Identification and Robust Fault Detection of Industrial Gas Turbine Prototype Using LLNF Model

Leila Shahmohamadi[a,*], Mahdi AliyariShoorehdeli[b], Sharareh Talaie[a]

[a]*Department of Electrical Engineering, Islamic Azad University, South Tehran Branch Tehran, Iran*
[b]*Faculty of Electrical Engineering, K. N. Toosi University of Technology Tehran, Iran*

Abstract

In this study, detection and identification of common faults in industrial gas turbines is investigated. We propose a model-based robust fault detection(FD) method based on multiple models. For residual generation a bank of Local Linear Neuro-Fuzzy (LLNF) models is used. Moreover, in fault detection step, a passive approach based on adaptive threshold is employed. To achieve this purpose, the adaptive threshold band is made by a sliding window technique to make decision whether a fault occurred or not. In order to show the effectiveness of proposed FD method, it is used to identify a simulated single-shaft industrial gas turbine prototype model, which works in various operation points. This model is a reference simulation which is used in many similar researches with the aim of fault detection in gas turbines.

Keywords: Adaptive Threshold, LLNF Model, Multiple Model, Residual, Robust Fault Detection.

1. Introduction

Each industrial process is designed to produce a specified suitable output or to perform an expected operation. However, it is not possible to achieve an ideal behavior of the system in all stages of operations. Unusual factors in system performance cause declines in the ability of the components and the cause of these factors is called “Fault” and detection and identification of that is so important in systems because it may lead to system “Failure” [1]. Various methods and algorithms are presented to detect faults in different systems whose aim is advanced supervision, fault management, improved reliability, availability and optimized maintenance. In [2], a review of existing methods in fault detection and identification is presented. The model-based fault detection and identification methods consist of two main steps [3]: In the first step, one or several signals are generated, called residual, in order to characterize each fault and then the residual is evaluated in the second step as when the fault occurred, the time and the place of occurrence is detected. Fault detection is converted into two main groups of quantity and quality and each one is available to be considered with different methods [4]. In [5] parity space method, in [6] factorization method, in [7] state estimator method, in [8] parameter identify method and in [9] fault detection filter are presented. A general scheme of fault detection and isolation is shown in Fig.1 In this work, the proposed fault detection (FD) method is validated with industrial gas turbine prototype model developed at ABB–ALSTOM power, the United Kingdom.

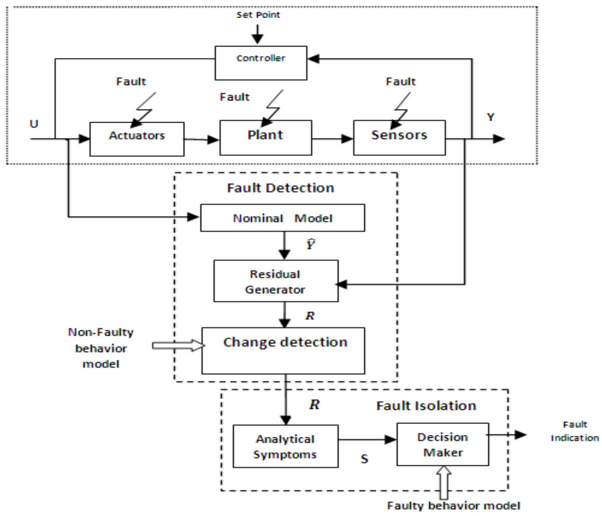

Fig. 1. General scheme of fault detection and isolation [10]

The study is organized as follows: in section 2, industrial gas turbine prototype model described; in section 3, with

* Corresponding author. Email: Leila.shahmohamadi1@gmail.com

LLNF models trained by LOLIMOT algorithm, models for normal and faulty situation of gas turbine are designed and residuals generated; in section 4, detection fault is discussed; and in section 5, simulation results are discussed and conclusions follow.

2. System Description

A gas turbine essentially brings together air that it compresses in its compressor module, and fuel, which are then ignited. Resulting gases are expended through a turbine. That turbine's shaft continues to rotate and drive the compressor which is on the same shaft, and operation continues.

For simulation purposes, SIMULINK prototype model of such an industrial gas turbine developed at ABB – ALSTOM power, United Kingdom, was used. A scheme diagram for a simple-cycle gas turbine, for power generation, is shown in Fig. 2. Four fault situations were designed in this prototype model where the faul f_1 represents the compressor contamination fault (component fault), the fault f_2 represents the thermocouple sensor fault (output sensor fault), the fault f_3 represents the high pressure turbine seal damage (component fault), and the fault f_4 represents the fuel actuator friction wear (actuator fault) [10]. The model has two inputs and 28 output measurements which among 28 output measurements, four of them have been shown to be fault sensitive [11]. Valve angle (a_v) and fuel flow (ff)are the input measurements and four measurements called compressor torque (Q_{OC}), compressor outlet temperature (T_{OC}), combustion chamber outlet pressure (P_{IC}) are the considered output measurements used during the fault detection procedure [10].

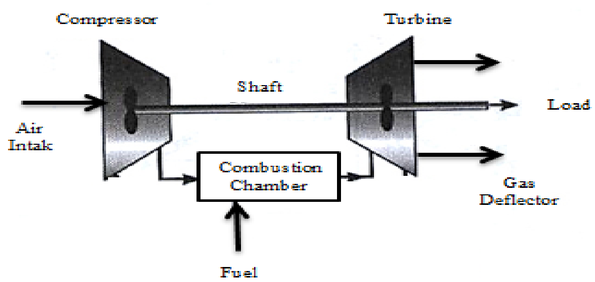

Fig. 2. The simple-cycle gas turbine block diagram [7]

3. Proposed Fault Detection Method

The proposed fault detection scheme is shown in "Fig. 3" and split into two parts: neural network based multiple model residual and adaptive threshold generation, and decision making for residual evaluation.

Locally Linear Neuro-Fuzzy (LLNF) network is used to identify the normal and faulty condition of gas turbine and the Locally Linear Model Tree (LOLIMOT) algorithm to find the best structure of the network. In the following LLNF and LOLIMOT algorithm is reviewed briefly.

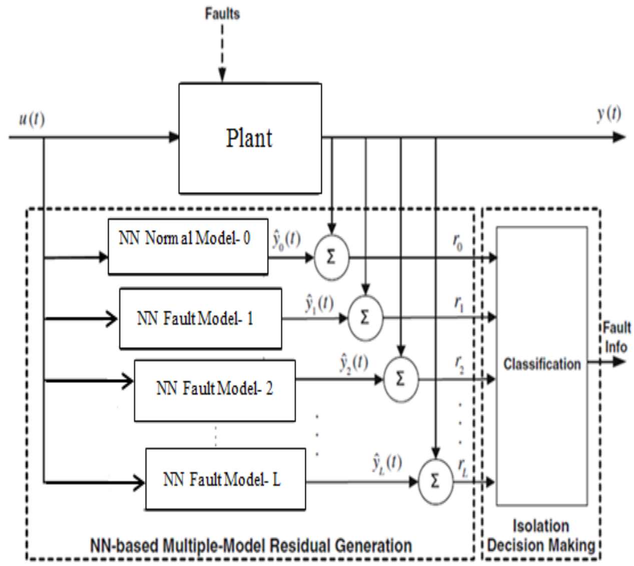

Fig. 3. General method of fault detection and isolation, neural network-based multiple model [17]

A. LLNF and LOLIMOT

The most important reason why LLNF models trained with LOLIMOT learning algorithm is selected as follows [12]:

a) High accuracy; b) Robustness; c) Smooth switch for multiple model; d) Low computational cost

The network structure of LLNF is depicted in Fig. 4. Each neuron is a Local Linear Model (LLM) and associated validity function that determines the region of validity of the LLM [13]. The output of LLMs is defined by:

$$\hat{y}_i = w_{i0} + w_{i1}u_1 + ... + w_{ip}u_p \tag{1}$$

Where w_{ij} denotes the LLM parameters for i-the neuron. If the validity functions are chosen a normalized Gaussians, then:

$$\sum_{i=1}^{M} \phi_i(u) = 1 \tag{2}$$

Finally, the output of a Local Linear Neuro-Fuzzy (LLNF) model is defined by:

$$\hat{y} = \sum_{i=1}^{M} \left(\underbrace{w_{i0} + w_{i1}u_1 + w_{i2}u_2 + ... + w_{ip}u_p}_{\hat{y}_i} \right) \phi_i(u) \quad (3)$$

The LOLIMOT algorithm consists of an outer loop in which the rule premise structure is determined and a nested inner loop in which the rule consequent parameters are optimized by local estimation in [12]. This loop can be summarized as a five step algorithm [13, 14]:

1. Start with an initial LLM which is an optimal least-square estimation.
2. Find the worst LLM which has maximum local loss function.
3. Check all hyper-rectangles to split (through)

3a. Construction of the multi-dimensional fuzzy membership functions for both hyper rectangles.

3b. Construction of all validity functions.

3c. Local estimation of the rule consequent parameters for both newly generated LLMs.

3d. Calculation of the loss functions for the current overall model.

4. Find best division (the best of the alternatives checked in step 3, and increment the number of LLMs : $M \to M+1$).
5. Test for convergence. If the termination criterion is met, then stop, else go to step 2.

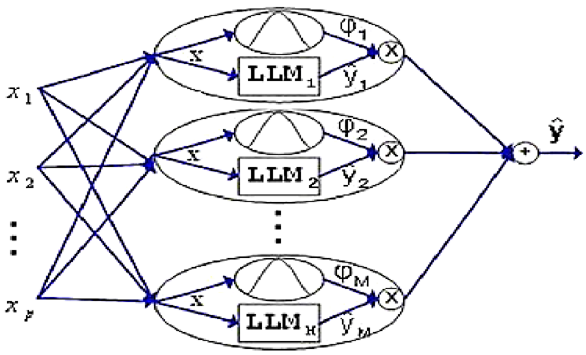

Fig. 4. Network structure of a Local Linear Neuro-Fuzzy model [12]

B. Residual Generation

The residual signals are generated based on a comparison between the measurements coming from plant and predicted signals given by LLNF models, so the residual are calculated as follows:

$$R_i(k) = y_i(k) - \hat{y}_i(k) \quad (4)$$

Where $y_i(k)$ and $\hat{y}_i(k)$ are process measurements and predictions. Under ideal conditions, when no fault occurs in the system, the residual is equal to zero and when the fault occurs, the deviation of residual from zero should appear [3].

4. Robust Fault Detection

Every model-based fault detection scheme consists of a unit called decision making, in which the evaluation of the residual signal takes place and, subsequently, the decision about faults is made in the form of an alarm. The residual evaluation is nothing but a logic decision making process that transforms quantitative knowledge into qualitative Yes-No statements [14, 15].

To evaluate residuals and to obtain information about faults, simple (constant) threshold can be applied. If residual are smaller than threshold value, a process is considered to be healthy, otherwise it is faulty [16]. The performance of fault detection is always subjected to uncontrolled effects including noise, disturbance, changing dynamic, etc. [17]. Thus the idea of simple threshold could not be effective enough to cope with such uncontrolled factors; small constant threshold values lead to increased false alarm rate caused by uncertainty, and also greater threshold values lead to increased detection delay [15]. In this research, we use a passive approach named adaptive threshold whose main idea is that threshold should vary in time since disturbance and other uncontrolled effects can also vary in time.

5. Simulation Results

LLNF models are used to identify the normal and faulty condition of gas turbine prototype, normal models of system are shown in Figs. 5-8. For evaluation of identified models, the mean square error (MSE) used performance criterion. MSE for each LLNF model is listed in Table 1. Then these models are used to generate residuals by running the industrial gas turbine prototype simulator through fault-free and then all faulty cases operating one by one over the complete operating range by using the scheme presented in Fig. 3.

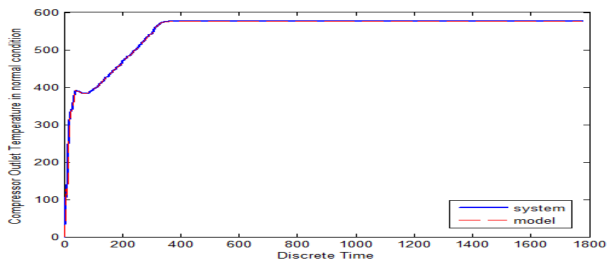

Fig. 5. LLNF model performance for Compressor Outlet Temperature

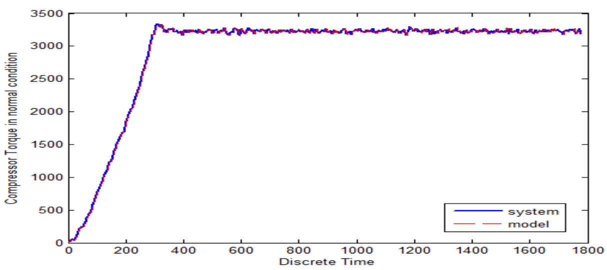

Fig. 6. LLNF model performance for Compressor Torque

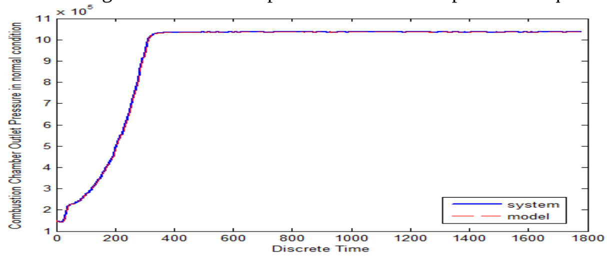

Fig. 7. LLNF model performance for Combustion Chamber Outlet Pressure

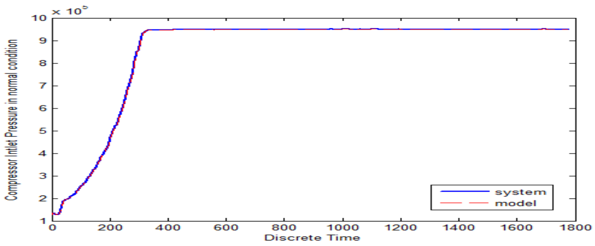

Fig. 8: LLNF model performance for Compressor Inlet Pressure

Table 1
Mean square error of LLNF models

Output	Normal	F1	F2	F3	F4
T_{OC}	2.7678 e-6	2.7670 e-6	2.7649 e-6	2.7677e-6	2.7508 e-6
Q_C	4.1796 e-7	4.3264 e-7	4.1796 e-7	4.1808 e-7	4.0139 e-7
P_{OC}	3.2949 e-7	3.2004 e-7	3.2949 e-7	3.2949 e-7	3.3004 e-7
P_{IC}	2.7582 e-7	2.7593 e-7	2.7582 e-7	2.7565 e-7	2.7603 e-7

Residuals generated in different faulty conditions are shown in Figs. 9-12. In order to perform fault detection, both simple and adaptive threshold methods presented in section 4 are used. Simple thresholds are shown in Fig. 13, and the generated adaptive thresholds for different faulty condition as well as decision made are also shown in Figs. 14-17.

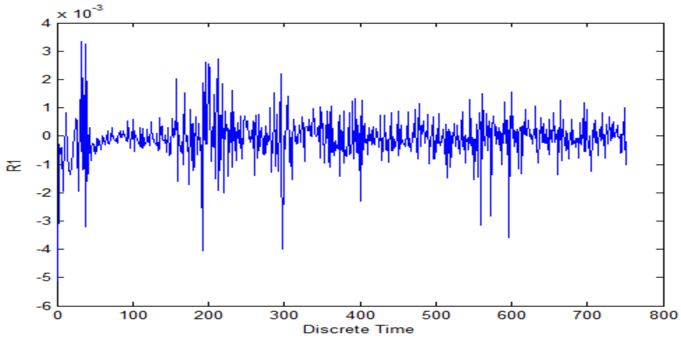

Fig. 9.Generated residual based on Q_{OC} for f_1

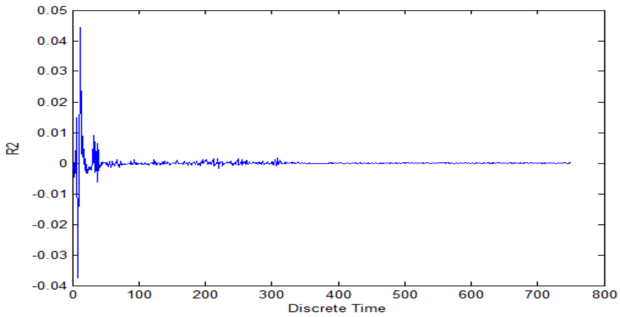

Fig. 10.Generated residual based on T_{OC} for f_2

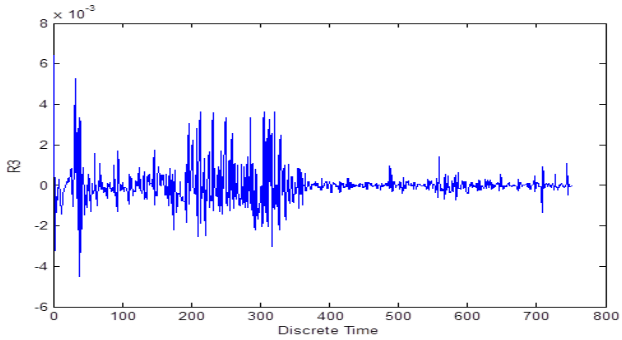

Fig. 11.Generated residual based on P_{OC} for f_3

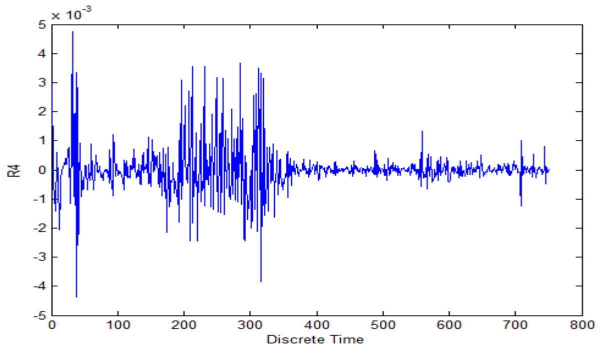

Fig. 12. Generated residual based on P_{IC} for f_4

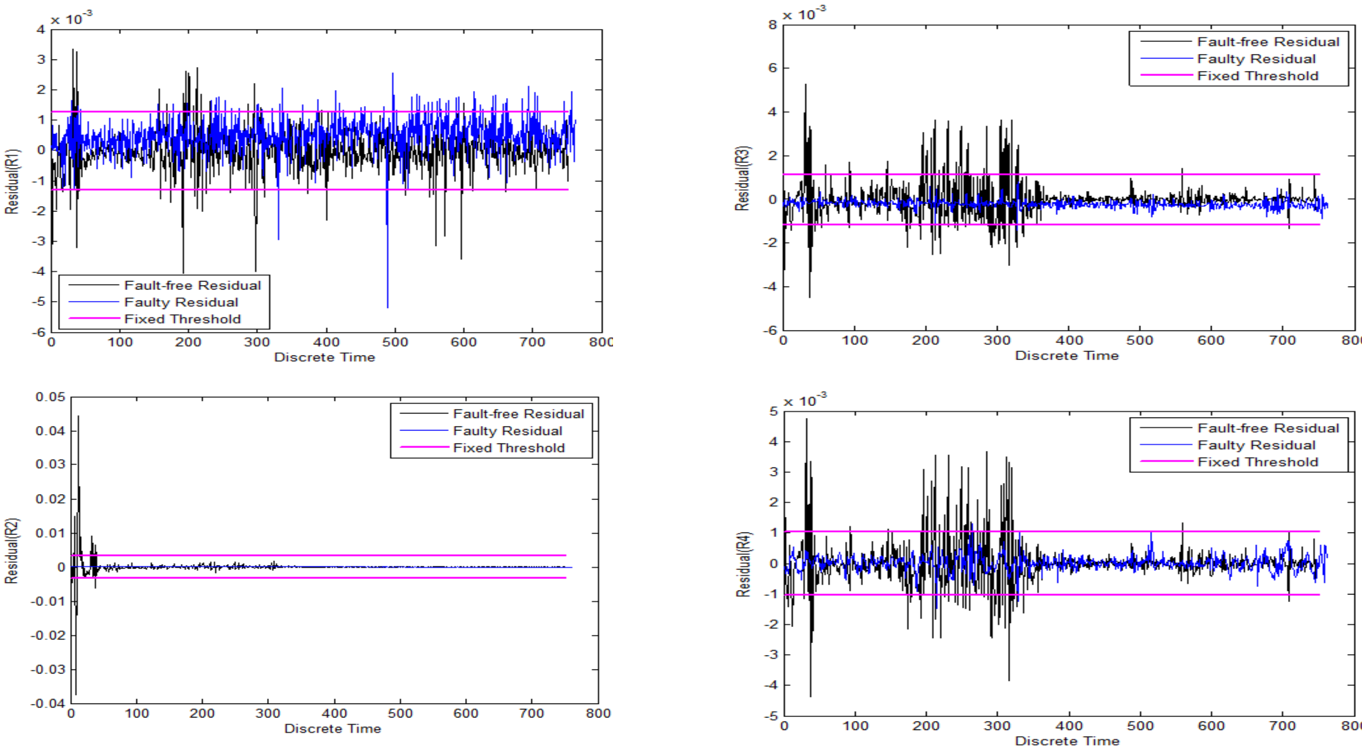

Fig. 13. Generated residuals and constant threshold in the test phase for f_1 , f_2 , f_3 , f_4

By comparing the obtained results from fault detection methods in Table 2, it can be concluded that the proposed adaptive fault detection method demonstrates almost more reliable behaviour than the simple threshold.

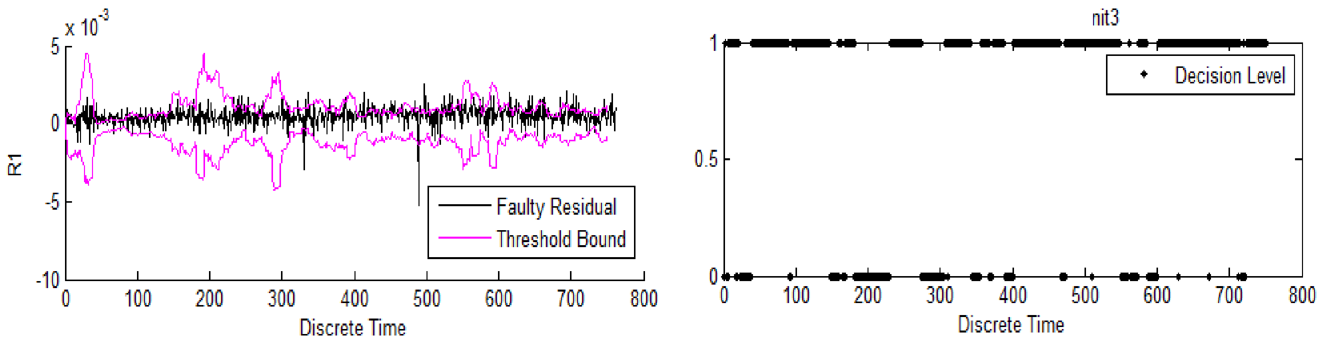

Fig. 14.Fault detection using adaptive threshold and decision making for f_1 using Compressor Torque

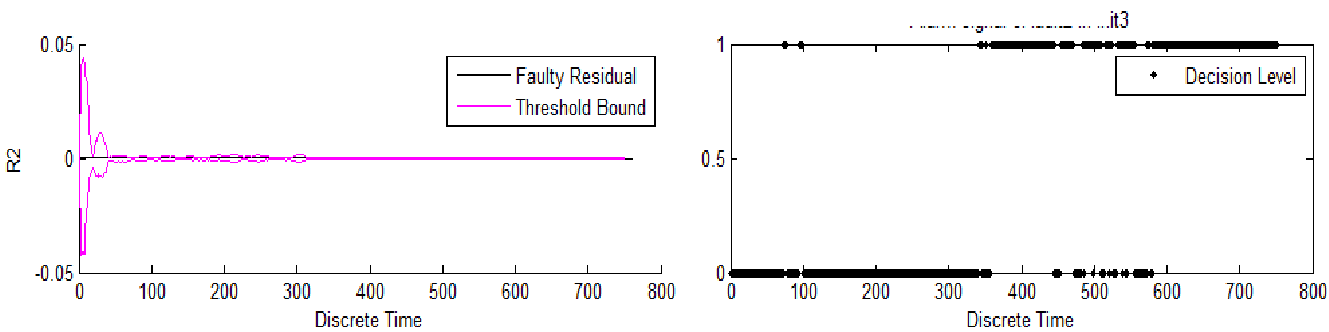

Fig. 15.Fault detection using adaptive threshold and decision making for f_2 using Compressor Outlet Temperature

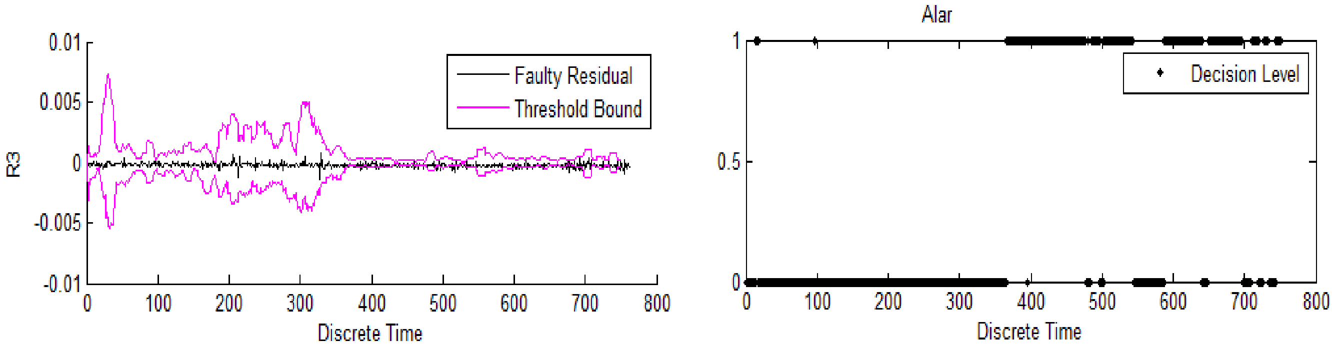

Fig. 16. Fault detection using adaptive threshold and decision making for f_3 using Combustion Chamber Outlet Pressure

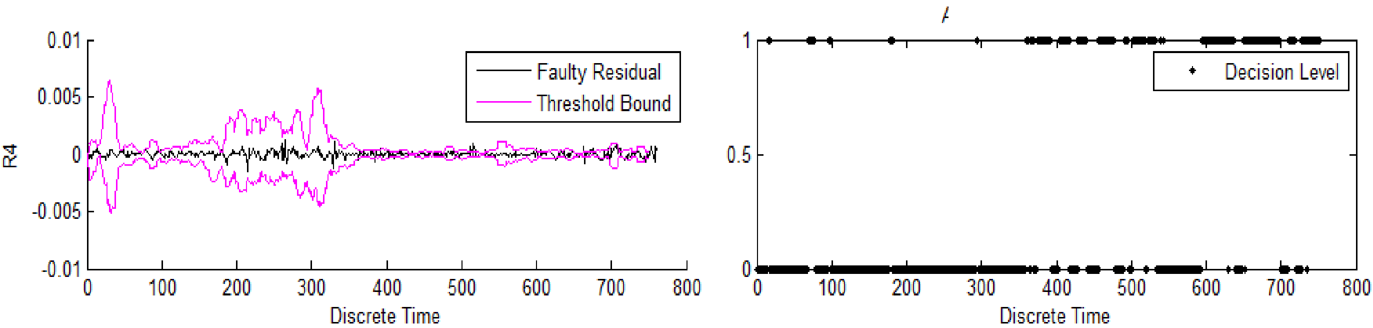

Fig. 17. Fault detection using adaptive threshold and decision making for f_4 using Compressor Inlet Pressure

Table 2
Obtained results from fault detection and comparison with the reference [10]

Obtained result in this work			
Threshold	**Fault**	**False alarm rate [%]**	**Missed detection rate [%]**
Simple	f_1	32.35	27.35
	f_2	40.90	5.20
	f_3	69.70	15.35
	f_4	79.44	30.40
Adaptive	f_1	15.64	27.81
	f_2	12.93	7.81
	f_3	15.64	10.12
	f_4	14.28	33.03
Obtained result in reference [10]			
Threshold	**Fault**	**False alarm rate [%]**	**Missed detection rate [%]**
Simple	f_1	37.35	28.20
	f_2	44.92	4.35
	f_3	73.73	18.38
	f_4	86.44	31.47
Adaptive	f_1	4.24	33.37
	f_2	10.17	8.51
	f_3	8.47	24.37
	f_4	6.78	43.54

For assessing the performance of the proposed FD method, we used missed detection rate (r_{md}) and false alarm rate (r_{fd}) as the two criteria in the area of fault detection. In this area, the r_{md} criterion is more important than the r_{fd} criterion. The reason for preference for r_{md} criterion is specified by the definitions of these two. The false alarm rate is given by

$$r_{fd} = \frac{NF_{\det}}{N_n} \tag{5}$$

Where N_n is the number of normal pattern data and $NF_{\det}$ is the number of process normal data samples incorrectly detected as faulty patterns.

And, missed detection rate is given by

$$r_{md} = \frac{FN_{\det}}{N_f} \tag{6}$$

Where N_f is the number of faulty condition data samples and $FN_{\det}$ is number of process faulty data samples incorrectly detected as normal patterns. According to the definition, a system with less r_{md} criterion means a system which demonstrates more sensitivity in fault detection and a system with less r_{fd} criterion means a system whose normal status indicates fewer false alarms. Given that warning, the fault occurrence when it hasnot actually occurred is less damaging than not warning it when it has actually taken place. This can prove the importance of r_{md} criterion compared to the r_{fd} criterion. In comparing with other reference in Table 2,it is observed that r_{md} criterion is better than r_{md} criterion in reference[10].

6. Conclusion

In this study, nonlinear system identification method was used for identification, and detection of the fault process in industrial gas turbine prototype. To this end, first, with LLNF models and LOLIMOT learning algorithm, the normal and faulty condition of gas turbine were identified. Then residuals were generated in different conditions. Finally In order to make robustness to fault detection method against unexpected effects such as disturbance, noise and uncertainty, an adaptive threshold method is used and the combination ofthese methods leads to a robust fault detection method. The results of the fault detection algorithm performance indicate that an effective method has been obtained with a successful application on industrial gas turbine prototype.

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