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Robust Model- Based Fault Detection and Isolation for V47/660kW Wind Turbine

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ABSTRACT

In this paper, in order to increase the efficiency, to reduce the cost and to prevent the failures of wind turbines, which lead to an extensive break down, a robust fault diagnosis system is proposed for V47/660kW wind turbine operated in Manjil wind farm, Gilan province, Iran. According to the acquired data from Iran wind turbine industry, common faults of the wind turbine such as sensor faults, actuator faults and component faults are identified and considered in Fault Detection and Isolation (FDI) system design. Various Faults in abrupt and incipient natures can be detected and isolated using the indicators of faults, namely residuals, that are derived based on Unknown Input Observer (UIO) approach. Moreover, some thresholds are exploited to evaluate the produced residuals. The robustness of the proposed method against parameter uncertainties is shown as well. Simulations are performed in Matlab/Simulink environment to demonstrate the effectiveness of the proposed method using the actual parameters derived from the turbine model.

KEYWORDS

Fault Detection and Isolation(FDI), Renewable Energy, Robust, Unknown Input Observer (UIO), Wind Turbine.

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1- INTRODUCTION

In recent years, human life is completely dependent on the electrical energy. Different types of renewable energy have been widely used due to solving energy, exhaustion of fossil fuels and environmental problems resulting from the consumption of these fuels. In these renewable energies, the wind energy is a plentiful and accessible kind of energy. Therefore, surveys in this subject rapidly grow to utilize this renewable energy. Nowadays, by developing the wind turbines technology, rotor diameter and capacity of the turbines are significantly increasing, and there is a moving to areas with much greater wind resource and speed. These issues have been seriously highlighted the maintenance and fault diagnosis subjects of the wind turbines. The main components of wind turbines, which are generally subjected to faults, are generator, blades and gearbox. Most failures and breakdowns of wind turbine are related to the abovementioned faults [1].

The FDI design of wind turbine has been the subject of many literatures. FDI system design methods for wind turbine system may be categorized as data driven and model - based methods. In data driven methods, the characteristics of some signals are verified for the fault detection. In [2], the monitoring and fault diagnosis of bearing and gearbox of a wind turbine are studied based on gathering the experimental data from vibration and oil debris sensor by using a signal processing techniques. An inter - turn fault of a stator phase winding in induction generator of a wind turbine is diagnosed based on the processing of stator current signal in [3]. A bearing fault diagnosis system based on the processing of stator current is proposed in [4]. In [5], the data - driven design of robust fault detection system for wind turbines is proposed and a robust residual vector instead of a single residual signal is generated under a given performance index and an optimization criterion. The data - driven method is used for FDI purpose due to some reasons such as nonlinear dynamics of wind turbines, unknown disturbances and measurement noises. The proposed method is robust against the disturbances and cannot guarantee robustness against parametric uncertainties and only sensor and actuator faults are considered. To make timely and accurate diagnosis for gearbox, an expert system based on Fault Tree Analysis (FTA) is developed in [6].

On the other hand, model based FDI methods use the mathemtical model of the system as the redundancy information. In [7], Dolan described the detection of an individual blade pitch misalignment using a model - based approach. The residuals are obtained by using a Kalman filter method. In [8], the problem of fault diagnosis of a wind farm is addressed using interval nonlinear parameter varying (NLPV) parity equations. Fault detection approach is based on the use of parity equations assuming unknown but bounded description of the noise and modeling errors. A set - valued approach to FDI and Fault Tolerant Control (FTC) of wind turbines is proposed in [9] and wind turbine model is considered to be linear parameter varying system. The main advantage of the proposed method is the development of FDI methods for uncertain linear time - varying systems, with the promising results in terms of the time required to diagnose the faults. The considered FDI methods is integrated with robust control synthesis and a new FTC algorithms is proposed, which can stabilize the plant under the faulty conditions. The FDI algorithm is assessed by available wind turbine benchmark model, using Monte Carlo simulation runs. Fault diagnosis of a wind turbine benchmark via identified fuzzy models, in the form of Takagi - Sugeno prototypes, is addressed in [10]. Fuzzy model allows to approximate uncertain models and to manage noisy data. These fuzzy models represent the residual generators used for the fault detection and isolation.

A survey of fault detection and isolation in wind turbine drives is presented in [11]. To handle any fault occurred in the current sensor of Doubly Fed Induction Generator (DFIG) of wind turbine, model - based methods such as Kalman filter approach, generalized observer scheme and dedicated observer scheme are used to detect the sensor fault. The problem of current sensor FDI of a DFIG in wind turbine using a bank of Kalman filters is tackled in [12]. In [13], Support Vector Machines (SVM) and a Kalman - like observer method were employed to isolate the faults of different types at different locations of the FAST benchmark, which simulates a closed - loop three - bladed wind turbine, and their limitation and benefits are described. In [14] , a test benchmark model for the fault detection of wind turbine is presented. The faults in this benchmark includes sensor and hydraulic faults of pitch system, encoder faults of generator and rotor speed, internal fault of converter and drive train fault which is detected using rotational speeds measurement. In this paper, the generator is modeled by a first order transfer function and complex nonlinear dynamics of induction generator of wind turbine are neglected, so the critical faults of rotor and stator, which have high failure frequency, cannot be detected. Five FDI solutions including: Gaussian Kernel Support Machine Solution (GKSV), Estimation - Based Solution (EB), Up - Down Solution (UDC) and Combined Observer and Kalman Filter Solution (COK), are also compared.

The robustness of FDI system is also highlighted in some literatures. In [15], Hwas and et al. proposed an observer - based FDI method using a multi - objective optimization procedure. A robust fault diagnosis system for rotor and generator speed sensors is designed based on the observer scheme. The optimization methods are used in the above - mentioned proposed observer, which is based on the linear state space model of a 5 MW wind turbine defined at wind speed of 10 m/s. Robust fault detection and isolation of wind turbines using interval observers are studied in [16]. Fault detection is addressed using interval observers and unknown but bounded descriptions of the noise and modeling errors. In [17], a set - valued observer is utilized for FDI of wind turbines. A simple wind turbine model is presented along with possible faulty scenarios. The set - valued observer algorithm is built upon these dynamics, taking into account process disturbances, model uncertainties, and measurement noise. The FDI system is applied on a common benchmark model, using Monte - Carlo simulation runs. Detection and isolation of sensor faults of wind turbines are concerned using sliding mode observers in [18]. In order to eliminate the effects of unknown aerodynamic rotor torque, a reduced order model of the drive train system is considered. A bank of sliding mode observer is utilized for an accurate estimation of output signal in the presence of faults.

UIO method is used in many works for the fault detection and fault tolerant purposes. An UIO based fault diagnosis system is used in [19] for sensor faults of generator speed, rotor speed and generator torque. In [20] , a fault tolerant UIO based scheme is proposed to estimate the generator speed in a wind turbine control system during generator and rotor speed sensors faults. In [21], a bank of UIOs is used for the fault detection and isolation of sensors and actuators and effectiveness of the proposed method is shown for a linear dynamic of three - tank system for actuator and sensor faults.

One thing that must be highlighted in the aforementioned approaches is that the proposed FDI systems are restricted to sensor and actuator faults, but the introduced FDI method in this work deals with all types of common faults in different natures. In this current paper, the model of wind turbine is derived based on real values from Manjil wind farm, Gilan province, Iran. It is worth noting that the detailed dynamic of generator is considered in the model, which is neglected in many works, and thus some critical faults can be detected and isolated. Common faults of wind turbine in Iran section are identified and can be detected in the FDI method. In addition to common actuator and sensor faults, common component faults are also noticed in the FDI design. The proposed FDI method can detect various faults with incipient or abrupt nature and robust analysis of the method is presented for the parametric uncertainties. In brief, the proposed method is according to the requirements of Iran wind industry and has great performance for various faults in different natures. By considering common faults in the wind turbines, such as: component faults of generator, pitch angle actuator and sensors faults, which cause breakdown, an FDI system is proposed by using the UIO method. This observer is based on the obtained model of experimental data of V47/660kW wind turbine.

The organization of the paper is as follows: In section 2, the general model of wind turbine and its experimental parameters are described. In section 3, different faults and the modeling procedure of these faults are defined. The proposed FDI system based on the UIO method is presented in section 4 and the simulation results based on the experimental data and robustness analysis are shown in section 5.

2- SYSTEM MODEL

In this paper, a 660kW wind turbine, which is located in Manjil wind farm, is considered. Different parts of the wind turbine and their models are described in this section.

A- WIND MODEL

Wind speed is an important and inseparable part of wind turbine modelling. Wind speed model consists of two parts:

$$v = v_m + v_t(t) \tag{1}$$

where v_m and $v_t(t)$ are the mean value and the turbulent part of the wind speed, respectively.

The turbulent part of wind is as (2):

$$v_t(t) = \sum_{k=1}^{K} a_k \cos w_k t + b_k \sin w_k t \tag{2}$$

Where a_k and b_k are normal with zero mean and their variance is completely dependent on the site specification [22].

According to the information received from Manjil wind farm, the simulated wind sequence is shown in Fig. 1.

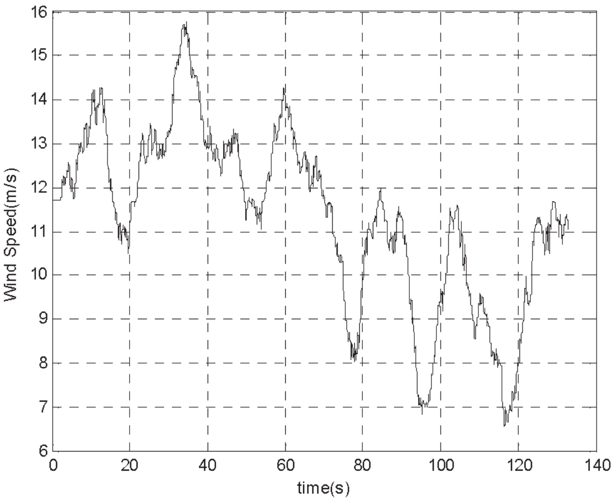

FIG.1 THE SIMULATED WIND SEQUENCE

Although often, the equation of wind does not appear in the state space model of wind turbine directly, it has great influence on the aerodynamic part.

B- AERODYNAMIC PART

In the aerodynamic part, kinetic energy of wind turns to mechanical energy by aerodynamic blades. Generated torque in this part is given as (3):

$$T_{wt} = \frac{P_{wt}}{w_{wt}} \tag{3}$$

where:

$$P_{wt} = \frac{1}{2}\rho\pi R^2 v^3 C_p(\lambda,\beta)$$
$$C_p(\lambda,\beta) = (0.44 - 0.0167\beta)\sin\left(\frac{\pi(\lambda-2)}{13-0.3\beta}\right) - 0.00184(\lambda-2)\beta$$
$$\lambda = \frac{\omega R}{V} \tag{4}$$

Where ρ is the air density, ν is the wind speed, R is the rotor radius, and C_p is the efficiency coefficient which is a function of the blade pitch angle β and the tip speed ratio λ.

In a wind turbine, each blade has a pitch actuator, which is used to vary the angle attack of the blade. The relation between the pitch angle of blade β and the pitch demand β_d is expressed by the following transfer function:

$$\beta = \frac{1}{\tau_{pitch}.s+1}\beta_d \tag{5}$$

Where τ_{pitch} is time constant that depends on the actuator.

C- MECHANICAL DRIVE TRAIN

Mechanical drive train consists of a gearbox and shafts. Shaft rotates and rotational speed is increased by gearbox and become appropriate for the electrical part. In this paper, a two mass model of mechanical drive train is used. This model is described as:

$$T_{wt} = J_T\dot{\omega}_{wt} + K_s\theta_k + C_s\omega_{wt} - \frac{C_s}{n_g}\omega_g$$
$$T_e^c = -J_G\dot{\omega}_g + \frac{K_s}{n_g}\theta_k + \frac{C_s}{n_g}\omega_{wt} - \frac{C_s}{n_g^2}\omega_g$$
$$\dot{\theta}_k = \omega_{wt} - \frac{\omega_g}{n_g} \tag{6}$$

Where T_e^c is the control torque, K_s is the torsional stiffness, C_S is the torsional damping, T_{wt} is the aerodynamic torque, J_T is the turbine inertia, J_G is the generator inertia, n_g is the gearbox ratio, ω_{wt} is the rotor speed and ω_g is the generator speed. For Vestas V47 turbine, which is considered in this paper, gearbox ratio is 52.6.

D- GENERATOR

Nonlinear model of generator has been expressed in [23] as below.

$$\psi_{ds} = L_m \left|\vec{i}_{ms}\right|, \ \psi_{qs} = L_s i_{qs} + L_m i_{qr} = 0$$
$$\psi_{dr} = L_m^2 \left|\vec{i}_{ms}\right| + \sigma L_r i_{dr}, \ \psi_{qr} = \sigma L_r i_{qr} \quad (7)$$

Where $\left|\vec{i}_{ms}\right| = \left|\vec{v}_s\right| / \omega_s L_m$, $\sigma = 1 - L_m^2 / L_s L_r$ is used for the leakage coefficient and $\left|\vec{v}_s\right| = \sqrt{3}\, V_s$, which V_s is the stator voltage.

By considering some assumptions about generator for observability condition as stated in [23], the reduced order model may be rewritten as (8).

$$v_{ds} = R_s i_{ds} - \omega_s \psi_{qs} + \frac{d\psi_{ds}}{dt} = 0$$
$$v_{qs} = R_s i_{qs} + \omega_s \psi_{ds} + \frac{d\psi_{qs}}{dt} \approx \omega_s \psi_{ds} = \left|\vec{v}_s\right|$$
$$v_{dr} = \sigma L_r \frac{di_{dr}}{dt} + R_r i_{dr} - (\omega_s - \omega_m)\sigma L_r i_{qr}$$
$$v_{qr} = \sigma L_r \frac{di_{qr}}{dt} + R_r i_{qr} + (\omega_s - \omega_m)(\sigma L_r i_{dr} + \frac{\sqrt{3} L_m V_s}{\omega_s L_s}) \quad (8)$$

Where $\psi_{qs}, \psi_{qr}, i_{ds}, i_{qs}, i_{dr}, i_{qr}, v_{ds}, v_{qs}, v_{dr}, v_{qr}$ are stator and rotor flux, current and voltage in d - q frame. R_s, R_r, L_s and L_r are stator and rotor resistance and inductance. L_m is the mutual inductance and ω_s is the synchronous speed.

The nonlinear model of generator is written as:

$$\begin{bmatrix} \frac{di_{dr}}{dt} \\ \frac{di_{qr}}{dt} \end{bmatrix} = \begin{bmatrix} \frac{1}{\sigma L_r} v_{dr} - \frac{R_r}{\sigma L_r} i_{dr} + (w_s - w_m) i_{qr} \\ \frac{1}{\sigma L_r} v_{qr} - \frac{R_r}{\sigma L_r} i_{qr} - (w_s - w_m) i_{dr} - \frac{\sqrt{3} V_s . L_m}{\sigma L_r L_s} + \frac{\sqrt{3} V_s . L_m}{\sigma L_r L_s w_s} w_m \end{bmatrix} \quad (9)$$

The output equation is:

$$T_e = \frac{n_p \sqrt{3} L_m V_s i_{qr}}{L_s w_s}$$

By linearization of nonlinear model, the generator model is described as:

$$\begin{bmatrix} \frac{di_{dr}}{dt} \\ \frac{di_{qr}}{dt} \end{bmatrix} = \begin{bmatrix} \frac{1}{\sigma L_r} v_{dr} - \frac{R_r}{\sigma L_r} i_{dr} + (w_s - \overline{w}_m) i_{qr} - i_{qr0} w_m \\ (\frac{1}{\sigma L_r} - \overline{k}) v_{qr} - \frac{R_r}{\sigma L_r} i_{qr} - (w_s - \overline{w}_m) i_{dr} + (i_{dr0} + \frac{\sqrt{3} V_s . L_m}{\sigma L_r L_s w_s}) w_m \end{bmatrix} \quad (10)$$

Where $\overline{w}_m$, i_{qr0} and i_{dr0} are generator speed, d - axis and q - axis stator current at operation point. $\overline{k}$ is defined as:

$$\overline{k} = \frac{\sqrt{3} L_m V_s}{\sigma L_s L_r \overline{v}_{qr}^{\ 2}}$$

The generalized form of linearized state space model of wind turbine system is described as (11):

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) + Du(t) \end{cases} \quad (11)$$

By considering the dynamic of pitch angle actuator, mechanical drive train and induction generator of wind turbine described above, the state space matrices can be stated as follows:

$$A = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & \frac{-1}{n_g} & 0 & 0 \\ 0 & \frac{-K_s}{J_T} & \frac{-C_s}{J_T} & \frac{-C_s}{J_T n_g} & 0 & 0 \\ 0 & \frac{K_s}{J_G n_g} & \frac{C_s}{J_G n_g} & \frac{-C_s}{J_G n_g^2} & 0 & 0 \\ 0 & 0 & 0 & -i_{qr0} & \frac{-R_r}{\sigma L_r} & (w_s - \overline{w}_m) \\ 0 & 0 & 0 & i_{dr0} + \frac{\sqrt{3} L_m V_s}{\sigma L_s L_r w_s} & -(w_s - \overline{w}_m) & \frac{-R_r}{\sigma L_r} \end{bmatrix}$$

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{1}{J_T} & 0 & 0 & 0 \\ 0 & 0 & \frac{-1}{J_G} & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{\sigma L_r} & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{\sigma L_r} - \overline{k} \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \Xi \end{bmatrix}, \quad \Xi = \frac{-\sqrt{3} n_p L_m V_s K_c}{\sigma L_r L_s w_s}$$

Where $\dot{\theta} = \omega_{wt} - \frac{\omega_g}{n_g}$, $K_c = 0.84$ and D is the zero matrix.

State vector, inputs and outputs of the system are listed as follows.

$$x = [\beta, \theta_K, \omega_{wt}, \omega_g, i_{dr}, i_{qr}]^T,$$
$$u = [\beta_d, T_{wt}, T_e^c, v_{dr}, v_{qr}]^T,$$
$$y = [\beta, \omega_{wt}, \omega_g, T_e]$$

Rated values of the system parameters for the considered wind turbine are given in [24, 25].

3- FAULTS MODELING

Common faults of the wind turbines, that may cause critical conditions, are firstly expressed and analyzed according to the acquired data from Iran renewable energy organization (SANA). The corresponding faults are defined in this model and an FDI system based on the UIO is also designed, which it can detect and isolate these faults. The considered faults are listed below as follows in Table I.

Table 1

THE CONSIDERED FAULTS OF WIND TURBINE

f_1	Increasing temperature in rotor of the induction generator
f_2	Stator winding fault of the induction generator
f_3	Pitch actuator fault
f_4	Rotor speed sensor fault
f_5	Generator speed sensor fault

Since, f_1 fault can directly effect on the resistor of the rotor and leads to an increase in the resistance value; this fault is modeled as the component fault. The effect of temperature on this resistance is given by (12).

$$R = R_0(1+\alpha\Delta T) \tag{12}$$

Where R is the resistance value, R_0 is the resistance value at the reference temperature $T_0 = 25^\circ C$ and ΔT is the increasing temperature [26].

According to (2), increasing temperature in rotor leads to increase in the resistance value. This incremental value is considered as $\Delta R_r = 1.3R_r$.

f_2 is considered as inter - turn stator phase winding fault, that may happen due to the problems of insulation. This fault is defined as a short circuit of the stator phase winding. When the inter - turn fault occurred in stator or rotor phase winding, their three - phase currents become asymmetrical. In [27], three phases current has been analyzed under different fault degrees, which is set to the short circuit for 1 turn, 5 turns and 10 turns. When this fault occurs in A - phase, the A - phase and B - phase currents will increase, while C - phase current is remained constant [27]. In this paper, 5 - turn short circuit in A - phase is considered. i_q is described as:

$$i_q = \frac{1}{\sqrt{2}} i_B - \frac{1}{\sqrt{2}} i_C \tag{13}$$

Thus, f_2 fault leads to increase in i_q , and incremental value of i_q is considered as $\Delta i_q = 0.5 i_q$.

The f_3 is the actuator fault, which is modeled as an abrupt nature. It is also worth noting that the f_4 and f_5 are defined as incipient faults of sensors.

In this current paper, various types of faults are considered in the FDI system design and based on this assumption; the system model is determined as follows (14):

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + Bf_a(t) + f_c(t) \\ y(t) = Cx(t) + Du(t) + Df_a(t) + f_s(t) \end{cases} \tag{14}$$

Where f_a , f_c and f_s are actuator, system and sensor faults, respectively.

4- FDI SYSTEM DESIGN

As illustrated in Fig.2, the model - based FDI methods consist of two steps [28]: 1 - residual generation 2 - decision - making.

The residual generation is the main step in model - based FDI system design and different methods are proposed in this regard. Because of the non - deterministic nature of wind units as the main input of wind turbine system, the UIOs are introduced in this paper.

A- UNKNOWN INPUT OBSERVER

The UIOs have received much attention as one of the robust residual generation methods in the FDI system design. In the presence of unknown inputs, such as: external disturbance, noise and modeling uncertainties in the system, the UIO may be used to obtain the robust performance of FDI system [29]. Robust residual generation can be achieved by using the UIO, in which the residuals are completely decoupled from unknown inputs. The system equations are defined as follows (15):

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + Ed(t) \\ y(t) = Cx(t) \end{cases} \tag{15}$$

Where *d(t)* is the unknown input vector and *E* is the distribution matrix of unknown inputs.

The structure of the desirable UIO is also defined as follows (16):

$$\begin{cases} \dot{z}(t) = Fz(t) + TBu(t) + Ky(t) \\ \hat{x}(t) = z(t) + Hy(t) \end{cases} \tag{16}$$

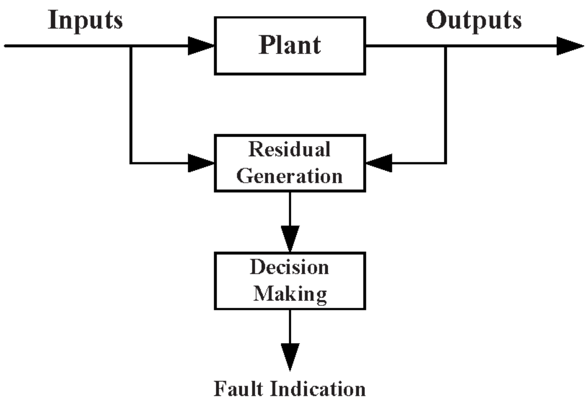

FIG.2 THE STRUCTURE OF A MODEL BASED FDI

where

$(HC-I)E=0$

T = I - HC

F = A - HCA - $K_1C = A_1 - K_1C$

$K_2 = FH$

K= $K_1 + K_2$

It must be mentioned that necessary and sufficient conditions for existing the UIO according to [28] are:

$rank(\mathrm{CE}) = rank(E)$

$(\mathrm{C}, \mathrm{A}_1 = \mathrm{TA})$ is detectable pair.

B- RESIDUAL GENERATION

There is a direct relation between speed of wind and aerodynamic torque in wind turbines. The speed of wind has non - deterministic and random nature. Therefore, in the defined system as (15), the aerodynamic torque is considered as an unknown input. With regard to this fact, the system matrices are changed below as follows.

$$d(t) = T_{wt} \ , E = [0 \quad 0 \quad \frac{1}{J_T} \quad 0 \quad 0 \quad 0]^T$$

$$u = [\beta_d, T_e^c, v_{dr}, v_{qr}]^T, \ B = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & \frac{-1}{J_G} & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

The main structure of the UIO for two intended sensor faults is depicted in Fig.3. As illustrated in Fig.3, to design sensor fault isolation schemes, all actuators are assumed to be fault - free and the residual generator is driven by all inputs and all but one Outputs.

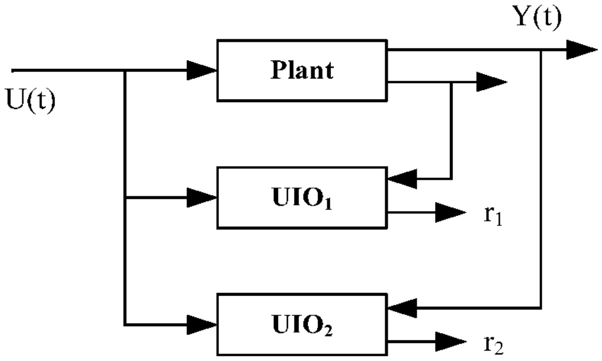

FIG.3 THE STRUCTURE OF SENSOR FAULT OBSERVER

The state space model of the system may be expressed as [28]:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + Ed(t) \\ y^j(t) = C^j x(t) + f_s^j(t) \qquad \text{for } j = 1, 2 \\ y_j(t) = c_j x(t) + f_{sj}(t) \end{cases} \tag{17}$$

Where C_j is the j - th row of C matrix, C^j is C matrix by removing j - th row, $y_j(t)$ is j - th element of y and $y^j(t)$ is a vector by removing j - th element. The required equations for generating residual vector are defined as follows (18):

$$\begin{cases} \dot{z}^j(t) = F^j z^j(t) + T^j Bu(t) + K^j y^j(t) \\ r^j(t) = (I - C^j H^j) y^j(t) - C^j z^j(t) \end{cases} \tag{18}$$

When actuator fault occurred, the system equations may be stated below as follows.

$$\dot{x} = Ax + Bu + E_d d_d + F_a f_a \tag{19}$$

By considering component faults of f_1 and f_2, the system structure can be changed according to (20).

$$\begin{aligned} &\dot{x} = Ax + Bu + E_d d_d + F_{a1} f_{a1} + F_{a2} f_{a2} \\ &F_{a1} f_{a1} = \Delta A_{f1}.x_6 \ , \ F_{a2} f_{a2} = \Delta A_{f2}.x_4 \end{aligned} \tag{20}$$

In this case, the component fault as well as the actuator fault may be added in the system dynamic as an additive fault. Three observers are used as the FDI system for detection and isolation of component and actuator faults; and thus, it can be rewritten as follows:

$$\begin{cases} \dot{x}(t) = Ax(t) + B^i u^i(t) + B^i f_a^i(t) + E^i d^i(t) \\ y = Cx(t) \end{cases}$$

$$E^i = [E \quad (\mathrm{b}_i) or (\Delta A_i)] \ , \ \mathrm{d}^i(t) = \begin{bmatrix} d(t) \\ u_i(t) + f_{ai}(t) \end{bmatrix} \tag{21}$$

In the previous Eq., b_i is the i - th column of B matrix,

B^i is B matrix by removing i - th column, u_i is i - th input element and u^i is a vector by removing i - th element of input vector. The residuals can be obtained as (22).

$$\begin{cases} \dot{z}^i(t) = F^i z^i(t) + T^i B^i u^i(t) + K^i y(t) \\ r^i(t) = (I - CH^i) y(t) - C z^i(t) \end{cases} \tag{22}$$

According to (20), the following equations are kept for component faults.

$$\Delta A_{f1} = [0 \quad 0 \quad 0 \quad 0 \quad 0 \quad \frac{-\Delta R_r}{\sigma L_r}]^T$$

$$\Delta A_{f2} = [0 \quad 0 \quad 0 \; -\Delta i_q \quad 0 \quad 0]^T$$

Based on the above - mentioned description, the residual for each type of the considered fault can be exploited.

C- DECISION - MAKING

In this section, a decision is made on the occurrence of a fault in the system based on the associated residuals. Because of the residual generation procedure, which is robust to disturbances and model uncertainties, a simple threshold is used in decision - making step as (23).

$$T = m + v \tag{23}$$

Where m and ν are the mean value and standard deviation of the residuals, respectively. The decision is made based on (24).

$$\begin{cases} r_i(t) \le T_i \Rightarrow f_i = 0 \\ r_i(t) > T_i \Rightarrow f_i \ne 0 \end{cases}, \; i = 1,\dots,5 \tag{24}$$

If any residual is violated from its predefined threshold, then a fault occurrence is declared.

5- SIMULATION RESULTS

By using the state space model in (11) and the parameters of V47/660kW wind turbine of Manjil site, the simulation is applied in the Simulink platform of MATLAB software by assuming the average speed of wind as 10m/s. The UIOs are designed based on the model that is obtained through using the experimental values. In order to show the effectiveness of the proposed method, different faults of sensors, actuators and component in various natures are injected into the system, and the residuals are investigated. By applying the defined threshold in (23), different faults can be detected. The results of fault detection are shown in Fig.4 to Fig.8.

A- DIFFERENT FAULT SCENARIOS

In the first fault assumption, a sensor fault is injected at t=30 sec in the system. As shown in Fig.4, by applying an appropriate threshold, the fault in rotor speed sensor can be detected.

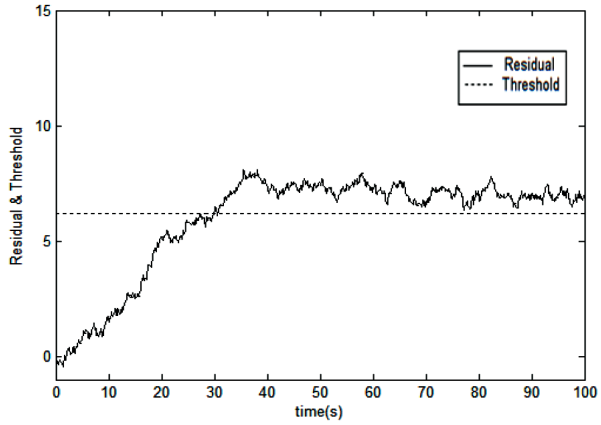

FIG.4 THE RESIDUAL OF ROTOR SPEED SENSOR FAULT AND ITS THRESHOLD

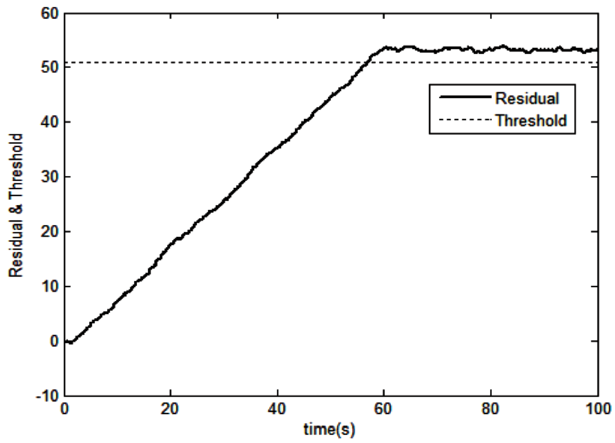

FIG.5 THE RESIDUAL OF GENERATOR SPEED SENSOR FAULT AND ITS THRESHOLD

It can be seen from Fig.5 that the generator speed sensor fault can be detected at t=55sec.

The result of the pitch actuator fault is shown in Fig.6. The fault occurrence can be declared at t=70sec.

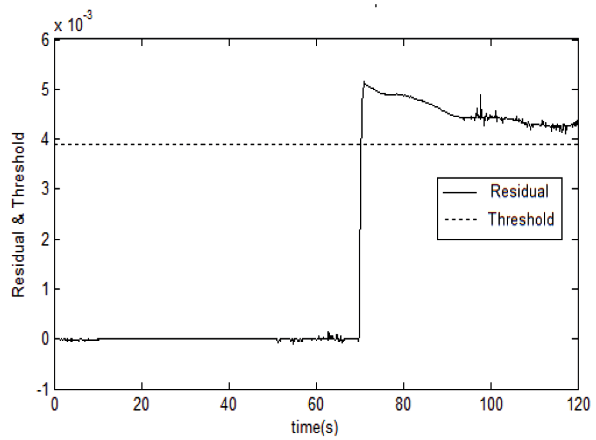

FIG.6 THE RESIDUAL OF PITCH ANGLE ACTUATOR FAULT AND ITS THRESHOLD

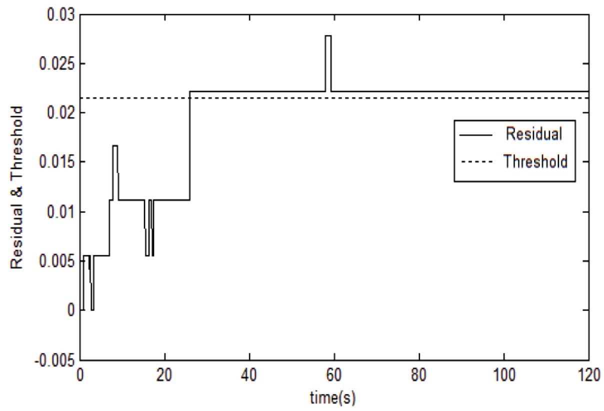

FIG.7 THE RESIDUAL OF STATOR WINDING FAULT AND ITS THRESHOLD

According to Fig.7, the component fault of stator winding is detected at t=28sec.

Increasing the temperature of rotor fault is very destructive. Therefore, timely and rapid detection of this fault is so important, which was depicted in Fig. 8.

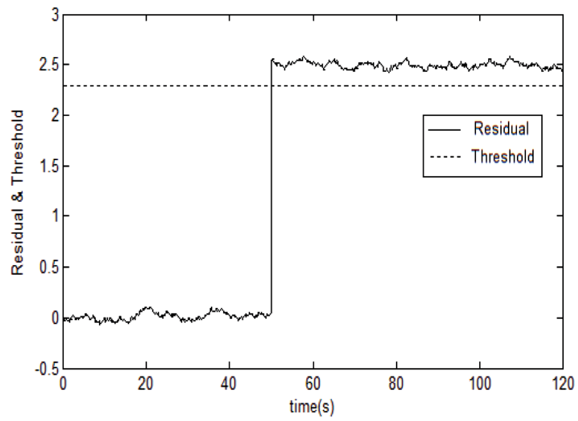

FIG.8 THE RESIDUAL OF ROTOR TEMPERATURE FAULT AND ITS THRESHOLD

Based on the obtained results, the proposed FDI method can detect different faults that can cause critical conditions.

In order to isolate the considered faults, isolation logic is used, which are based on the sensitivity analysis. The results of sensitivity analysis are given in Table II. In this Table, element "1" indicates that the residual is sensitive for considering fault and vice versa. Based on the observed residuals, the corresponding fault can be detected and isolated.

Table 2

THE FAULT ISOLATION TABLE

Residual \ Fault	f_1	f_2	f_3	f_4	f_5
r_1	1	0	0	0	0
r_2	0	1	0	0	0
r_3	0	0	1	0	0
r_4	0	0	1	1	0
r_5	0	0	0	0	1

B- ROBUSTNESS ANALYSIS AGAINST PARAMETER UNCERTAINTY

In this section, the robustness of the proposed method against structured uncertainty is evaluated. The fault detection based on UIOs has also a certain degree of robustness against the parameter variations [28]. Some application results of UIO and its robustness are reported in [30].

To show the robustness of FDI system, some uncertainties are considered in system and the results are compared with the observer, which is designed based on the nominal model of the system. By consideration of the parameter uncertainties and without any fault injection, the residuals are analyzed and the robustness of the proposed method is demonstrated. In this condition, the state space model of the system is written as:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + E'd'(t) \\ E'd'(t) = Ed(t) + \Delta A.x(t) + \Delta B.u(t) \\ y(t) = Cx(t) \end{cases} \tag{25}$$

Where ΔA and ΔB are the effects of the parameter uncertainties in wind turbine model, which are defined as follows.

$$\Delta A = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -0.09\alpha_{24} & 0 & 0 \\ 0 & -0.09\alpha_{32} & -0.09\alpha_{33} & -0.09\alpha_{34} & 0 & 0 \\ 0 & -0.09\alpha_{42} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & -0.09\alpha_{56} \\ 0 & 0 & 0 & -0.09\alpha_{64} & -0.09\alpha_{65} & 0 \end{bmatrix}$$

$$\Delta B = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & -0.02b_{42} & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Where α_{ij}, b_{ij} are elements of A and B matrices, which were located at ith row and jth column.

The residual in normal condition are generated and the results show the robustness of the proposed method. The residuals in this condition are shown in Fig.9.

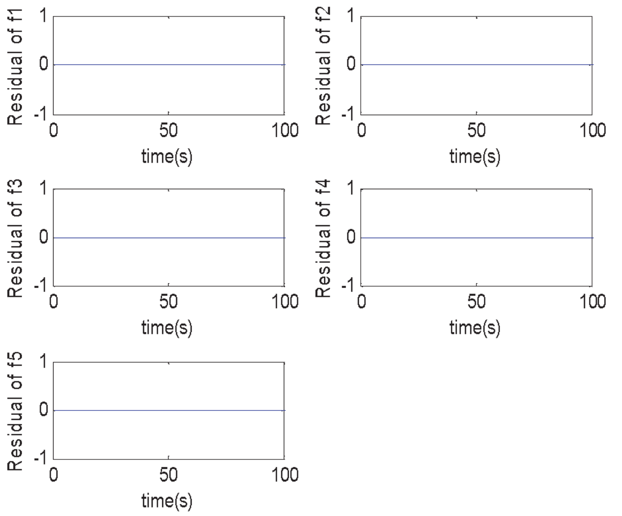

Fig.9 Residuals in normal condition with consideration of model uncertainties

As it can be seen from Fig.9, the residuals are not sensitive to the considered uncertainties in parameters of A and B. In other words, the FDI system is robust against the structured uncertainties, which are considered for the parameters of the system.

The fault sensitivity of FDI system with and without parameter uncertainties is shown in Fig.10 and Fig.11 for rotor and generator speed sensor faults, respectively. According to the figures, the fault sensitivity is acceptable and FDI system has great performance in uncertain condition. On the other hand, the FDI system is robust against parameter uncertainties and can detect various faults with different natures as well.

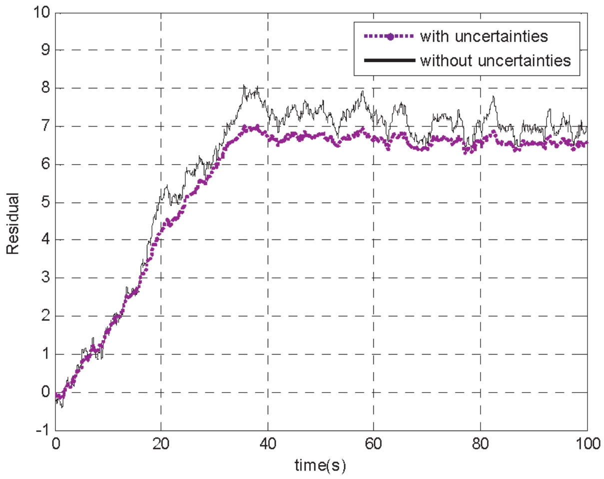

Fig.10 Residual with and without uncertainty for rotor speed sensor fault

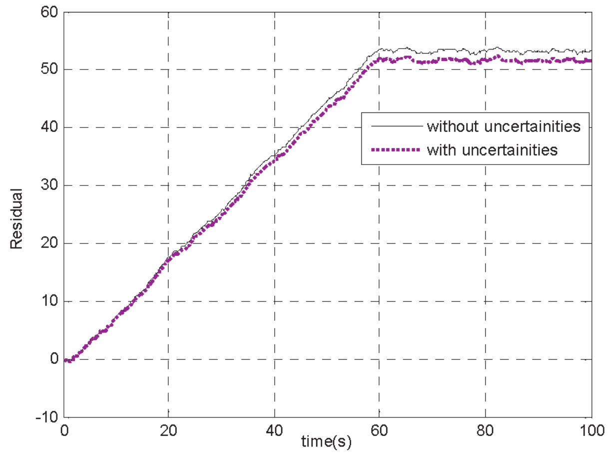

Fig.11 Residual with and without uncertainty for generator speed sensor fault

6- CONCLUSION

In order to operate the wind farms effectively, many researchers have focused on the FDI system. In this paper, some critical faults of wind turbine, which can cause large break down, are considered. Robust detection of faults has played an important role in model - based FDI system, due to the existence of modeling uncertainty, noises and disturbances. For robust FDI system, the UIO is used to improve the performance of the system in terms of modeling uncertainties and disturbances due to stochastic nature of wind. By applying a simple threshold in decision - making step, the time of fault occurrence was identified and various faults were isolated based on isolation logic. In addition to sensor faults, which have been investigated in many literatures, component faults and actuator faults were considered in this paper. The robustness of FDI system against parameter uncertainties was also analyzed. The proposed method, which is based on the experimental model of a wind turbine, can detect and isolate various faults in different natures, and can be significantly used in wind turbine units.

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