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ABSTRACT

The main aim of the present work is development of an active fault tolerant control for two shafts gas turbine fault detection and isolation based on a neuro fuzzy inference system adaptive approach. This approach combines the advantages of the neural networks with the fuzzy inference systems. The reconfiguration mechanism of the proposed active fault tolerant control is performed by detecting the malfunction of the studied gas turbine in an automatic manner. The obtained experimental results are presented to illustrate the great interest of the developed active fault tolerant control approach and to demonstrate its effectiveness in maintaining the stability with acceptable performance under the presence of defects in the presented gas turbine.

Introduction

To achieve the objectives and requirements of the performance, quality robustness of the industrial process control and monitoring, sophisticated methods are used. The main purpose of all these sophisticated methods is to improve the performance, diagnosis, availability, and the operation safety of these processes. Indeed, it is well obvious that the need for operation safety and fault diagnosis are even more crucial when it comes to sensitive systems where a fault can be humanly and financially costly, which is the case of the gas turbine system presented in this work. Therefore, in order to meet the above mentioned requirements of the studied system, it is mandatory to associate it with diagnostic modules for detecting any change in its behavior compared to the desired behavior, and even in some situations to reconfigure the operation system to meet the desired behavior.

In fact, a diagnostic strategy is carried out by performing three steps: the fault detection, the fault localization, and the fault isolation. These steps can

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be incorporated and associated with a faults tolerant control strategy. In many several previous works that have been achieved, the effectiveness of this fault tolerant control in several industrial applications has been shown. Very recently in 2016, Jianglin Lan and Ron J. Patton have proposed a new strategy based on faults observers for the integration and the estimation of faults in fault tolerant control system (Jianglin Lan 2016), Simani et al. have proposed a fault tolerant control applied to a hydroelectric system where they have proved the effectiveness of this control based on the validations presented in their work (Simani, Alvisi, and Venturini 2016), Li Bing Wu and Yang Guang-Hong have applied this type of fault tolerant control in an adaptive appearance for a class of uncertain nonlinear systems with multiple delays, where they have demonstrate the robustness of this approach (Lyantsev et al. 2004), Zhiyao et al. have added a return stat using fuzzy condition for switching the fault tolerant control for the same class of nonlinear systems under a stochastic faults case (Zhiyao, Tong, and Yongming 2016), Boyuan et al. have synthesized a law of fault tolerant control applied in the domain of electric vehicle (Boyuan, Haiping, and Weihua 2016), Salahshoor and Kordestani, in 2014, have designed an active fault tolerant control system for industrial steam turbine (Salahshoor and Kordestani 2010), Salahshoor et al., in 2010 and 2011, have made detection and diagnosis system of an industrial turbine using adaptive neuro fuzzy inference system for classifying defects (Salahshoor and Kordestani 2014; Kulikov, Yu Arkov, and Abdulnagimov 2013). Nozari et al., in 2012, have proposed a robust fault detection based on a fault tolerant control applied to an industrial gas turbine prototype (Jianglin Lan 2016), Guasch et al., in 2000, have proposed a diagnostic system for a gas turbine based on this type of fault detection robust control (Guasch, Quevedo, and Milne 2000). In 2011, Berrios et al. have studied the measurement system under fault detection based on fuzzy Takagi Sugeno models for a gas turbine installed in a power plant with combined cycle (Berrios, Núñez, and Cipriano 2011), Ogaji et al., in 2002, have studied the sensor faults in a gas turbine with two shafts (Ogaji, Singh, and Probert 2002).

The purpose of this work is to focus on the research of certain fault characteristics at the time of their occurrence, where the main goal is to allow deciding which action to take on the system to ensure the continuous and high performance operating of the considered system and even to stop it completely in case of major fault, which may include damages and malfunction of the considered system.

The proposed idea presented in this paper is the development of an active fault tolerant control applied to a gas turbine with two shafts. This control is basically based on an adaptive approach of neuro fuzzy inference system to ensure the fault detection and insulation, if one or more faults affect the sensors. So, any anomaly or failure of this nature are quickly detected and localized to avoid the human and material damage that could affect the installation of this rotating machine. To represent the dynamic behavior of the studied gas turbine, an innovative approach, based on an adaptive configuration of a neuro fuzzy inference system in combination with multiple models of Takagi Sugeno Kang (TSK), was introduced. This representation allows to characterize the relationship between the system input and output variables and in the same time to optimize the fuzzy inference rules that are organized in adaptive network.

The purpose of this work is to propose a fault tolerant control for gas turbines with two shafts, to ensure the faults conditioning or the controller reconfiguration, and to keep the presented system under safe operating conditions. The obtained performance under the proposed control has been validated by the use of linear dynamic models based on real data collected on site of the studied gas turbine. Indeed the used active control tolerant for fault detection and conditioning presented in this work has shown a great enhancement of the security and the availability of the studied system, on the other side it has shown that an acceptable performance was ensured allowing degraded mode system operating. It can be said that the presented control can greatly help in enriching the modern methods of monitoring and control of the studied gas turbine.

Active faults tolerant control applied to a gas turbine

The fault tolerant control has two types of control approaches: the passive approach and the active approach (Guasch, Quevedo, and Milne 2000; Salahshoor and Kordestani 2014). The present work deals with the active approach, including a diagnostic module applied to a gas turbine with two shaft types MS5002C, installed in gas compression station at Hassi Messaoud in the south of Algeria. Indeed several studies have presented the control of such systems, unfortunately, most of this work is treated based on conventional control (linear systems) or for systems operating in a restricted domain (Djaidir, Hafaifa, and Kouzou 2016; Djeddi, Hafaifa, and Salam 2015; Guemana 2015; Hafaifa 2016; Mohamed, Hafaifa, and Guemana 2016; Shi and Patton 2015). The objective of this work is to develop an active faults tolerant control based on a detection algorithm and a fault isolation algorithm while reconfiguring the control law online to maintain the stability and the performance capabilities of the studied system of gas turbine with two shafts.

The structure of the proposed active faults tolerant control is shown in Figure 1. In this configuration, the faults detection and isolation module is placed in the diagnosis function, where each faults in the system should be detected and isolated as quickly as possible. On the other side, the default parameters, the system state/the output variables, must be

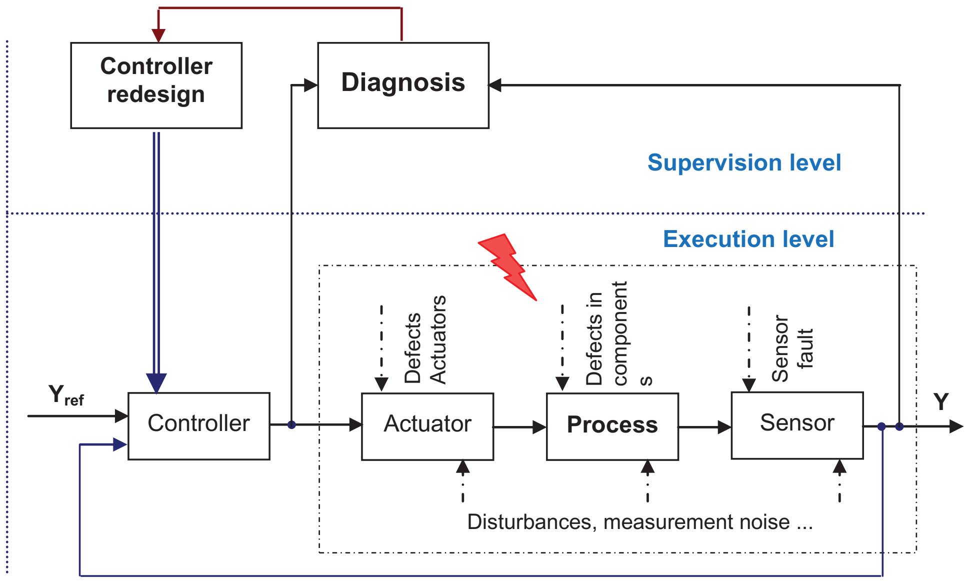


Figure 1. Structure of the proposed active faults tolerant control.

estimated online in real time to ensure the instantaneous controller reconfiguration.

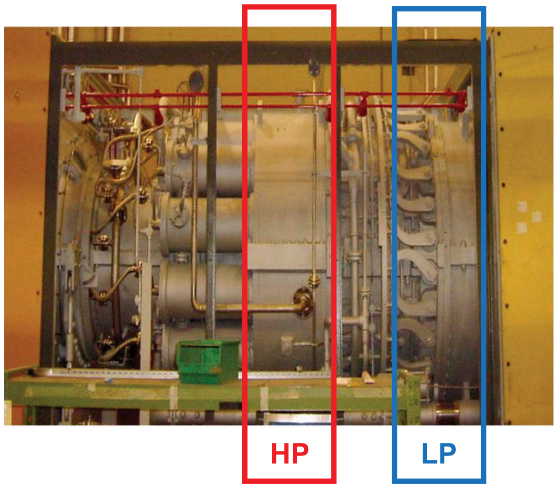
To achieve an implementation of the proposed active faults tolerant control structure, a mathematical modeling of the gas turbine with two shaft is necessary. However, in this section this modeling is presented firstly during the start-up phase of this studied rotating machine.

It is important to clarify that during the start-up phase of the gas turbine with two shafts a mechanical torque is required at the input of the air compressor. This turbine is divided into two mechanically separated section: the high pressure section (HP) and the low pressure section (LP), as shown in Figure 2.

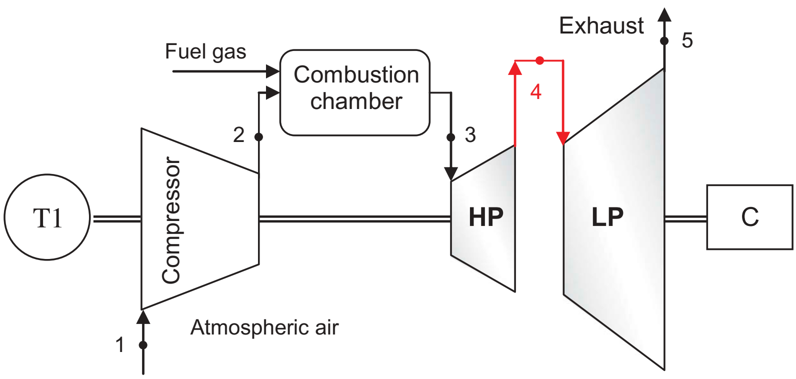
The first HP turbine section operates at a constant speed with a range of variable power, and drives exclusively an axial compressor, and the second LP turbine section can change its speed of rotation independently of the HP turbine section, where the variations of temperatures of this machine in the operating phase are given in the TS cycle diagram of the studied gas turbine with two shafts as shown in Figure 3. Hence the compressor temperature is calculated by the following equation:

$$T_2 = T_1\left(1 + \frac{r_p^{\frac{\gamma_a - 1}{\gamma_a}} - 1}{\eta_c}\right) \tag{1}$$

With T_1 and T_2 are the ambient temperature and the compressor temperature, respectively; r_P and $\eta_c = \frac{T_{2s} - T_1}{T_2 - T_1}$ is the compressor efficiency and $\gamma_a = C_{p_a}/C_v = 1.4$ is the specific heat ratio.



A: Examined gas turbine with two-shaft



B: Gas turbine with two-shaft

Figure 2. (a) Examined gas turbine with two-shaft. (b) Gas turbine with two-shaft.

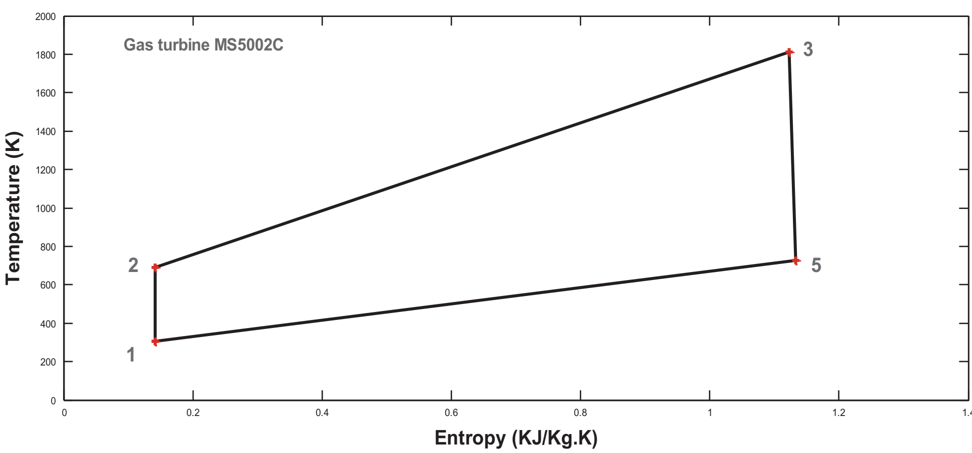


Figure 3. Two shaft gas turbine (MS5002C) cycle diagram.

The temperature of the gas turbine HP gas exhaust is given by Equation (2) and the temperature of the gas turbine LP gas exhaust is given by Equation (3).

$$T_4 = T_3\left(1 - \eta_t\left(1 - \frac{1}{r_p^{\frac{\gamma_g - 1}{\gamma_g}}}\right)\right) \tag{2}$$

where $\gamma_g = 1.333$

$$T_5 = T_4\left(1 - \eta_t\left(1 - \frac{T_{5s}}{T_4}\right)\right) \tag{3}$$

Where the thermal efficiency of turbine is $\eta_t = \frac{T_4 - T_5}{T_4 - T_{5s}}$, which leads to the thermal efficiency of the cycle expressed by $\eta_{th} = \frac{T_4 - T_5}{T_3 - T_2}$.

Active control implementation strategy

The proposed active faults tolerant control presented in this work for the control of the two shafts gas turbine system is based on the neural networks and the fuzzy logic, where the two shafts gas turbine is modeled by Takagi models fuzzy Sugeno (Benyounes, Hafaifa, and Guemana 2016; Topalov et al. 2011). Based on the dynamic models developed in the work of Kulikov et al. (Kulikov 1989a, 1989b; Li-Bing and Yang 2016), as well as in Hafaifa (2015), Arkov, Kulikov, and Breikin (2002), Mohammadi and Montazeri-Gh (2015), Rahmoune (2015), Guemana (2015), Nozari et al., (2012), and Breikin et al., (2006), a dynamic linear model of the studied two shafts gas turbine type MS5002C is considered under the following structure:

$$\begin{cases} \Delta\dot{n}_{LP} = -\frac{1}{L_{eng}}\Delta n_{LP} + \frac{K_{eng}}{L_{eng}}\Delta W_f \\ \Delta\dot{n}_{HP} = -\frac{1}{L_t}\Delta n_{HP} + \frac{K_t}{L_t}\Delta W_f \end{cases} \tag{4}$$

Where the manipulated variables are: n_{LP} the shaft speed of the section LP, n_{HP} the shaft speed of the section HP, T_c^* is the compressor temperature, T_t^* is the turbine temperature, T_{comb}^* is the combustion chamber temperature, W_a is the air mass flow, F is the force carry on the rotor, P_t^* is the output turbine pressure, $P_{c.HP}^*$ is the compressor output pressure, and ΔWf is the controlling factor. $K_{eng}$and K_t are the non-linear impact coefficients defined from the dynamic, the relationship between the LP shaft speed and the HP shaft speed defined as $\Delta n_{LP} = K \times \Delta n_{HP}$.

To use this model of the two shaft gas turbine, which is highly nonlinear, a Taylor series is subsequently used for its linearization at the operating points of the studied gas turbine. The representation of the model expressed by

Equation (4) can be presented furthermore based on the state space representation as follows:

$$\frac{d}{dt}\Delta X = f(\Delta X, \Delta\mu, t) \tag{5}$$

Considering the state variables $\Delta x_1 = \Delta n_{LP}$ and $\Delta x_2 = \Delta n_{HP}$, the final equation of state space can be rewritten as:

$$\frac{d}{dt}\Delta X = \frac{d}{dt}\begin{bmatrix}\Delta x_1\\ \Delta x_2\end{bmatrix} = \frac{d}{dt}\begin{bmatrix}\Delta n_{LP}\\ \Delta n_{HP}\end{bmatrix} = \begin{bmatrix}f_1\\ f_2\end{bmatrix} \tag{6}$$

With $f_1 = -\frac{1}{L_{eng}}\Delta x_1 + \frac{K_{eng}}{L_{eng}}\Delta u$ this is the first equation of the state space for the machine, L_{eng} is the time constant for the machine, $f_2 = -\frac{1}{L_t}\Delta x_2 + \frac{K_t}{L_t}\Delta u$ is the second equation of the state space for the turbine, L_t is the time constant for the turbine (the wheel space between HP and LP).

On the other side Equation (4), presenting the two shafts gas turbine system is nonlinear and complex to be used directly in the control. In order to linearize this system, Jacobian matrices, that are specific to the studied gas turbine system, have to be determined. The elements of the first and second order are given by $\frac{\partial f_i}{\partial x_1}|_{x=x_0}$ and $\frac{\partial f_i}{\partial x_2}|_{x=x_0}$, or the partial derivatives represent these Jacobian matrices can be defined by:

$$\frac{\partial f}{\partial x}|_{x=x_0} = A^{n\times n} = \left.\begin{bmatrix}\frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \cdots & \frac{\partial f_1}{\partial x_n}\\ \frac{\partial f_2}{\partial x_1} & \ddots & & \vdots\\ \vdots & & \ddots & \vdots\\ \frac{\partial f_n}{\partial x_1} & \cdots & \cdots & \frac{\partial f_n}{\partial x_n}\end{bmatrix}\right|_{x=x_0} \tag{7}$$

The Jacobian matrix of the studied gas turbine is based on the following model:

$$A = \begin{bmatrix}a_{11} & a_{12}\\ a_{21} & a_{22}\end{bmatrix} = \left.\begin{bmatrix}\frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2}\\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2}\end{bmatrix}\right|_{x=x_0} = \left.\begin{bmatrix}-\frac{1}{L_{eng}} & -\frac{K}{L_{eng}}\\ -\frac{1}{K.L_t} & -\frac{1}{L_t}\end{bmatrix}\right|_{x=x_0} \tag{8}$$

Where, $A = \begin{bmatrix}-0.324 & 1.56\\ 0.39 & -2.23\end{bmatrix}$, $B = \left.\frac{\partial f}{\partial u}\right|_{\substack{x=x_0\\ u=u_0}} = \begin{bmatrix}\frac{K_{eng}}{L_{eng}}\\ \frac{K_t}{L_t}\end{bmatrix} = \begin{bmatrix}8144.0\\ 3706.0\end{bmatrix}$.

By applying the model developed in this section, the overall gas turbine model output is presented in the following form:

$$y = \begin{bmatrix} \Delta T^*_{comb} \\ \Delta T^*_t \\ \Delta P^*_t \\ \Delta P^*_{c.HP} \\ \Delta T^*_c \\ \Delta W_a \\ \Delta F \end{bmatrix} = \begin{bmatrix} -0.00044 & 0.01 \\ -0.0098 & 0.01 \\ 0.00011 & 0.000018 \\ -0.0015 & 0.0027 \\ 0.025 & 0.012 \\ 0.0034 & 0.0001 \\ 0.3 & 0.044 \end{bmatrix} \begin{bmatrix} \Delta n_{LP} \\ \Delta n_{HP} \end{bmatrix} + \begin{bmatrix} 555.00 \\ 459.00 \\ 0.6700 \\ 3.0000 \\ 34.000 \\ -0.034 \\ 1791.0 \end{bmatrix} \Delta w_f \tag{9}$$

The accuracy of the two shaft gas turbine modeling is performed based on the actual real on site data used for this modeling and the linearization method used. Indeed, the performance and the efficiency of these models is also apparent on their implementation in the control. Some control strategies are interesting to be studied to demonstrate and to validate the benefits of the proposed active control approach based on neuro fuzzy inference system for the detection and the localization of faults in a two shafts gas turbine. Among these strategies, the linear quadratic (LQR) control systems presented by the following form:

$$\begin{cases} \Delta \dot{x} = A\Delta x + B\Delta u \\ \Delta u(t) = -K\Delta x(t) \end{cases} \tag{10}$$

where K is a LQR control vector.

To minimize the performance, index J given by:

$$J = \int_0^\infty (\Delta x * Q\Delta x + \Delta u * R\Delta u)\ dt \tag{11}$$

Where Q is the symmetric positive definite matrix and R is the Hermitian symmetric matrix.

For this LQR control system, the following expressions can be obtained:

$$\begin{aligned} &(A - BK) * P + P(A - BK) = -(Q + K * RK) \\ &\Rightarrow \mathrm{A * P + PA - PBR^{-1}B * P + Q = 0} \end{aligned} \tag{12}$$

Where P is a hermitian matrix positive definite or a real symmetric matrix.

This allows to obtain the resulting system of the studied gas turbine around the operating point, and to guarantee the stability of their outputs using a conventional PID control, in the case where the active fault tolerant control is not used. This is specified by a set of matrices presented as follows:

$$\begin{bmatrix} \Delta \dot{n}_{LP} \\ \Delta \dot{n}_{HP} \end{bmatrix} = \begin{bmatrix} -0.324 & 1.56 \\ 0.39 & -2.23 \end{bmatrix} \begin{bmatrix} \Delta n_{LP} \\ \Delta n_{HP} \end{bmatrix} + \begin{bmatrix} 8144.0 \\ 3706.0 \end{bmatrix} \Delta Wf \tag{13}$$

To represent the gas turbine system, to be stabilized by the state feedback control system $u = -Kx$, a matrix representation is defined by:

$$A - BK = \begin{bmatrix} -0.324 & 1.56 \\ 0.39 & -2.23 \end{bmatrix} - \begin{bmatrix} 8144.0 \\ 3706.0 \end{bmatrix} [k_1\ k_2] \\ = \begin{bmatrix} -0.324 - 8144.0k_1 & 1.56 - 8144k_2 \\ 0.39 - 3706k_1 & -2.23 - 3706k_2 \end{bmatrix} \tag{14}$$

Therefore, the characteristic equation of the gas turbine system becomes:

$$|sI - A + BK| = \begin{vmatrix} s + 0.324 + 8144.0k_1 & -1.56 + 8144k_2 \\ -0.39 + 3706k_1 & s + 2.23 + 3706k_2 \end{vmatrix} \\ = (s + 0.324 + 8144.0k_1)\ (s + 2.23 + 3706k_2) = 0 \tag{15}$$

The poles in closed loop are determined as: $s = -0.324 - 8144.0\ k_1$ and $s = -2.23 - 3706\ k_2$, the matrices Q and R are the quadratic performance index, given by $Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$, $R = [1]$, and the resultant solution is $K_1 = [0.9614 \quad 0.3017]$ with the poles are: −8947.57, −2.72.

In the following application section, the LQR control results will be presented in order to compare the active tolerant faults control responses compared by the results of the LQR control strategy without active tolerant faults on the examined gas turbine variables, view on the same figures, both the variation of the turbine with variable settings of the tolerant faults control and without the tolerant faults. In order to show the fault tolerance of the proposed control applied to the studied gas turbine.

Gas turbine modeling based on fuzzy neural system

In this section, a two shafts gas turbine modeling is proposed using the fuzzy neural system to evaluate and to represent the dynamics of this rotating machine. This approach is based on the use of ANFIS type fuzzy neural network techniques. This allows to integrate the knowledge expertise, which is expressed in the form of fuzzy rules, and the knowledge issued from the actual on site data in the neural network training phase, which will allow to adjust the parameters of the overall used models structure, subsequently, to the active fault tolerant control in the studied system.

Adaptive neuro fuzzy inference system (ANFIS)

Recently, several applications of neuro fuzzy systems have been achieved and developed for the modeling and the control of industrial systems (Benyounes, Hafaifa, and Guemana 2016; Kulikov, Yu Arkov, and Abdulnagimov 2013; Mohamed, Hafaifa, and Guemana 2016; Salahshoor, Khoshro, and Kordestani 2011; Topalov et al. 2011; Zhiyao, Tong, and Yongming 2016). However, ANFIS systems allow to automatically generate fuzzy rule-based models based on the inference model of Takagi Sugeno. Indeed, this concept

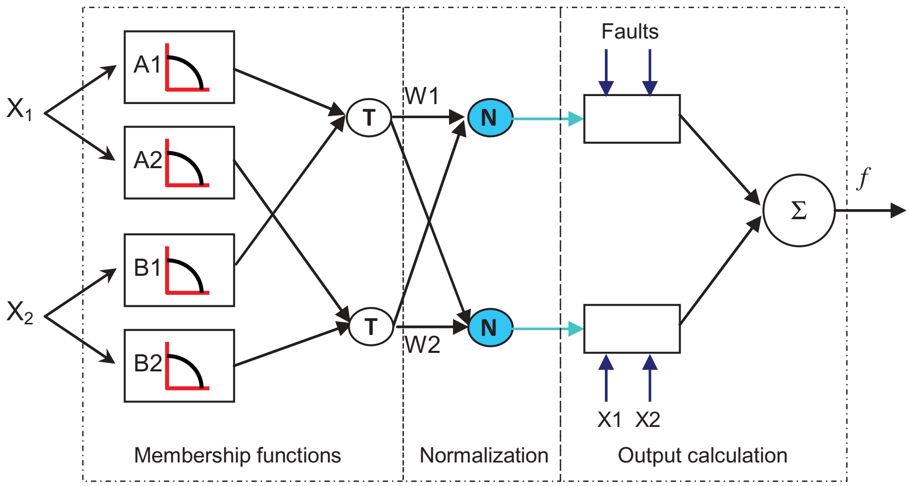


Figure 4. Adaptive neuro fuzzy inference system structure ANFIS.

was originally proposed by Jang in 1993 (Jang 1993; Jang and Sun 1993) and made a great success for modeling the complex nonlinear systems. The ANFIS system configuration adopted in this work, to acieve the active control, is composed of five layers, as described in Figure 4.

To apply the adaptive neuro fuzzy inference system structure ANFIS model, shown in Figure 4, a fuzzy inference system of type Sugeno of first order is considered, with the supposition of two inputs linguistic variables x_1, x_2, and one output y, and that the basic rules contains two types of rules:

$$\begin{array}{l} \text{Rule 1 : If } x_1 \text{ is } A_1 \text{ and } x_2 \text{ is } B_1 \text{ Then } y_1 = f_1(x,y) = p_1x + q_1y + r_1 \\ \text{Rule 2 : If } x_1 \text{ is } A_2 \text{ and } x_2 \text{ is } B_2 \text{ Then } y_2 = f_2(x,y) = p_2x + q_2y + r_2 \end{array} \tag{16}$$

The outputs of the first layer represents the degrees of membership of the input variables x_1 and x_2, given by:

$$O_i^1 = \mu_{A_i}(x)\ ;\ i = 1,2 \tag{17}$$

Each node in the second layer is a fixed node noted by Π and each one generates as output the product of its inputs, using the fuzzy operator AND to calculate the degree of activation of the premises, which corresponds to the degree of membership of the rule concerned:

$$O_i^2 = w_i = \mu_{Ai}(x) \times \mu_{Bi}(x)\ ;\ i = 1,2 \tag{18}$$

Each node in the third layer is also a fixed node, it achieves the normalization of fuzzy rules weight. The normalization of weight is obtained according to the following relationship:

$$O_i^{3} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \; ; i = 1, 2 \tag{19}$$

In the fourth layer, each node is adaptive and calculates the outputs of the rules for determining the substantial parameters by performing the following function:

$$O_i^{4} = \bar{w}_i \times f_i = \bar{w}_i(p_i x + q_i y + r_i) \; ; i = 1, 2 \tag{20}$$

The fifth layer which is also in the network is determined by the following relationship:

$$O_i^{5} = f = \sum_i \bar{w}_i \times f_i \tag{21}$$

The ANFIS system applies the learning mechanism of fuzzy neuron on the fuzzy inference techniques, where their memberships function parameters are adjusted using the learning algorithm of gradient descent in combination with less square algorithm.

ANFIS gas turbine model

The monitoring system for two shafts gas turbine presented in this work is based on the input and outputs variables of the studied rotating machine. These variables are used based on the choice of neuro fuzzy systems (ANFIS) configuration to achieve the modeling for the MS 5002C gas turbine, where the ANFIS system allows in particular to ensure the system operation under degraded mode under the presence of sensor faults by the synthesis of an active fault tolerant control strategy. So the gas turbine system is modeled by Equations (7), which represents all the manipulated input–output relations, given in the following equation:

$$\begin{cases} \Delta T_{comb} = ANFIS_1(\Delta W_f, \Delta W_a, \Delta T_c, \Delta F) \\ \Delta T_t = ANFIS_2(\Delta W_f, \Delta T_{comb}, \Delta P_c, \Delta T_c, \Delta W_a) \\ \Delta P_t = ANFIS_3(\Delta W_f, \Delta P_c, \Delta T_t, \Delta W_a, \Delta F) \\ \Delta P_{c.HP} = ANFIS_4(\Delta W_f, \Delta T_c, \Delta W_a, \Delta F) \\ \Delta T_c = ANFIS_5(\Delta W_f, \Delta P_c, \Delta W_a, \Delta F) \\ \Delta W_a = ANFIS_6(\Delta W_f, \Delta F, P_{c.HP}) \\ \Delta F = ANFIS_7(\Delta W_f, \Delta W_a, \Delta P_t, \Delta P_{c.HP}) \end{cases} \tag{22}$$

To well present the studied gas turbine system, 6270 samples data input/output spread over 4 days of operation without faults and stop were used in this modeling. The ANFIS network model uses these inputs to generate a single output. Each input is fuzzified by three fuzzy sets type Gaussian. Figure 5 shows the variation in mass flow rate given by ΔW_a and their surface is shown in Figure 6.

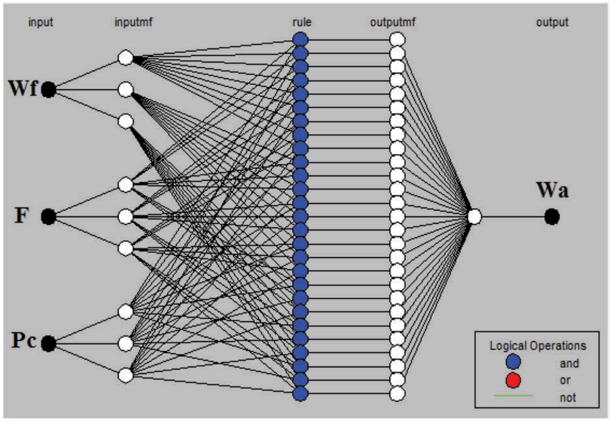


Figure 5. ANFIS network model for the variable air mass flow ΔW_a.

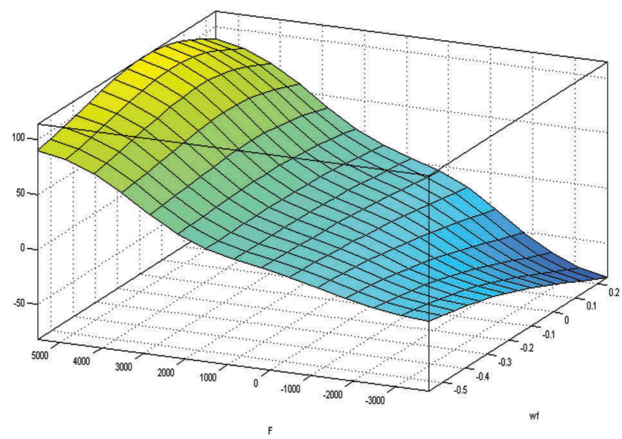
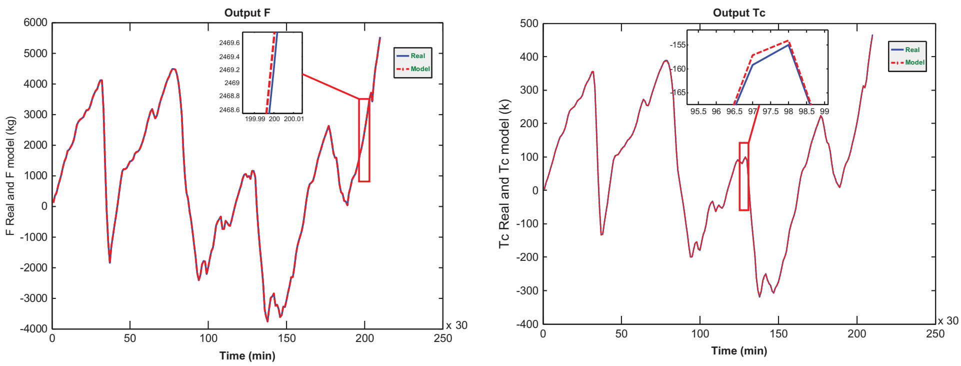


Figure 6. ANFIS model output area for the variable air mass flow ΔW_a.

Figure 7 shows the variations of the gas turbine system outputs compared with ANFIS outputs model for the manipulated variables. Whereas, Figure 7 (a) shows the variation of the force carry on the rotor; Figure 7(b) shows the variation of the compressor temperature; Figure 7(c) shows the variation of the compressor pressure; Figure 7(d) shows the variation of the temperature of the combustion chamber; Figure 7(e) shows the variation of the temperature of the turbine; Figure 7(f) shows the variation of mass flow; and Figure 7 (g) shows the variation of the turbine pressure.

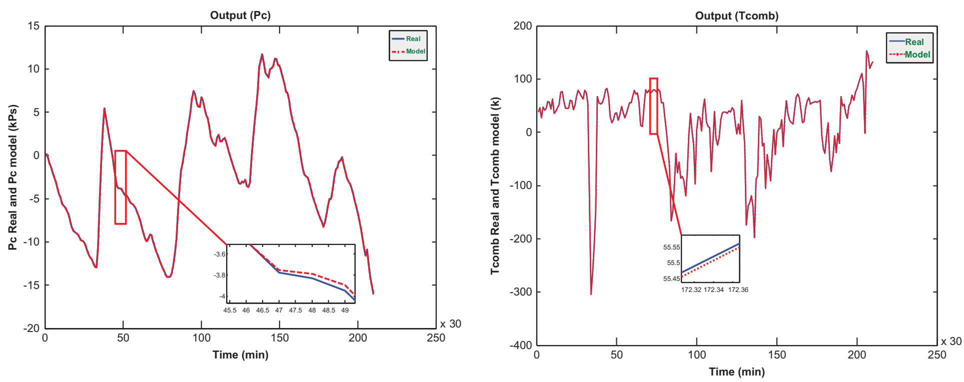
Active fault tolerant control applied to a gas turbine

The active fault tolerant control approach in this section of work extends to the case of gas turbine diagnostic systems, and define the diagnosis as detection, localization, and identification of faults model-based for the gas



A: variation of the force carry on the rotor F

B: variation of the compressor temperature T_c^*



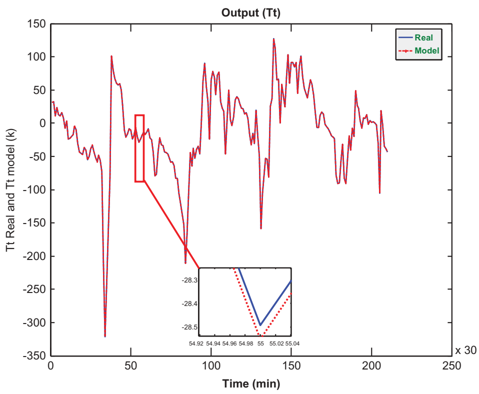
C: variation of the compressor pressure $P_{c.HP}^*$

D: variation of the temperature of the combustion chamber T_{comb}^*

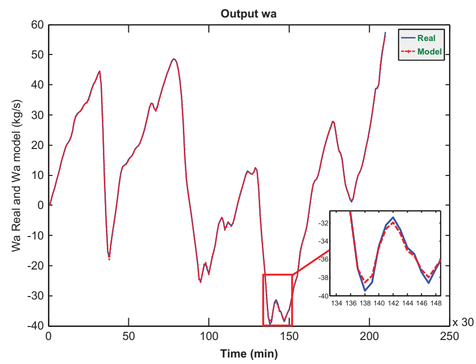
Figure 7. Variations of the manipulated variables of the examined gas turbine system outputs compared with ANFIS output model. (a) Variation of the force carry on the rotor F. (b) Variation of the compressor temperature T_c^*. (c) Variation of the compressor pressure $P_{c.HP}^*$. (d) Variation of the temperature of the combustion chamber T_{comb}^*. (e) Variation of the temperature of the turbine T_t^*. (f) Variation of air mass flow W_a. (g) Variation of the turbine pressure $P_{c.HP}^*$.

turbine controller reconfiguration. However, the detection can detect any deviation from the normal behavior of the system and alert operators to the presence of a fault. The localization allows to trace the origin of the anomaly and locate the defective components, this localization is important, because the propagation of failure often causes the appearance of new faults. Finally, identification determines the time of occurrence of the failure, its duration and its importance.

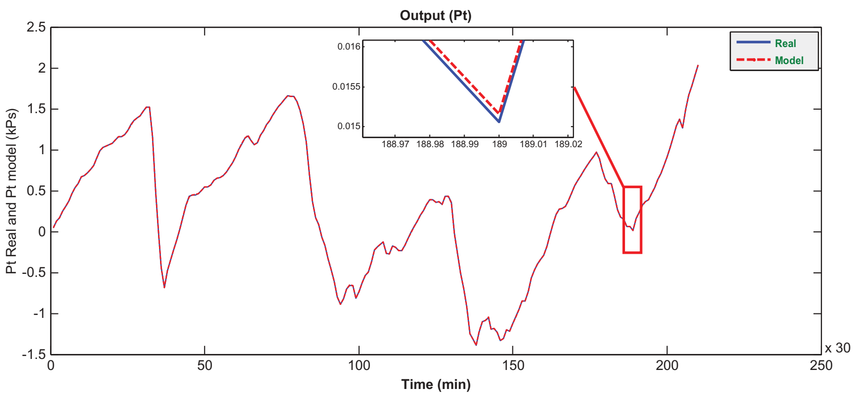
In the context of the gas industry, including gas turbine, diagnosis helps operators to monitor the machine and therefore to make a decision to perform a reconfiguration of the control system, in case of non-tolerable defects. To characterize the performed diagnostic system, residues generation of the operating system was carried out, these residues are the differences between the output signals measured and their



E: variation of the temperature of the turbine T_t^*



F: variation of air mass flow W_a



G: variation of the turbine pressure $P_{c.HP}^*$

Figure 7. (Continued).

estimation by the proposed ANFIS models, it is expressed by the following relationship:

$$R(t) = y_r(t) - y_{\text{mod}}(t) \tag{23}$$

The residues represent the relations between the inputs/outputs of the studied gas turbine system, given by Equation (22) and shown in Figure 7, were generated. In their evaluations, the card Average method of Shewhart, given in Andrew and Deming (1939), and Basseville and Nikiforov (1993) was used to detected the sudden change of the studied system statistical characteristic. With the idea to divide the control strategy into three lines; the first is the main line and the two other lines are named limitations "upper control limit (UCL)" and "Lower control limit (LCL)."

This method uses the normal laws to calculate their standard deviation; for reference data $N \succ 100$ and an average $\mu = \sum X/N$. The standard deviation values is given by $\sigma = \sqrt{\sum^{(x-\mu)^2}/N}$, and for sample n and average $m = \sum X_i/n$ the standard deviation values is given by $s = \sqrt{\sum (x_i - m)^2/(n-1)}$.

The residues generation process on the actual data of the studied turbine is being centered following the normal laws (average m and standard deviation μ), where samples follow the normal laws (average m and standard deviation $s/\sqrt{n}$) with thresholds detection (limits of detection) and fixed to $(UCL, LCL) \pm K_1 * s\tan dard\ deviation$ and $K_1$is the standard deviation number. Table 1 summarizes the average m and the standard deviation of each residue generated output signal.

After the step of residues generation, the next step is their evaluation for the fault detection. For this, neuro fuzzy model type ANFIS has been proposed to decide and to localize the type of faults in the studied gas turbine system from the residues generated previously, this step is shown in Figure 8.

The proposed strategy for the gas turbine diagnosis is shown in Figure 9, a residual generation mechanism is integrated in this configuration to carry out the active fault tolerant control based ANFIS approach. This step required the measures and the turbine inputs/outputs data, to estimates the dynamic state and the occurrence of faults during operation phase. This strategy takes into account the total failure of the sensors, which will enable the reconfiguration of the used fault-tolerant control strategy.

After the residual generation and the affirmation of the occurrence of faults, reconfiguration in turbine system controllers is used, according to a decision made by the residual evaluation mechanism. The obtained results

Table 1. Detection threshold.

	$\bar{X}$	S	(UCL,LCL)
e_{Tcomb}	$-2 * 10^{-5}$	1.14	0.42
e_{Tt}	$-4 * 10^{-5}$	1.11	0.33
e_{Pt}	$-9 * 10^{-8}$	0.0013	0.004
$e_{Pc.HP}$	$-9.42 * 10^{-7}$	0.07	0.2
e_{Tc}	$3.11 * 10^{-5}$	1	3
e_{Wa}	$2 * 10^{-6}$	0.33	1
e_F	$1.01 * 10^{-4}$	1	3

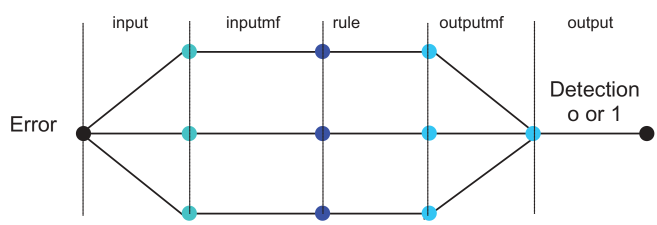


Figure 8. Defect detection system based on ANFIS system.

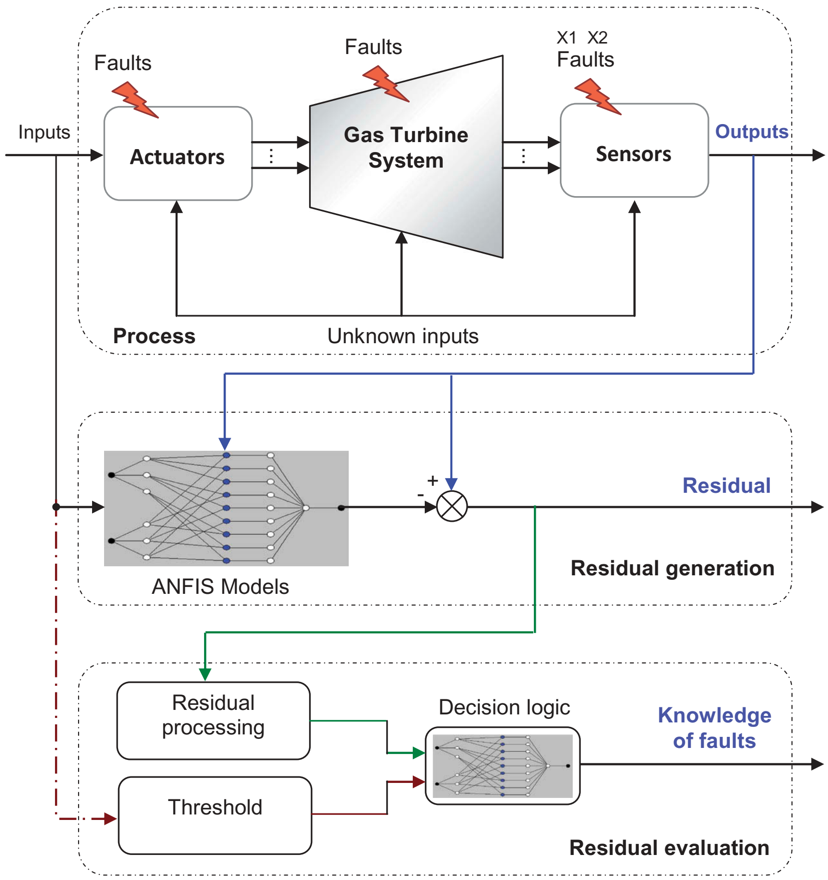
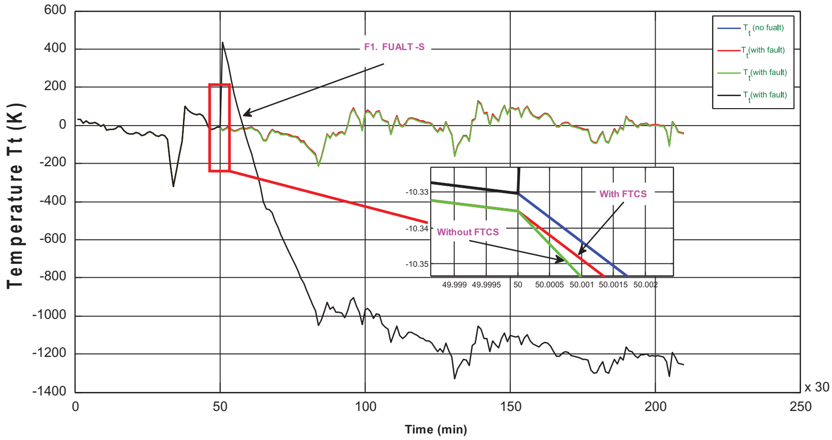


Figure 9. Diagnostic system configuration model based system.

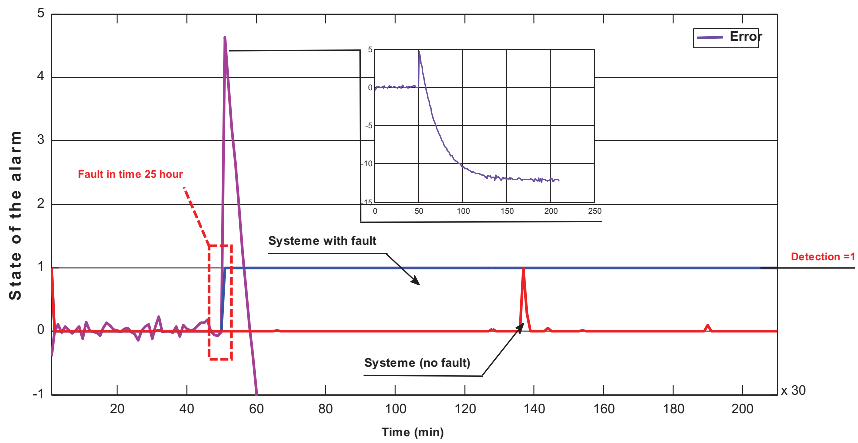
of this approach will be presented in the next section to show the contribution in this work of active fault tolerant control affecting a two shaft gas turbine.

Applications results

In this section, various tests were carried out in emulating defects, in order to show the efficacy of the proposed active fault tolerant control strategy applied to two shaft gas turbine. The control actions are applied to ensure an acceptable turbine operation on one hand and on the other, to ensure the overall stability of the turbine system based on an on-line solution in terms of reconfiguration of controllers in the system. Indeed, the results obtained can perform the detection, the isolation and the estimation of faults in the studied gas turbine based on the assessment and the evaluation of the residuals for each test.



A: Gas turbine outputs with and without FTC using ANFIS model (Deviation of temperature-turbine $\Delta T_t^* (K)$)



B: State of the detection alarm (with and without faults)

Figure 10. (a) Gas turbine outputs with and without FTC using ANFIS model (Deviation of temperature-turbine $\Delta T_t^*(K)$). (b) State of the detection alarm (with and without faults).

Figure 10(a) shows the variation of the gas turbine output temperature deviation under fault tolerant control using the ANFIS model in red colour and without fault-tolerant control using only the LQR control in green colour to stabilize the output. At $t = 50$ a sensor fault is detected by the active control system, based on the residues variation of this variable shown in Figure 10(b). By analyzing this figure, it can be seen that the capacity of ANFIS model for detecting the fault, with its fixed thresholds for estimating the faults on the temperature variable. Contrary with the use of the LQR control upon the same fault occurrence, it is noted that the temperature drops causing the instability of the system.

To demonstrate the performance and the robustness of the active fault tolerant control strategy other tests were performed, the inputs/outputs data are used for ANFIS modeling of the studied gas turbine containing seven variables. Figure 11(a) shows the variation of the deviation of the compressor pressure $\Delta P^{*}_{c.HP}(kPa)$) with fault tolerant control using the ANFIS model and the response without fault tolerant control. The fault, which was occurred at $t = 25h$, was detected by the proposed strategy, the variation of residues of this variable is shown in Figure 11(b). The pressure in the turbine falls when the fault occurred with the LQR control. This dysfunction causes instability of the turbine and may lead to adverse consequences on the turbine and the gas facility. In contrast, the the active fault tolerant control preserved performance in degraded mode, that is to say when the fault occurs the stability of the turbine system is provided.

Figure 12(a) shows the comparison between the active fault tolerant control active fault tolerant control algorithm (AFTC) using the ANFIS model and the LQR control in the case of the variation of the output temperature in the combustion chamber $\Delta T^{*}_{comb}(K)$. It can be noticed that in presence of the fault, the active fault tolerant control system AFTC ensures an acceptable performance against the LQR control, where its performance degraded function of time, and the temperature in the combustion chamber continues to rise and take away from the operating point. The variation of the residues of this variable is shown in Figure 12(b), the residues estimation results are satisfactory, the diagnostic mechanism is activated in the presence of faults and allows automatic reconfiguration of the AFTC control.

Figure 13(a) shows the evolution of the output turbine pressure deviation $\Delta P^{*}_{t}(kPa)$ with fault tolerant control using the ANFIS model and without fault tolerant control. The occurrence of faults of low vibration is detected and isolated, and the estimation of these faults has been built and detected from the residue, as shown in Figure 13(b).

Figure 14(a) shows the evolution of the output compressor temperature deviation $\Delta T^{*}_{c}(K)$ with fault tolerant control using the ANFIS model and without tolerant control fault. The variation of the residues is shown in Figure 14(b), where it can be noticed that the appearance of faults is detected and isolated.

Nevertheless, the effectiveness of the active fault tolerant control depends on the amplitude of faults. Indeed, Figure 15(a) shows the deflection output variation of the air mass flow $\Delta W^{*}_{a}(Kg/s)$ with fault tolerant control using the ANFIS model and the variation of this variable using the optimal control (LQR). The variation of the generated residues is illustrated in Figure 15(b), where the fault is correctly estimated under the consideration that the modeling of the system is well done.

The obtained results are very satisfactory and show that the active fault tolerant control is perfectly beneficial for the two shafts gas turbine control, where the appearance of faults is detected and located and no false alarm is generated. The experimental study presented in this work based on real on site

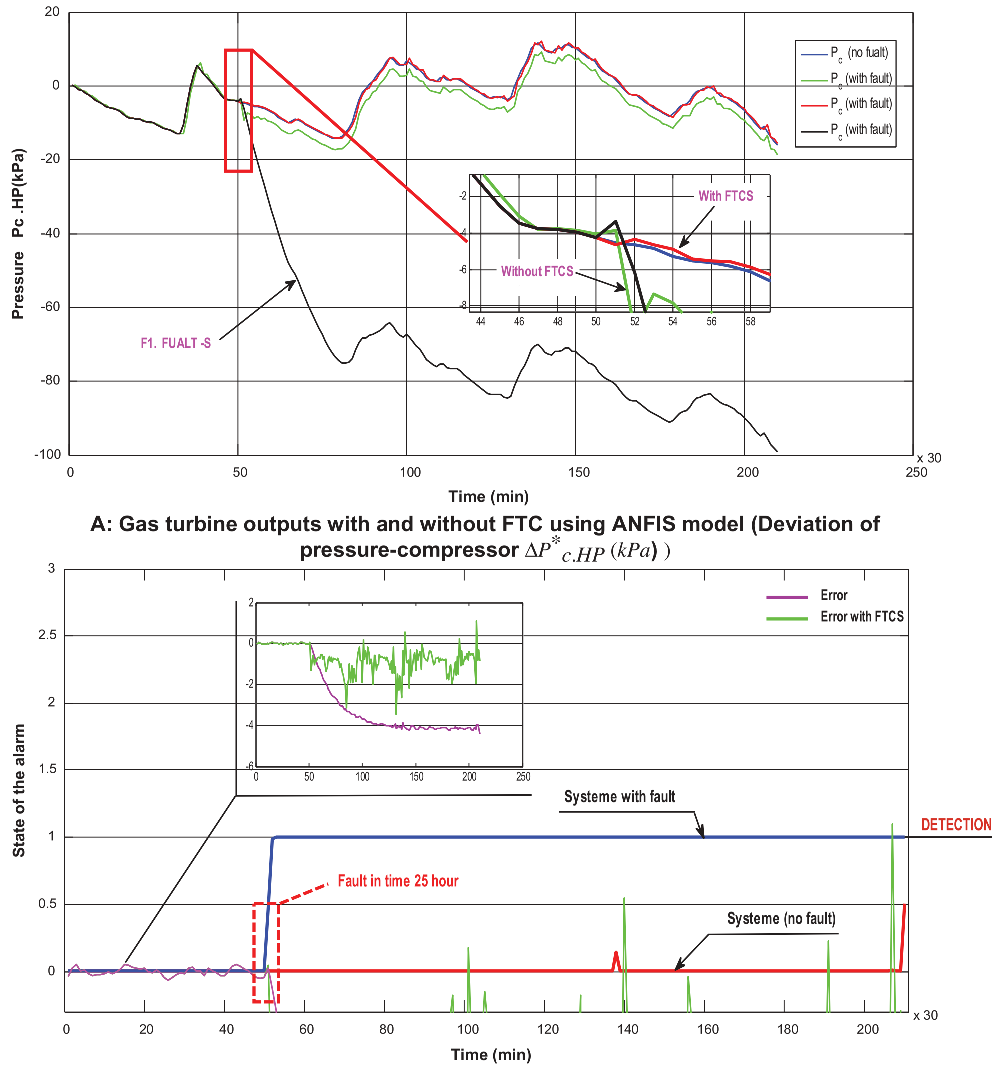
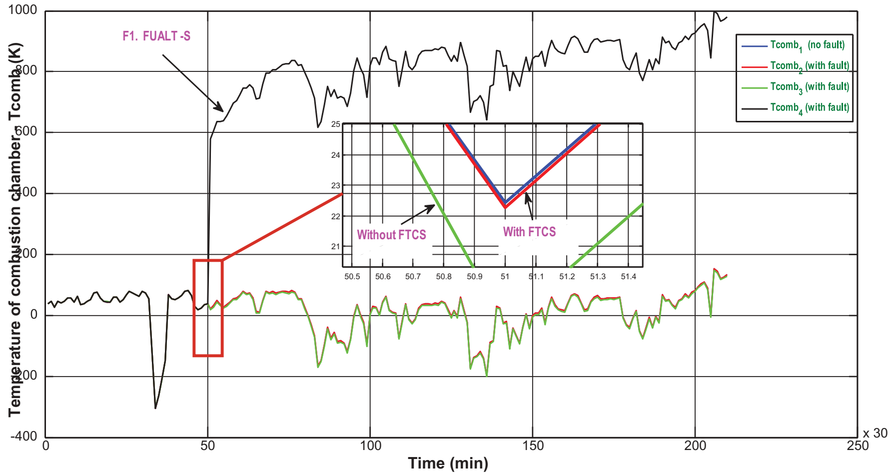
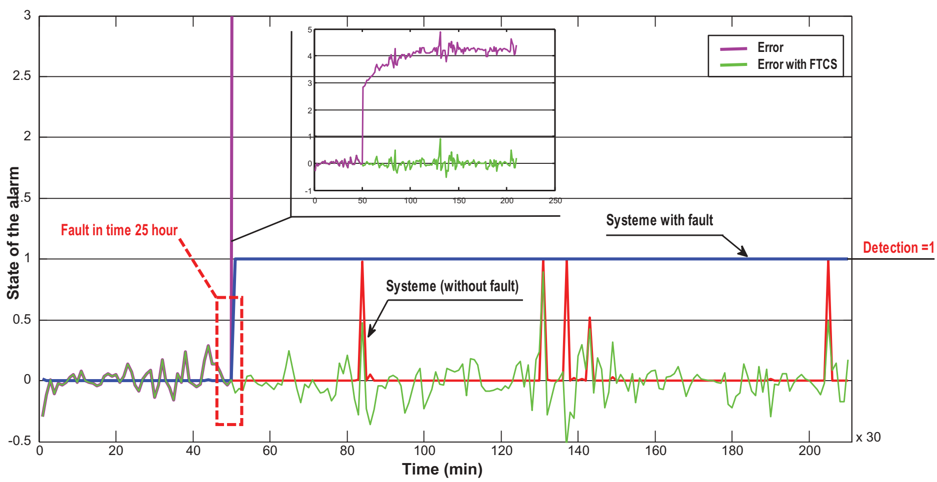


Figure 11. (a) Gas turbine outputs with and without FTC using ANFIS model (Deviation of pressure-compressor $\Delta P^*_{c.HP}(kPa)$). (b) State of the detection alarm (with and without faults).



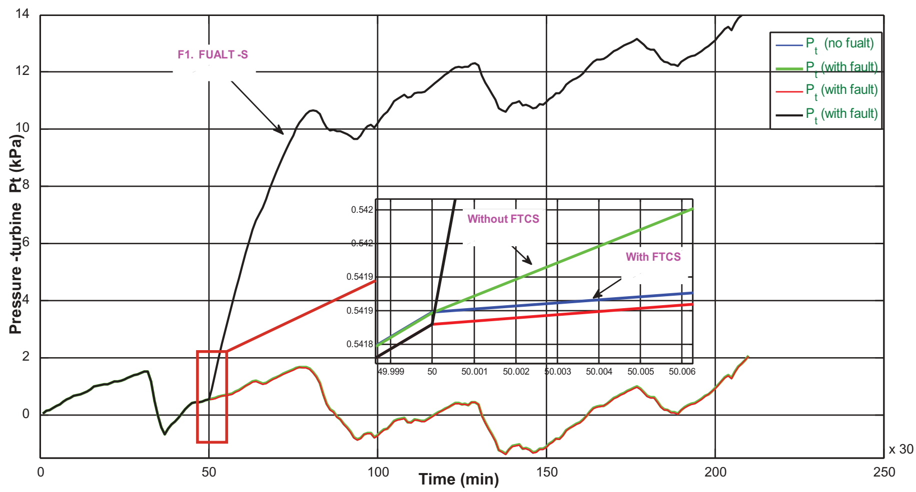
A: Gas turbine outputs with and without FTC using ANFIS model (output temperature deviation in the combustion chamber$\Delta T^{*}_{comb}\,(K)$)



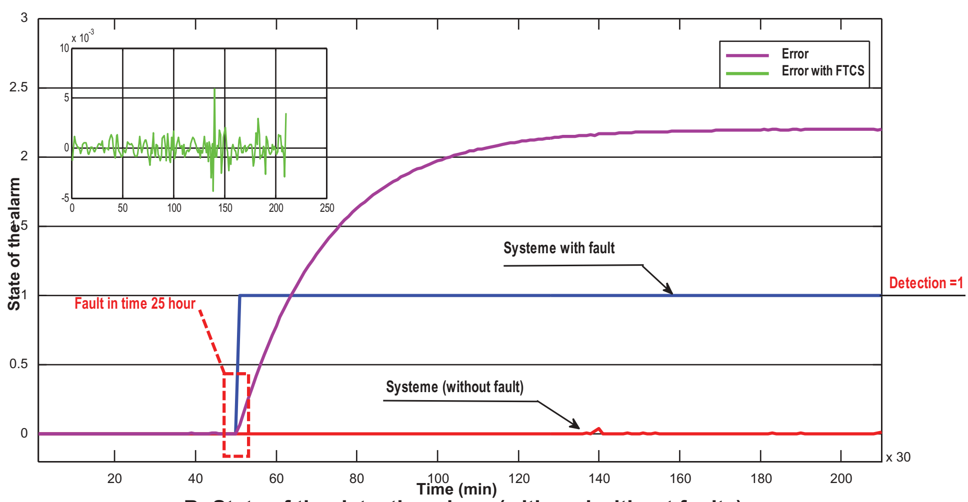
B: State of the detection alarm (with and without faults)

Figure 12. (a) Gas turbine outputs with and without FTC using ANFIS model (output temperature deviation in the combustion chamber $\Delta T^{*}_{comb}(K)$). (b) State of the detection alarm (with and without faults).

data shows the effectiveness of the active fault tolerant control using the ANFIS modeling approach, its originality is presented in its application to an industrial process of the two shafts gas turbine case. The ANFIS models based diagnostic algorithms have been implemented and validated the present work on a two shafts gas turbine system. The inputs/outputs data collected from real measurements on site have allowed to apply AFTC in real time. Their principles reside in the generation of fault indicators or signs based on the comparison of significant symptoms of faults with measurements taken directly from the gas



A: Gas turbine outputs with and without FTC using ANFIS model (Deviation of pressure -turbine $\Delta P^*_t\,(kPa)$)



B: State of the detection alarm (with and without faults)

Figure 13. (a) Gas turbine outputs with and without FTC using ANFIS model (Deviation of pressure – turbine $\Delta P^*_t(kPa)$). (b) State of the detection alarm (with and without faults).

turbine system. The fault occurrence is detected via residues calculations, which consist of the difference between the measured and the estimated quantities, and this comparison allows to detect the occurrence of the fault precisely.

Conclusion

In this work, the active fault tolerant control has been developed and applied to a two shaft gas turbine used in gas transportation, based on adaptive neuro fuzzy inference system (ANFIS) approach. Indeed, the advantage of this approach was

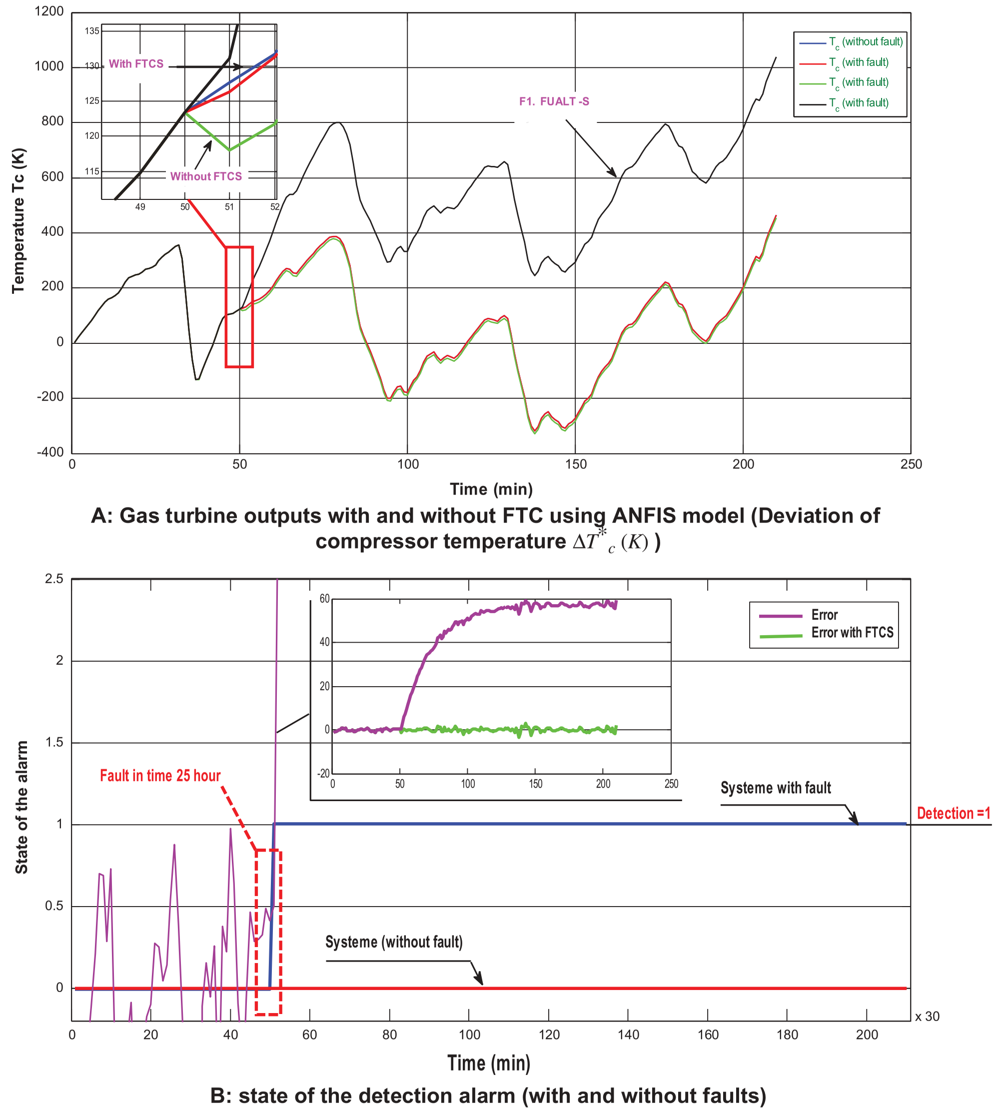


Figure 14. (a) Gas turbine outputs with and without FTC using ANFIS model (Deviation of compressor temperature $\Delta T_c^*(K)$). (b) State of the detection alarm (with and without faults).

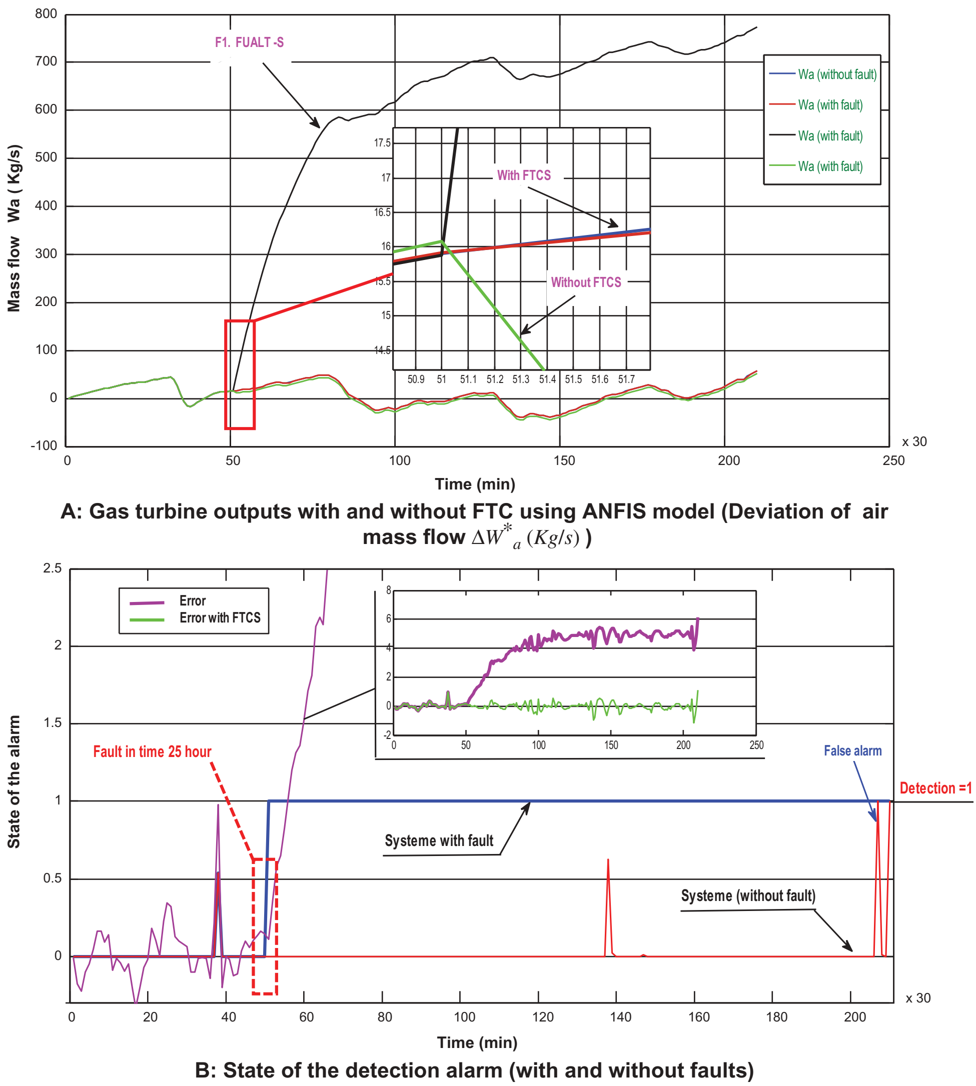


Figure 15. (a) Gas turbine outputs with and without FTC using ANFIS model (Deviation of air mass flow $\Delta W_a^*(Kg/s)$). (b) State of the detection alarm (with and without faults).

presented in the context of the studied gas turbine type MS5002C ANFIS modeling, where the choice of this approach is justified by its many advantages. Especially, the ease use of these models in control strategies implementation and their reconfigurable control system. The objective of this work consists in improving the gas turbine operating system safety while ensuring the continuity of production under the fault presence, allowing the gas turbine operation in degraded mode with acceptable performance and while ensuring system stability. This approach has also been validated in the detection of faults in sensors of gas turbine system, despite the varying parameters of the turbine. The obtained results show the effectiveness of the active fault tolerant control developed with the reconfiguration of the control in gas turbine, where the faults are detected and localized by the technique of residues and automatic mechanism for ensuring the control system reconfiguration to provide the performances and the stability of the operation system under fault. The presented control can be a promising solution against fault occurrence in two shafts gas turbine systems.

References

Andrew, S. W., and W. E. Deming. 1939. Statistical method from the viewpoint of quality control. Massachusetts, United States: Courier Corporation.

Arkov, V. Y., G. G. Kulikov, and T. V. Breikin 2002. Life cycle support for dynamic modelling of gas turbines. Proceedings of the 15th Triennial IFAC World Congress, Barcelona, Spain. 2135–40.

Basseville, M., and I. V. Nikiforov. 1993. *Detection of abrupt changes: Therory and application*. New Jersey, United States: Prentice-Hall.

Benyounes, A., A. Hafaifa, and M. Guemana. 2016. Gas turbine modelling based on fuzzy clustering algorithm using experimental data. *Journal of Applied Artificial Intelligence, Taylor & Francis* 30(1):29–51. doi:10.1080/08839514.2016.1138808.

Berrios, R., F. Núñez, and A. Cipriano. 2011. Fault tolerant measurement system based on Takagi–Sugeno fuzzy models for a gas turbine in a combined cycle power plant. *Fuzzy Sets and Systems* 174(1):114–30. doi:10.1016/j.fss.2011.02.011.

Boyuan, L., D. Haiping, and L. Weihua. 2016. Fault-tolerant control of electric vehicles with in-wheel motors using actuator-grouping sliding mode controllers. *Mechanical Systems and Signal Processing* 72–73:462–85.

Breikin, T. V., V. Y. Arkov, and G. G. Kulikov. 2006. Application of Markov chains to identification of gas turbine engine dynamic models. *International Journal of Systems Science* 73(3):197–205. doi:10.1080/00207720600566065.

Djaidir, B., A. Hafaifa, and A. Kouzou. 2016. Vibration detection in gas turbine rotor usingartificial neural network. Proceedings of the International Conference on Acoustics and Vibration ATAVI'16, Hammamet –Tunisia, March 21-23

Djeddi, A. Z., A. Hafaifa, and A. Salam. 2015. Gas turbine reliability model based on tangent hyperbolic reliability function. *Journal of Theoretical and Applied Mechanics* 53(3):723–30. doi:10.15632/jtam-pl.53.3.723.

Guasch, A., J. Quevedo, and R. Milne. 2000. Fault diagnosis for gas turbines based on the control system. *Engineering Applications of Artificial Intelligence* 13(4):477–84. doi:10.1016/S0952-1976(00)00014-2.

Guemana, M., Ahmed Hafaifa, and Mohamed Ben Rahmoune. 2015. Reliability study of gas turbines for improving their availability by ensuring optimal exploitation. *OIL GAS European Magazine* 2:88–91.

Hafaifa, A., M. Guemana and A. Daoudi. 2015. Vibration supervision in gas turbine based on parity space approach to increasing efficiency. *Journal of Vibration and Control* 21:1622–32. doi:10.1177/1077546313499927.

Hafaifa, A., G. Mouloud, and S. Boulanouar. 2016. Monitoring system based on real data acquisition for vibrations control in gas turbine system. *Revue De Nature & Technologie: A-Sciences Fondamentales Et Engineering* 14:13–18.

Jang, J.-S. R. 1993. ANFIS: Adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man, and Cybernetics* 23(3):665–85. doi:10.1109/21.256541.

Jang, J.-S. R., and C. T. Sun. 1993. Functional equivalence between radial basis function networks and fuzzy inference systems. *IEEE Transactions on Neural Networks* 4(1):156–59. doi:10.1109/72.182710.

Jianglin Lan, R. J. 2016. Patton, A new strategy for integration of fault estimation within fault-tolerant control. *Automatica* 69:48–59. doi:10.1016/j.automatica.2016.02.014.

Kulikov, G. G. 1989a. Dynamic characteristic of gas turbine engine. In *Optimisation of multivariable control systems of aero gas turbine engines*, ed. A. A. Shevyakov, and T. S. Martyanova, 35–41. Moscow: Mashinostroenie. (In Russian).

Kulikov, G. G. 1989b. Nonlinear perforrnance-based static and dynarnic models of gas turbine engines. In *Optimisation of multivariable control systems of aero gas turbine engines*, ed. S. Aa, and M. Ts, 30–35. Moscow: Mashinostroenie. (In Russian).

Kulikov, G. G., V. Yu Arkov, and A. I. Abdulnagimov. 2013. *System safety of gas turbines: Hierarchical fuzzy Markov modelling*. Book chapter by Ernesto Benini. London, United Kingdom: InTech.

Li-Bing, W., and G.-H. Yang. 2016. Robust adaptive fault-tolerant control for a class of uncertain nonlinear systems with multiple time delays. *Journal of Process Control* 41:1–13. doi:10.1016/j.jprocont.2016.02.001.

Lyantsev, O. D., T. V. Breikin, G. G. Kulikov, and V. Y. Arkov. 2004. Optimal multi-variable control of gas turbine engines. *International Journal of Systems Science* 35(2):79–86. doi:10.1080/00207720310001657036.

Mohamed, B. R., A. Hafaifa, and M. Guemana. 2016. Fault diagnosis in gas turbine based on neural networks: Vibrations speed application. Proceedings of the International Conference on Acoustics and Vibration ATAVI'16, Hammamet –Tunisia, March 21-23.

Mohammadi, E., and M. Montazeri-Gh. 2015. A fuzzy-based gas turbine fault detection and identification system for full and part-load performance deterioration. *Aerospace Science and Technology* 46:82–93. doi:10.1016/j.ast.2015.07.002.

Nozari, H. A., M. A. Shoorehdeli, S. Simani, and H. D. Banadaki. 2012. Model based robust fault detection and isolation of an industrial gas turbine prototype using soft computing techniques. *Neurocomputing* 91:29–47. doi:10.1016/j.neucom.2012.02.014.

Ogaji, S. O. T., R. Singh, and S. D. Probert. 2002. Multiple-sensor fault-diagnoses for a 2-shaft stationary gas-turbine. *Applied Energy* 71(4):321–39. doi:10.1016/S0306-2619(02)00015-6.

Rahmoune, M. B., A. Hafaifa and M. Guemana. 2015. Vibration modeling improves pipeline performance, costs. *Oil & Gas Journal* 113(3):98–100.

Salahshoor, K., M. S. Khoshro, and M. Kordestani. 2011. Fault detection and diagnosis of an industrial steam turbine using a distributed configuration of adaptive neuro-fuzzy inference systems. *Simulation Modelling Practice and Theory* 19(5):1280–93. doi:10.1016/j.simpat.2011.01.005.

Salahshoor, K., and M. Kordestani. 2014. Design of an active fault tolerant control system for a simulated industrial steam turbine. *Applied Mathematical Modelling* 38(5–6):1753–74. doi:10.1016/j.apm.2013.09.015.

Salahshoor, K., and M. S. Mojtaba Kordestani. 2010. Khoshro, Fault detection and diagnosis of an industrial steam turbine using fusion of SVM (support vector machine) and ANFIS (adaptive neuro-fuzzy inference system) classifiers. *Energy* 35(12):5472–82. doi:10.1016/j.energy.2010.06.001.

Shi, F., and R. Patton. 2015. An active fault tolerant control approach to an offshore wind turbine model. *Renewable Energy* 75:788–98. doi:10.1016/j.renene.2014.10.061.

Simani, S., S. Alvisi, and M. Venturini. 2016. Fault tolerant control of a simulated hydroelectric system. *Control Engineering Practice* 51:13–25. doi:10.1016/j.conengprac.2016.03.010.

Topalov, A. V., Y. Oniz, E. Kayacan, and O. Kaynak. 2011. Neuro-fuzzy control of antilock braking system using sliding mode incremental learning algorithm. *Neurocomputing* 74 (11):1883–93. doi:10.1016/j.neucom.2010.07.035.

Zhiyao, M., S. Tong, and L. Yongming. 2016. Fuzzy adaptive state-feedback fault-tolerant control for switched stochastic nonlinear systems with faults. *Neurocomputing* 186:35–43. doi:10.1016/j.neucom.2015.12.080.