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Robust Detection and Isolation of faults in Industrial Boiler using Neural Networks

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Abstract : The problem of Robust fault Detection and Isolation (FDI) of an industrial Boiler using artificial neural network is presented in this paper. Here the water tube type steam boiler which is used for producing electricity in fertilizer industry is considered. The proposed FDI scheme detects and isolates the normal failures occurring in the important sections of the boiler namely combustion chamber, drum and tube and super heater. The common faults in boiler are corrosion, erosion, tube cracking at welding points, tube rupture, scale formation inside the tubes, external ash deposits and high flue gas temperature caused by short term and long term overheating. The inherent non-linear behavior of boiler makes neural network suitable for FDI of various faults. Fault detection is done by generating residuals, which is the difference between real plant output and estimated output by neural model. These estimated outputs are derived from the neural model which is trained with real time data. The real time data of power plant is collected and used for residual generation. Neural network weights are updated according to modified back propagation scheme. Residuals will be generated for two output parameters which are considered very important. If the residual surpasses threshold value which is calculated on account of process and measurement noise, modeling error, disturbances and uncertainties indicates various types of faults in the boiler and makes FDI scheme robust against these things. To isolate the faults, the residuals are normalized and its magnitude are compared which varies to their severity. More the severity more will be the magnitude of fault inside the boiler. FDI by neural network is more advantages as it is more sensitive to faults and less sensitive to uncertainties and disturbances etc. The required data and fault knowledge for the research work is collected from 55 tons per hour capacity, BHEL make water tube boiler available in Madras fertilizer Ltd.(MFL), Chennai.

Keywords : Fault detection, Isolation, Neural network, Residual, Boiler and non-linear system.

1. INTRODUCTION

The problem of fault detection and isolation (FDI) received great attention during past several years. Industrial applications like manufacturing process, hazardous waste management systems, aircraft maintenance, power plant and transmission lines often exhibits unpredictable behavior, poor performance or unsafe operations which leads to shutting down of the entire process. This necessitates early detection of faults and remedial action to recover the system of operation.

The industrial Boiler also one such system plays very important role in Power plants, Fertilizer industries, Petrochemical and in other process industries. In such industries the steam from the boiler actuates turbines for generating electric power, compressors for pneumatic power supply etc. The overall performance and efficiency of these plants is depending on the quality of steam produced in terms of its flow rate, pressure, temperature and reliability. It consists of sections like combustion chamber, boiler drum and tubes, super heater, economizer and air- preheater etc.

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The purpose of combustion chamber is to burn the fuel to produce heat energy and supplying it to boiler tubes, super heater, economizer and air-preheater .The boiler drum and tubes converts feed water in to steam, super heater rises the temperature of saturated steam to still higher value and removes water droplets and moisture completely, so that the steam behaves like a perfect gas. Here the three sections namely combustion chamber, drum and tubes and super-heater requires more maintenance and faults are frequent in nature. In this work only these three sections of the boiler is considered for detection and isolation of faults.

Fault detection is categorized onto broadly two methods: Process variable monitoring and model based methods. In case of simple processes monitoring variation in parameters can be used for detecting faults, where as in complicated systems it is very difficult to measure all the parameters of the plant, in this case analytical methods which use redundant analytical relationships are more suitable. The traditional methods like physical or hardware redundancy requires additional equipment, more the space and maintenance cost.

In the model based approach the difference between plant output and output of the model is generated as residual which is very important in analyzing faults in model based approaches. Kalman filter[18] and Luenberger observer are used to estimate the output of the model for stochastic and deterministic systems respectively. These analytical methods require precise mathematical models, modeling of non-linear system is a complicated task and any modeling error will affect the performance FDI scheme. Design of threshold also varies with nature of the system and faults. Neural network makes modeling of complex non-linear systems simple by training them for real plant data using modified back propagation algorithm and FDI works well even if the complete information of the system is not available and in the noisy environments.

Recent methods like neural network, fuzzy and neuro-fuzzy[5] are used to detect and isolate faults successfully. Neural network is useful for robust implementation and functioning of the FDI scheme. The isolation of faults is done by valuating the residual making use of neural clustering methods.

The neural network based FDI scheme presented in this paper detects faults and isolates the normal problems occurring in the complete boiler units like Combustion chamber, boiler drum and tube and super heater. The common faults in the boiler will be tube welding cracks, tube rupture, blockage inside tubes by foreign matter, scale formation inside and outside the tubes, external ash deposits, corrosion, erosion and high flue gas temperature caused by short term and long term overheating. Neural training has been used to model non-linear systems, where the implementation of FDI is fast and robust to various disturbances.

Neural network based FDI compares real output of the plant with output of the neural model and the discrepancy is called residual, if this residual surpasses certain threshold is considered as faults. Here the outputs are estimated by making use of neural model which are trained for real time data. This paper presents neural modeling and decision making methods using normalized values of residuals. First neural model for normal operations are identified, then the residual is generated by comparing real data with neural model outputs and isolated based on severity of faults expressed in percentage for various combinations of range of residuals. The availability of good model detects and isolates faults accurately even in the presence of noise[6] and disturbances. If the process noise, modeling error disturbance and uncertainties are not taken in to account while designing FDI scheme, there is a chance of wrong detection of faults even if it does not occurred.

The paper is organized as follows: The next chapter describes the process for which FDI is designed and simulated in this paper. One such example is the boiler, the important part in the fertilizer industry is considered for our study. Chapter 3 presents neural network approach modeling, in which the details about variables of boiler to be considered and formulation of neural model. Chapter 4 presents the scheme of detection and isolation of faults and detailed information about these two stages. The chapter 5 discusses the simulation of FDI for detecting and isolating important faults of the systems considered and finally it is concluded in the last chapter.

2. PROCESS DESCRIPTION AND MODELLING

A. Process Description

Boiler consists of four main circuits namely feed water circuit, air fuel circuit, steam circuit and cooling water circuit. The diagram of boiler is shown in figure 1. The purpose of air fuel circuit is the combustion of furnace oil in the combustion chamber and supplying the heat energy generated to the boiler water tubes, super heater, economizer and preheater mainly by convection and conduction[37]. Furnace oil is atomized by mixing it with atomizing air or steam before burning it with air to make combustion process more efficient. The air required to burn the fuel is obtained from air-flue gas circuit managed by forced draft (FD) at the input side and induced draft (ID) at the output side.

In the feed water circuit the condensate water coming out of condenser and demineralized makeup water from the water treatment plant together is given as feed water to the boiler through economizer. The feed water is heated up by heat energy left in the flue gases in the economizer before entering the boiler. Control valve is provided to control flow of feed water to the boiler.

The combustion gas flows over the boiler tubes and steam of high pressure and temperature is generated in the steam circuit. This saturated steam produced in the steam drum have water droplets which are eliminated by heating it further in super-heater at any pressure and the output steam will behave as perfect gas thereafter.

The heat energy coming from economizer is used to preheat the combustion air in the air-preheater. The FD fan supplies sufficient air into the combustion chamber and the ID fan sends waste flue gas from preheater to chimney. With the balanced action of FD fan and ID fan slight negative pressure is maintained in the furnace to have perfect combustion.

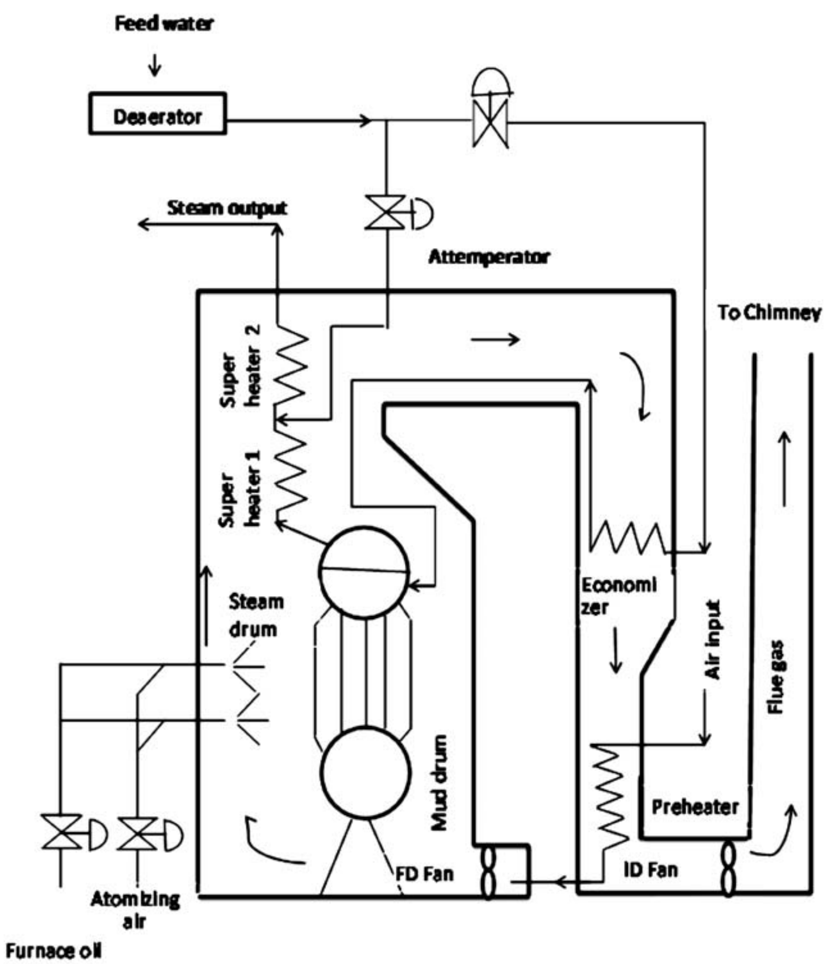


Figure 1: Industrial boiler

B. Model Equations

Water tube type boiler is considered here for our study. It is a complex non-linear process due to interaction of many input and output variables in the subsystems. Hence for deriving mathematical model, internal structure and functions of subsystem of the boiler should be studied. This mathematical model of the boiler is derived from basic mass and energy balance equations. The boiler is modeled for various sections of it.

Furnace heat balance equation for combustion is given in equation (1)

$$C_F w_F + h_A w_A + h_G w_G - Q_{ir} - Q_{is} - w_{EG} R_s (1 + y/100) h_{EG} = V_F \, d/dt(\rho_{EG} h_{EG}) \tag{1}$$

C_F – Fuel calorific value

w_F – fuel flow

h_A – air specific enthalpy

w_A – air flow

h_G – exhaust gas specific enthalpy

w_G – exhaust gas flow

Q_{ir} – heat transferred by radiation to risers

Q_{is} – heat transferred by radiation to Super heater

w_{EG} – gas mass flow through the boiler

R_s – Stoichiometric air/fuel volume ratio

y – Percentage air level

h_{EG} – gas specific enthalpy

V_F – combustion chamber volume

ρ_{EG} – gas density

equation (2) gives Furnace Mass balance equation for combustion

$$w_F + w_A + w_G - W_{EG} = V_F \, d/dt \, \rho_{EG} \tag{2}$$

The Mass and heat balance equation of riser is give in equations (3) and (4)

$$W_d - w_r = V_r \, d/dt(\rho_r) \tag{3}$$

W_d – water mass flow from the down comer

w_r – riser liquid-vapour mixture mass flow

V_r – riser volume

ρ_r – liquid vapour mixture density at the riser

$$Q_r + w_d h_w = w_r h_r + V_r \, d/dt(\rho_r h_r) \tag{4}$$

Q_r – heat transferred to steam

h_w – specific enthalpy of down comer and drum water

h_r – specific enthalpy of liquid-water mixture

In the similar manner the mass and heat balance equations of boiler drum is given in equations (5) and (6)

$$W_e + (1 - x) w_r - w_d - w_e = d/dt(m_{dl}) \tag{5}$$

W_e – feed water flow

x – steam quality

w_r – Liquid-vapour mixture mass flow

w_d – water mass flow out to the down comer

w_{ec} – drum liquid mass evaporation

m_{dl} – drum liquid mass

$$W_e h_e + (1-x)\, w_r h_{wv} = w_d h_w - w_{ec} h_v + d/dt(m_{dl} h_w) \quad (6)$$

h_e – feed water specific enthalpy

h_{wv} – specific enthalpy of saturated water

h_w – specific enthalpy of drum water

h_v – Specific enthalpy of saturated steam

The mass and heat balance equations of boiler super heater is given in equations (7) and (8)

$$w_v - w_s + w_a = V_s\, d/dt(\rho_s) \quad (7)$$

w_v – steam mass flow from drum to superheater

w_s – steam mass flow out from super heater

w_a – attemporator water mass flow

V_s – superheater volume

ρ_s – super heated steam density

$$Q_s + w_v h_v = w_s h_s - (h_a - h_f) w_a + V_s\, d/dt(\rho_s h_s) \quad (8)$$

h_s – Specific enthalpy of super heated steam

h_a – Specific enthalpy of attemporation water

h_f – Specific enthalpy of evaporation

3. NUERAL NETWORK APPROACH

A. Modelling

Neural network refers to interconnection of artificial neurons of different layers [9] of the system. In three layer neural network, the first layer have input neurons which is used to send data to second layer called hidden layer via synapses shown in the figure 2[21,30] and then to third layer of output neurons with more synapses[2]. More the hidden layer more the network is complicated. The synapses stores parameter called weight that manipulates data during calculation. The weights between input and hidden layer and weights between hidden layer and output layer are considered. The neural network uses three types of parameters namely the interconnection between different layers of the network which deals with structure of input, output and hidden layer of network. Next is the learning algorithm for updating weights of the network like gradient descent back propagation algorithm is used. Third is the activation function that converts neuron weighted output to activation.

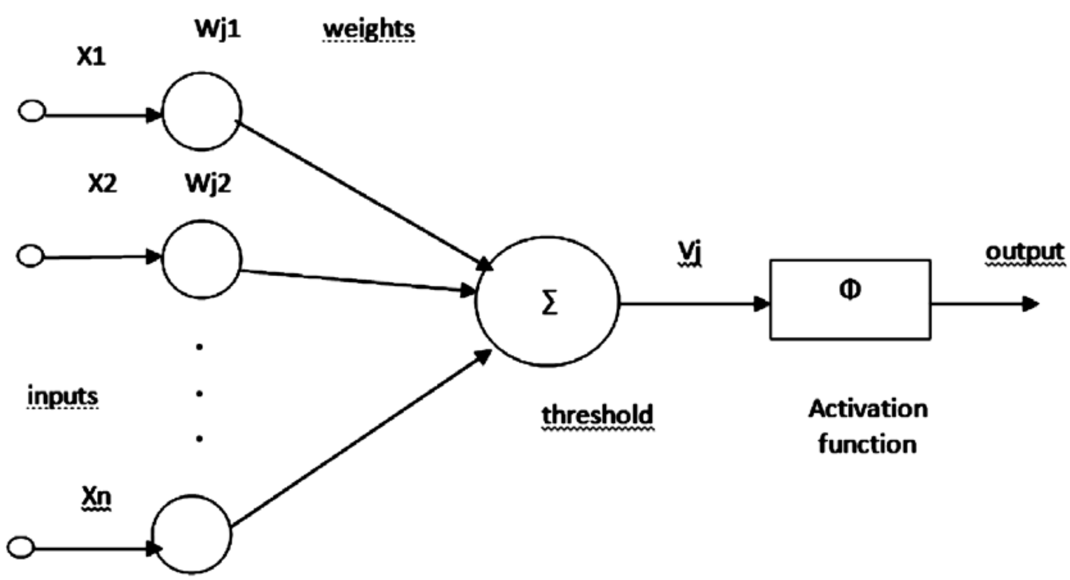


Figure 2: Neuron model

The back-propagation algorithm is used to minimize the error of the network by modifying the weights between the neurons. During the forward propagation the error between the nominal and the actual value is calculated. During the backward propagation the weights are modified in order to minimize this error using gradient descent method.

Robustness

Our modified back-propagation [1,3,19] algorithm is able to increase the quality of a net by monotonic net updating. The training starts with a net of few hidden neurons. Badly trained neurons are split periodically while learning the training set. The old weights are distributed by chance between the two new neurons. This is done until a maximum number of neurons within a hidden layer are reached. By training the net with the modified back-propagation algorithm[35,36] a better minimum of the error is reached in shorter time. Any change in the plant parameter that causes change in the estimated outputs are minimized and neural model becomes robust.

The step-by-step procedure[33] of the algorithm used is as follows: (*a*) initialize the weights in the network by a random number generator, (*b*) present the network with a training set with samples of input $X_i(n)$ and desired output $d_i(n)$, where, n is the iteration number, and (*c*) calculate the output of a neuron using the Sigmoid function, so that the activation becomes:

$$Vj = 1/(1 - e^{-Vj}) \tag{9}$$

Where

$$Vj(n) = \sum_{i=0}^{n} Xi\, Wji - \theta\, j \tag{10}$$

Compare the calculated output c_k with the desired output d_k to find the error

$$ek(\mathrm{I}) = 0.5 \sum_{i=1}^{p} \sum_{j=1}^{m} (dk - ck)^2 \tag{11}$$

where '*i*' is the iteration number, and m is the number of data sets, if $e_k(n)$ is less than a preset error level ϵ, then stop, otherwise continue, and (*f*) if $e_k(n) < e_k(n-1)$, then the learning rate lr = lr × t and continue, otherwise set lr = lr × r and if lr < 0.05 then lr = 0.05.

Set

$$W_{ji}(n+1) = W_{ji}(n-1) \tag{12}$$

and go back to step (*b*)

B. Input and output Parameters

The input, output parameter with its normal 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 is collected from the data sheets/ control room and operator[25].

4. NEURAL NETWORK BASED FDI SCHEME

The problem here is to detect and isolate the faults in sections of boiler based on the knowledge of input and output. Neural network model is found for combustion chamber, drum and tubes and super heater. This section is divided into fault detection and isolation

A. Fault detection

Neural network based FDI uses neural models formulated[4] directly from the real time boiler data. Detection of faults requires neural based model for a boiler running in normal condition. The input to the sections of the boiler like super heater is the input steam temperature (STSHI), input steam flow (SFSHI), flue gas temperature (FGTSHI), flue gas flow(FGFSHI) and the outputs considered are output steam temperature (STSHO), output steam pressure (SPSHO).

Detection of fault is based on the value of residual when it surpasses predetermined threshold value[11]. The threshold(δ)value is observed as 5% to 10% [3]variation of data being considered normal due to modeling error and process noise, uncertainties etc. the detection scheme [5] is shown in the figure 3.

Table 1
Boiler Parameters

Boiler section	*Signal*	*Residual-generated*	*Parameter*	*Abbreviation*	*Operating value*	*Unit*
Combustion Chamber	Input1	–	Fuel flow	FFCI	3.5	MT/hr
	Input2	–	Fuel temperature	FTCI	100	degree
	Input3	–	Combustion air temperature	CATCI	180	degree
	Input4	–	Combustion air flow	CAFCI	12	Nm^3/sec
	Output1	*r*1	Flue gas temperature	FGTCO	1050	degree
	Output2	*r*2	Flue gas flow	FGFCO	14	Nm^3/sec
Drum and Tubes	Input1	–	Flue gas temperature	FGTDI	750	degree
	Input2	–	Flue gas flow	FGFDI	14.5	Nm^3/sec
	Input3	–	Feed water temperature	FWTDI	149	degree
	Input4	–	Feed water flow	FWFDI	52	MT/hr
	Output1	*r*3	Saturated steam temperature	SSTDO	256	degree
	Output2	*r*4	Drum level	DLDO	295	mm
Super Heater	Input1	–	Saturated steam temperature	STSHI	256	degree
	Input2	–	Saturated steam flow	SFSHI	55	MT/hr
	Input3	–	Flue gas temperature	FGTSHI	925	degree
	Input4		Flue gas flow	FGFDI	14.5	Nm^3/sec
	Output1	*r*5	Superheated steam temperature	STSHO	400	degree
	Output2	*r*6	Superheated steam pressure	SPSHO	45	Kg/cm^2

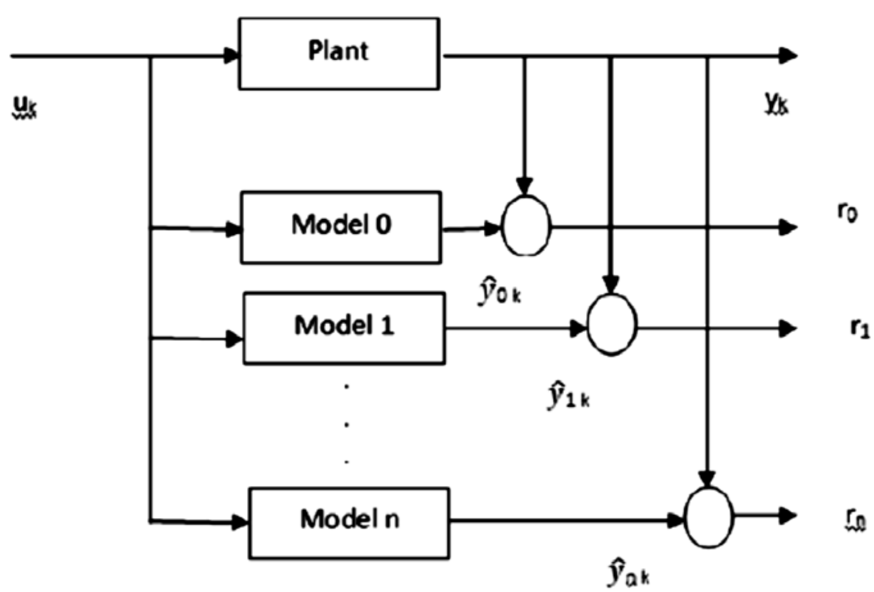


Figure 3: Model based fault detection

The residual is calculated as the difference between output of neural model and real time boiler data

$$r_i = y_i - \hat{y}_i \; ;$$

where i = number of outputs(taken as 2) (13)

r_i is the residual of i^{th} output, y_i is the real time data of the boiler and $\hat{y}_i$ is the output of the neural model for the normal input. If this residual surpasses certain calculated threshold 'δ'[1] based on modeling error and disturbances, indicates fault.

B. Fault Isolation

In our proposed scheme every fault is isolated by evaluation of normalized values residuals r_1 and r_2 [8]. At each sampling instant the output is normalized in order to be constrained in the range (–1 to + 1) as per equation 14. Here i represents i^{th} value of output. Depending on the nature of faults the value of residual varies or in other words the range of residual differs for various types of faults. The residual are analyzed by comparing with decision rules. In analyzing residual the value of residuals can be classified[17] so that each must be corresponding to faults at different locations. An effective and reliable FDI should take care of modeling error and uncertainties which normally affect fault sensitivity.

$$i_n(k) = (i(k) - \min(i)) /(\max(i) - \min(i))$$

In our case the faults are isolated based on nature of fault severity[15,21] given in figure 4. The fault severity [28] can be calculated from the value of residual for different types of faults. The fault severities are denoted as normal, level-1 fault and level-2 faults.

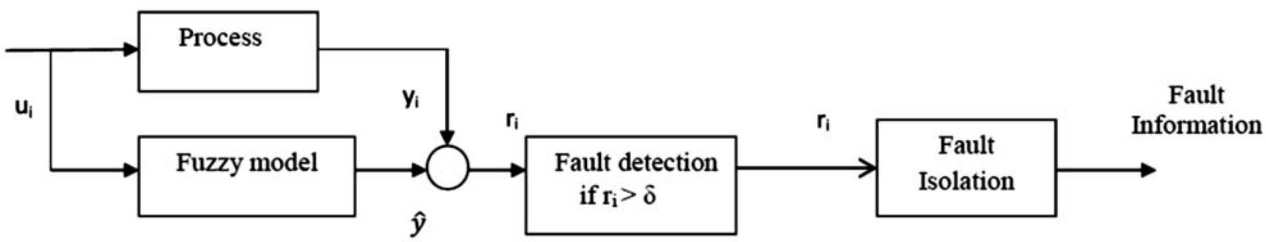


Figure 4: Fault detection and Isolation Scheme

More the ranges of residual more will be the complication of faults. some of the causes for the faults are, the internal corrosion of steam tube that will increase temperature to 30% because it accumulate heat energy if it is at level 1, and it increases pressure also to 40 units for the diameter of the tube decreases. If the scale formation is at level-1 the temperature decreases by less than 30% since thicker layer reduces heat transfer rate. External ash deposit at the steam pipe will reduce the temperature to level-1, the welding cracks in the tubes will also reduce the pressure at level-1. Tube blockage by foreign objects and tube rupture will increase and decrease the pressure to level-2 respectively. High flue gas temperature caused by long term or short term temperature will rise the temperature to level-2.

5. SIMULATION RESULTS

A. Model validation

The collected data is used to neural model the sections of the boiler and the estimated output of the model are validated with the real time plant output. Flue gas flow at output of the combustion chamber (FGFCO), saturated steam temperature at output of the drum (SSTDO) and super-heated steam temperature of super heater (STSHO) are compared with real plant data and the variation of less than ± 10 % is observed from the graph. The neural network is trained by assuming suitable parameter and it estimates the correct outputs. The validation and regression plots are shown in the figure 5. It is evident that test and validation plots are overlapping with each other and in the regression also output is linearly equal to target.

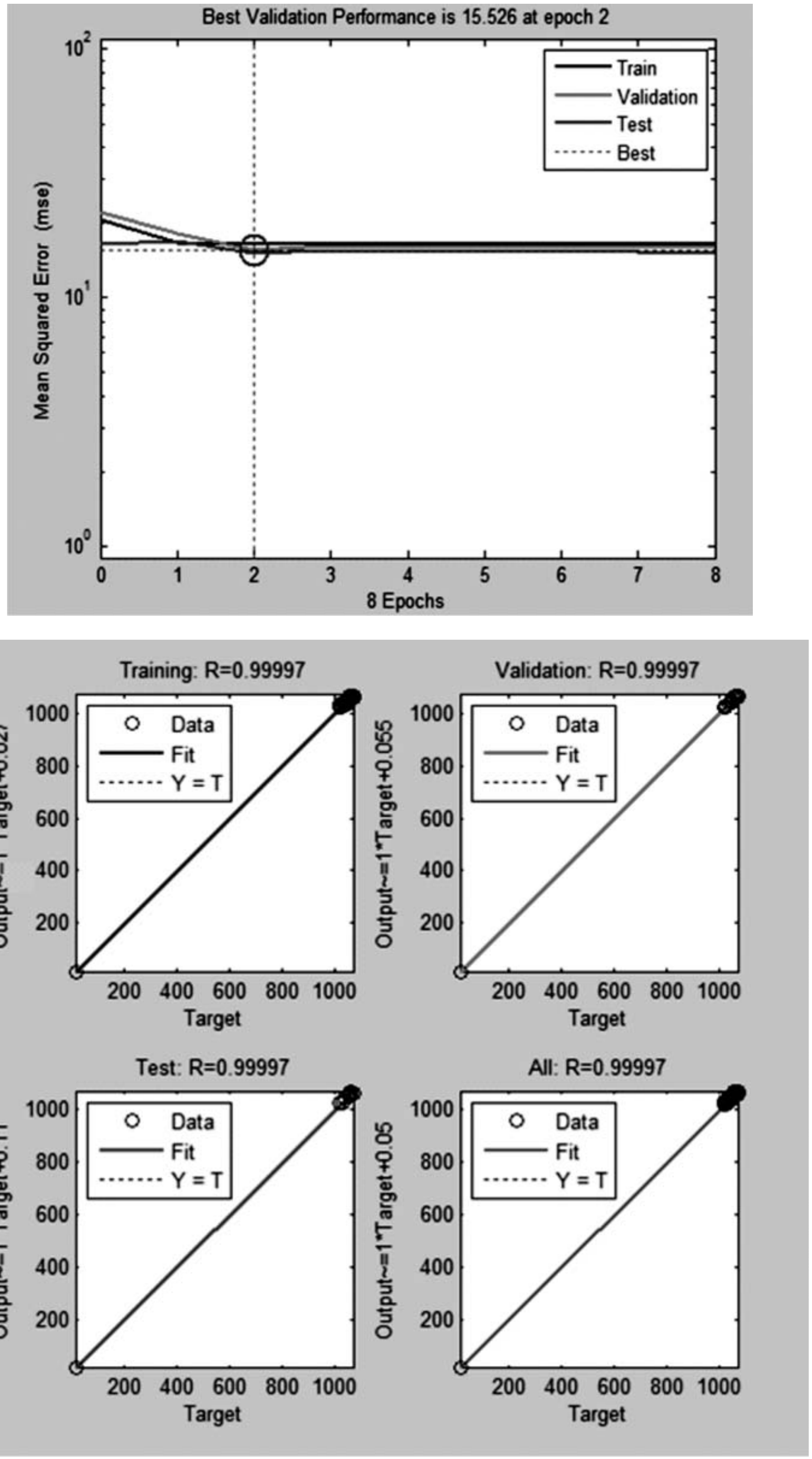


Figure 5: Validation and regression plots of neural model of combustion chamber.

B. Fault detection

The different types of faults from various sections of the boiler are detected when the residual surpasses threshold value. The threshold(δ) value is normally set at ±10% of the output and this is based on the variance of the output due to noises, modeling error, uncertainty etc. This threshold is calculated based on the variation of real time data which is normally ± 5% to ± 10%[1]. Some of the measured residual for normal operating conditions are shown in the figure 6. In all cases the normal residual lies within ± 10% is observed.

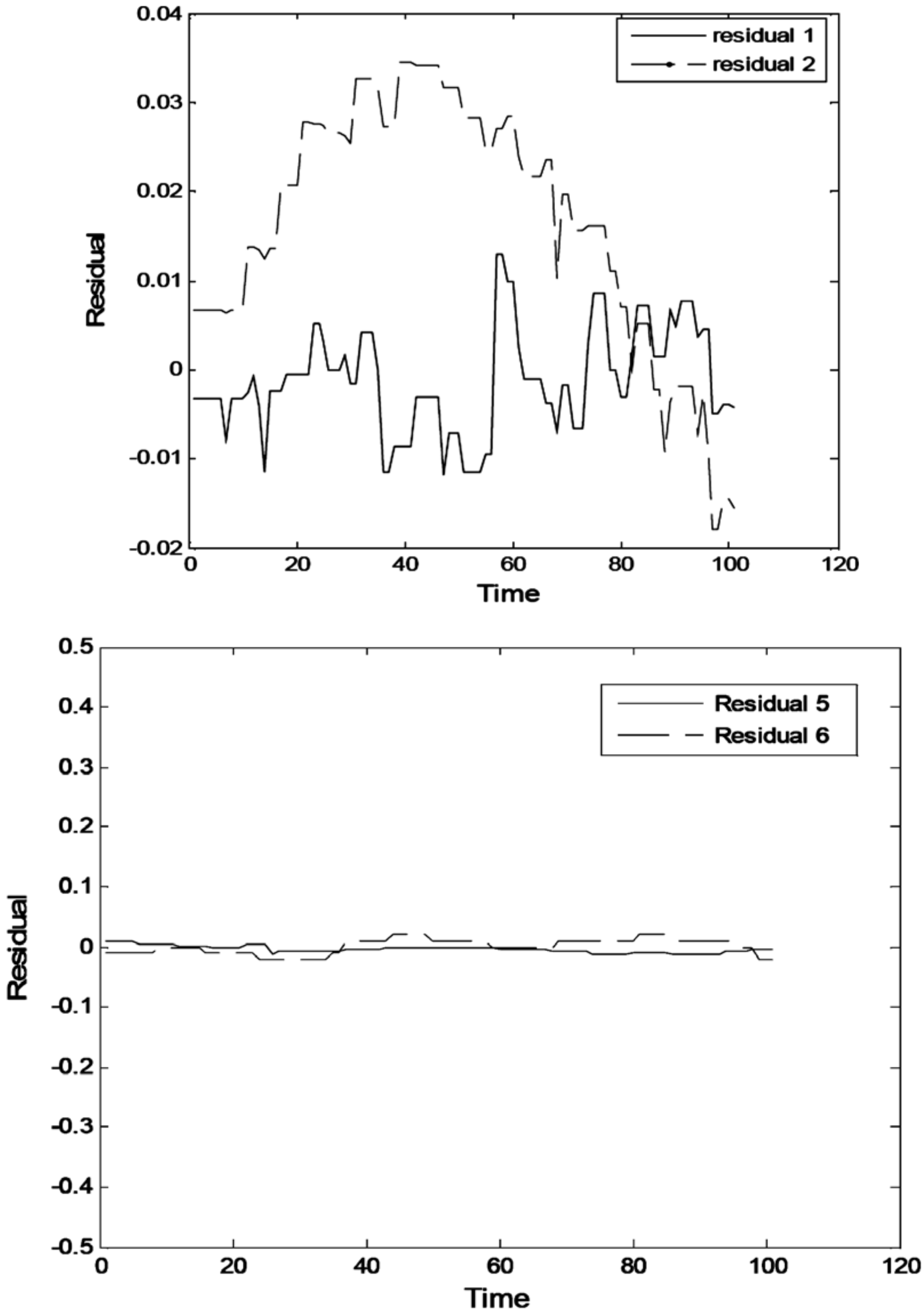


Figure 6: Residual of normal operation of combustion chamber and super heater.

The fault data for various faults like welding cracks, tube rupture, corrosion, erosion, external ash deposits and internal scale formation etc. are simulated using MATLAB/SIMULINK tool boxes. When the residual becomes more than 10% indicates starting of the faults and as it increases more, more will be the severity of the fault.

The residual for level-1 fault of combustion chamber, drum and tubes and super heater are shown in the figure 7. It is observed that more than 0.25 deviations in one of its residuals indicates fault of various kinds.

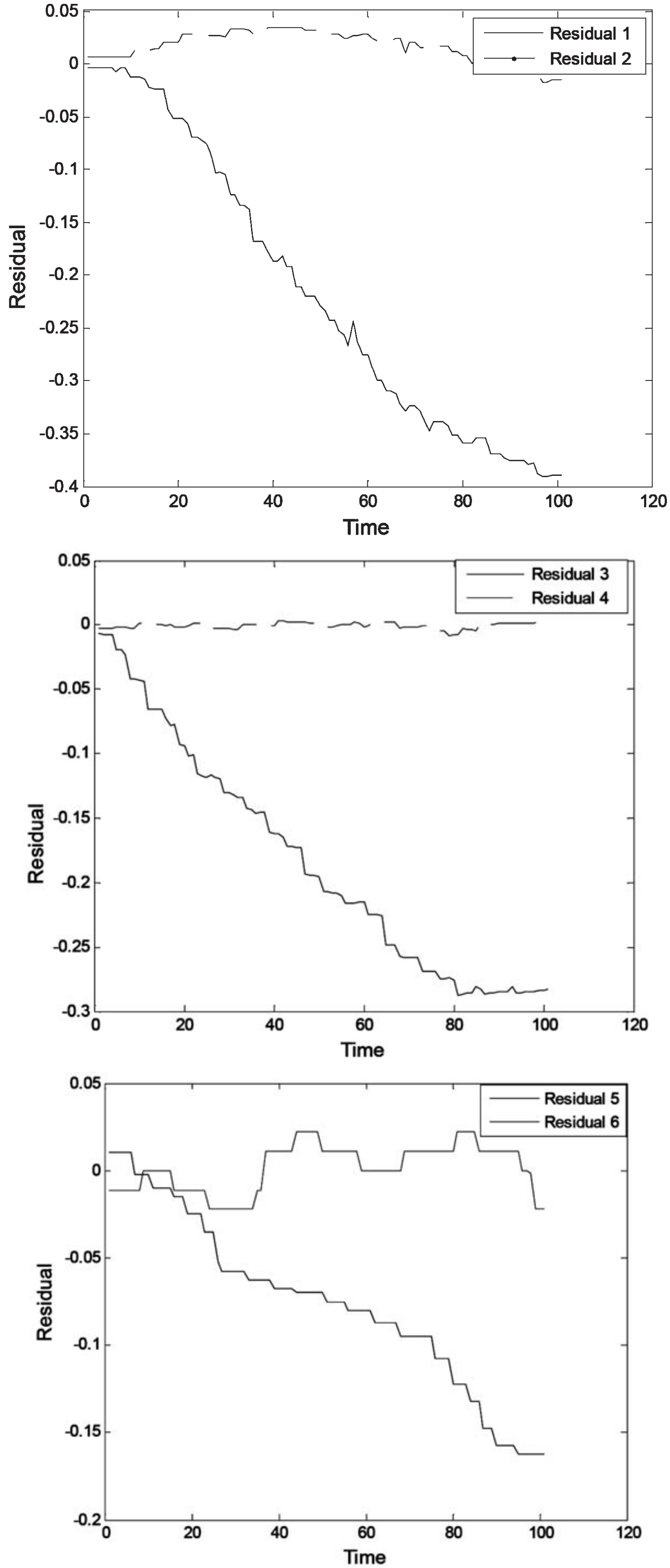


Figure 7: Residuals for level1 faults

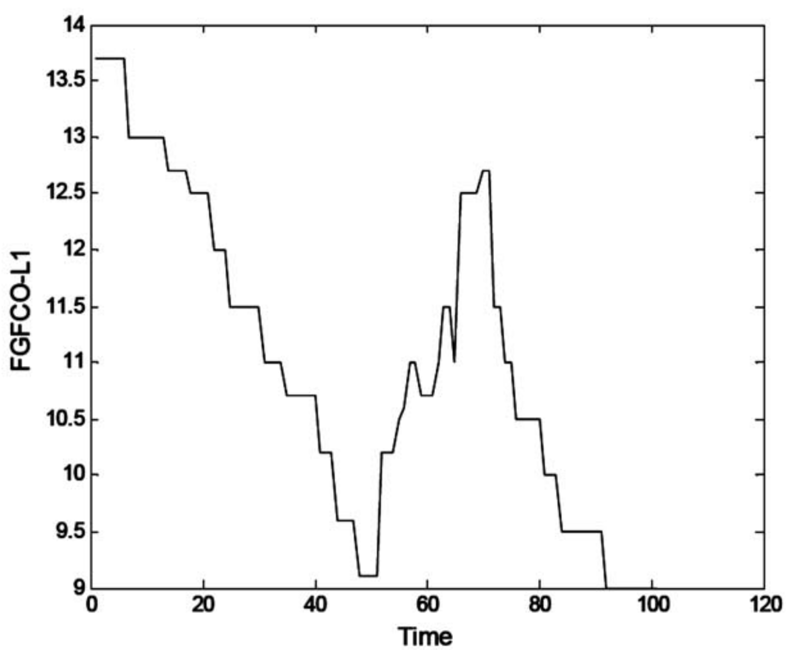
C. Fault Isolation

Fault isolation is identifying the nature of fault and locating it[14] appropriately. In our case faults are classified as level-1 and level-2 according to the severity. If the residual is ranging from 0.15 to 0.4 of normalized value indicates level-1 fault of less severity and residual ranging from 0.4 to 0.6 shows level-2 fault of more severity. The various types of boiler faults and their symptoms[16,29] are listed in the table 2.

Table 2
Nature of Faults for Various Ranges of Residuals

Boiler section	*Output*	*Resid-ual*	*-0.4 to -0.6*	*-0.16 to -0.4*	*-0.15 to +0.15*	*+0.16 to +0.4*	*+0.4 to +0.6*
Combustion Chamber	FGTCO	r1	Fuel feeder failure	Coke formation in burner	Normal operation	Fuel valve mal-function	ID/FD failure
	FGFCO	r2	ID/FD failure	ID/FD control problems	Normal operation	Fuel valve mal-function	ID/FD problem
Drum and Tubes	SSTDO	r3	Tube puncture	Gauge glass crack/ scale formation	Normal operation	Corrosion/erosion of tubes	Drop of load
	DLDO	r4	Feed water valve failure	Water tube cracks	Normal operation	Feed water valve malfunction	Drop of load
Super Heater	STSHO	r5	Improper com-bustion	Ash deposits in tubes	Normal operation	Corrosion/erosion of tubes	In adequate spray water
	SPSHO	r6	Firing system failure	Increase of load	Normal operation	Fuel value failure	Sudden Drop of load

The level-1 fault of residual ($r1$) and level-2 fault of residual ($r2$) of combustion chamber is shown in figure 8. The flue gas temperature has the smaller decrease in its value and correspondingly the residual decreases and fault severity shows more than 0.35. This level-2 failure of flue gas flow indicates failure of ID/FD system and coke formation of burner mention in the table 2. Failure of ID/FD system stops the draft system and flue gas flow reduces.



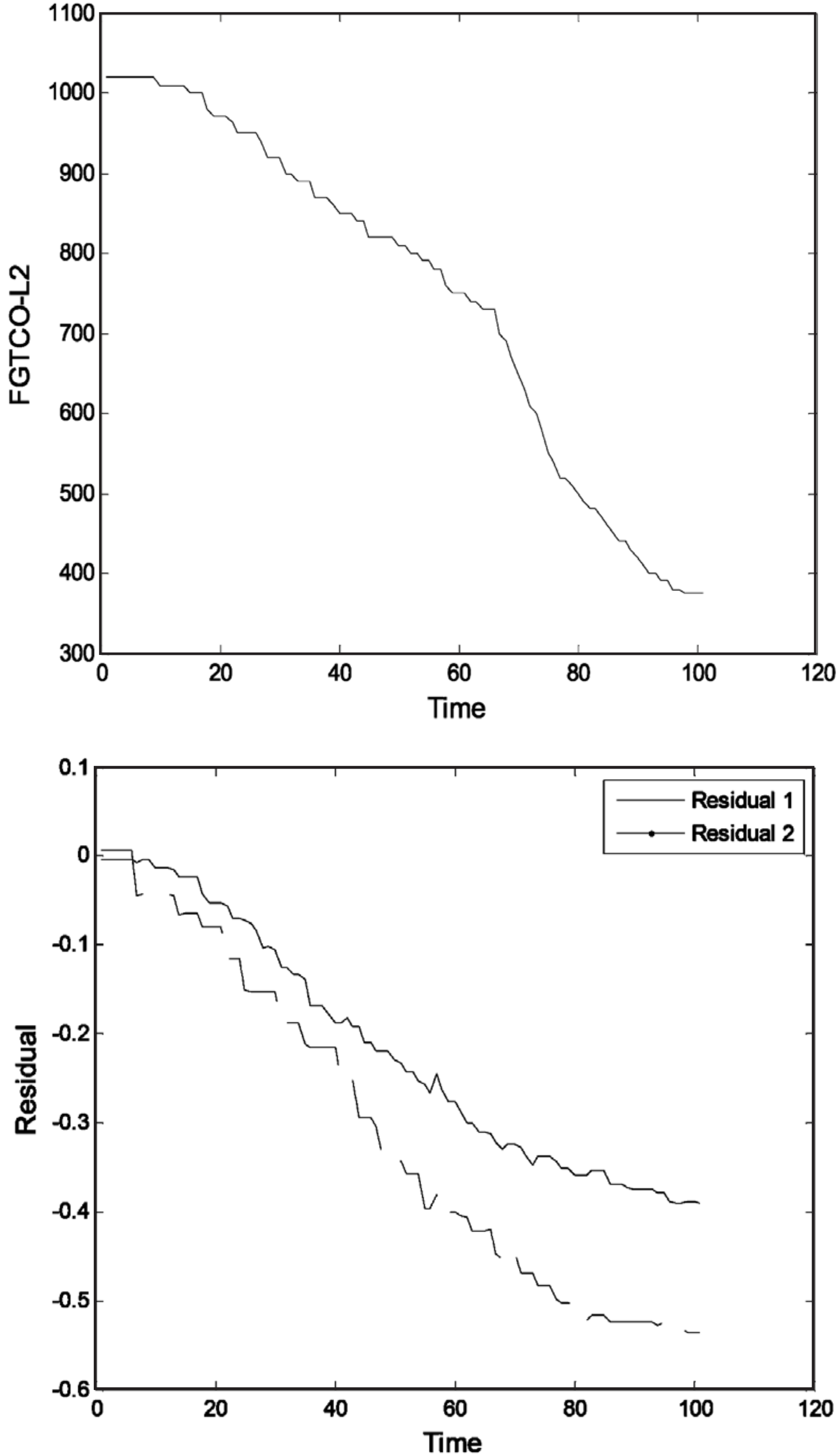


Figure 8: Level-1 and level-2 faults of FGTCO and FDFCO

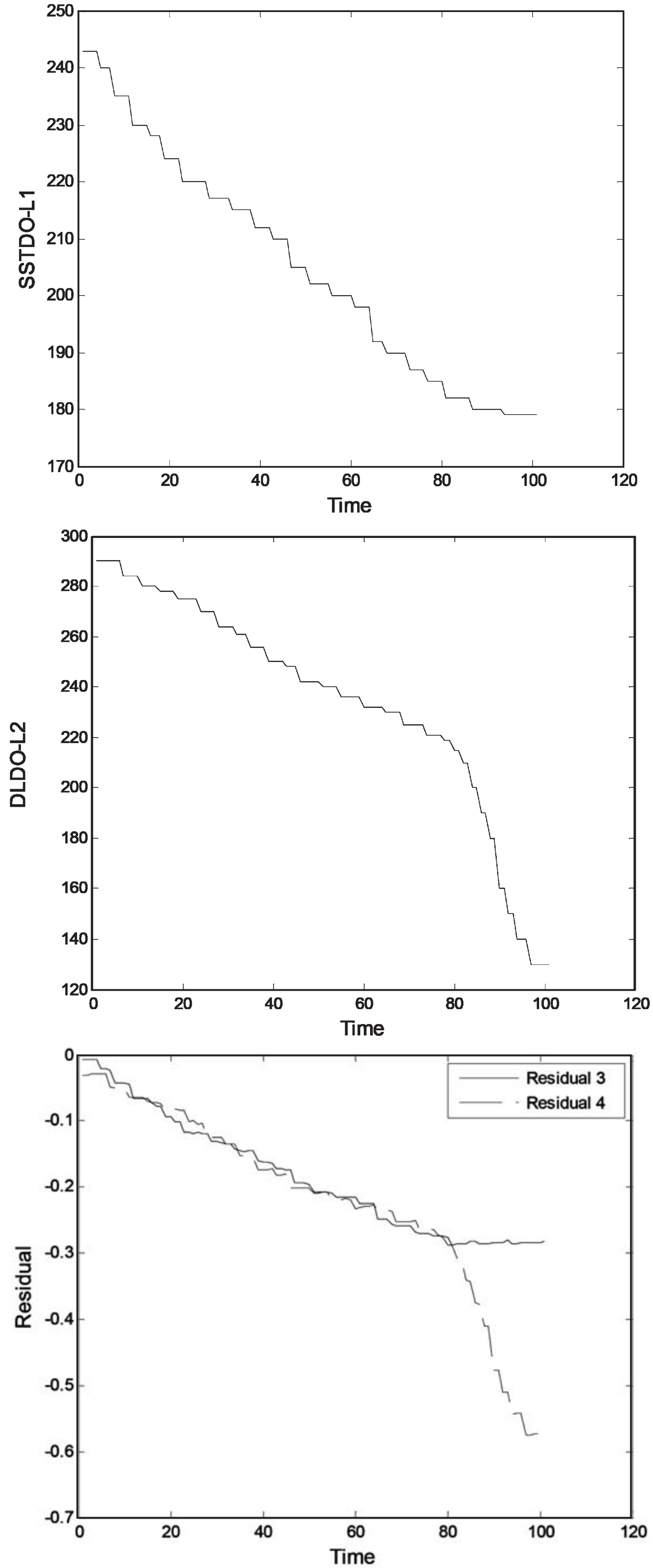


Figure 9: Level-1 and level-2 faults of SSTDO and DLDO

The 0.6 decrease in the drum level and 0.3 decrease in normalized residual of steam temperature shown in the figure 9 indicates feed water valve failure and scale formation of tubes.

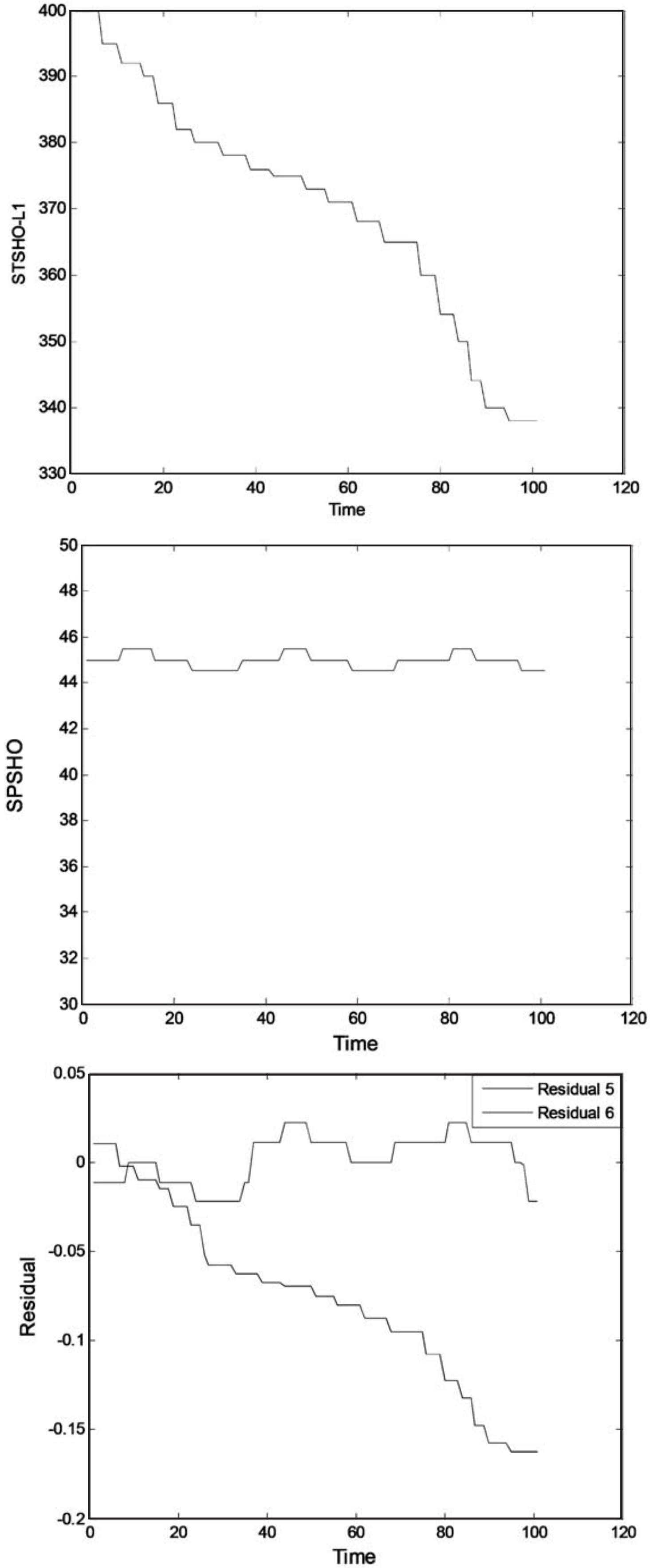
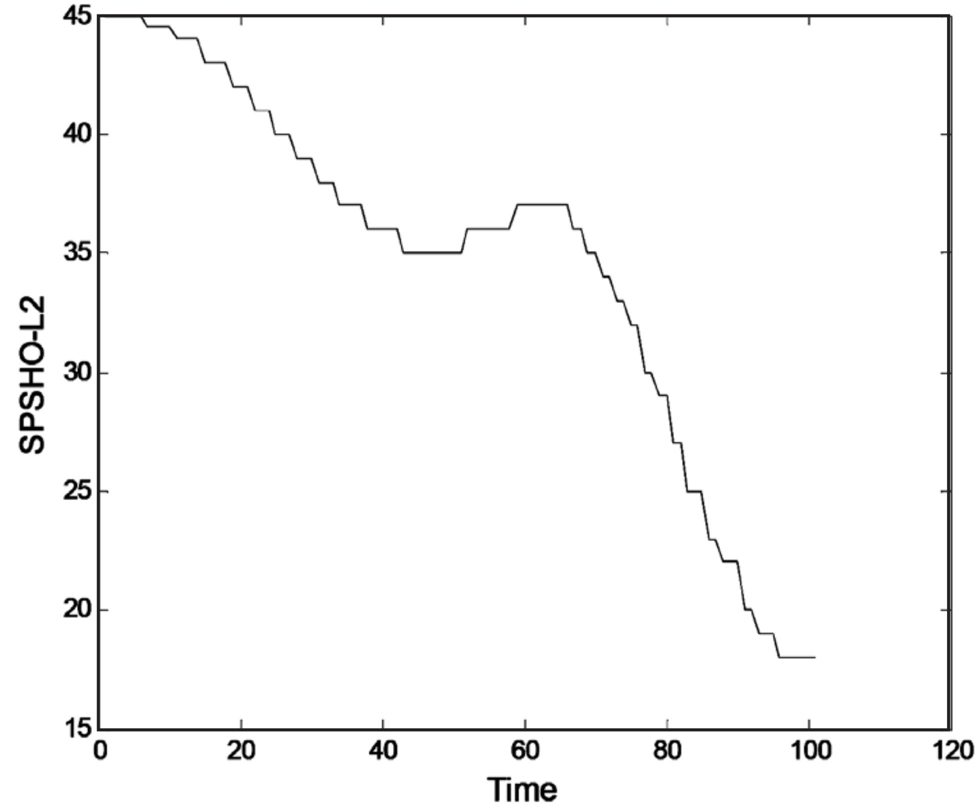
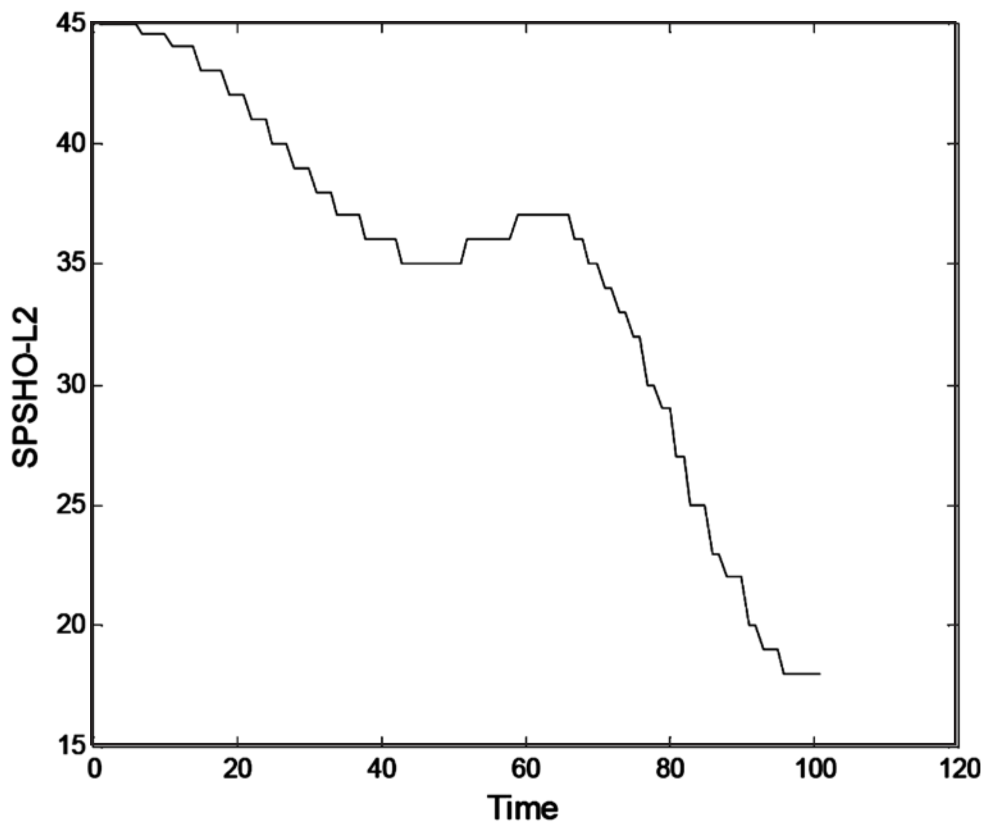


Figure 10: Level-1 faults of SSTDO and DLDO normal

The decrease in the superheated steam temperature and residual generated are shown in the figure 10. It was observed that for the level-1 faults like ash deposits in the tubes will decrease the residual of up to 0.3. In this case residual for drum level appears to be normal.





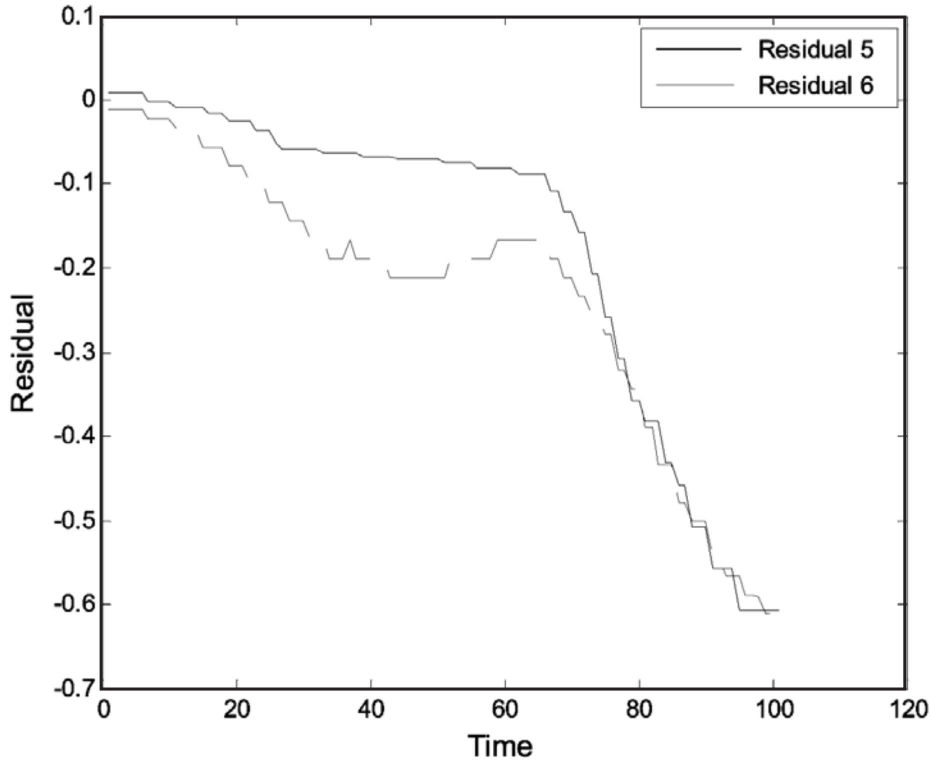


Figure 11: Level-2 fault of STSHO and SPSHO

The residual of variation for simulation of firing system failure are shown in the figure11. Both the steam temperature and pressure variation are at level-2. The corresponding residual reaches more than 0.5 of normalized value of residuals.

The MATLAB/SIMULINK diagram[6] used for all simulation is also given in figure 12.

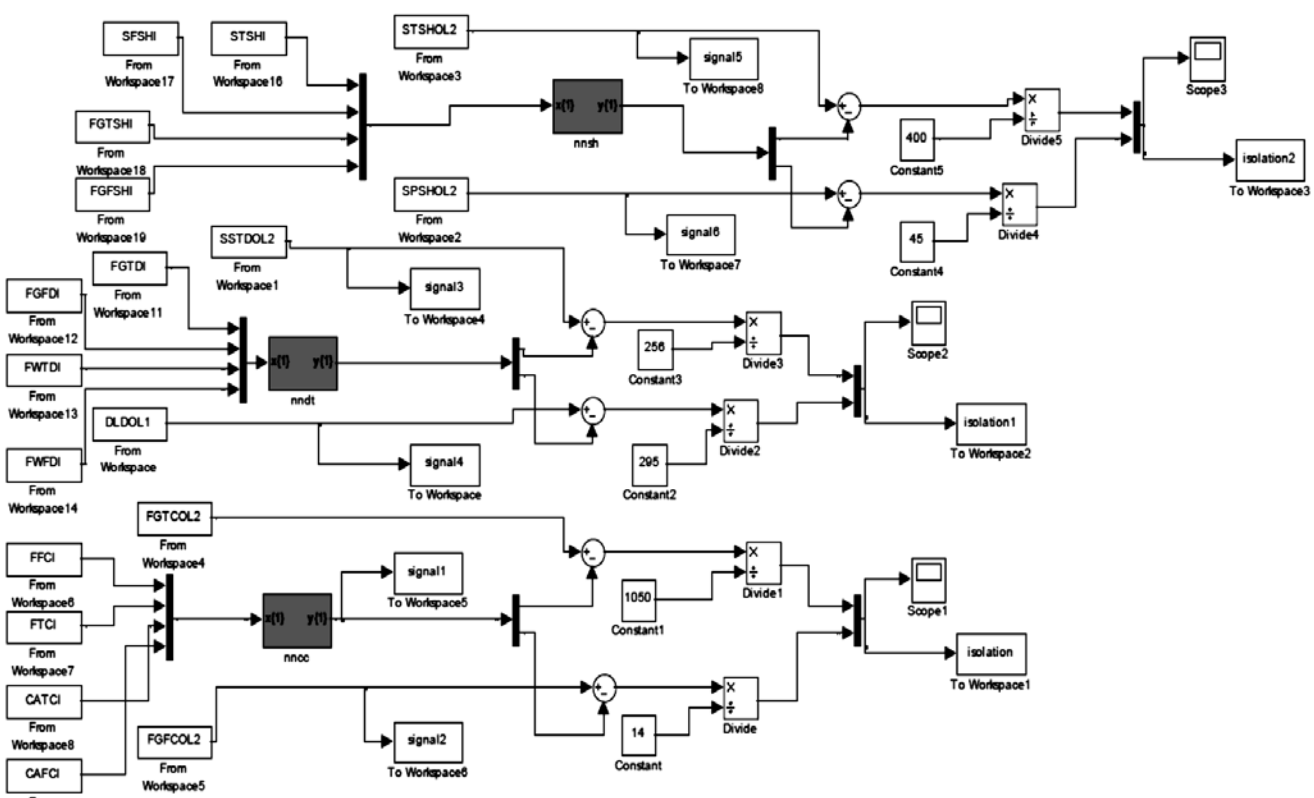


Figure 12: MATLAB/SIMULINK diagram

6. CONCLUSION

The goal of this FDI scheme is to give alarm in the times of faults even at level-1 or level-2 stage by generating normalized residuals and differentiating with threshold limits. This was simulated and obtained correct output for different cases of level-1 fault. In the same manner the faults are isolated based on severity of faults by expressing it in normalized values, and it is up to 0.4 for level-1 faults and up to 0.6 for level-2 faults at output. In this neural method of modeling simplifies difficulty of non-linear modeling, and the neural network is trained with real time data by modified back propagation algorithm to FDI robust to various disturbances and most appropriate model is obtained. The false alarm is also avoided by considering residual well above the threshold values which is calculated based on the variations of data that avoids error due to process noise, modeling error and uncertainties. The various faults of combustion chamber, drum and tube and super heater are simulated for level-1 and level-2 fault severity and this FDI method detects and isolates all such faults accurately within time bounds. The scheme was shown robust against these inherent variations of real time plant being used.

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