Neuro-Fuzzy Logic Based Robust Detection and Isolation of Economizer and Air Pre-Heater Faults in Steam Boiler

Navaseelan P, Nagarajan S, Chinthamani B, Nagalakshmi B, Chitra B K

Abstract: ***The technique of Fault Detection and Isolation (FDI) of Economizer and Air-preheater of Boiler using Neuro-fuzzy system is presented in this paper. FDI using model based approach and intelligent methods are the current trend applied in space industries, process industries and power plants. Intelligent methods like Fuzzy, Neural network and Neuro-fuzzy methods are simpler for modeling and faster for detection and isolation of faults. Here the water wall type steam boiler which is used for producing steam in fertilizer industry is studied. The proposed scheme is detecting and isolating the faults and failures happens in the economizer and air preheater of boiler. The common faults are corrosion, erosion, cracking of boiler tubes at welding points, tube rupturing, scale formation in the tubes, external ash deposits etc. The inherent non-linearity of boiler makes Neuro-fuzzy logic method suitable for FDI for all possible faults. The detection of faults is carried out by computing residuals, which are the differences between real process output and estimated output by neuro-fuzzy logic model. These estimated outputs were obtained from the neuro-fuzzy logic model which is trained using real time data by Adaptive Neuro-fuzzy Inference Systems (ANFIS). The real time data of economizer and air-preheater of boiler is collected and used for residual generation. The residuals will be formed for two outputs which are playing important role. If the residual exceeds threshold value indicates various faults in the boiler components and makes the proposed FDI scheme robust against process and measurement noises, process modeling error, disturbances and all uncertainties etc. The threshold band is calculated using model error model method. To isolate the faults, the residuals are normalized and its magnitudes are compared with present fault severity limits. More the range of severity more will be the magnitude of faults in the boiler. FDI by neuro-fuzzy method is more advantages as it combines the advantage of artificial neural network and fuzzy logic methods. The neural networks are more adaptable and have more learning ability. Fuzzy systems are dealing with human reasoning and decision making. As a result the designed FDI scheme is more sensitive to faults and less sensitive to uncertainties and disturbances etc. makes the scheme robust. The required data and fault knowledge for the research work is collected from BHEL make 55 tons per hour capacity, water tube type boiler available in Madras fertilizer Limited (MFL), Chennai.***

Keywords**:** ***Air-preheater, Economize, Fault detection, Isolation, Neuro-fuzzy logic and Residual..***

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I. INTRODUCTION

The necessity of fault detection and isolation (FDI) for any non-linear system is more significant to ensure reliability [1] and safety of a plant. Some of the Industrial process like production, waste management systems, aircraft automation, power plants and transmission systems often exhibits unpredictable behavior, poor performance or unsafe operations which lead to shutting down of the entire process. This necessitates early detection of faults and remedial action to recover the system operation.

Industrial Boiler is also one such system plays important role in Electric Power plants, Refineries, Fertilizer production and in process industries. In that industrial processes the steam from the boiler actuates steam turbines for electric power generation, compressors for pneumatic power etc. The efficiency and optimum performance of these industries are depending on the steam quality in terms of its temperature, flow rate, pressure and its reliability. Boiler consists of components like combustion chamber, drum and tubes, super heater, economizer and auxiliary air pre-heater etc.

Fault detection methods are divided broadly into two types called Process monitoring and model based methods. In case of processes monitoring variation in output variables can be used for detecting faults, in case of complicated systems it is surely difficult to measure all the variables of the plant, in such situations the methods which use redundant analytical relationships are more suitable.

In case of model based approaches[14] the difference between process output and model output is generated as residual which is analyzed for finding faults in these[3,20] methods. The important types of Kalman filter and Luenberger observer are used to estimate the outputs of the plant model for stochastic and deterministic process respectively. These analytical methods require accurate mathematical models. Modeling of non-linear system is a difficult task and any modeling error above certain value will degrade the performance of FDI scheme.

Intelligent methods like fuzzy logic, artificial neural network, and neuro-fuzzy systems are used to detect and isolate all kinds of faults successfully.

Neuro-fuzzy logic method makes modeling of non-linear and interacting systems very simple by training them with real data and FDI performs well even if the complete knowlege of the system is not available and also in noisy environments. This method is also useful for robust implementation and functioning of the FDI scheme. The isolation of faults is done by valuating the residual and decision making with fault severity levels.

The neuro-fuzzy logic based FDI scheme discussed in this paper detects faults and isolates the normal problems happening in the boiler components like economizer and boiler auxiliary air pre-heater. The common faults will be tube welding cracks, tube rupture, scale formation inside as well as outside the tubes, ash deposits, corrosion and erosion. The adaptive neuro-fuzzy inference system (ANFIS) is being used to model non-linear systems. Neuro-fuzzy logic based FDI compares output of the plant with neuro-fuzzy model output and the difference is called residual [1], if this residual exceeds designed threshold is detected as fault. In the first step neuro-fuzzy logic model for normal operating conditions are identified, then the residual is generated by comparing real-time plant data with model outputs and faults are isolated based on the severity expressed in percentage for various residuals. If the process and measurement noise, modeling errors, disturbances and process uncertainties[1] are not considered while designing FDI scheme, then there is a chance of wrong detection of faults even in the no fault conditions.

The paper is presented as follows: The forth-coming chapter II explains the process of economizer and Air-preheater of the boiler. Chapter III presents neuro-fuzzy approach of modeling considered. Chapter IV presents the FDI scheme and discussion about the two stages of detection and isolation. The V chapter discusses the FDI scheme for detecting and isolating important of simulated faults in the boiler components and finally in the last chapter merits and results are presented.

II. BOILER PROCESS

A. Process Description

An industrial boiler works with four main circuits namely air-fuel circuit, feed water circuit, steam circuit and cooling water circuit. In feed water circuit the condensate water coming from condenser and de-mineralized makeup water from the treatment plant are added and given as feed water to the economizer as shown in Fig. 1. The feed water is getting heated up to certain level in the economizer itself by heat energy left in the flue gases. Pneumatic control valve is provided to control feed water flow to the boiler.

The use of air-fuel circuit is to burn of furnace oil in the combustion chamber and supplying the heat energy liberated the form of flue gas to the drum and tubes, super heater, economizer and preheater mainly by convection and conduction [13]. The furnace oil is atomized by mixing it with steam at high pressure, before burning in air to make combustion more efficient. The air needed for combustion of the fuel is received from air-flue gas circuit run by forced draft (FD) fan at the input side and induced draft (ID) fan at the output side of boiler.

The liberated flue gas flows over the water wall to produce steam of high pressure and temperature in the steam circuit. This steam produced in the boiler drum is called saturated steam; normally have water droplets which are eliminated by heating it further in super-heater at high temperature and the output steam will behave as perfect gas thereafter.

The energy left in flue gas from economizer is used to preheat the combustion air in the air pre-heater shown in Fig. 2. The FD fan drives sufficient air into the combustion chamber and the ID fan derives waste flue gas from preheater to chimney. Slight negative pressure is maintained in the furnace to have air circulation for perfect combustion process with the balanced action of FD fan and ID fan.

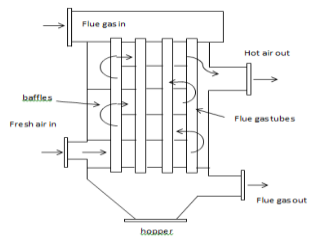

Fig. 1. Economizer

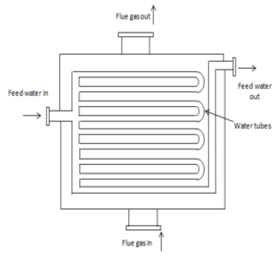

Fig.2. Air preheater

B. Model Equations

Water wall type boiler is considered here for our study. The boiler is a non-linear process due to interaction of many input and output variables. Hence for deriving model equations [12], internal structure and operations of subsystem of the economizer and air preheater should be studied. The model is derived from basic mass and energy balance equations. The mass balance equation is given by:

Rate of mass accumulation of water = rate of mass input – rate of mass output (1)

The mass balance equation of economizer is:

$$w_{ei} - w_{eo} = V_e \, d/dt(\rho_e) \quad (2)$$

w_{ei} – economizer input feed water flow

w_{eo} - economizer ouput feed water flow

V_e - volume of economizer

ρ_e – economizer watervdensity

Heat balance equation of flue gas is:

$$Q_{es} = Q_e + M_e \, C_e \, d/dt(T_{et}) \quad (3)$$

Q_{es} – heat absorbed in economizer surface

Q_e – heat transferred to economizer water

M_e – tube mass of economizer

C_e –capacitance of economizer tubes

T_{et} – economizer tubes temperature

Heat balance equations for water are:

$$Q_e + w_{ei} + h_{ei} = w_{eo} \, h_{eo} + V_e \, d/dt(\rho_e h_{eo}) \quad (4)$$

h_{ei} – specific enthalpy of inlet water

h_{eo} - specific enthalpy of outlet water

Similar equations are derived and available for air preheater also.

III. NUERO-FUZZY APPROACH

Adaptive Neuro-Fuzzy Inference Systems (ANFIS) is the combination of artificial neural network and fuzzy logic systems to have advantages of both systems together. In this approach fuzzy set and neural network deals efficiently in two distinct ways. Fuzzy sets are framed in the form of If-then rules, membership functions [16] of input-output variables and knowledge base are intelligent implementation of human skill. ANFIS models have transparency, and human logic can be seen from their structure.

But considerable time consumption is the disadvantage of fuzzy method. Similarly neural networks have powerful learning ability [7, 8], can able to model any non-linear systems. On the other hand neural networks are not transparent like fuzzy.

Neuro-fuzzy method will have transparency similar to fuzzy systems and learning ability of neural network in a single structure. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) are fuzzy TSK model [3,4] whose membership functions are tuned with neural network. The common learning algorithm of hybrid and back propagation are being used for tuning of the membership functions and other variables in ANFIS systems. Speed of convergence will be more if hybrid method is used and learning will be more precise in case of back propagation algorithm. The BPA [21] is used to minimize the error of the network. In the forward propagation the error between the nominal and the actual value is calculated and in the backward propagation the weights are updated in order to minimize this error using gradient descent method.

A. Modeling

ANFIS has three elements namely fuzzification, fuzzy inference and defuzzification. In artificial neural networks weights between input layer and hidden layer1 and weights between last hidden layer and output layer determines the behavior of the system [10]. In fuzzy methods these vaiables are found in the process of fuzzification and defuzzification[15] that has to be trained[7]. This finds degrees of membership function in the rule layer using If-then rules. The ANFIS [8] learn from given data and finds suitable model using hybrid or back propagation gradient descent method [5]. The mapping of neuro-fuzzy technologies and neural network into fuzzy-neuro systems [6] shown in Fig. 3.

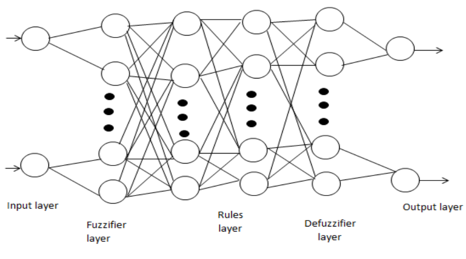

Fig.3. Structure of ANFIS

B. Input and output Variables

The input, output variables with its normal operating values of 55 tons/hour boiler is given in the Table 1. The data for the period of 10 days for the research work and fault data and knowledge [11] is collected from the data sheets/ control room and operator.

IV. NEURO-FUZZY LOGIC BASED FDI

The role of FDI is detecting and isolating of faults in components of boiler based on the knowledge of input and outputs. This section discusses neuro-fuzzy detection and isolation of faults in boiler systems.

A. Fault detection and Isolation

Neuro-fuzzy method of FDI uses Adaptive Neuro-Fuzzy Interference System (ANFIS) models are derived from the real-time plant data. Detection of faults needs neuro-fuzzy model[18] of boiler components running in normal condition. The boiler component like economizer and auxiliary air pre-heater are modeled using real-time input and output data. The estimated output of components of the ANFIS model is compared with plant output with added noise, disturbance, modeling error and step change of output to generate residual.

TABLE- I: Variables of Economizer and air-preheater

Boiler Com-ponent	Signal	Parameter	Abbre-viation	Operating value	Unit
Econo-mizer	Input1	Feed water temperature at economizer input	FWTEI	109	deg. C
	Input2	Feed water flow at economizer input	FWFEI	52	MT/hr.
	Input3	Flue gas temperature at economizer input	FGTEI	370	deg. C
	Output 1 (r7)	Feed water temperature at economizer output	FWTEO	149	deg. C
	Output 2 (r8)	Feed water flow at economizer output	FWFEO	52	MT/hr.
Air-Preheater	Input1	Air temperature at preheater input	ATPHI	35	deg. C
	Input2	Air flow at preheater input	AFPHI	12	Nm^3/sec
	Input3	Flue gas temperature at preheater input	FGTPHI	274	deg. C
	Output 1 (r9)	Combustion air temperature at preheater output	CATPHO	180	deg. C
	Output 2	Combustion air flow at	CAFPHO	12	Nm^3/sec

	(r10)	preheater output			

The residual generated is the difference between plant output and output of model or filter denoted as 'r_i'.

$r_i = y_i - \hat{y}_i$; where i = number of outputs (5)

y_i - real-time data of the boiler with added noise and disturbance $\hat{y}_i$ - the estimated output of the ANFIS model

The residual is normalized in the range between +1 and -1 using (6). Threshold is generated using Model Error Model (MEM) method to make the fault detection robust against modeling error, noise and disturbances [19].

Allowable amount of noise and modeling error of approximately 5% is added with actual plant output and this is compared with the model output to produce residual. ANFIS based error model is tuned to make the difference between this residual and error model zero. After tuning, the output of the error model gives allowable band or confidence region for robust detection and isolation. Fault is detected, if the normalized residual surpasses threshold band (δ), which is a gap between upper 'T_u' and lower 'T_L' threshold limits. The residual surpasses threshold levels are compared with fault severity limits and finally correlated with fault knowledge given in Table 2. Severity within ±0.4 is classified as incipient faults and up to ±0.6 is isolated as abrupt faults, which is decided based on boiler operator's knowledge and experience.

$$x_i' = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)} \qquad (6)$$

where,

x_i – i^{th} output

x_i' –normalized value of i^{th} output

$\min(x_i)$ – minimum value of i^{th} output from set of data

$\max(x_i)$ – maximum value of i^{th} output from set of data

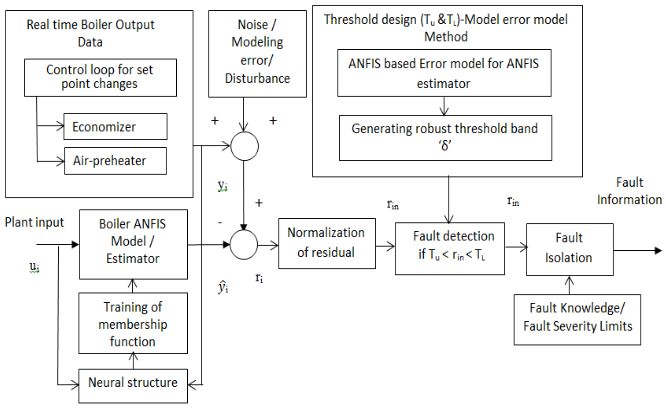

Fig. 4. ANFIS based fault detection and isolation scheme

B. Threshold Design

The robust threshold band (δ) is generated using model error model method [22] to accommodate residual in the presence of noise, disturbance and modeling error. If the threshold band is too large, FDI scheme will lose fault sensitivity[17]; if the band is too small, there is a chance of mis-alarm. Therefore, there should always be a compromise between the number of the false alarms and fault detection time. In order to avoid all these confusions and to improve the performance of FDI scheme even in the presence of fictitious noise and modeling error, threshold band is designed using model error model method.

Fig. 5. Shows training of ANFIS based error model for its output of residual with maximum possible noise and modeling error. Fig. 6. Shows building of confidence region by error model for various estimated outputs of ANFIS model for boiler components. The model of the process is obtained and the ANFIS error model can be obtained by using the data collected from the difference between the process output 'Y' and the model output 'Y_m'. The identification of residual 'r' provides the model error model.

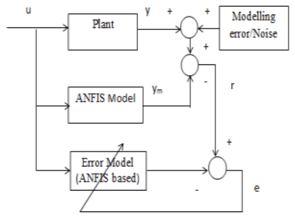

Fig. 5. Training of error model in Model error model method

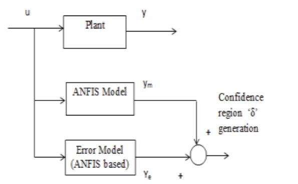

Fig. 6. Robust threshold band generation in MEM method

To design robust threshold the output of ANFIS model is added with error model which indicates the error signal due to noise and disturbance and modeling error shown in Fig. 6. Then, the upper threshold (T_u) and the lower threshold (T_L) can be calculated using (7) and (8). The threshold band 'δ' is the gap between 'T_u' and 'T_L'.

The upper threshold $T_u = Y_m + Y_e + t_\beta \gamma$ (7)

The lower threshold $T_L = Y_m + Y_e - t_\beta \gamma$ (8)

where,

Y_m- output of nominal model

Y_e - output of error model

γ - standard deviation of 'Y_e' $= \sqrt{\frac{y_{e1}^2 + y_{e2}^2 + \cdots + y_{en}^2}{n}}$ (9)

t_β - N(0,1) Normal distribution

= 0.9946 from Standard Normal distribution chart

The 't_β' is found using normal distribution chart for the values of standard deviation 'γ'for all outputs of boiler components.

C. Fault Knowledge

The fault measurement relationships are given in the Table 2. for the boiler components. The various important faults for both increasing and decreasing conditions are given from the history of boiler operation and operators experience.

TABLE - II: Fault -Measurement Relationship of Boiler

Boiler Component	Outputs	Decreases more than 40%	Decreases till 40%	Increases till 40%	Increases more than 40%
Economizer	FWTEO	Fuel valve failure (stopped)	scale formation /Ash deposits in tubes	Corrosion/erosion of tubes	ID fan not working
	FWFEO	Feed water Pump/valve failure	Deaerator makeup water valve failure	scale formation inside the tubes	Feed water valve mal-function (allows more water)

Air pre-heater	CATPHO	Fuel valve failure (stopped)	scale formation /Ash deposits in tubes	Corrosion/erosion of tubes	ID fan not working
	CAFPHO	FD fan not working	Damper system malfunction (fail to open)	Damper system malfunction (fail to close)	FD/ID malfunction (runs at high speed)

The important faults in boiler components and their symptoms measured will be discussed briefly as follows:

- **Fuel valve failure**: In fuel valves air supply failure will decrease fuel flow to combustion chamber that reduces combustion rate that will in turn decrease the flue gas temperature.
- **ID/FD fan failure**: this will decrease/ increase flow of flue gas and combustion rate. Decrease in combustion decreases / increases saturated steam temperature.
- **Feed water valve failure:** will decrease/ increase feed water flow rate at economizer that decreases/ increases steam generation.
- **Scale / coke formation on boiler tubes:** this reduces amount of conduction of heat energy and will in turn decrease temperature.
- **Corrosion/ erosion of tubes:** this reduces thickness of tubes and due to this temperature of many components increases.
- **Deaerator valve failure:** this decreases feed water flow to boiler drum and steam flow, pressure decreases.

SIMULATION RESULTS

A. Model validation

The collected data is used to ANFIS model the components of the economizer and air preheater. The real time data are used for tuning of fuzzy membership functions. The suitable fuzzy architecture is selected and it is trained and the model is validated [8] using test data and check data of added noise, if any deviation is observed in the response it is again trained till convergence. These ANFIS models are used in the Simulink environment [9] to generate residual and it is normalized and analyzed for isolation of faults.

The economizer with inputs FWTEI, FWFEI, FGTEI and outputs FWTEO, FWFEO are modeled, validated and results are shown in the Fig. 7.

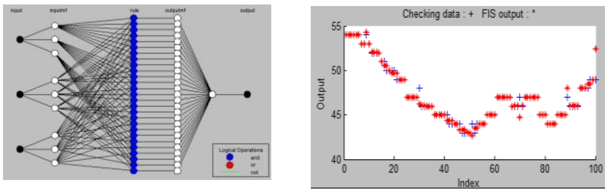

Fig. 7. f ANFIS model- economizer for feed water flow.

The error plot and checking of model also showed lying within allowable limits. The neural network trains the fuzzy membership function and it is optimized for best performance. The input membership functions of ANFIS are shown in Fig.8. Its surface viewer for input and output is also shown in Fig. 9.

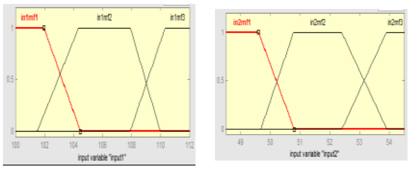

Fig. 8.Membership functions of economizer inputs

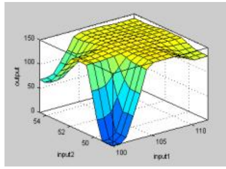

Fig. 9. Fuzzy surface viewer of economizer input model

B. Validation Plots

The ANFIS model is validated by giving the real-time plant data. The validation for economizer is shown in Fig. 10; the plant output and model outputs are overlapping with each other.

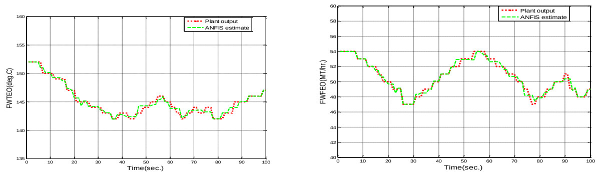

Fig. 10. Validation of economizer outputs

C. Threshold Band Generation

The threshold band is designed for robust detection of faults using model error model method as explained in previous sections. The ANFIS model is compared with plant data to generate error and the ANFIS based error model is trained for this error data. The signal from error model is added with ANFIS model output to update any change in signal due to addition of uncertainty, noise and disturbance. The calculated values of threshold and its normalized values are tabulated in Table 3. for boiler components.

TABLE- III: Robust Threshold for ANFIS Based FDI

component	Variable	Nominal value	T_u	T_L	T_u (Normalized)	T_L (Normalized)
Economizer	FETEO	149	155.5	140.9	0.044	- 0.055
	FWFEO	52	54.28	49.55	0.044	- 0.047
Air-pre heater	CATPHO	180	188.9	176.9	0.05	- 0.017
	CAFPHO	12	12.48	11.51	0.04	- 0.041

D. Method of Fault detection and Isolation(FDI)

The fault on economizer and air pre-heater is simulated for various incipient and abrupt fault cases. The faulty data is given to the FDI scheme to generate residual. This residual exceeds threshold band in the presence of noise and disturbances indicates robustness in fault detection. The fault of fuel valve failure reflects in many places, wherever flue gas passes through. The decrease in temperature of economizer output is simulated as shown in Fig. 11. It detects this kind of faults with short duration of 5 seconds and isolates after 65 seconds. The fuel valve failure decreases combustion rate and consequently flue gas temperature and feed water temperature are decreases.

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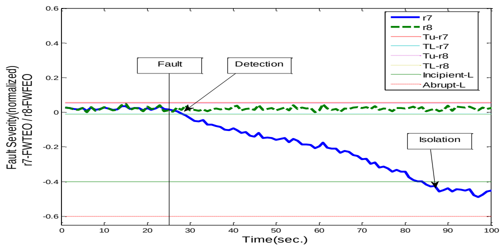

Fig. 11. FWTEO (r_7) decreases for the fault of fuel valve failure

The fuel valve failure and Deaerator makeup water valve failure are also simulated as shown in Fig.12 with added noise. The fault of makeup water valve failure in Deaerator causes decrease in the feed water flow and it is detected within 5 seconds and isolated before 25 seconds. The other output is the temperature change of feed water which is gradual, and takes more time to detect and isolate the faults.

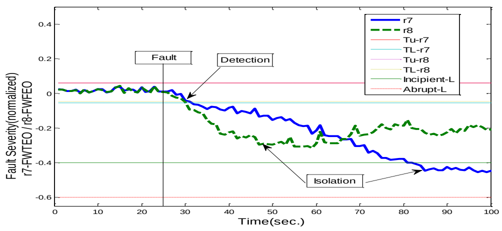

Fig. 12. FETEO &FWFEO for fuel & makeup water valve failure

The abrupt fault of fuel valve failure with added noise and disturbances causes to drop its temperature to a low value. This takes more time for isolation, since temperature is a slowly varying variable, but less time for detection shown in Fig. 13. The next fault of FD fan failure causes abrupt fault of decrease in flow and Corrosion/erosion of flue gas tubes increases temperature as shown in Fig. 14. Here the air flow falls suddenly to lower value making detection and isolation faster, but temperature takes some more time for isolation.

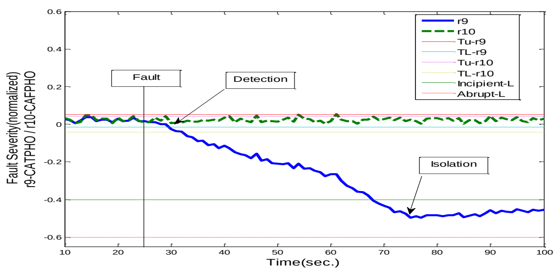

Fig.13.CAPHO (r_9) for fuel valve failure.

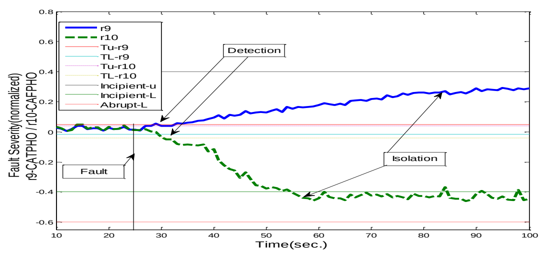

Fig. 14.CATPHO&CAFPHO for corrosion & FD fan failure.

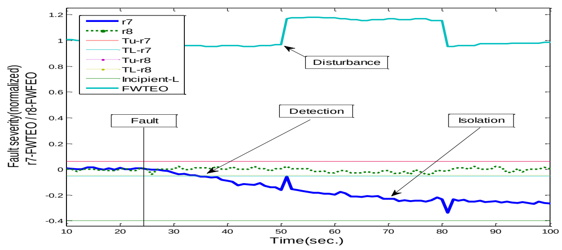

Fig.15.FWTEO with disturbance detects and isolates scale formation in tubes.

The disturbance of 20% long duration pulse is applied to feed water temperature of economizer. This load disturbance causes small spikes during increase and decrease of pulse, but detects and isolates scale formation in economizer tubes without loss of sensitivity shown in Fig. 15.

E. Time for Detection and Isolation of Fault

The detection time (T_{fd}) and isolation times (T_{fi}) of faults play vital role in the methods of fault detection and isolation, since early detection and isolation of fault will safeguard the plant from severe accidents and explosion. In this section the detection and isolation times of economizer and air-preheater were compared. If the output parameter happens to be temperature, the time taken for both detection and isolation will be more as shown in Table 4.

TABLE –IV: Detection Time (T_{fd}) and Isolation Time (T_{fi})

Output variable	Residual	Incipient Fault		Abrupt Fault	
		Detection time(T_{fd}) (sec.)	Isolation time(T_{fi}) (sec.)	Detection time(T_{fd}) (sec.)	Isolation time(T_{fi}) (sec.)
FWTEO	r_7	03	36	04	52
CATPHO	r_9	11	47	03	46
FWFEO	r_8	03	11	03	14
CAFPHO	r_{10}	04	16	02	26

V. CONCLUSION

The presented robust FDI scheme should alarm during faults for incipient and abrupt cases by generating normalized residuals and comparing with threshold limits. FDI was tested for different types of simulated faults. After detection, faults are isolated based on severity levels by its normalized values up to 0.4 for incipient faults and up to 0.6 for abrupt faults at outputs. In this ANFIS method of modeling reduces difficulty in non-linear method of modeling, and the associated fuzzy membership functions are formed with neural network by real time boiler data. Compared to fuzzy and neural network the residual generated by this method lies well within the limits of tolerance. This indicates that the scheme is robust to various disturbances and noises simulated with noise. The false alarms are also eliminated by designing residual well above the threshold values which is calculated based on the variations of data due to process and measurement noises, process modeling error and uncertainties. The detection and isolation of all types of simulated faults in economizer and air-preheater are tested and found working for robustness, fault alarms and for the case of simultaneous and multiple faults.

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