Sensors Fault Estimation, Isolation and Detection Using MIMO Extended Kalman Filter for Industrial Applications

Ahmed Mostafa Bardawily[1], M.Abdel-Geliel[2], Mohamed Tamazin[1]and A.A.A.Nasser[1]
[1]Electronics and Communications Engineering Department
[2]Electrical and Control Engineering Department
Arab Academy for Science, Technology and Maritime Transport, Alexandria, Egypt
Email: ahmed_elbardawili@yahoo.com

Abstract

Fault Detection and Isolation (FDI) technique became a necessary part in most industrial systems. This paper introduces a new fault state estimation and isolation technique based on Extended Multiple Model Adaptive Estimator (EMMAE) technique for industrial applications especially for industrial boiler systems. The boiler system contains six sensors in the input and three sensors in the output that used to identify linear system dynamics using state space model. System state and multiple sensor faults are estimated, isolated and detected using Extended Kalman Filter (EKF). Based on the estimated fault for each sensor features extraction, the faulty sensor is classified. The proposed technique is applied on real industrial boiler plant measurements data to demonstrate and validate the ability of proposed technique to implement online in real world.

Keywords: **Fault Detection and Isolation, Model Based, State Space identification, Kalman Filter, Extended Kalman Filter, Multiple Model Adaptive Estimators, Extended Multiple Model Adaptive Estimators.**

1. Introduction

The safety automatic control system is a critical requirement in the most critical industrial plants applications such as refining petrochemical, power generation, and nuclear plants. This type of application requires high reliability, availability, maintainability and especially higher safeguards levels. From a critical industry point of view, achieving high safety level is depending on choosing a control system that designed to perform the aforementioned requirements. Depending on choosing a suitable control system the production loss, equipment damage and bad environmental impacts is minimized. Prompt fault identification, isolation, and detection system prevents the plant from abnormal situations. Also, it avoids suddenly shutdown and decrease the failure probability of plant operation system failure can be occurred due to faults. The difference between fault, failure and error is define in [1].

The fault can be occurs in process, actuators, sensors and system parameters. The sensor fault, actuator fault, disturbances are called additive faults and the system parameter faults are called multiplicative faults [1]. Fault Detection and Isolation (FDI) techniques are one of the most important branches applied to process control engineering [2] that used to identify fault and define its location. The main FDI is shown in (Fig. 1).

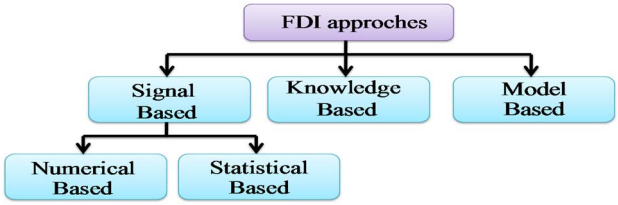


Fig.1. FDI approches

(a) Signal based: divided into two categories the first category named ***(a.1) Numerical based*****:** depends on signal processing techniques to extract the signal features such as frequency, amplitude, phase and spectrum that related to fault occurs in process using suitable analysis such as spectral analysis, wavelet analysis, short term Fourier analysis, etc. [3].The second category called ***(a.2) Statistical based:*** depends on designing a mapping chart related to a sophisticated faults occurs in a multivariate process, which the data are modeled using a suitable statistical techniques such as principle component analysis(PCA),squared prediction error(SPE),partial least squares (PLS),independent component analysis(ICA) ,etc [4].

(b)knowledge based: requires a knowledge of process function ,structure, historical information and it's situation under various fault, so the model design needs training and learning before use to detect the fault wherefore using suitable machine learning model such as neural network analysis ,fuzzy analysis [5].

(c) Model based : depends on the difference between process measurements and model measurement (residuals) to detect the fault occurs in process using suitable model such as parity space, state estimation and parameter estimation [1]. These methods are based on discrete state space model, which utilizes as FDI techniques and procedures, which aim to avoid the beginning of faults in a safety critical system. State estimation method depends on observation of the generated residuals, so by using the residual state property the fault can be detected. Kalman Filter (KF) is a good state estimator in which can be deal with linear systems, however it is not accurate estimator to be use in nonlinear applications [6],[7],[8].

Extended Kalman Filter (EKF) is the extension of KF that operates as state estimator in which used in sensor FDI method [9],[10],[11] in case of nonlinear systems. New method is chosen to deal with real world multiple sensors faults called Multiple Model Adaptive Estimators (MMAE). MMAE is a bank of KFs that operate together at the same time [12]. In nonlinear application, MMAE is not accurate estimator to be

used in nonlinear multiple faults state estimation. MMAE is developed using a bank of EKFs resulting new method called Extended Multiple Model Adaptive Estimator (EMMAE) [13].

The paper proposes a model based FDI to detect and isolate sensor faults for industrial boiler unit located in Alexandria National Refining and Petrochemicals Company (ANRPC) which selected to be a case study. The real measurements database has been collected online from the current control system (Siemens fail safe S7-400FH), which will be used to implement in proposed model. The paper is organized as follows:

The possibility of applying FDI techniques to use in automatic control systems are introduced in section 1.Section 2 defines and discusses industrial Boiler unit as a case study. Section 3 shows the proposed technique that applied for detection and isolation sensors faults. Section 4 describes the ability of applying the KF and EKF algorithms with real data implementation and results .Finally in section 5 illustrates the conclusion and future works.

2. Case Study

An industrial boiler illustrated in (Fig. 2) is used as a case study for real implementation. The boiler contains two pressurized reservoir one is located at upper side of the boiler which contains water with steam; and the other is located at lower side of the boiler. Two burners are located from the left side to heat the corresponding pipelines that contain the water. The main process specification is to supply a super heated steam with a pressure of *20 bar*, temperature of *320°c* and capacity of *100ton/hr*. The boiler control system contains a set of control loops, which can be represented as following: ***1) Feed water loop:*** contains one flow sensor (FT100),one level sensor (LT100) and one actuator (FCV100) in which operate as flow control loop to achieve the required amount of water which are heated and converted to high pressurized steam. ***2) Combustion air control loop:*** contains one flow sensor (FT300) and one actuator (FCV300) in which used to control the flow of combustion air that used to complete the firing process. ***3) Fuel gas control loop:*** contains one flow sensor (FT210) and one temperature sensor (TT210) and one pressure sensor (PT210) that used to compensate the fuel due to the change of steam is required, also contain one actuator (FCV210). ***4) Steam control loop:*** contains one pressure sensor (PT151), one flow sensor (FT150) and one temperature sensor (TT151) that used to monitoring the amount of required generated steam. ***5) Master control loop:*** is the main automated loop which used to control the percentage combustion air (FIC300) to fuel gas (FIC210) ratio according to the required amount of steam

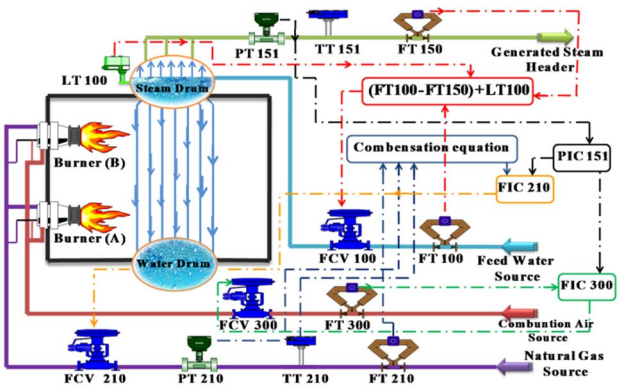


Fig.2. Schematic diagram of industrial boiler

The main task of master loop is to increase the boiler capacity with constant pressure by increasing the amount of inlet feed water, amount of natural gas and increasing amount of combustion air all of them at the same time .

3. Proposed FDI Technique

The proposed method employs the technique of EMMAE as shown in (Fig. 3).

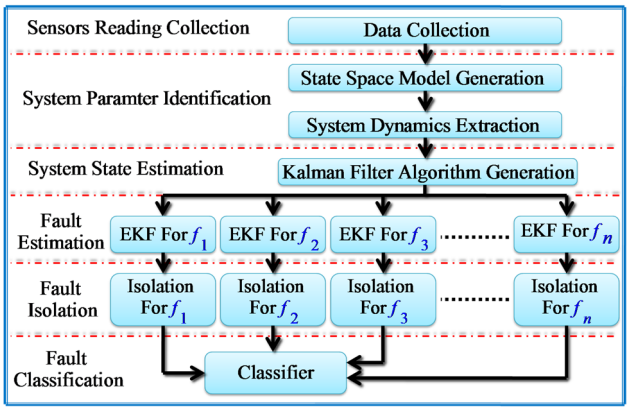


Fig.3. Proposed technique block diagram

3.1. Sensor Reading Collection

The sensors reading is classified as shown in (Fig. 4) into total input sensor measurements u_t which are divided into two subsets, actuated input sensors u_n and unactuated input sensors u_d (disturbance) and total output sensor y_t

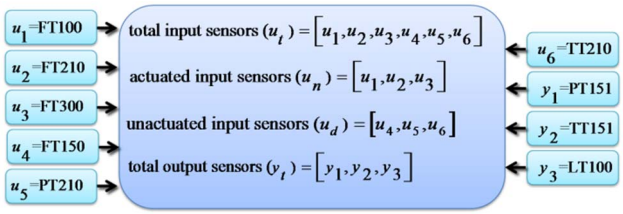


Fig.4. Data collection procedures

3.2. System Parameters Identification

The state space identification model [14] is represents in(Fig.5).

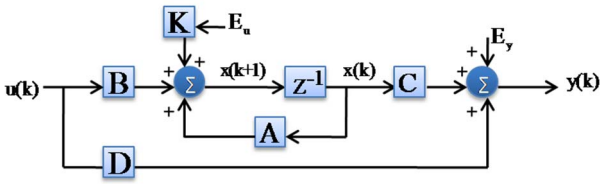


Fig.5. Normal state space block diagram

As shown in (Fig. 5) the system initial state $x(k+1)$ and the system output $y(k)$ is given by

$$x(k+1) = Ax(k) + Bu(k) + KE_u \quad (1)$$

$$y(k) = Cx(k) + Du(k) + E_y \quad (2)$$

Where (A, B, C, D) the system parameters, (E_u, E_y) is the plant disturbances and K is the distribution matrix of input matrix. All parameters are identified using state space model as shown in (Fig. 6).

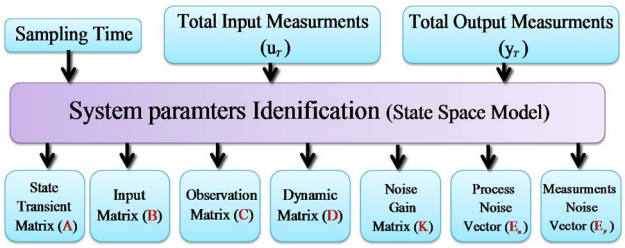


Fig.6. System dynamics identification

3.3. System State Estimation

KF is a state estimator algorithm that used to generate the discrete time system state output [15],[16] to compare with the nominal values. The KF algorithm and steps of operation are shown in (Fig. 7).

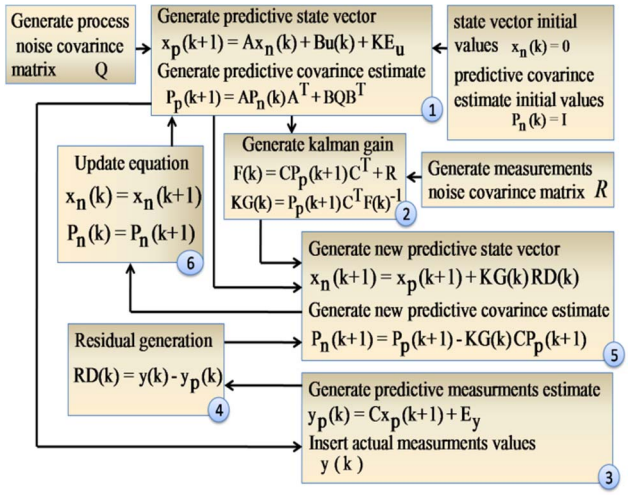


Fig.7. The Kalman filter algorithm procedure

3.4. Fault Estimation and Isolation

***Case (1)*: EKF in case of input faulty sensor**

The fault in input sensor (measure actuated signal) can be simulated in the system model based on EKF as shown in equation (3)

$$x_E(k+1) = \begin{pmatrix} x_p(k+1) \\ f_u(k) \end{pmatrix} = \begin{pmatrix} A & B_n \\ 0 & I \end{pmatrix} \begin{pmatrix} x_n(k) \\ f_u(k) \end{pmatrix} + \begin{pmatrix} B_n & B_d \\ 0 & 0 \end{pmatrix} \begin{pmatrix} u_n(k) + f_u(k) \\ u_d \end{pmatrix} + KE_u \quad (3)$$

The state vector x_E divided into two subsection nominal state x_p and fault sensor measurements f_u as an additional state. The estimation of the new state x_E is obtained as shown in (Fig. 7) by replacing x_n by x_E and system parameter in case of input faulty sensor as shown in equation (4)

$$\bar{A} = \begin{pmatrix} A & B_n \\ 0 & I \end{pmatrix}, \quad \bar{B} = \begin{pmatrix} B_n & B_d \\ 0 & 0 \end{pmatrix}, \quad \bar{C} = (C \quad 0) \quad (4)$$

***Case (2)*: EKF in case of output faulty sensor**

The fault in output sensor (measure actuated signal) can be simulated in the system model based on EKF as shown in equation (5) and equation (6).

$$x_E(k+1) = \begin{pmatrix} xp(k+1) \\ fy(k) \end{pmatrix} = \begin{pmatrix} A & 0 \\ 0 & I \end{pmatrix} \begin{pmatrix} xn(k) \\ fy(k) \end{pmatrix} + \begin{pmatrix} B \\ 0 \end{pmatrix} \begin{pmatrix} u(k) \\ 0 \end{pmatrix} + KE_y \quad (5)$$

$$y_p(k) = (C \quad I) \begin{pmatrix} xp(k+1) \\ fy(k) \end{pmatrix} + E_y \quad (6)$$

Where the system parameters is change in case of output faulty sensor as shown in equation (7).

$$\bar{A} = \begin{pmatrix} A & B_n \\ 0 & I \end{pmatrix}, \quad \bar{B} = \begin{pmatrix} B \\ 0 \end{pmatrix}, \quad \bar{C} = (C \quad I) \quad (7)$$

3.5. Fault Classification

The fault is classified as shown in (Fig. 8) based on the calculated features (mean, variance, RMS, accumulated error) [17] are compared for each sensor. If all features are maximum then the fault is true otherwise the fault is false.

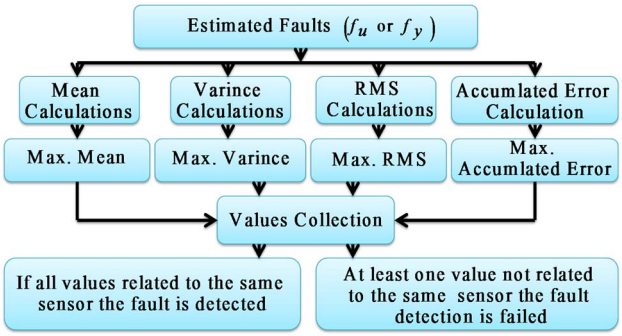


Fig.8. Classifier block diagram

4. Real Implementation

The data are collected for normal operation and different faulty situation to be used in the validation of the proposed technique based on the faulty cases. The system parameters are generated using state space identification as shown in (Fig. 5).

Faulty case (1):

The sensor measurements are collected as shown in (Fig. 4), with 0.5s sampling time and 28800 total samples contain 6560 samples in case of normal operation and 22240samples in case of fault.

As shown in (Fig. 7) the KF consist of two main parts the first part called propagation equation

$$x_p(k+1) = Ax_n(k) + Bu(k) + KE_u \quad (8)$$

$$P_p(k+1) = AP_n(k)A^T + BQB^T \quad (9)$$

The second part called update equation

$$KG(k) = \frac{CPp(k+1)C^T + R}{Pp(k+1)C^T \left(CPp(k+1)C^T + R\right)^{-1}} \quad (10)$$

$$RD(k) = y(k) - y_p(k) \quad (11)$$

$$x_n(k+1) = x_p(k+1) + KG(k)RD(k) \quad (12)$$

$$P_n(k+1) = P_p(k+1) - KG(k)CP_p(k+1) \quad (13)$$

The actual actuated input measurements U_{actual} (without fault) can be determined as shown in equation (14)

$$U_{actual} = U_{faulty} - f_u \quad (14)$$

The equation (15) shows the residuals calculation

$$\mathrm{Re}sidual = f_u = U_{faulty} - U_{actual} \quad (15)$$

The following figures show the actual values and estimated values generated by KF for the actuated inputs measurements.

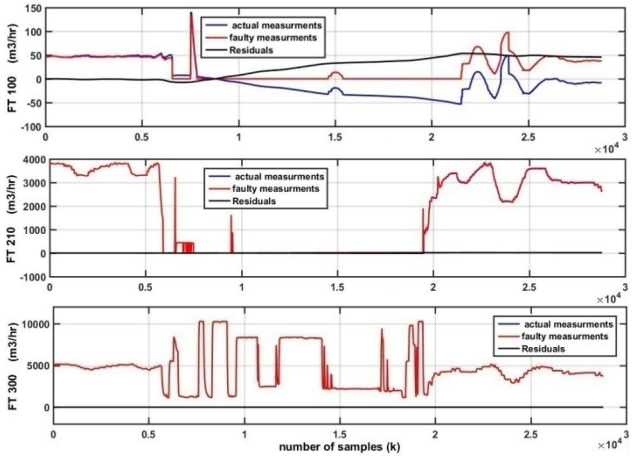


Fig. 9. Actuated input sensors measurements

Referring to equation (3) the estimated fault for each actuated input sensor are represents as shown in (Fig. 10).

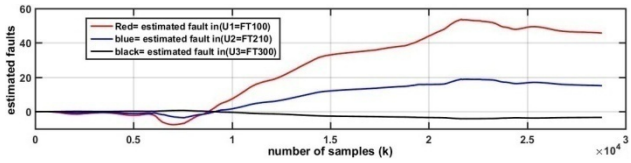


Fig.10. Actuated input sensors estimated faults

The estimated fault signal are framed by 28771 frames each frame have 15s frame size and 0.5s frame shift the classifier decision is depend on the steps shown in (Fig. 8). (Fig. 11) shows the feature values of each actuated input sensor.

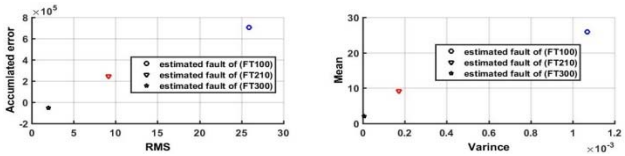


Fig.11. Estimated faults features classification

As shown in (Fig. 11), the fault occurs for the actuated input sensor with highest classified values, which is the feed water flow meter sensor (FT100)

.

Faulty case (2):

The sensor measurements are collected as shown in (Fig. 4), with 0.5s sampling time and 288000 total samples contain 135700 samples in case of normal operation and 152300 samples in case of fault. The following figures show the actual values and estimated values generated by KF for the actuated inputs measurements.

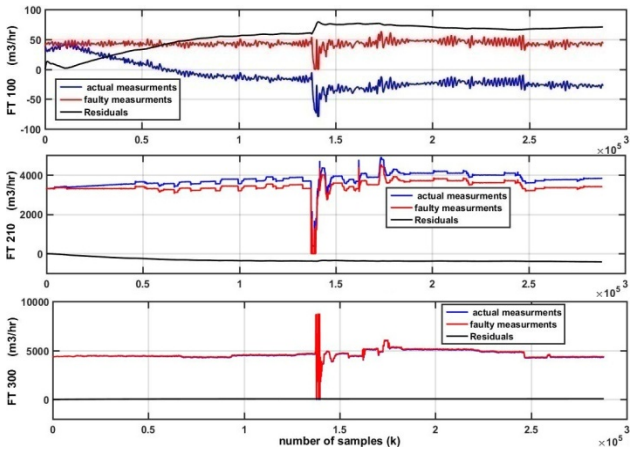


Fig.12. Actuated input sensors measurements

Referring to equation (3) the estimated fault for each actuated input sensor are represents as shown in (Fig.13)

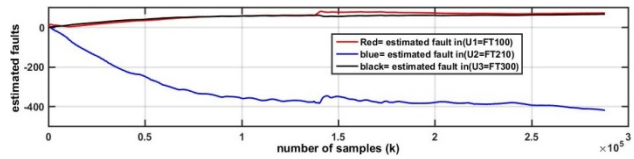


Fig.13. Actuated input sensors estimated faults

The estimated fault signal are framed by 287971 frames each frame have 15s frame size and 0.5s frame shift. (Fig. 14) shows the feature values for each actuated input sensor.

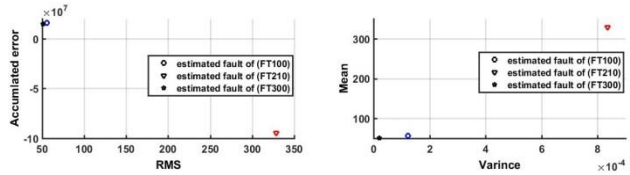
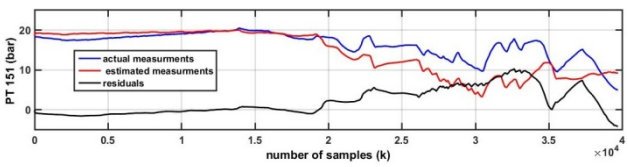


Fig.14. Estimated faults features classification

As shown in (Fig. 14), the fault occurs for the actuated input sensor with highest classified values, which is the natural gas flow meter sensor (FT210).

Faulty case (3):

The sensor measurements are collected as shown in (Fig. 4) with 0.5s sampling time and 39720 total samples contain 18670 samples in case of normal operation and 21050 samples in case of fault. The following figures show the actual values and estimated values generated by KF for the actuated output measurments.



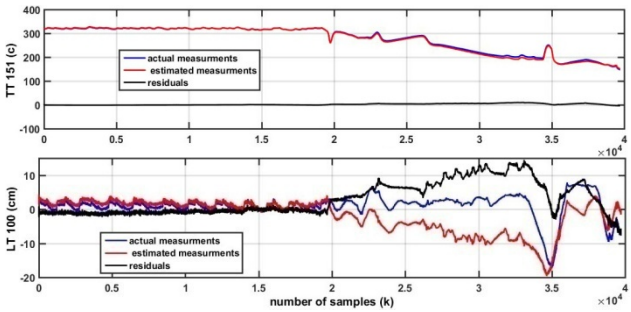


Fig.15. Actuated output sensors measurements

Referring to equation (5) the estimated fault for each actuated output sensor are represents as shown in (Fig.16).

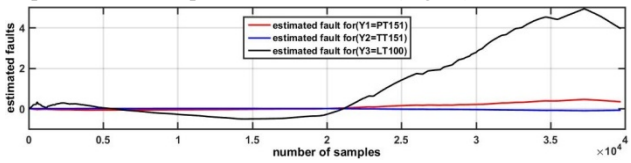


Fig.16. Actuated output sensors estimated faults

The estimated fault signal are framed by 39691 frames each frame have 15s frame size and 0.5s frame shift. (Fig. 17) shows the feature values for each output sensor.

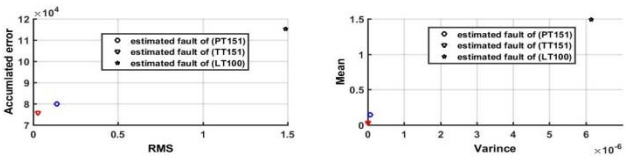


Fig.17. Estimated faults features classification

As shown in (Fig. 17), the fault occurs for the output sensor with highest classified values, which is the water level meter sensor (LT100).

Therefore all the real faults are identified correctly according to real situations. The experimental results show the proposed method has accurate and fast response to isolate the fault.

5. Conclusion and Future Work

The proposed FDI based on EMMAE is implemented for industrial boiler plant and is validated using real plant sensors measurements data. The state variables of all sensor faults are estimated based on the available real measurements using multiple EKF estimators. Based on the real implementation and experience of operators in real faulty situation, EMMAE shows successful and fast sensors fault estimation, isolation and detection in the presence of nonlinearity in the model. The future work is extended to apply EMMAE in case of actuators and model parameters faults.

6. References

[1] R. Isermann, "Model-based fault-detection and diagnosis–status and applications," *Annual Reviews in control,* vol. 29, no. 1, pp. 71-85, 2005.

[2] J.-P. Corriou, *Process control: theory and applications*. Springer Science & Business Media, 2013.

[3] Z. Gao, C. Cecati, and S. X. Ding, "A survey of fault diagnosis and fault-tolerant techniques—Part I: Fault diagnosis with model-based and signal-based approaches," *IEEE Transactions on Industrial Electronics,* vol. 62, no. 6, pp. 3757-3767, 2015.

[4] M. Mansouri *et al.*, "Statistical fault detection of chemical process-comparative studies," *J. Chem. Eng. Process Technol,* vol. 7, no. 1, pp. 1-10, 2016.

[5] C. Cecati, "A survey of fault diagnosis and fault-tolerant techniques—part II: fault diagnosis with knowledge-based and hybrid/active approaches," *IEEE Transactions on Industrial Electronics,* 2015.

[6] T. Kobayashi and D. L. Simon, "Evaluation of an enhanced bank of Kalman filters for in-flight aircraft engine sensor fault diagnostics," *Journal of Engineering for Gas Turbines and Power(Transactions of the ASME),* vol. 127, no. 3, pp. 497-504, 2005.

[7] T. Kobayashi and D. L. Simon, "Hybrid kalman filter approach for aircraft engine in-flight diagnostics: Sensor fault detection case," *Journal of engineering for gas turbines and power,* vol. 129, no. 3, pp. 746-754, 2007.

[8] S. Simani, C. Fantuzzi, and S. Beghelli, "Diagnosis techniques for sensor faults of industrial processes," *IEEE Transactions on Control Systems Technology,* vol. 8, no. 5, pp. 848-855, 2000.

[9] D. Del Gobbo, M. Napolitano, P. Famouri, and M. Innocenti, "Experimental application of extended Kalman filtering for sensor validation," *IEEE transactions on control systems technology,* vol. 9, no. 2, pp. 376-380, 2001.

[10] M. Grötsch, M. Gundermann, M. Mangold, A. Kienle, and K. Sundmacher, "Development and experimental investigation of an extended Kalman filter for an industrial molten carbonate fuel cell system," *Journal of process control,* vol. 16, no. 9, pp. 985-992, 2006.

[11] D. Simon, *Optimal state estimation: Kalman, H infinity, and nonlinear approaches*. John Wiley & Sons, 2006.

[12] N. Meskin, E. Naderi, and K. Khorasani, "A multiple model-based approach for fault diagnosis of jet engines," *IEEE Transactions on Control Systems Technology,* vol. 21, no. 1, pp. 254-262, 2013.

[13] G. J. Ducard, *Fault-tolerant flight control and guidance systems: Practical methods for small unmanned aerial vehicles*. Springer Science & Business Media, 2009.

[14] B. Friedland, *Control system design: an introduction to state-space methods*. Courier Corporation, 2012.

[15] T. Singhal, A. Harit, and D. Vishwakarma, "Kalman filter implementation on an accelerometer sensor data for three state estimation of a dynamic system," *International Journal of Research in Engineering and Technology,* vol. 1, no. 6, pp. 330-334, 2012.

[16] K. A. Fisher and P. S. Maybeck, "Multiple model adaptive estimation with filter spawning," *IEEE Transactions on aerospace and electronic systems,* vol. 38, no. 3, pp. 755-768, 2002.

[17] G. S. Nayak and D. Nayak, "Classification of ECG signals using ANN with resilient back propagation algorithm," *International Journal of Computer Applications,* vol. 54, no. 6, 2012.