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Application of Multi-Model Fault Diagnosis for an Industrial system

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Abstract—**since complete isolation of a fault set in an industrial plant using a single Fault Detection and Isolation (FDI) technique is so difficult, a hybrid fault detection techniques is preferred. An observer based technique is applied to isolate a certain unknown fault in an industrial boiler placed in Sidi Kerir Petrochemicals (SIDPEC) in a previous work [1]. A fault has been detected using single observer based method but it has failed to isolate it. Therefore in this work, a combined method of multi-model and parameter estimation fault diagnosis techniques (hybrid technique) is implemented here to diagnosis a real abnormal situation. The most important part of the boiler, which is called master loop, is addressed. The master loop is identified based on online data. The master loop has been subdivided into three parts named: fuel flow subsystem, airflow and burner subsystem and the whole system. Different fault scenarios are simulated on the identified models in order to validate the fault detection algorithm. Finally the fault diagnosis algorithm is applied on a real abnormal behavior to identify it. The fault is detected and accurately isolated.**

KEY WARDS: *FAULT DIAGNOSIS, FAULT TOLERANT, OBSERVER, MULTI-MODEL*

I. INTRODUCTION

Enhancement of availability, reliability and safety of an industrial system is an essential demand especially for safety critical system such as petrochemical industries. Hence to enhance availability and reduce the shut down times, the implementation of fault diagnosis methods will play a great role in early identification of faults and selecting the most suitable fault tolerant scenario without losing the services. Since fault 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. Therefore, fault diagnosis methods are necessary to be applied for industrial system, in particular safety critical system.

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 [2], [3],[5]. The major FDI methods stated in literature can be classified into three broad categories; (a) Model based, (b) Knowledge based, and (3) signal based. Further, Model-based approaches are typically grouped into quantitative and qualitative models [4], [5], [7], [2].

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Model-based approaches depend on the analysis of the deviation between model and the real system responses to generate so-called residuals [2] , [3], [5], [6]. Most of Model-based FDI systems depend mainly on the analysis of residuals. The residual generation is based, e.g., on parameters estimation, parity equation or state observers of the process [2]. A system, which designed to provide both sensitivity to fault and robustness to modeling error or disturbances, is called a robust FDI scheme[12], [4], [9]. The following part explains the idea of fault modeling.

The system model with faults for a discrete linear time invariant (LTI) system, shown in Fig. 1, can be represented in the following form:

$$\begin{aligned} \mathbf{x}(k+1) &= \left(\mathbf{A}+\mathbf{A}_f(k)\right)\mathbf{x}(k)+\left(\mathbf{B}+\mathbf{B}_f(k)\right)\mathbf{u}(k)+\mathbf{R}_a\mathbf{f}_a(k) \\ \mathbf{y}(k) &= \left(\mathbf{C}+\mathbf{C}_f(k)\right)\mathbf{x}(k)+\mathbf{R}_y\mathbf{f}_y \end{aligned} \quad (1)$$

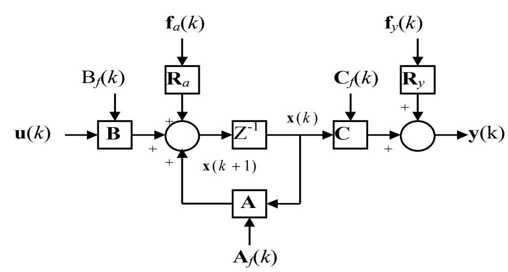


Fig. 1 State space and fault modeling

where $\mathbf{x}$ is the state vector, $\mathbf{u}$ is the input vector, $\mathbf{y}$ is the output vector, $\mathbf{f}_a$ is the input or state variable fault and $\mathbf{f}_y$ the output faults, which represent the additive faults; $\mathbf{A}_f$, $\mathbf{B}_f$, and $\mathbf{C}_f$ are fault parameters, which represent the multiplicative faults; $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{C}$ are the nominal system parameters; $\mathbf{R}_a$ and $\mathbf{R}_y$ are distribution fault matrix with appropriate dimensions.

The fault in actuator and sensor appear as additive term (additive fault) while the parameter faults appear as multiplicative term (multiplicative fault). The additive fault can be detected and isolated using observer based and/or parity space techniques. While multiplicative fault can be isolated using parameter estimation [2], [4].

Boilers are considered as the stem of the most of real industries such as power plant generation and petrochemical industry. A sudden shut down of a boiler unit causes a huge loss of the operating revenue. Utility boiler, located in Sidi Kerir Petrochemicals (SIDPEC) plant in Alexandria, Egypt, is one of the critical units in the plant [11]. Any malfunction or sudden shutdown of the boiler causes a huge loss and series side effects. Therefore, the boiler faults detection is addressed in [1]. An observer based fault detection is applied in [1] to diagnosis an abnormal situation of the boiler. Although a fault has been detected, the fault isolation has been failed to be completed using a single observer.

Practically, it is difficult to design single observer that can detect and isolate all additive faults (sensor and actuator). Moreover, multiplicative faults can be identified using fault detection by parameter estimation [2] instead of observer based technique. In real application, single technique either observer based or parameter estimation cannot be used alone to isolate real faults but a combined fault detection methods are used to detect and isolate faults [4]. Thus, a combined method based on multi-model based technique [12] and parameter estimation based technique (hybrid technique), is addressed, here, to isolate the abnormal behavior of industrial boiler. 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 is carried out on it.

The paper is organized as follow: section II gives an idea about master control loop of the case study (utility boiler of SIDPIC company); section III explains the multi-model fault detection techniques that is used; section IV explains the identification of the main models that are used in the case study; section V applies the proposed technique of the identified models for a real data to detect and identify the unknown fault has been occurred suddenly; finally, the results are analyzed and discussed in the conclusion.

II. MATER CONTROL LOOP OF UTILITY BOILER

Utility Boiler is considered to be a vital unit for many industries in particular petrochemicals industries. Hence, Utility boiler in Sidi Kerir Petrochemicals (SIDPEC) plants is selected as the case study of this work [11] The boiler configuration and components are explained in [1].

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, which are pressure, flow, level, temperature and analyzers control loops [1].

In this paper, the combustion subsystem of master control loop is addressed. 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 as shown in Fig. 2:

1- Boiler pressure control loop;
2- NG Fuel control into boiler burner;
3- Combustion air flow;
4- Flue gas oxygen control

The master loop has six sensors and two actuators their descriptions are illustrated in Table 1. The boiler pressure control loop uses flow and pressure sensors to compensate the pressure due to the change of steam demand by increasing the fuel flow as the pressure increases 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 employing the actual feedback signals from air flow and fuel flow transmitters. These loops are responsible to adjust fuel and combustion control.

Since the pressure control loop is directly affected by the fuel control and combustion system, the fuel and combustion system are addressed. So four sensors and two actuators are only employed, which are item 1 to item 6 in Table 1. Since the system diagnosis is applied on the open loop system, this subsystem can be represented 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.

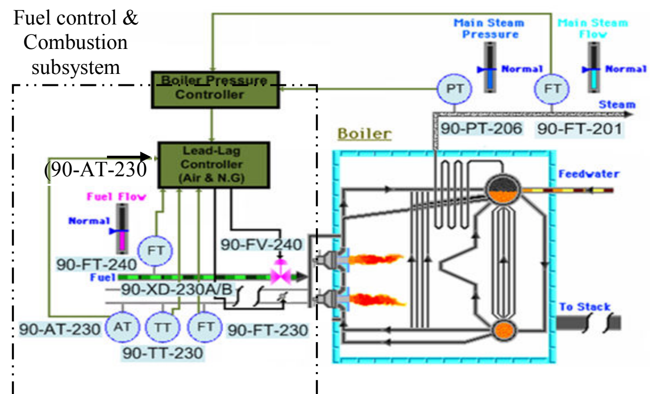


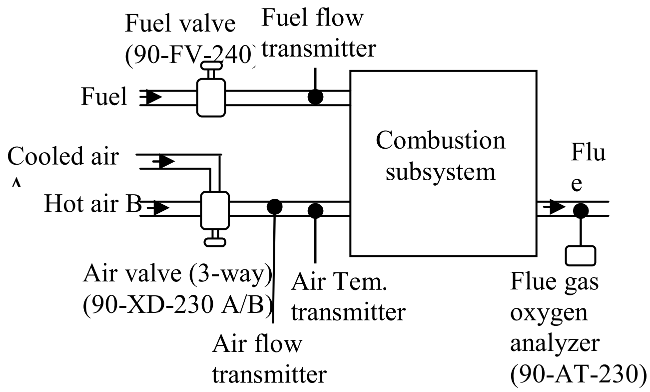
Fig. 2 Master control loop of utility boiler

Table 1 Sensors and actuator of master loop

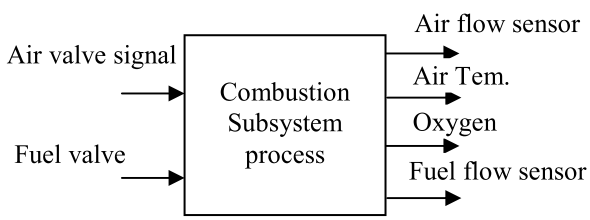
	Device	*Type*	*Unit*	*Definition*
1	90-XD-230 (FDF)A/B	Actuator (Act.1)	%	It stands for the air inlet damper of the ***F**orce **D**raft **F**an* (FDF) in the ***Air*** loop
2	90-FV-240	Actuator (Act.2)	%	It stands for the fuel ***F**low **V**alve* in the ***Fuel*** loop.
3	90-FT-230	Sensor (Sen.1)	Nm^3/hr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

III. MULTI-MODEL FAULT DETECTION AND ISOLATION SYSTEM

Systems subject to failures cannot be modeled well by a single set of equations for the state that varies continuously rather than system nonlinearity. One of the most effective approaches for such problems is based on the use of Multiple Models (MMs) [12], [4]. It runs a bank of filters in parallel, each based on a model matching to a particular mode (i.e. structure or behavior pattern) of the system. Since a system subject to a failure is a typical hybrid system, MM algorithms for FDI have been developed for different names, such as multiple hypothesis test detector, and Multiple Model Adaptive Estimator (MMAE) algorithm. In addition, a so-called dedicated observer scheme, which uses a bank of observer for FDI of deterministic system, and a generalized dedicated observer to enhance the robustness of FDI, see for example [12] and [5] for more details.



a. Sensors and actuator distribution



b. Open loop block diagram

Fig. 3 Fuel control and combustion subsystem

Fig. 4 shows the general diagram for a hybrid fault diagnosis scheme employing Multi-Model and fault estimation approaches. The system is described by a set of models $M=\{M_0, M_1,..., M_z\}$ and each model is designed to distinguish one fault mode of the fault mode set [14].

All fault detection and estimators (FDE) are driven by the system input "$\mathbf{u}$" and the measurements "$\mathbf{y}$" and operate in parallel to generate an individual residual for each one. All residuals are treated in the residual evaluation logic. The resulting faults are reflected in the alarm signal in the decision statements $S=\{a_1, a_2, ..., a_z\}$; $a_i \in \{0,1\}$. The decision of each model, a_i, is calculated from the following equation

$$a_i = \begin{cases} 1 \; if \; |\mathbf{r}_i| \leq T_{ith} \\ 0 \; if \; |\mathbf{r}_i| \geq T_{ith} \end{cases} \quad (2)$$

where $\mathbf{r}_i$ is the residual vector generated from model number i and T_{ith} is the threshold value for the same model.

The task of the diagnosis system is to generate a diagnosis statement "S" and fault type "F". "S" contains information about which fault models that can explain the behavior of the process and "F" determines a complete fault data (type, location, size).

The decision system, in Fig. 4, uses the residuals of each model and estimated fault values in order to completely isolate the fault employing the decision theory based on probability theory.

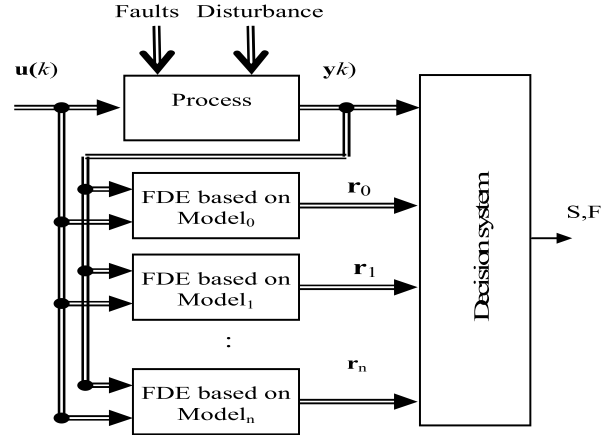


Fig. 4 Multi-Model fault detection method

The idea of residual generation is based on observer based fault detection as shown in Fig. 5 in addition to fault estimation. The estimated state is obtained from [5]

$$\hat{\mathbf{x}}(k+1) = \mathrm{A}\hat{\mathbf{x}}(k) + \mathrm{B}\mathbf{u}(k) + \mathrm{H}\mathbf{e}(k) \quad (3)$$

The output error is calculated from

$$\mathbf{e}(k) = \mathbf{y}(k) - \mathrm{C}\hat{\mathbf{x}}(k) \quad (4)$$

Additive faults (sensor and actuators) is calculated from the following equations

$$\mathbf{e}_x(k+1) = (\mathbf{A} - \mathbf{HC})\mathbf{e}_x(k) + \mathbf{R}_a\mathbf{f}_a(k) - \mathbf{HR}_y\mathbf{f}_y(k) \quad (5)$$

$$\mathbf{e}(k) = \mathbf{C}\mathbf{e}_x(k) + \mathbf{R}_y\mathbf{f}_y(k) \quad (6)$$

Moreover the residual is generated based on

$$\mathbf{r}(k) = \mathrm{W}\,\boldsymbol{e}(\boldsymbol{k}) \quad (7)$$

where $\mathbf{e}_x(k+1) = \mathbf{x}(k+1) - \hat{\mathbf{x}}(k+1)$ (8)

H is the observer matrix.

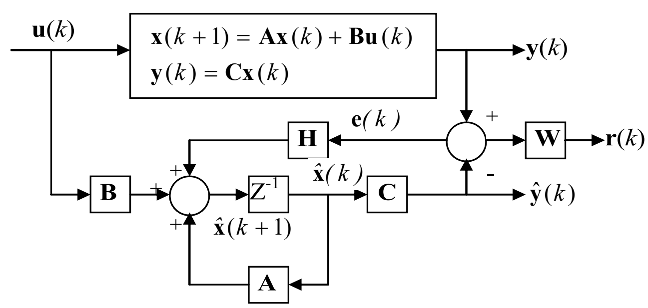


Fig. 5 Residual generation based state observer

Suitable fault detection and isolation is depending on the selection of **H** and **W** matrices.

1) ***Fault Estimation:*** one possibility to isolate the fault by estimating the fault magnitude from the measured data, see for example [1], [8] and [4]. The method is basically based on the estimation of the fault values from the input-output data employing the faulty model. Faulty model is the model of equation (1) by deleting all faults except the considered one. For example, suppose a fault in actuator #1 the related faulty model will be

$$\begin{aligned} \mathbf{x}(k+1) &= (\mathbf{A})\mathbf{x}(k) + (\mathbf{B})\mathbf{u}(k) + \mathbf{R}_a f_{a1}(k) \\ \mathbf{y}(k) &= (\mathbf{C})\mathbf{x}(k) \end{aligned} \quad (9)$$

where $\mathbf{R}_a$ is the first column of Matrix **B** and f_{a1} is the fault of actuator # 1. f_{a1} may be a bias or/and draft fault that are called actuator fault set (Σ_1).

For each faulty model the unknown fault parameter "$\gamma_i \in \Sigma_i$" which simulates unknown multiplicative or unknown additive faults can be estimated by solving equation (10) subject to the system model of the fault mode number i of the fault set Σ_i

$$\hat{\boldsymbol{\gamma}}_i = \arg\left(\min_{\gamma_i \in \Sigma_i} \sum_{l=0}^{N-1} \left\| (\mathbf{y}(k-l) - \hat{\mathbf{y}}_i(k-l) \right\|_2^2 \right) \qquad (10)$$

where N is the estimation time and Σ_i represents all possible values of fault of fault mode number i. That means Σ_i is all possible fault function for example, bias, draft, and etc. Fault mode means fault types for example actuator fault, sensor fault, etc. γ_i is f_{a1} in case of actuator fault mode for model of equation *(9)*.

IV. FAULT MODE AND MODEL IDENTIFICATION

Since the discussed fault diagnosis in part III is a model based technique, the mathematical model is mandatory to be obtained. 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).

The master loop is a Multi-Input/Multi-Output system with nonlinearity. Since the loop contains a huge number of unknown parameters and nonlinearities, determining the loop model from the basic principle is so difficult. Moreover, the boiler almost operates around a fixed operating point. Therefore linearized models are identified experimentaly.

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 [10] Least square method, Output error method, Filtering method and Filter error method. Output Error (OE) method is applied here, more details about this method is explained in [9] , [1].

The measurement of the sensors and actuators in normal operation are used to identify the master loop model. The dedicated master loop contains 4 sensor and 2 actuators as explained in section II.

Based on Multi-Model fault detection and isolation technique discussed in section III, for each fault to be detected and isolated a dedicated model must be determined. To identify the required model for different fault mode, the dedicated combustion subsystem of master loop is divided into three loops:

1- Fuel flow control loop;
2- Air flow control loop;
3- Combined fuel and air flow loop, MIMO.

The fuel flow control loop is a Single Input-Single Output (SISO) loop, where the input is the fuel flow valve signal and the output is fuel flow.

The air flow control loop is a Single Input- Multi Output (SIMO) loop, where the input is the air flow valve signal and the outputs are the oxygen rate in flue gases, air flow temperature and air flow.

The combined loop represents the whole fuel and combustion subsystem. It is a Multi Input-Multi Output loop (MIMO) has two inputs and four outputs of the two previous loops. Therefore, the measured inputs and outputs signals are used to identify the fuel flow loop, air flow loop and the whole combustion subsystem.

The identified on-line model parameters of the whole combustion subsystem (MIMO) are

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

$$\mathrm{B} = \begin{bmatrix} \mathbf{0.12298} & \mathbf{-1.3471} \\ \mathbf{-0.29457} & \mathbf{-1.3924} \\ \mathbf{0.0025389} & \mathbf{0.22279} \\ \mathbf{-0.023572} & \mathbf{0.67538} \\ \mathbf{0.31268} & \mathbf{1.1963} \end{bmatrix}; \mathrm{D} = \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix}, \ \mathbf{x}(0) = \begin{bmatrix} \mathbf{-0.13126} \\ \mathbf{-0.15889} \\ \mathbf{0.23791} \\ \mathbf{-0.028161} \\ \mathbf{-0.031554} \end{bmatrix}$$

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

Also the identified parameters of fuel flow control loop, SISO, are

$$\mathrm{A} = \begin{bmatrix} \mathbf{0.9864} & \mathbf{-0.21613} & \mathbf{-0.24437} \\ \mathbf{0.36211} & \mathbf{0.58693} & \mathbf{0.7391} \\ \mathbf{0.0019668} & \mathbf{-0.37329} & \mathbf{0.74796} \end{bmatrix}; \mathrm{B} = \begin{bmatrix} \mathbf{-0.36181} \\ \mathbf{-0.26058} \\ \mathbf{-0.67149} \end{bmatrix};$$

$$\mathrm{C} = [\mathbf{25.822} \quad \mathbf{20.807} \quad \mathbf{5.1223}]; \mathrm{D} = [\mathbf{0}]; \mathbf{x}(0) = \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix}$$

By the same way the air flow control loop, SIMO, parameters are identified.

Hence, three groups of models are employed based on the three subsystems, air flow control loop, fuel flow control loop and the whole combustion subsystem. Each group is designed, based on one of the identified model, to be sensitive to a certain set of faults in sensors and actuators. Group 1 is related to the fuel flow control loop (SISO model) and it consists of 2 models, one dedicated for fuel flow sensor called "Sen4-SISO" and the other for fuel flow actuator called "Act2-SISO". By the same way, group 2 is related to the air flow control loop (SIMO model) and it consists of 4 models called "Sen1-SIMO", "Sen2-SIMO", "Sen3-SIMO" and Act1-SIMO". Group 3 is related to the whole combustion subsystem (MIMO model) and it consists of 6 models called "Sen1-MIMO", "Sen2-MIMO", "Sen3-MIMO", "Sen4-MIMO", "Act1-MIMO" and "Act2-MIMO". These models configurations are designed so that for each actuator and sensor there is a main model from group 3 and a redundant model from group 1 or group 2. Each model name is indexed by two parts; the first refers to sensor (Sen) or actuator (Act) and the second part refers to model group. For example model named "Act1-MIMO" means that the model for actuator # 1(air flow actuator) based on the MIMO model of group 3 of the whole combustion subsystem. By the same way, "Act1-SIMO" it indicates actuator #1 based on SIMO model group 2, air flow control loop.

V. IMPLEMENTATION OF MULTI-MODEL 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. Some simulation results are illustrated in [1].

The fault detection and Isolation algorithm is applied for a real abnormal behavior that has been occurred suddenly. The abnormal behavior may be due to a sudden fault in actuators, sensors or parameters. Based on the identified models, there are three groups; group 1 is based on SISO model, group 2 is based on SIMO model and group 3 is based on MIMO model. Therefore, there are 4 models for detecting and isolating actuator faults; two models for each actuator based on the master loop (Group 3; MIMO) model which are "Act1-MIMO" and "Act2-MIMO", one for fuel control loop (Group1;SISO) which is "Act2-SISO" model and the last one is based on air flow loop (Group2;SIMO) model which is "Act1-SIMO". i.e. the four models for actuators represent two main models based on MIMO loop and two redundant models based on other loops, SISO and SIMO, to enhance the fault isolation. Similarly for sensors faults, 8 models are employed; 4 models are based on the MIMO model, 3 models are based on SIMO model and the last model is based on SISO model. Therefore to discriminate between actuators and sensors faults, 12 models are employed. Actuators models responses are shown in figures from Fig. 6 to Fig. 8 for actuators XD-230 (air flow control valve) and FV-230 (fuel flow control valve) respectively.

The residual threshold is selected to by 10% which compensate the effect of model approximation due to linearization.

By analyzing the responses and estimated faults, it is found that MIMO models indicates that each residual is less than the threshold (10%) while the other two models based on SIMO and SISO is higher than its threshold. By applying equation (2), it is deduced that the master loop (MIMO) detected two faults in the two actuators while the other models (SISO and SIMO) could not grantee that i.e. the faults are not actually in the actuators.

Table 2 summaries the results of the fault detection and isolation system as discussed in section III. Where a_i is the alarm signal generated from the analysis of the residuals based on equation (2). The columns contain the decision of actuators and sensors faults, Act.1, Act.2, Sen.1, Sen.2, Sen.3and Sen.4 that are described in Table 1, from items 1 to item 6 sequentially. Each column contains two decisions for example Act.1 has a_1=1 and a_3=0 and the final decision of this actuator is obtained by logic function as follow:

$$a_{\text{act.1}} = a_1 \text{ AND } a_3 \tag{11}$$

The final row gives the final decision of each sensor and actuators. It is noted that there are two faults in Sen.2 and Sen. 3 that represent the abnormal behavior in the process. The fault in Sen.2 is detected by two different models that enhance each other; model #6 (Sen2-MIMO model) and model #10(Sen2-SIMO). The fault in Sen.3 is detected by another two different models that enhance each other; model #7 (Sen3-MIMO model) and model #11(Sen3-SIMO). The two faults are in air temperature transmitter and flue gases oxygen analyzer transmitter. The result is realistic because any change in air temperature causes a change in oxygen ration in flue gases, which indicates the effectiveness of fuel combustion.

At this point, using multi-model fault detection reduces the selection to be between faults in air temperature transmitter or/and flue gases oxygen analyzer transmitter. Therefore, the decision system, in Fig. 4, uses the residuals of each model of the two sensors (#6, #10, #7 and #11) and its estimated fault value to decide which sensor represents the fault correctly employing the probability theory.

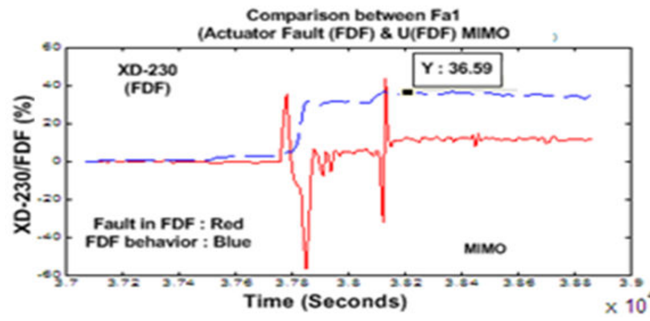


Fig. 6 Real fault estimation of actuator 1using MIMO model #1

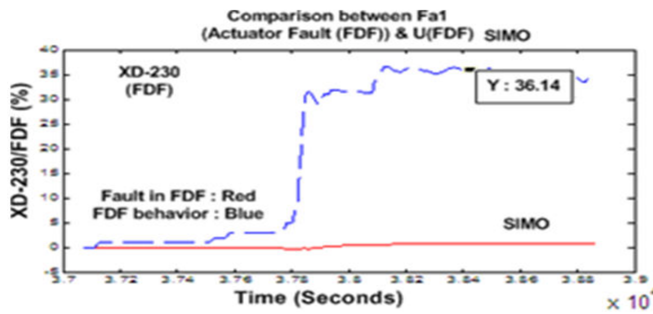


Fig. 7 Real fault estimation of actuator 1 using SIMO model #3

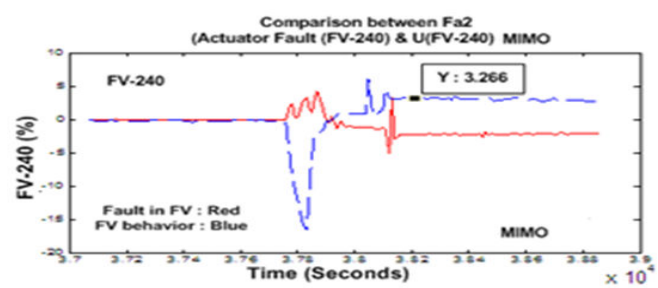


Fig. 8 Real fault estimation of actuator 2 using MIMO model #2 #7

Table 2 Practical fault results

#	Model	Act. 1	Act.2	Sen.1	Sen.2	Sen.3	Sen.4
1	(Act1- MIMO)	a_1=1					
2	(Act2- MIMO)		a_2=1				
3	(Act1- SIMO)	a_3=0					
4	(Act2- SISO)		a_4=0				
5	(Sen1- MIMO)			a_5=0			
6	(Sen2- MIMO)				a_6=1		
7	(Sen3- MIMO)					a_7=1	
8	(Sen4- MIMO)						a_8=0
9	(Sen1- SIMO)			a_9=0			
10	(Sen2- SIMO)				a_{10}=1		
11	(Sen3- SIMO)					a_{11}=1	
12	(Sen4- SISO)						a_{12}=0
	a_{total}=0	0	0	0	1	1	0

Since the probability to have two faults at the same time is low, the estimated fault value and response are used to decide which fault has higher probability than the other in the decision system shown in Fig. 4. Hence, the analysis of estimated faults increases the probability of flue gases oxygen analyzer transmitter (Sen.3). The analysis is carried out by comparing the values of estimated faults of MIMO (models #6 and #7) and SIMO (models #10 and #11) as shown in Fig. 9, Fig. 10, **Fig**. 11 and Fig. . In flue gases oxygen analyzer transmitter, the estimated fault in Fig. 9 about 5% and in Fig. 10 about 1.7%, then the ratio between the faults estimated using model #7 and model#11 is around 3 times. While in air temperature transmitter, the ratio between the faults estimated using model #6 and model#10 is higher than 8 times (the estimated fault in **Fig**. 11 is -25% while in **Fig.** 12. Then the probability of oxygen analyzer transmitter fault is increased to be 0.66 (66%) while the probability of air temperature fault is 0.34 (34%).

Then the fault that cause the abnormal behavior is the fault in flue air oxygen analyzer transmitter (Sen.3= 90-AT-230).

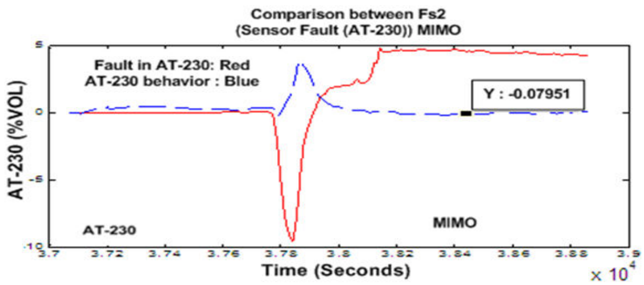


Fig. 9 Estimated flue gas oxygen analyzer transmitter fault using model

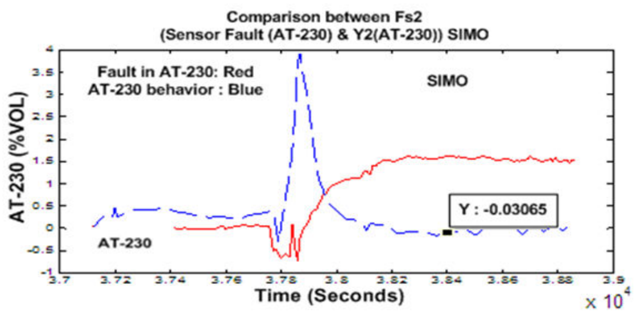


Fig. 10 Estimated flue gas oxygen analyzer transmitter fault using model #11

VI. Conclusion

The utility boiler is a very import part in industrial processes especially petrochemical. Therefore it is necessary to enhance the boiler safety and availability and increase productivity by early detection of faults and accommodate it. So a combined multi-model and parameter estimation techniques are implemented for an industrial boiler of SIDPEC Company as a case study. The suggested hybrid technique is implemented instead of single technique such as observer based FDI because it is difficult to isolate all faults using single method. The suggested method of FDI is classified as model based and it applies modified multi-model fault detection. Thus on-line identification is carried out in order to obtain the loops models based on the least square error identification technique. The fault detection algorithm is implemented on a real data represents a sudden abnormal situation in order to diagnosis it. The implemented algorithm, in this paper, detect fault correctly and isolate the fault completely. The diagnosis of all boiler loops and the design of fault tolerant controller to eliminate sudden shutdown of the boiler will be discussed.

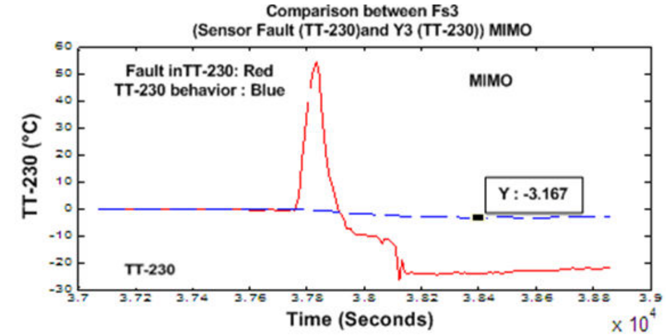


Fig. 11 Estimated air temperature fault using model #6

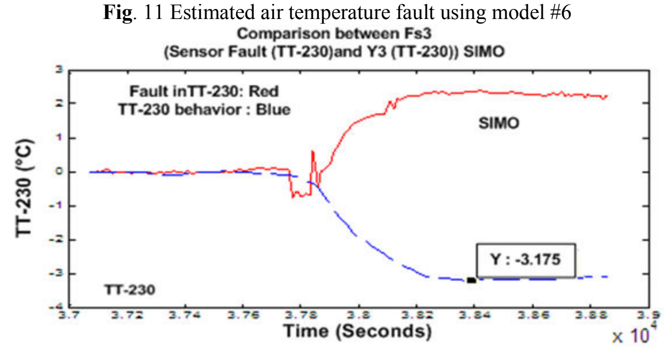


Fig. 12 Estimated air temperature fault using model #10

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