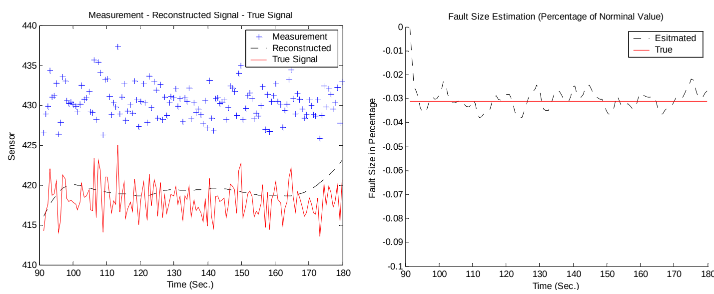

Fig. 8. Fault size reconstruction

As shown in figure 8, the measurement (in blue) deviates from the true signal (in red), and the reconstructed sensor signal (in black) follows the true signal very well. As a result, the fault size is accurately estimated based on the proposed fault size estimation technique.

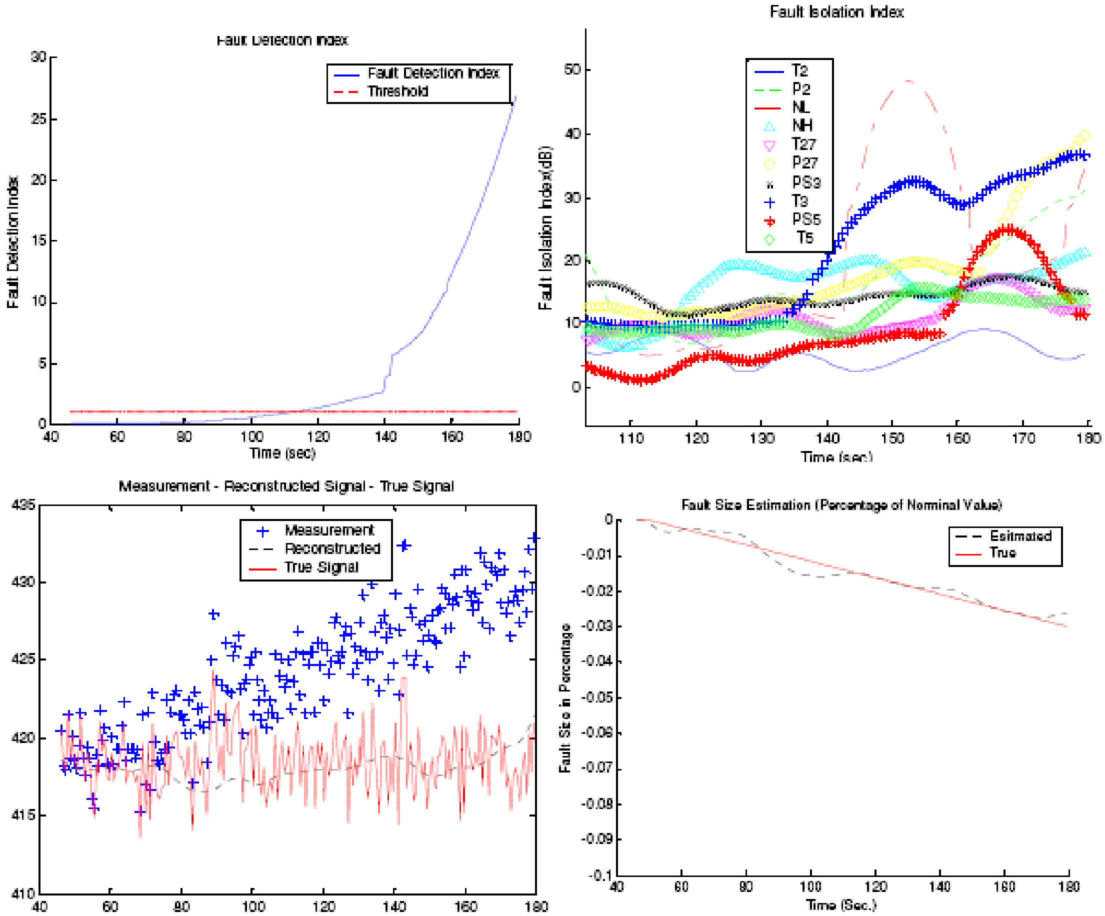

Fig. 9. Drift Fault Detection, Isolation, and Size Estimation

3.2 Drift Fault

Figure 9 shows the simulation results when the sensor measurement of sensor 1 (T2) begins to drift with the rate of 0.00023 per second (i.e., change of 0.023% of the normalized maximum nominal sensor value per second) at t=50 second. The increasing SWR shows the occurrence of a fault. To reduce the false alarm rate, we set a SWR threshold to 1 and a fault is detected around 110 second. The isolation logic is activated to determine the fault location. The smallest filtered SWR for T2 indicates a sensor fault on T2. Finally, the sensor drifting rate around 0.00023/s is estimated accurately.

4. Performance Evaluation

The Receiver Operating Characteristic (ROC) Curves are utilized to analyze the performance of the NLMCA based FDI approach. As an example, the ROC curves for sensors T2, NL, NH, and T5 are plotted in Figure 10.

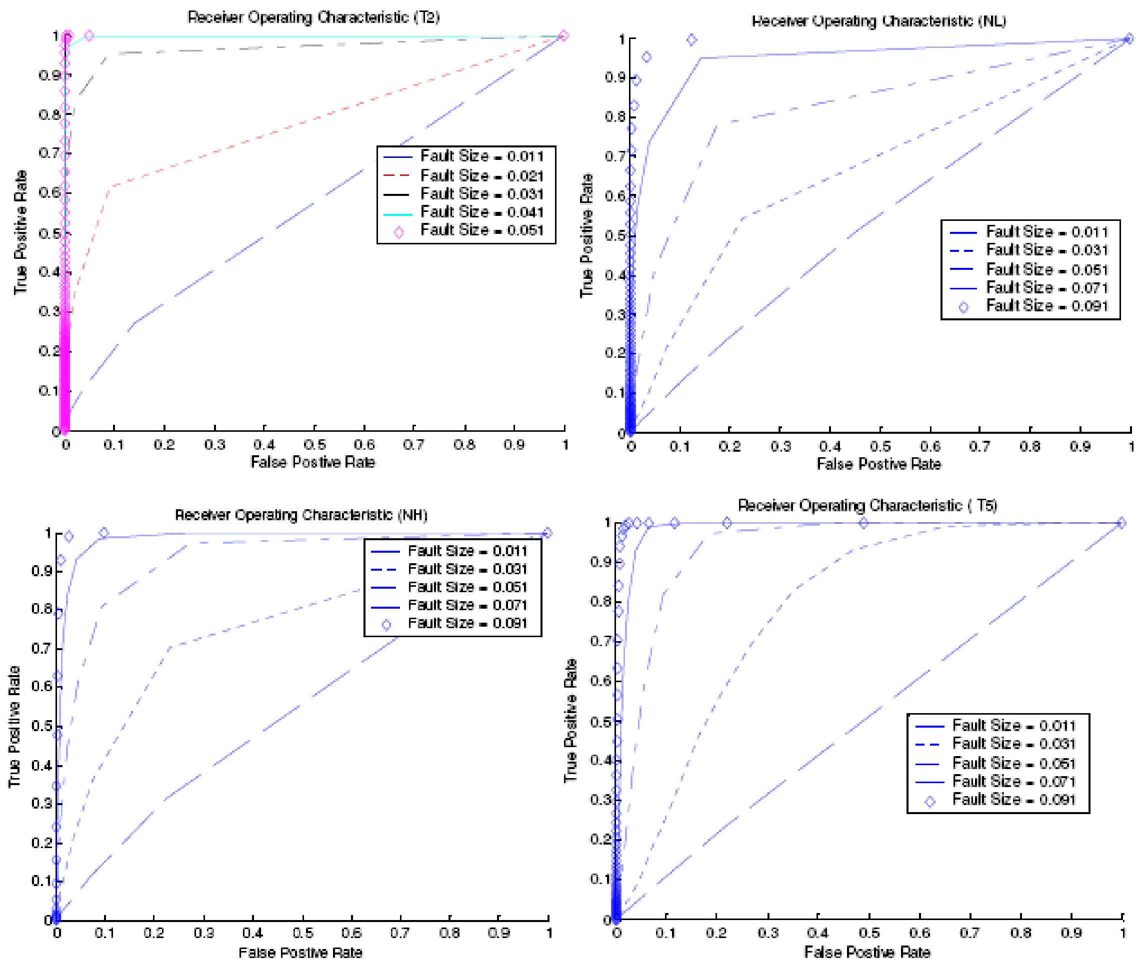

Fig 10. ROC Curves

ROC curves show the relationship between the False Positive Rate (FPR) and the True Positive Rate (TPR). When the fault size increases, the false positive rate decreases and the true positive rate increases and the fault detection performance are satisfying when the fault size is significant. According to the ROC curves and design requirements for the false alarm rate and fault detection rate, the minimum detectable fault size for each sensor can be determined. On the other hand, based on the generated ROC curves, sensor specifications like accuracy can be computed to meet the diagnostic requirements and therefore helps select the suitable sensor for control and monitoring purposes.

5. Summary

In this paper, the Nonlinear Minor Component Analysis (NLMCA) based FDI approach is presented. This approach is especially suitable when the model of a dynamic system is either unavailable or inaccurate, and when the system is non-linear (all real systems contain more or less nonlinearities). Our innovative approach requires only normal operational data for training. With this approach, fault detection and isolation is accomplished through a fault detection NLMCA model and a bank of fault isolation NLMCA models. Meanwhile, a reverse scan method is utilized for the fault size estimation purpose and simulation results with performance analysis are reported to illustrate the proposed approach

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