AUT JOURNAL OF MODELING AND SIMULATION

AUT Journal of Modeling and Simulation

AUT J. Model. Simul., 51(2) (2019) 83-90
DOI: 10.22060/miscj.2019.16453.5158

Robust Fault Detection on Boiler-turbine Unit Actuators Using Dynamic Neural Networks

A. Daneshnia[1,*], M.B. Menhaj[1], F. Barazandeh[2], and A. Kazemi[1]

[1] Department of Electrical Engineering, Amirkabir University of Technology, Tehran, Iran
[2] Department of Mechanical Engineering, Amirkabir University of Technology, Tehran, Iran

ABSTRACT: Due to the important role of the boiler-turbine units in industries and electricity generation, it is important to diagnose different types of faults in different parts of boiler-turbine system. Different parts of a boiler-turbine system like the sensor or actuator or plant can be affected by various types of faults. In this paper, the effects of the occurrence of faults on the actuators are investigated and analyzed and fault detection of boiler-turbine actuators is studied. For fault detection purpose, a dynamic neural network with an internal feedback is applied to generate the residual. After generating the residuals, the decision making step, as the most crucial part of the fault detection process, has to be followed. For designing a proper threshold, which is sensitive to different types of faults and insensitive to noise, the robust threshold is designed using the model error modeling method. The robust threshold is designed using a dynamic neural network with an internal feedback. The results for multiple types of faults and various outputs show the effectiveness of this approach for designing the threshold. As a practical case of study the dynamic model of the boiler-turbine unit, which was represented by Bell and Astrom in their paper, is considered.

Review History:

Received: 2019-06-18
Revised: 2019-07-23
Accepted: 2019-07-25
Available Online: 2019-12-01

Keywords:

boiler-turbine
actuator
neural network
model error modeling

I. Introduction

It is inevitable that the Boiler-turbine units are one of the most crucial part of power generation and like any other component in industries, their performance can be affected by various faults caused due to various reasons. A fault is any deviation of the system structure or parameters from the nominal one[1]. To decrease the damages in such systems, it is vital to detect fault as immediate and as accurate as possible. By comparing the actual behavior of the system and the expected one, the fault detection system can detect the occurrence of the fault in the system and generates an alarm[2]. Early fault detection can reduce the equipment loss, bad environmental impacts and costs. There are different types of fault which can occur on different components of the mentioned unit. Therefore, the false alarms in the detection process has to be decreased and the sensitivity of the fault diagnosis process to diverse types of faults has to be elevated.

During the past years, various researches have been done with the main focus on boiler fault diagnosis. For instance, in papers such as [3-5] fault detection of boiler fluid transmission line (such as leakage in boiler tube) is investigated. In [3] four-tube leakage fault diagnosis using threshold value principle has been presented. The fault law and the links between different types of faults can be shown using the proposed method of detection. Moreover, fuzzy neural networks have been applied to diagnose tube rupture fault [4]. In [5, 6] a model-based least-squares algorithm has been used in order to detect the leakage in boiler steam-water systems.

*Corresponding author's email: arash_daneshnia@yahoo.com

In [2] the fault diagnosis has been discussed on a real boiler master loop. The boiler has multi loops of which the most important one is the master loop. A state observer has been used to detect the faults in the boiler master loop. In [7] the robust fault detection filter (RFDF) design problem for linear time-invariant (LTI) system, which has been performed on boiler drum systems, is investigated. The robustness against disturbances and sensitivity to faults is achieved simultaneously using the residual model generator to formulate the robust fault detection filter as a robust H_∞ model matching problem.

In [8] the PCA method is applied to data extracted from a power plant drum-type boiler. To increase the performance of fault detection, the optimal number of PCs has been decided using the most valuable singular value method. Also using the H-index norm technique as one of the RFDF methods for fault detection on a real boiler is investigated. In this approach, a continuous H-index method is applied to a real boiler. To raise the high frequency response, a high pass filter is augmented[9].

In [10] data mining and neural networks approach are used to detect fault in a boiler burner system. The proposed method includes data mining, data preprocessing, learning and prediction processes by neural networks. In [11] the effects of faults on actuator is studied. A method based on analytical redundancy relations, which are generated using a bipartite graph, is applied to detect fault in actuators. Using structural

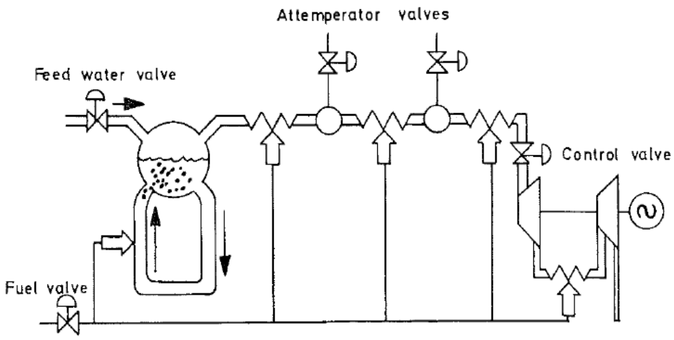

Fig. 1 . Schematic of a boiler-turbine unit [13]

analysis based on the elimination of the unmeasured variables of the system, the detection and isolation can be achieved.

The fault detection on the HP drum of the boiler is investigated. For this purpose, the boiler of the Kerman combined cycle power plant is used. The combination of SVM and Principle component analysis (PCA) is applied. Data is collected regarding the healthy and faulty conditions of the aforementioned boiler [12].

The modeling and fault detection of petrochemical boilers is also studied. To obtain the mathematical model, the data is collected from the real time operation of the boiler. The parameters are identified using the non-linear ARX and Hammerstein-Wienerand approaches. Detecting the fault has been done using the model based approaches like Kalman filter and by generating the residual, the occurrence of the fault is detected. Using this approach, all the process variables at the input side, output side and inside the boiler are estimated [13].

It is feasible for fault to happen in different parts of a system like actuators, sensors or components. In this paper, the fault detection of boiler-turbine actuators is discussed. Three fault scenarios are considered. 1) The actuators are stuck 2) Actuators are degraded and 3) Bias in the actuators.

The paper is organized as following. In section II the boiler-turbine unit model is presented. In section III the model equations are represented. In section IV the linearized model is obtained and in section V the controller has been designed using loop shaping H_∞ controller. The fault detection method using the dynamic neural network is discussed in section VI. For the purpose of designing the neural network the data is collected by Matlab Simulink. Also the method for designing the threshold is presented in this section. In section VII the results are presented. In section VIII some conclusions are presented.

The present paper, has been represented in the 4th International Conference on Control, Instrumentation, and Automation (ICCIA), 2016 and this paper is the extended version [14].

II. boiler-turbine model

In this section, the model for the boiler-turbine unit is represented. Two groups were struggling to develop the nonlinear dynamic model of the boiler-turbine unit during 1970s [15-18] :

1. The model which was developed by Astrom and Bell in 1979 to 1987

2. Morton-Price in 1971 to 1977

The same model as the one which was presented in [15-18] is considered in here. Fig. 1 shows a simple boiler-turbine structure. In the boiler-turbine configuration a single boiler is used to generate and feed the steam to the turbine [6]. The mentioned system has three actuators. One of the actuators is used to control the fuel flow rate, the other one is used to control the feed-water, and the third actuator is used for controlling the steam. The steam is produced due to the heated water in the drum. The control valve is used to control the resulted steam Fig. 1. Regulation of the temperature related to the steam is the role of the attemperator valve. The desired electrical power output is generated using the produced steam.

A thorough review can be found regarding the multiple approaches which have been used for designing the controller for boiler-turbine units [19]. As mentioned before, three outputs are considered in the system. Regarding the electrical output, the mentioned output must be able to meet the load demand. The necessity of keeping the water in the steam drum at a desired level is to prevent the overheating of the drum. Also the steam pressure has to be kept at a desired level to prevent overheating of the superheaters and prevents the wet steam from entering the turbine. Also the level of the air should be at desired level to make the mixture of the air and flow meet the standards for safety and environment [6].

In this paper in order to reach the desired performance of the model, a H_∞ robust controller has been used[20]. In this approach a loop shaping H_∞ controller is designed for nonlinear boiler-turbine system. The controller is reduced to a multivariable PID controller. Some of the advantages of such controller are disturbance rejection, good tracking and robustness against variations of the operation points. The more detailed information regarding the mentioned controller can be found in [20]. The outputs of the boiler-turbine system of Fig. 1 are drum pressure, power output and water level.

Parameters of this model were estimated using the data measured from the Synvendska Kraft AB Plant in Malmo, Sweden. The boiler is oil-dried and the rated power is 160MW [13].

III. Boiler-Turbine model equations

Bell-Astrom boiler-turbine model equations can be considered as follow [15-18]:

$$\begin{cases} \frac{dP}{dt} = -0.0018u_2P^{\frac{9}{8}} + 0.9u_1 - 0.15u_3 \\ \frac{dP_o}{dt} = (0.073u_2 - .016)P^{\frac{9}{8}} - 0.1P_o \\ \frac{d\rho_f}{dt} = \frac{\left(141u_3 - (1.1u_2 - 0.19)P\right)}{85} \\ y_1 = P \\ y_2 = P_o \\ y_3 = 0.5\left(.13073P + 100a_{cs} + q_e/9 - 67.975\right) \\ a_{cs} = \frac{\left(1-0.00153\rho_f\right)\left(0.8P-25.6\right)}{\rho_f\left(1.0394 - .0012304P\right)} \\ q_e = \left(0.854u_2 - 0.147\right)P + 45.59u_1 - 2.514u_3 - 2.096 \end{cases} \quad (1)$$

Where u_1, u_2, u_3 are valves position of fuel flow, steam control and feed-water flow, respectively. The state variable P is drum pressure (kg/cm^2), P_o is turbine electrical output (MW) and ρ_f is fluid density (kg/m^3). The output y_3 is drum water level (m) and a_{cs} and q_e are steam quality and evaporation rate (kg/s).

IV. Boiler-Turbine linearized model

The operating points of the Bell-Astrom model are as table I. The linearization has been done around the fourth operating point. The state space equations are as follow[20]:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) + Du(t) \end{cases} \quad (2)$$

Where

$$A = \begin{pmatrix} -0.0025 & 0 & 0 \\ 0.0694 & -0.1 & 0 \\ -0.0067 & 0 & 0 \end{pmatrix} \quad (3)$$

$$B = \begin{pmatrix} -0.9 & -0.349 & -0.15 \\ 0 & 14.155 & 0 \\ 0 & -1.398 & 1.659 \end{pmatrix} \quad (4)$$

$$C = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0.0063 & 0 & 0.0047 \end{pmatrix} \quad (5)$$

$$D = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0.253 & 0.512 & -0.014 \end{pmatrix} \quad (6)$$

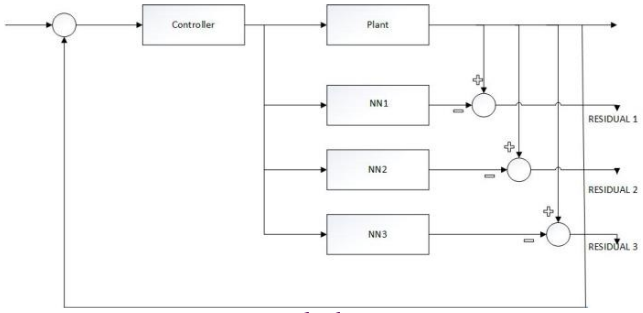

Fig. 2 . Residual generation

TABLE I.

	# 1	# 2	# 3	# 4	# 5	# 6	# 7
x_1^0	75.6	86.4	97.2	108	118.8	129.6	140.4
x_2^0	15.27	36.65	50.52	66.65	85.06	105.8	128.9
x_3^0	299.6	342.4	385.2	428	470.8	513.6	556.4
u_1^0	0.156	0.209	0.271	0.34	0.418	0.505	0.6
u_2^0	0.483	0.552	0.621	0.69	0.759	0.828	0.897
u_3^0	0.183	0.256	0.34	0.433	0.543	0.663	0.793
y_3^0	−0.97	−0.65	−0.32	0	0.32	0.64	0.98

V. Boiler-Turbine Controller

As mentioned in section II, a robust loop-shaping controller has been designed for Bell-Astrom model in [20]. The designed controller has good tracking and disturbance rejection properties and also robustness against variations of operation points due to plant nonlinearity[20].The simplified H_∞ multivariable controller is as follow:

$$K(s) = \begin{pmatrix} 0.0736 + \frac{0.0034}{s} & 0 & 0.9338 + \frac{0.0282}{s} \\ 0 & 0.0331 + \frac{0.0121}{s} & 0 \\ 0 & 0 & 5.6035 + \frac{0.1694}{s} \end{pmatrix} \quad (7)$$

VI. fault detection using dynamic neural network

The fault detection approach is discussed in this section. In Fig. 1 the fault detection scheme is illustrated. As was mentioned before, three types of faults are considered in here. Following equations are used to introduce the mentioned faults.

1) Actuators are stuck:

$$\begin{aligned} & u_f(t) = Tu + \alpha \\ & T = 0 \;\Rightarrow\; u_f(t) = \alpha \end{aligned} \quad (8)$$

2) Actuators are degraded:

$$\begin{aligned} & u_f(t) = Tu + \alpha \\ & \alpha = 0 \;\Rightarrow\; u_f(t) = Tu \end{aligned} \quad (9)$$

3) Actuators are biased:

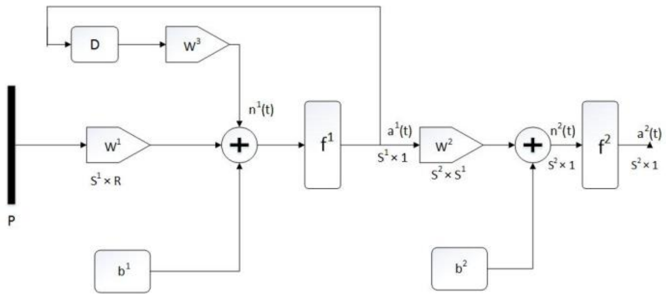

Fig. 3 .Dynamic neural network with internal feedback structure

$$u_f(t) = Tu + \alpha$$
$$T = 1 \;\Rightarrow\; u_f(t) = u + \alpha \tag{10}$$

Equations (8-10), u_f represents the output of the actuator and u is the input of the actuator and the signal which is generated by the controller. In healthy operation, $T = 1$

And $\alpha = 0$. When the occurred fault causes the actuators to get stuck, the u signal doesn't affect the system. Also for the actuator degradation fault scenario, the amount of T shows the fault severity and for the situation where a fault causes a bias in the actuator, T and α can have a specific value which shows the fault severity. For the values of T and α, no assumptions are considered. The control inputs are presented as follows due to the limitations of actuators [21].

$$\begin{gathered} 0 \le u_i \le 1 \\ -0.007 \le \dot{u}_1 \le 0.007 \\ -2 \le \dot{u}_2 \le 0.02 \\ -0.05 \le \dot{u}_3 \le 0.05 \end{gathered} \tag{11}$$

In order to escalate the performance of the fault diagnosis process, the calculations of accuracy, precision and fault detection time are as follows:

Accuracy:

$$\frac{t.n + t.p}{t.n + f.n + f.p + t.p} \tag{12}$$

Precision:

$$\frac{t.n}{t.n + f.n} \tag{13}$$

In the faulty mode, $t.n$ is the number of samples detected as faulty while $t.p$ is the number of samples detected as normal while the system is in healthy mode. On the other hand, $f.p$ is the number of samples which are considered as faulty during the healthy operation of system and $f.n$ is the number of samples detected as healthy when the system is operating in faulty mode.

A.NResidual Generation Using Dynamic Neural Networks

One of the most important phases in model-based fault detection approaches is residual generation. Dynamic neural networks can be used for proper generation of the residual. Artificial neural networks have been applied not only to nonlinear dynamic modeling but also for fault diagnosis. Because of the ability of the neural networks to learn and generalize the nonlinear relationship between input and output, they provide a

Great tool to detect fault in a system. For estimation of the process output in healthy situation, internal dynamic neural network is applied. For that purpose, three dynamic neural networks are used for the three outputs of the system. The structure of the dynamic neural network is shown in Fig. 3. The equations for input-output of the dynamic neural network can be represented as follows:

$$\underline{a}^1(t) = f^1(W^1\underline{P}(t) + \underline{b}^1 + W^3\underline{a}^1(t-1)) \tag{14}$$

$$\underline{a}^2(t) = f^2(\underline{n}^2(t)) \tag{15}$$

$$\underline{n}^2(t) = W^2\underline{a}^1(t) + \underline{b}^2 \tag{16}$$

$$\underline{a}^2(t) = f^2(W^2\underline{a}^1(t) + \underline{b}^2) \tag{17}$$

where $\underline{a}^1(t)$ is the output of the first layer, $\underline{a}^2(t)$ is the output of the second layer, f^1 is the activation function of the first layer, f^2 is the activation function of the second layer and W^1, W^2 are the weight matrices of the first and second layer and W^3 is the weight matrix of the feedback layer. For the weight matrices and bias vectors adjustment purpose, back propagation through time algorithm is applied. Equations (14-17) can be achieved considering the structure of the neural network which is depicted in Fig 3. By designing the dynamic neural network, the residual generation process can be shown as Fig 2.It is possible to assume two situations in here. The first assumption can happen in normal operation when the output of the neural network and the output of the process are nearly the same. As a result, the residual in normal operation is approximately equal to zero. Due to the fault occurrence, the output of the process differs from the neural network output. Consequently, the generated residual diverges from zero. Proper designation of threshold, which is presented in the next section, is essential for fault occurrence detection in the process.

B. Designing the Threshold Using Model Error Modeling Approach

Different approaches, such as the simple threshold designing techniques like ξ-standard deviation or robust fault diagnosis approaches, for designation of the proper threshold for decision making purpose are available. One of the main problems of using the simple threshold designing methods is that because of the modeling uncertainty and measurement noise, it is necessary to assign a value greater than zero to reduce the false alarms. This kind of assignment may result in reduction in fault sensitivity. In order to achieve the robustness in fault detection one can use active or passive approaches [22]. In passive approaches, the robustness is achieved through designing the adaptive thresholds. Different types of threshold designing approaches, such as adaptive thresholds, fuzzy adaptation thresholds and model error modeling method, can be used to diagnose fault robustly. Avoiding the fast adaptation to the residual changes can be done using the momentum parameter in adaptive threshold designing method in which the proper selection of the momentum term can be challenging[22]. In [23] the application of model error modeling approach on a gas turbine model is presented. For constructing the error model the local linear neuro-fuzzy model is presented. For training of the model, LOLIMOT algorithm has been used[23].

One of the most important characteristics that should be considered for fault diagnosis approaches is the ability to detect the occurrence of incipient faults as well as abrupt faults in the system. In other words the proposed approach must be able to detect the faults which are slowly changing the system behavior during time[23].

As mentioned before, simple threshold designing approaches can be used to evaluate the generated residual. The threshold constant can be determined using the following equations[22]:

$$T = t_\beta \upsilon + m \tag{18}$$

In which m is the mean value and υ is the standard deviation value of the residual.

In ξ-standard deviation method, the upper bound and lower bound constants can be calculated as follow[22]:

$$T = m \pm \xi \upsilon \tag{19}$$

In which m is the mean value and υ is the standard deviation value of the residual. Also ξ can be 1, 2 or 3. Considering the value 1 for the ξ parameter, the rate of false alarm increases but the detection time decreases as well. By choosing the value 3 for the ξ parameter, the false alarm rate decreases but the sensitivity to detect the faults decreases as well and the detection time increases too.

By comparison between the actual process output and the model output, which has been generated by the neural network, the residual signals are created. In healthy operation, due to the existence of the noise, disturbances or uncertainties, the residual usually is not equal to zero. As a result, there is a trade-off between the rate of the false alarms and fault detection time. The decision making step is done as follow

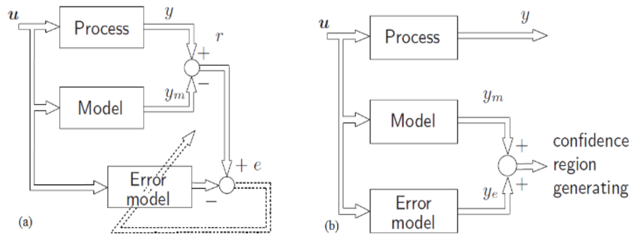

Fig. 4 .(a) Training process of the error model. (b) Generating the confidence region[22]

$$s(r) = \begin{Bmatrix} 0 \text{ if } |r(k)| \le T \\ 1 \text{ if } |r(k)| > T \end{Bmatrix} \tag{20}$$

In this approach, the main idea is to model the error of the modeling and use it in a way to generate the proper threshold.

After obtaining the proper model of the process, the error model can be designed using the data collected from the difference between the process output and the model output.

The identification of residuals provides the so-called model error model. The designing process of the robust threshold is done after the designation of the model error model and applying the (21) and (22), [22].

The center of the uncertainty region is defined as $y_c \approx y_m + y_e$ after the generation of the residual using dynamic neural network, where y_m is the output of nominal model of the process and y_e is the output of the error model. Afterwards, the upper bound and the lower bound can be calculated as follow:

$$T_u = y_m + y_e + t_\beta \upsilon \tag{21}$$

$$T_l = y_m + y_e - t_\beta \upsilon \tag{22}$$

Where υ is the standard deviation of y_e and t_β is decided by the value of the significance level β. The values of t_β are tabulated in statistical books. Dynamic neural networks can be applied for the model error modeling [22]. Designing procedure of an error model is described in the net section.

C. Designing the Error Model Using Dynamic Neural Network

Dynamic neural network with internal feedback is used with the purpose of designing the error model and calculating the y_e in (21) and (22). Fig. 4 shows the entire designing procedure. In Fig. 4 (a) the input of the error model is the input of the process which is u . The parameters of the neural networks are modified using the difference between the actual value of the residual and the output of the neural network. The completed training is achieved when the modeling error approaches to zero. Following the training phase, the error model is applied in the same way as it is illustrated in Fig. 4 (b), and the uncertainty region center y_c , is obtained in this phase. Then by using the (21) and (22), the designing procedure of the threshold is completed. The structure of the dynamic neural network is the same as the one represented in the section III.

VII. Results

Considering the mentioned points in sections VI, for detection of different actuator faults, dynamic neural networks are trained as follow:

1) Three dynamic neural networks are trained to generate the residual.

2) Three dynamic neural networks are trained to generate the error model.

For generating the residual, dynamic neural networks with one hidden layer and 15 neurons are considered. Generation of the error model can be done using a dynamic neural network with one hidden layer and 10 neurons. After generating the residual, the model error modeling stage is considered. As mentioned in section VI, to generate the error model, every neural network has three inputs. The differences between the residual and the output of the neural networks are used to modify and adjust the parameters of each neural network. After the training phase, different types of faults are considered in the system. For each fault scenario following assumptions are considered:

1) For each of the actuators, faults are occurred at 300 second.

2) There are no limitations for severity of faults, except for the actuators physical limitations.

3) After training the neural networks and obtaining the error model for each of the actuators, the rest of the process will be done in online mode.

Actuators are stuck: for this scenario, the (8) is considered. In this situation, the output of the actuator and input of the plant will be a constant value. Fig.5 to Fig.7 show the results for drum pressure, power output and drum level for this fault scenario. As mentioned before, the fault occurs at t=300. Fig. 5 shows the effect of the first actuator fault on the first output. Fig. 6 shows the effect of the second actuator fault on the second output and Fig. 7 represents the effect of the third actuator fault on the third output. By using the model error modeling method in section VI, the following Figures are achieved. The red bounds on each Figure, show the result of using the model error modeling approach to design the adaptive threshold. The results show the effectiveness of the model error modeling approach for designing the threshold. Because of the difference between the actual process inputs and error model inputs, the confidence bound cannot follow the changes after the occurrence of the fault in the system.

Actuators are degreded: for this scenario, the (9) is considered. In this situation, as mentioned before, the controller signal will be multiplied by a constant value which shows the severity of the fault. Fig.8 to Fig.10 show the results for drum pressure, power output and drum level for this fault scenario. As mentioned before, the fault occurs at t=300. Fig. 8 shows the effect of the first actuator fault on the first output. Fig. 9 shows the effect of the second actuator fault on the second output and Fig. 10 represents the effect of the third actuator fault on the third output.

Bias in the actuators: For the third fault scenario, the same situation is assumed. For this scenario, the (10) is considered. As one can see in the mentioned equation, the multiplicative value is equal to 1. Fig.11 to Fig.13 show the results for drum pressure, power output and drum level for this fault scenario. The fault occurs at t=300. Fig. 11 shows the effect of the first actuator fault on the first output. Fig. 12 represents the effect

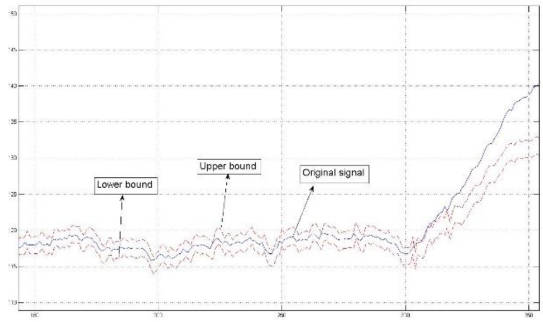

Fig. 5 .Fault 1 drum pressure output

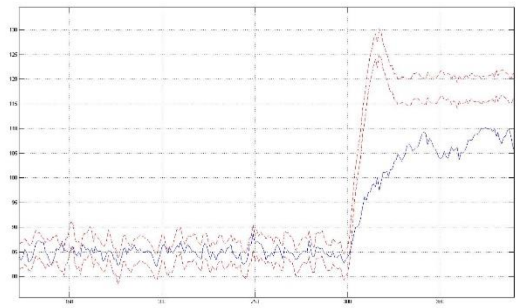

Fig. 6 .Fault 1 power output

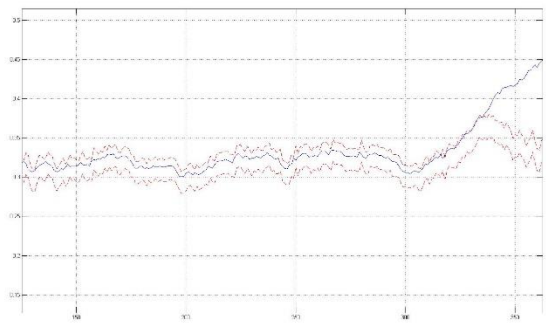

Fig. 7 .Fault 1 water level output

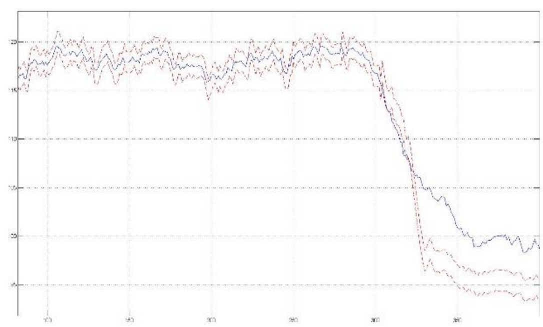

Fig. 8 .Fault 2 drum pressure output

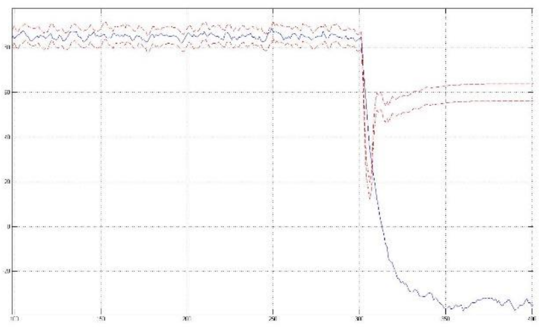

Fig. 9 .Fault 2 power output

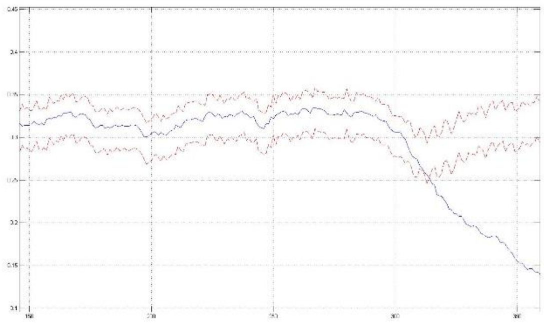

Fig. 10 .Fault 2 water level output

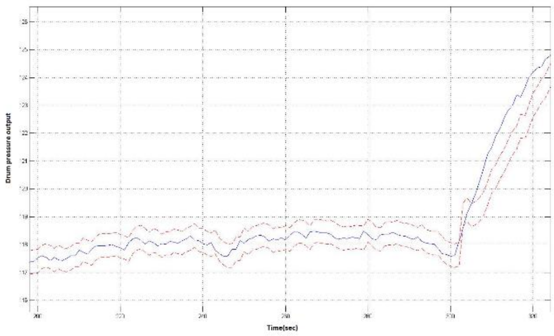

Fig. 11 .Fault 3 drum pressure output

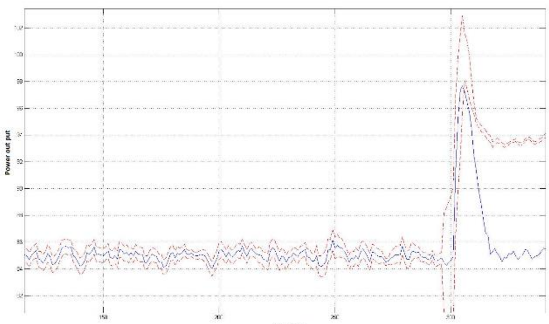

Fig. 12 .Fault 3 power output

of the second actuator fault on the second output and Fig. 13 shows the effect of the third actuator fault on the third output

Results show the effectiveness of the approach for all

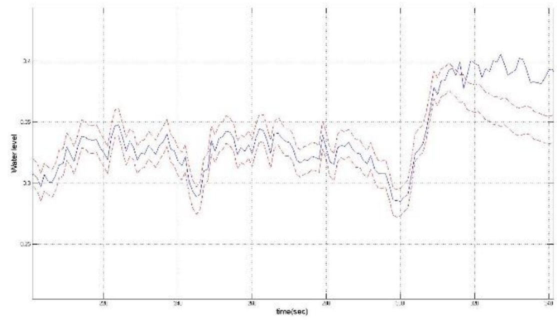

Fig. 13 .Fault 3 water level output

TABLE II.

F1	Fault1		
	Detection time	*Accuracy*	*Precision*
[a]Act1	[b]6s	99%	97.5%
[c]Act2	[d]2s	97%	99%
[e]Act3	[f]34s	93%	87.5%

TABLE III.

F2	Fault2		
	Detection time	*Accuracy*	*Precision*
[g]Act1	[h]10s	98.25%	97%
[i]Act2	[j]4s	100%	99.5%
[k]Act3	[l]13s	97%	95.5%

TABLE IV.

F2	Fault3		
	Detection time	*Accuracy*	*Precision*
[m]Act1	[n]5s	95.14%	91%
[o]Act2	[p]4s	100%	99.5%
[q]Act3	[r]15s	98%	95%

three types of fault scenarios. To evaluate the effectivness of the proposed methods, the accuracy and precision values are calculated and presented in tables II, III and IV. Also the detection time, which is an important factor in fault detection process, is calculated. In other words, the ability of the proposed approach to detect the fault in the shortest time is depicted in the mentioned tables. Also the false alarm rate can be found out from the values of the accuracy and precision in tables II and III and IV.

In tables II - IV, the values of the accuracy and precision and the detection time are shown. As one can see, for the first and second actuators, shorter time period is needed to detect the fault, but longer detection time for the third output is needed because of the gradual changes in the water level of the drum in presence of the third actuator fault. For all of the actuators, the high values of accuracy and precision show the minimum rate of false alarms. One of the other advantages of the model error modeling is the ability to detect faults which cause gradual changes in the output values.

VIII. Conclusions

In this paper the robust fault detection of boiler-turbine actuators was presented. The boiler-turbine model which was used in this paper, was the model represented by Bell-Astrom. The model was obtained from the real boiler-turbine in Malmo Sweden. Moreover, to reach the desired performance of the system, a H_∞ robust controller was used. Drum pressure, electrical output and water level are controlled by changing the position of fuel valve, steam valve and the feed-water valve. Three scenarios were considered for the occurrences of the faults. The first scenario was that the actuators get stuck. The second scenario was the Actuator degradation, and the third one was to consider bias in the actuators. For detecting the actuator fault, internal dynamic neural networks were used. For robust fault detection purpose, the threshold was designed using model error modeling approach. In order to generate the error model, three dynamic neural networks with internal feedback were used. For investigating the performance of proposed approach, precision, accuracy and the detection time of the system were calculated. Reducing the false alarms rate and increasing the sensitivity of the fault diagnosis approach to different types of fault are the most important properties of the fault diagnosis approach.

References

[1] M. Blanke, M. Kinnaert, J. Lunze, M. Staroswiecki, and J. Schrder, *Diagnosis and fault-tolerant control*: Springer Publishing Company, Incorporated, 2010.

[2] M. Addel-Geliel, S. Zakzouk, and M. El Sengaby, "Application of model based fault detection for an industrial boiler," in *Control & Automation (MED), 2012 20th Mediterranean Conference on*, 2012, pp. 98-103.

[3] G. Jianqiang, Y. Xianglei, and H. Zhifu, "Research on fuzzy recognition method of boiler four-tube leakage," in *Intelligent Control and Information Processing (ICICIP), 2011 2nd International Conference on*, 2011, pp. 391-393.

[4] X. Min, W. Ying, and L. Yanjun, "Notice of Retraction Fault diagnosis of marine boiler superheater tube rupture based on fuzzy neural network," in *Power Engineering and Automation Conference (PEAM), 2011 IEEE*, 2011, pp. 389-392.

[5] X. Sun, T. Chen, and H. J. Marquez, "Efficient model-based leak detection in boiler steam-water systems," *Computers & chemical engineering*, vol. 26, pp. 1643-1647, 2002.

[6] W. Tan, F. Fang, L. Tian, C. Fu, and J. Liu, "Linear control of a boiler–turbine unit: Analysis and design," *ISA transactions*, vol. 47, pp. 189-197, 2008.

[7] L. Khoshnevisan, H.-R. Momeni, and A. Ashraf-Modarres, "H∞ robust fault detection filter in drum boiler systems," in *GCC Conference and Exhibition (GCC), 2011 IEEE*, 2011, pp. 577-580.

[8] A. Ghamari, H. Khaloozadeh, A. Ashraf-Modarres, and H. Ghamari, "Application of quantitative data-based fault detection methods on a drum-type boiler," in *The 3rd Conference on Thermal Power Plants*, 2011.

[9] L. Khoshnevisan, S. Ozgoli, and M. H. Shojaei, "An ILMI approach to robust fault detection filter for a drum boiler system through a time-domain H-index norm method," in *Electrical Engineering (ICEE), 2012 20th Iranian Conference on*, 2012, pp. 922-927.

[10] E. Rakhshani, I. Sariri, and K. Rouzbehi, "Application of data mining on fault detection and prediction in Boiler of power plant using artificial neural network," in *Power Engineering, Energy and Electrical Drives, 2009. POWERENG'09. International Conference on*, 2009, pp. 473-478.

[11] A. Aitouche and B. Ould Bouamama, "Detecting and isolating actuators faults of steam boiler," in *8th International Conference on Sciences and Techniques of Automatic control, Sousse, Tunisia*, 2007, pp. 5-7.

[12] M. Berahman, A. Safavi, and M. R. Shahrbabaki, "Fault detection in Kerman combined cycle power plant boilers by means of support vector machine classifier algorithms and PCA," in *Control, Instrumentation, and Automation (ICCIA), 2013 3rd International Conference on*, 2013, pp. 290-295.

[13] N. P. David and B. Swaminathan, "Modeling, identification and detection of faults in industrial boiler (July2015)," in *Technological Innovation in ICT for Agriculture and Rural Development (TIAR), 2015 IEEE*, 2015, pp. 197-201.

[14] A. Daneshnia, M. B. Menhaj, F. Barazandeh, and A. Kazemi, "Robust fault detection on boiler-turbine unit actuators using dynamic neural networks," in *2016 4th International Conference on Control, Instrumentation, and Automation (ICCIA)*, 2016, pp. 251-255.

[15] K. Astrom, "Simplified Models of Boiler—Turbine Units," 1987.

[16] K. Astrom and K. Eklund, "A simple non-linear drum boiler model," *International Journal of Control*, vol. 22, pp. 739-740, 1975.

[17] K. J. Åström and K. Eklund, "A simplified non-linear model of a drum boiler-turbine unit†," *International Journal of Control*, vol. 16, pp. 145-169, 1972.

[18] R. Bell and K. J. Åström, *Dynamic models for boiler-turbine-alternator units: data logs and parameter estimation for a 160 MW unit*: Lund Institute of Technology, Department of Automatic Control, 1987.

[19] H. Moradi, A. Alasty, M. Saffar-Avval, and F. Bakhtiari-Nejad, "Multivariable control of an industrial boiler-turbine unit with nonlinear model: A comparison between gain scheduling and feedback linearization approaches," *Scientia Iranica. Transaction B, Mechanical Engineering*, vol. 20, p. 1485, 2013.

[20] W. Tan, Y. Niu, and J. Liu, "H∞ control for a boiler-turbine unit," in *Control Applications, 1999. Proceedings of the 1999 IEEE International Conference on*, 1999, pp. 910-914.

[21] K. J. Åström and R. Bell, "Dynamic models for boiler-turbine alternator units: Data logs and parameter estimation for a 160 MW unit," *Technical Reports*, 1987.

[22] K. Patan, *Artificial neural networks for the modelling and fault diagnosis of technical processes* vol. 377: Springer Science & Business Media, 2008.

[23] H. A. Nozari, M. A. Shoorehdeli, and M. Mokhtareh, "Robust Fault Detection of an Industrial Gas Turbine Prototype: A Hybrid Passive Approach Based on Local Linear Neuro-Fuzzy Techniques."

HOW TO CITE THIS ARTICLE

A. Daneshnia, M.B. Menhaj, F. Barazandeh, A. Kazemi, Robust Fault Detection on Boiler-turbine Unit Actuators Using Dynamic Neural Networks, AUT J. Model. Simul., 51(2) (2019) 83-90.

DOI: 10.22060/miscj.2019.16453.5158