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Application of Model based Fault Detection for an Industrial Boiler

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Abstract— **Boilers are considered as the stem of the most of real industries such as power plant generation and petrochemical industry. So, it is essential to improve performance and safety related issues for a safe and efficient operation. A sudden shut down of a boiler unit causes a huge loss of the operating revenue. Hence to enhance availability and reduce the shut down times, the application of fault detection and diagnosis methods will play a great role in early identification of faults and selecting the most suitable fault tolerant scenario without losing the services. Utility boiler in Sidi Kerir Petrochemicals (SIDPEC) plants is selected as the case study of this work. The boiler has multi-loops, the most important loop, which is called the master loop, is identified on line. The identified model is used to detect a real abnormal situation that has been carried during the operation using model based fault diagnosis methods. Different fault scenarios are simulated on the identified model in order to validate the observer based fault detection algorithm. Finally the fault detection algorithm is applied on real abnormal behavior to identify it.**

KEY WARDS: *FAULT DETECTION, FAULT TOLERANT, OBSERVER*

I. INTRODUCTION

Reliability, safety and environmental protection are very important issues for modern industrial system, in particular for safety-critical systems such as chemical processes, nuclear plants and aircraft. Since faults consequences reduce safety and reliability and have a bad environmental impact, robust fault detection and reliable fault tolerant controller design became an essential demand. Moreover, early fault detection leads to decrease production loss, reduce equipment damage, and enhance Human Safety.

During the last decades, theoretical and technological researches have been developed to detect and diagnose faults. These methods distinguish between fault detection, which recognizes the occurrence of the fault, and fault diagnosis which finds the cause and location of the fault.

A fault detection system compares expected behavior of the system with the actual behavior. If the actual behavior deviates from the expected behavior, a symptom is detected and the detection system generates an alarm [1], [2], [3], [5]. In general, fault detection methods can be classified into three main categories as shown in Fig. 1 [4], [5], [7]; Model based, Knowledge based and Signal.

Model-based approaches depend on the analysis of the deviation between model and the real system responses. Model-based approaches are typically grouped into quantitative and qualitative models. Quantitative models (differential equations, state space methods, transfer functions, etc.) are used to generally utilize results from the field of the control theory [5]. In qualitative models, the relation between the variables to obtain the expected system behavior is expressed in terms of qualitative functions centered on different units in the process such as causal models and abstraction hierarchy [6] and [7]. They are used, in particular, for large and nonlinear systems. The analysis methods used in the qualitative model are FTA, FMEA, ETA, structure analysis, etc. These methods can provide an efficient solution for most fault detection problems. But in some cases it cannot give correct detection results since the valid process mathematical model required, in this technique, is difficult to be obtained in some industrial processes.

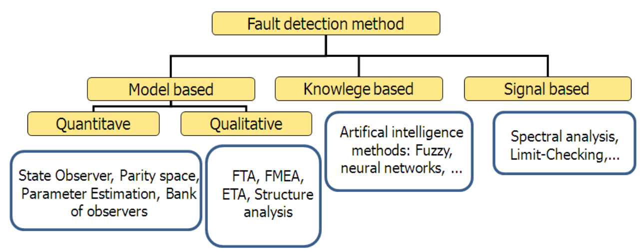

Fig. 1 Fault detection methods

Knowledge-based approaches utilize deep understanding of process structure, process unit functions and qualitative models of the process units under various faulty conditions. It can be used to detect faults for a complex production process or for the system in case of nonlinear and uncertain systems [8], [9]. Recent developments in empirical modeling, such as the use of Artificial Intelligence (AI) methods (neural networks, fuzzy logic, and combination of these methods), have broadened the scope of the quantitative modeling to include 'data based model', in additional to the traditional models based on physical principle [10], [11], [8]. Various algorithms based on fuzzy logic and AI have been implemented and scattered in literature see for example [4].

Signal based approaches depend on the analysis of measured signal without knowing the system model especially for large and/or complex. The fault can be detected by applying a simple analysis, such as the limit checking method, frequency analysis method, data characteristics analysis method, etc. or advanced technique such as, the principal-component analysis (PCA), wavelet and partial least-squares (PLS) analysis [18] and [19].

Since robust fault detection and identification enhance safety and availability of industrial system specially safety critical system, fault detection method are applied into an industrial utility boiler of Petrochemical Company called SIDPEC located in Alexandria, Egypt. Utility boiler of SIDPEC Company is a very important unit in the plant and any unscheduled shutdown causes a series side effects. So model based fault detection is implemented on some loop of

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the boiler. Model based technique is preferred because model based methods reduce hardware redundancy and helps in designing and tuning a suitable fault tolerant controller in condition that the model can be obtained or identified. Fault detection of industrial boiler has been addressed in some literature, see for example [2]

The boiler master loop represents a significant part of the boiler operation control system. The fuels used in the boiler are highly combustible and their handling is very critical from the safety point of view. Thus, master control loop is the focal point whose model is identified and fault detection methods will be applied on.

Different techniques are tested but one of them, so-called State Observer, is implemented in this work for fault detection. The method is illustrated and applied to the identified boiler model; according to the faults estimated, judgment on the specified method has taken place.

The paper is organized as follow: section II gives an overview on the case study (utility boiler of SIDPIC company); section III summaries the used fault detection techniques; section IV explains the identification of the main loop of the case study; section V applies the model based technique of the identified model for a real data to detect and identify the unknown fault that has been occurred during real operation of the system; finally, the results are analyzed and discussed in the conclusion.

II. OVERVIEW OF UTILITY BOILER

Utility Boiler is considered to be a vital unit for many process applications especially in petrochemicals industries. Hence, Utility boiler in Sidi Kerir Petrochemicals (SIDPEC) plants is selected as the case study of this work [17]. The high pressure steam (HP) steam is the main driving force for many types of equipment, such as compressors, pumps and turbines, as well as a heating source in some operation processes. Due to the importance of steam to process operations, the criticality of steam production unit (Utility Boiler) has to be controlled.

The schematic diagram of SIDPEC utility boiler unit is depicted in Fig. 2 . The boiler is consists of 5 subsections as follow:

- a- Daerator: which is the unit responsible for removing air bubbles from the feeding water to the boiler in order to eliminate the effect of air components such as oxygen and carbon dioxide that causes a corrosion in the boiler;
- b- Economizer: it is a unit used to heat the feed water before entering steam drum by using the heat of the exhaust gas to preheat the feed water which reduces the fuel requirements and increases the boiler efficiency and saves energy;
- c- Steam Drum and Water Circulation (Drum-Type Boiler);
- d- Combustion and Draft System (Burners and Forced-Draft-Fan) which generate the required heat by combustion of fuel gas and/or oil where the burner is combined oil and gas burner. The heat generated depend mainly on the fuel rate and fuel to air ratio;
- e- Superheated, De-Superheated and Heat Recovery system are responsible system for superheating of steam over saturated temperature and to regulate the steam temperature.

The utility boiler has a steam conditions of 43 bar and 400°C, design capacity of 92 ton / hour and steam drums conditions of 46 bar and 260 °C.

The main control objectives are to continuously supply a steam at the desired condition, perform normal and emergency operations safely, continuously operate the boiler with the maximum possible efficiency and maintain a high level of safety. Thus, the boiler system incorporates a various control loops to fulfill these objectives. These loops are classified as follow:

a. *Pressure Controls Loops*

Pressure control loops are used to control 1) Boiler pressure; 2) Burner inlet atomizing air supply pressure; 3) Turbine steam inlet pressure; 4) Steam pressure; 5) Deaerator storage tank steam pressure; 6) Diesel transfer pumps discharge pressure; 7) start up vent pressure control.

b. *Flow Control Loops*

Flow control loops are used to control 1) NG (Natural Gas) Fuel control into boiler burner; 2) Diesel Fuel control into boiler burner; 3) Combustion air flow; 4) Feed water into boiler.

c. *Level Control Loops*

Level control loops are used to control 1) Boiler steam drum water level; 2) Continuous blow down tank level; 3) Deaerator storage tank level.

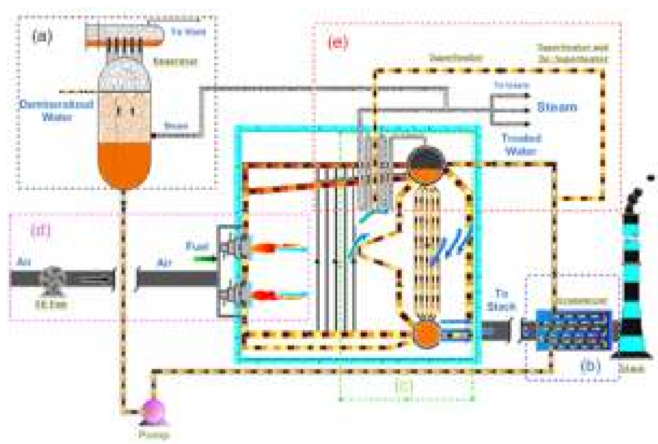

Fig. 2 Schematic digarm of utility boiler

d. *Temperature Control Loops*

Temperature control loops are used to control 1) De-superheated outlet temperature; 2) Discontinuous blow down tank drain temperature.

e. *Analyzers Control*

Flue gas oxygen control, which measure the oxygen in the flue gases to check the effectiveness of combustion.

The control tasks are performed using a SCADA and DCS system. The SCADA is implemented using WinCC of Siemens. The DCS system is implemented using SIMATIC PCS7 of Siemens Company.

In this paper, the master control loop is discussed. This loop is responsible of supplying the convenient amount of fuel (Natural Gas (NG)) and air (excess oxygen) for completing combustion process according to the steam

demand. The master loop consists of four control loops:
1- Boiler pressure control loop;
2- NG Fuel control into boiler burner;
3- Combustion air flow;
4- Flue gas oxygen control

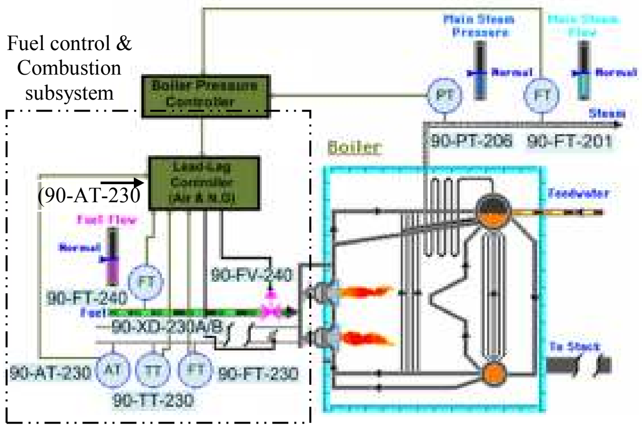

Fig. 3 Master control loop of utility boiler

Table 1 sensor and Actuators of Master loop

	Device	*Type*	*Unit*	*Definition*
1	90-XD-230 (FDF)A/B	Actuator	%	It stands for the air inlet damper of the ***F***orce ***D***raft ***F***an (FDF) in the ***Air*** loop
2	90-FV-240	Actuator	%	It stands for the fuel ***F***low ***V***alve in the ***Fuel*** loop.
3	90-FT-230	Sensor	Nm^3/hr	It stands for the air ***F***low ***T***ransmitter in the ***Air*** loop.
4	90-TT-230	Sensor	$°C$	It stands for the air ***T***emperature ***T***ransmitter in the ***Air*** loop
5	90-AT-230	Sensor	*%(Vol)*	It stands for the oxygen ***A***nalyzer ***T***ransmitter in the ***Oxygen*** loop
6	90-FT-240	Sensor	Nm^3/hr	It stands for the fuel ***F***low ***T***ransmitter which gives the compensated fuel flow value directly in the ***Fuel*** loop
7	90-PT-206	Sensor	*Bar*	It stands for steam ***P***ressure ***T***ransmitter in the ***Boiler Pressure*** loop.
8	90-FT-201	Sensor	Nm^3/hr	It stands for steam ***F***low ***T***ransmitter in the ***Boiler Pressure*** loop.

The master loop has six sensors and two actuators their descriptions are illustrated in Table **1**. The boiler pressure control loop employs flow and pressure sensors to compensate the pressure due to the change of steam demand by increasing the fuel flow as the pressure decreases and decreasing fuel flow rate as the pressure decreases. Therefore, pressure control loop determines the reference fuel flow rate.

The other loops operate together, through what is called Lead-Lag controller, to adjust the ratio between natural gas (fuel) and air ratio based on the fuel command, flue gas oxygen analyzer and flow air temperature. Therefore, this subsystem controls the actual feedback signals from air flow and fuel flow transmitters by employing the fuel command, flue gas oxygen analyzer and flow air temperature signals. These loops are responsible to adjust fuel and combustion control.

In this study only the fuel control and combustion subsystem is studied. So four sensors and two actuators are used, which are item 1 to item 6 in Table 1. This subsystem is highlighted as shown in Fig. 3. The controller of the combustion subsystem (Lead-Lag controller) send the input signals to the two actuator valves (air valve and fuel valve) based on the output signals, fuel flow sensor, air temperature sensor, air flow sensor and oxygen analyzer.

III. Model Based Fault Detection

Model based fault detection and Isolation (FDI) techniques depend mainly on the deviation between the measured signal and the estimated one employing process model to generate the residuals. By comparing these observed features (residuals) with their nominal values, applying methods of change detection, analytical symptoms (***s***) are generated [1]. These symptoms are the basis of fault diagnosis.

The residual generators of model-based FDI are classified into three main categories, observer-based, parity space and parameter estimation approaches [1], [2], [5], [10]. The observer based techniques are used in this work, so the observer based technique are briefly introduced in the next section.

A. State Observers Fault Detection Method

The concept of ***Observer-Based*** approaches is to estimate the system variables (state or outputs) with Luenberger observer for the deterministic case or a Kalman filter for the stochastic case, and use the estimate errors as residuals. The observer based method can be applied if the process parameters are known. The design of proper observer gain is done as suggested by various methods, such as eign structure assignment, unknown input observer, Kronecker canonical form, fault sensitive filter, frequency domain optimization approach, and etc. [5], [12]. Some applications use Kalman filter in FDI such as [13],[14] and [15]. A bank of observers method or Kalman filters method with distinct properties, which is defined as a class of multi-model FDI system, can be used in parallel to isolate faults [5], [15], [10]

The idea of observer based fault detection is illustrated in Fig. 4 for a state space model of a discrete-time system represented in equation (1)

$$\mathbf{x}(k+1) = \mathrm{A}\mathbf{x}(k) + \mathrm{B}\mathbf{u}(k) \qquad (1)$$
$$\mathbf{y}(k) = \mathrm{C}\mathbf{x}(k) + \mathrm{D}\mathbf{u}(k)$$

where k is the sample number, $\mathbf{x}(k)$ is the plant state vector; $\mathbf{u}(k)$ is its input vector, $\mathbf{y}(k)$ is its output vector and A,B, C and D are system parameters.

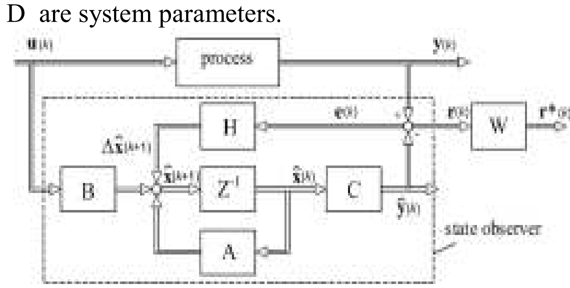

Fig. 4 Residual generation based on Stae observer

Consider D=0, the estimated state is obtained from

$$\hat{\mathbf{x}}(k+1) = \mathrm{A}\hat{\mathbf{x}}(k) + \mathrm{B}\mathbf{u}(k) + \mathrm{H}\mathbf{e}(k) \qquad (2)$$

The output error is calculated from

$$\mathbf{e}(k) = \mathbf{y}(k) - \mathrm{C}\hat{\mathbf{x}}(k) \tag{3}$$

where H is the observer matrix.

Substitute by the output error equation (3), $\mathbf{e}(k)$, in estimated state equation (2) the estimated state is computed from

$$\hat{\mathbf{x}}(k+1) = (\mathrm{A} - \mathrm{HC})\hat{\mathbf{x}}(k) + \mathrm{B}\mathbf{u}(k) + \mathrm{H}\mathbf{y}(k) \tag{4}$$

and state error $(\tilde{\mathbf{x}}(k+1) = \mathbf{x}(k+1) - \hat{\mathbf{x}}(k+1))$ is obtained from

$$\tilde{\mathbf{x}}(k+1) = (\mathrm{A} - \mathrm{HC})\tilde{\mathbf{x}}(\boldsymbol{k}) \tag{5}$$

Moreover the residual is generated based on

$$\mathbf{r}(k) = \mathrm{W}\,\boldsymbol{e}(\boldsymbol{k}) \tag{6}$$

Suitable fault detection and isolation is depend on the selection of H and W matrices

At normal operation output error, state error, and residual are in the accepted range while any fault may cause the deviation of these measured from the normal, which is explained below.

In real situation, the process is influenced by immeasurable disturbances $\mathbf{v}(k)$ and $\mathbf{n}(k)$ and/or actuator faults $\mathbf{F_a}(k)$, sensor faults $\mathbf{F_s}(k)$ and parameter faults. The sensor and actuator faults appear as additive term (additive fault) while parameter faults are represented as multiplicative term (multiplicative fault) in the model. Observer based FDI method is applicable only in additive faults, so additive faults are addressed here (sensor and actuator faults). The system model with disturbances, noise and additive faults is represented as shown in Fig. 5, [10], and the system model is represented as

$$\mathbf{x}(k+1) = \mathrm{A}\mathbf{x}(k) + \mathrm{B}\mathbf{u}(k) + \mathrm{V}\mathbf{v}(k) + \mathrm{L}\mathbf{F_a}(k) \tag{7}$$
$$\mathbf{y}(k) = \mathrm{C}\mathbf{x}(k) + \mathrm{N}\mathbf{n}(k) + \mathrm{M}\mathbf{F_s}(k)$$

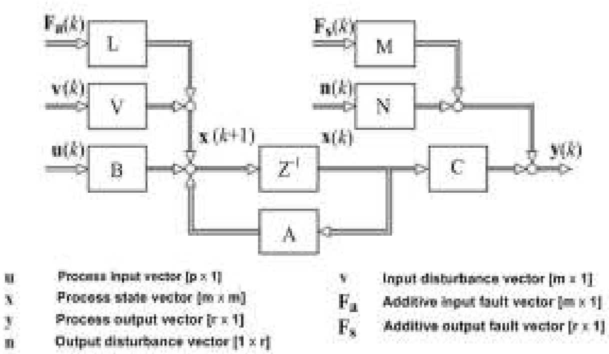

Fig. 5 Real system model with disturbance, noise and faults

Assuming that the disturbances, $\mathbf{v}(k)$ and $\mathbf{n}(k)$, are stationary white noise then their averages tend to zero. Therefore, estimated state error will be:

$$\tilde{\mathbf{x}}(k+1) = [\mathrm{A} - \mathrm{HC}]\tilde{\mathbf{x}}(k) + \mathrm{V}\mathbf{v}(k) + \mathrm{L}\mathbf{F_a}(k) - \mathrm{HN}\mathbf{n}(k) - \mathrm{HM}\mathbf{F_s}(k) \tag{8}$$

and the output error

$$\mathbf{e}(k) = \boldsymbol{y}(k) - \mathrm{C}\hat{\boldsymbol{x}}(k) = \mathrm{C}\tilde{\mathbf{x}}(k) + \mathrm{N}\mathbf{n}(k) + \mathrm{M}\mathbf{F_s}(k) \tag{9}$$

where L, M, V, N are distribution matrices with appropriate dimensions of faults, disturbances and noises on the system model.

It is clear that the state error, output error and residuals have influenced by additive faults, disturbances and noise. To discriminate between the effect of faults, disturbances and noise, robust residual generation design should be implemented. Robust residual generation is addressed by different way see for example [4] and [12]. The generated residual should also be sensitive to a certain fault in order to isolate it, so it is difficult to obtain observer parameters (W, H) that can detect all faults and identify them. Therefore different techniques are scattered in literature to generate a robust and sensitive residuals [1], [5].

A robust observer FDI based on threshold and adaptive threshold methods are applied [5]. Therefore, the residuals, by neglecting noise and disturbance terms, are obtained by compensating from equations (8) and (9) into (6). Since estimated state error in equation (8) are affected by actuator and sensor faults, the residual vector in equation (6) is also sensitive to both type of faults. To isolate each fault the selection of observer parameters (W,H) should not be unique for each fault type to be sensitive to that fault and less sensitive to the others. The conditions to design H and W are explained in [1]and [5]

IV. MASTER LOOP IDENTIFICATION

As discussed before the combustion subsystem of the boiler master loop contains 4 sensor and 2 actuators. Therefore to diagnosis and control the loop the mathematical model should be obtained in order to apply the suggested approach that discussed in section III.

Mathematical models of dynamic processes are obtained either analytically based on the physical principles and relations between the system components or experimentally (by identification methods).

Experimental modeling always starts with collecting a prior knowledge from measuring process variables to obtain the mathematical model. Inputs and outputs are measured and evaluated by means of identification methods in such a way that the relation between the input and output signals are expressed in a mathematical model. Identification technique can be classified into white, Black and Grey Box technique [1]. The methods of model identification can be classified into Least square method, Output error method, Filtering method and Filter error method [16].

The selection between these methods depends on [16] simplicity of the method, Reachable accuracy, allowable disturbance, Type of computing (on-line, offline), data processing (one shot – real time) and extendibility (time varying system – MIMO system – non linear system)

Among these methods, the output error method is selected since it provides accuracy, measurements of noise availability of the data for parameters estimation and extension of this method to be applied for MIMO systems.

This method is based on the assumption that observations contain measurement noise. Derivation of parameter estimation mechanism is based on maximizing likehood function (probability density function of the measurement evaluated at the given observation $\mathbf{z}$).

Let the system mathematical model be in the form of equation (1) and the relation between sensed output and actual output is

$$\mathbf{z}(k) = \mathbf{y}(k) + \mathbf{v}(k) \tag{10}$$

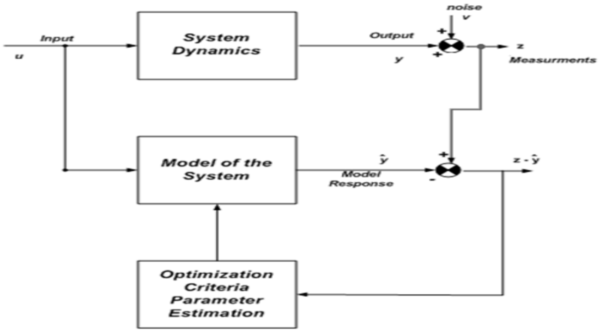

Fig. 6 Identification block diagram

where $\mathbf{y}(k)$ is the actual output signal of the system and $\mathbf{z}(k)$ is the sensed output i.e. measured by the sensor.

The output error method assumes that the measurement vector $\mathbf{z}$ is corrupted with white noise which is zero mean and has a Gaussian distribution with covariance $\mathbf{R}$, i.e. $v \approx N(O,R)$

Let the parameter vector, to be estimated, is represented by $\boldsymbol{\theta}$, where $\boldsymbol{\theta}$ is elements of *A, B, C, D* and the initial condition of state is $\mathbf{x}(0)$. Then the estimation of $\boldsymbol{\theta}$ is obtained by minimizing

$$\mathbf{J} = \frac{1}{2}\sum_{K=1}^{N}[\mathbf{z}(k)-\mathbf{y}(k)]^{\mathbf{T}}\ \mathbf{R}^{-1}[\mathbf{z}(k)-\mathbf{y}(k)] + \frac{N}{2}\ln|\mathbf{R}| \qquad (11)$$

The estimation of $\mathbf{R}$ can be obtained from

$$\widehat{\mathbf{R}} = \frac{1}{N}\sum_{k=1}^{N}[\mathbf{z}(k)-\hat{\mathbf{y}}(k)][\mathbf{z}(k)-\hat{\mathbf{y}}(k)]^{\mathbf{T}} \qquad (12)$$

The estimate of $\boldsymbol{\theta}$ at the $(i+1)^{\text{th}}$ iteration is obtained as

$$\boldsymbol{\theta}(i+1) = \boldsymbol{\theta}(i) + \left[\nabla_{\theta}^{2}\,\mathbf{J}(\boldsymbol{\theta})\right]^{-1}[\nabla_{\theta}\,\mathbf{J}(\boldsymbol{\theta})] \qquad (13)$$

where,

$$\nabla_{\theta}\,\mathbf{J}(\boldsymbol{\theta}) = \sum_{k=1}^{N}\left[\frac{\partial \mathbf{y}}{\partial \boldsymbol{\theta}}\right]^{\mathbf{T}}\mathbf{R}^{-1}\,[\mathbf{z}(k)-\mathbf{y}(k)]$$

$$\nabla_{\theta}^{2}\,\mathbf{J}(\boldsymbol{\theta}) = \sum_{k=1}^{N}\left[\frac{\partial \mathbf{y}}{\partial \boldsymbol{\theta}}(k)\right]^{\mathbf{T}}\ \mathbf{R}^{-1}\left[\frac{\partial \mathbf{y}}{\partial \boldsymbol{\theta}}(k)\right] \qquad (14)$$

Equation (14) is a Gauss-Newton approximation of the second gradient. This approximation helps to speed up the convergence without causing significant error in the estimation of $\boldsymbol{\theta}$.

The measurement of the sensors and actuators in normal operation are used to identify the master loop model. The identified model parameters are

A=

$$\begin{bmatrix} 1.0012 & -0.52949 & 0.13978 & -0.0040398 & -0.49641 \\ 0.043487 & 0.29679 & 0.094807 & -0.34989 & -0.39016 \\ -0.070838 & -0.21771 & 0.77005 & -0.091019 & -0.073007 \\ 0.1654 & 0.46532 & 0.21778 & 0.94757 & 0.4272 \\ 0.086793 & 0.62911 & 0.21188 & -0.77397 & 1.2897 \end{bmatrix}$$

$$B = \begin{bmatrix} 0.12298 & -1.3471 \\ -0.29457 & -1.3924 \\ 0.0025389 & 0.22279 \\ -0.023572 & 0.67538 \\ 0.31268 & 1.1963 \end{bmatrix}$$

C=

$$\begin{bmatrix} 1939 & -1992 & -145.1 & 224.19 & 198.06 \\ 0.43076 & -0.41592 & 0.34794 & -0.092957 & 0.1185 \\ -0.22201 & 0.0089251 & 0.010999 & 0.0093342 & -0.016418 \\ -9.4662 & 13.967 & -14.296 & 8.5842 & 3.4036 \end{bmatrix}$$

$$D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix},\ \mathbf{x}(0) = \begin{bmatrix} -0.13126 \\ -0.15889 \\ 0.23791 \\ -0.028161 \\ -0.031554 \end{bmatrix}$$

V. IMPLEMENTATION OF MODEL BASED FAULT DETECTION

To verify the technique of fault detection, different faults scenarios for sensors and actuators are imposed on the model then the estimated fault are compared with the imposed one. Only one test is illustrated here for the damper air flow actuator 90-XD-230 (Fa1).

By imposing a fault, as a ramp starts from 3.806*104 sec till 3.88*104 sec, on air flow valve, 90-XD-230/FDF, (Fa1) only and applying the state observer fault detection methods for each actuator, air flow valve and fuel flow valve, two residuals are generated based on the selection of W and H or each actuator fault. The residual corresponding to the fault of actuator 90-XD-230 is less than the threshold (T_{th}= 10%) while the other residual for the other actuator is higher than specified threshold. The estimated faults of the two actuators are shown in Fig. 7 and Fig. 8. It is found that there are estimated faults on 90-XD-230/FDF (Fa1) as well as on FV-240 (Fa2). Although there is no fault imposed on 90-FV-240 (Fax2=0), the estimated fault is considerable, i.e. one fault is exist, two faults are estimated. The imposed faults and the corresponding estimated ones are shown as dotted red line and continuous blue line respectively, in Fig. **7**. The estimated fault Fax2 is so high and its residual also higher than the threshold, which insures that its value does not represent the actual fault.

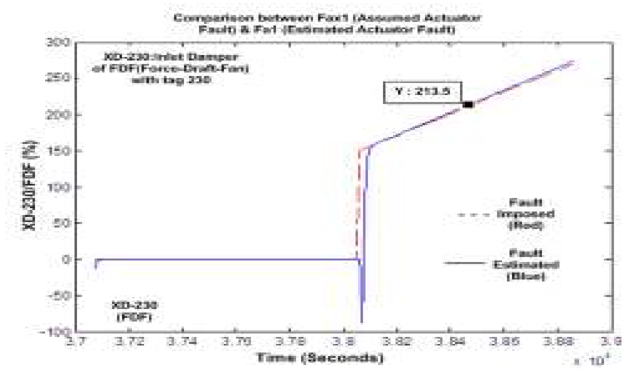

Fig. 7 Estimated and imposed fault in actuator 1

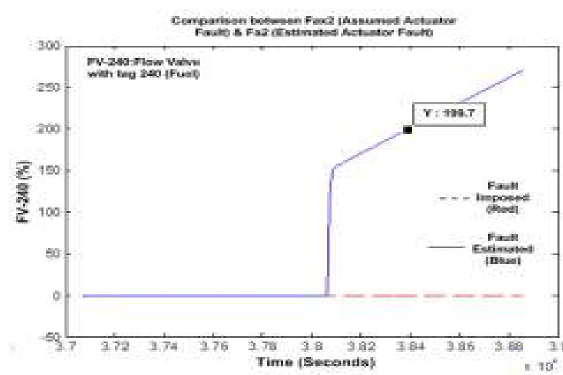

Fig. 8 Estimated fault in actuator 2 in case 1

As shown in Fig. 7 and Fig. 8 the estimated fault in actuator 1 (XD-230(FDF)) is almost equal to the imposed one while the estimated fault in case of FV-240 differs from the imposed one (zero fault).

The same procedure is applied in case of abnormal situation in the measured signal. The two faults of the two actuators are considered here only. Fig. 9 shows detected fault (red line) compared with the actuator response (blue line) of actuator 1 (90-XD-230(FDF)). The detected fault ***is considerable*** (33.6% >T_{th}) where T_{th} is the threshold limit (10%).

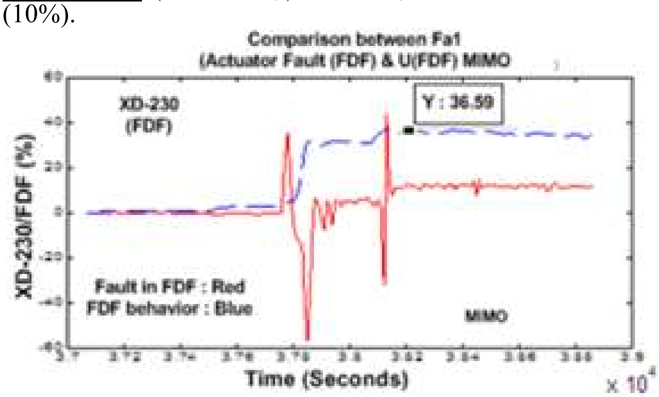

Fig. 9 Real fault estimation of actuator 1

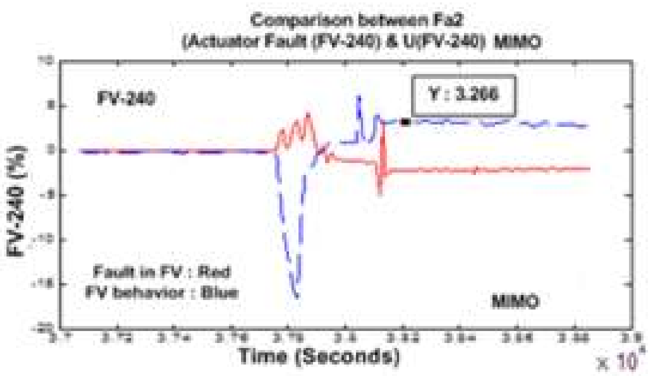

Fig. 10 real fault estimation of actuator 2

Fig. 10 shows the detected fault of actuator 2 (FV-240). The ratio of Fa2 (fault estimated on 90-FV-240) with respect to the behavior of 90-FV-240 is 64.4%

It is deduced that the faults detected in the actuator FV-240 is considerable (64.4% >10%) too.

The results show that the data can represent faults in both actuator but it is more considerable in actuator two. Decision making system inform that fault has high weight in actuator number two than one. The data may also represent a fault in the other components of the master loop not only the actuators. Therefore, other faults should be isolated to completely isolate the exact fault. Using bank of observer gives more robust isolation instead of one observer. It is not discussed in this paper.

VI. Conclusion

Observer based fault detection methods are implemented on an industrial boiler of SIDPEC Company as a case study to enhance the boiler safety and availability and increase productivity by early detection of faults and accommodate it. To apply observer based FDI it is necessary to have the process model. Thus on line data of the boiler is used to identify the most important loop in order to obtain the loop model using least square error identification technique. The identified model is used to validate the fault detection method by simulating different fault scenarios, on actuators only, and compare the estimated fault with the actual one. Then the fault detection algorithm is implemented on a real data represent a sudden abnormal situation to detect the unknown fault that has been occurred suddenly. Only observer based fault detection for isolating actuator faults are implemented. The implemented algorithm, in this paper, detect fault correctly but it could not isolate the fault completely. Complete isolation of fault and robustness of the techniques will be addressed. The diagnosis of all boiler loops and the design of fault tolerant controller to eliminate sudden shutdown of the boiler will be discussed.

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