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Robust Fault Diagnosis for Wind Turbine Systems Subjected to Multi-Faults

Sarah Odofin, Zhiwei Gao, Sun Kai

Abstract**—**Operations, maintenance and reliability of wind turbines have received much attention over the years due to the rapid expansion of wind farms. This paper explores early fault diagnosis technique for a 5MW wind turbine system subjected to multiple faults, where genetic optimization algorithm is employed to make the residual sensitive to the faults, but robust against disturbances. The proposed technique has a potential to reduce the downtime mostly caused by the breakdown of components and exploit the productivity consistency by providing timely fault alarms. Simulation results show the effectiveness of the robust fault detection methods used under Matlab/Simulink/Gatool environment.

Keywords**—**Disturbance robustness, fault monitoring and detection, genetic algorithm and observer technique.

I. Introduction

WIND energy is regarded as one of the fastest growing sources of low carbon footprint renewable energy in the world today. There is a rapid exponential growth of wind farm energy, which has contributed greatly to the future of energy production. The universal wind energy projects capacity will reach 536,000 MW by 2017, almost double its current size, with progress specifically focused in the Asia and Europe [1]. There is a need to constantly improve system reliability and reduce the costs of operations and maintenance of the renewable resources, coupled with various advantages in terms of energy supply [2]. Damaged components could cause high loses in energy production and perhaps destroy the wind turbine [3]. Maintenance of wind turbine (WT) is essential for the healthy state of components as well as to achieve designed purpose, which ensures system reliability and availability, improves the performance of system monitoring and sustains the components from the breakdowns [4]. Decrease in maintenance costs, operations as well as environmental sustainability would be a landmark achievement to the development of wind industry in the upcoming years [5]. Hence, early diagnosis of faults could save time and finances as well as avoid system breakdown, mission abortion, and reduce catastrophes events.

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Faults in wind turbine systems may not be permissible and must be spotted as early as possible [6] with the right monitoring techniques in place.

The diagnosis of abrupt fault is reasonably convenient, as their effects on the dynamic process are more than modelling uncertainty so, the abrupt faults can be easily spotted by assigning a suitable threshold on the residual. Incipient type of faults have minor upshot and nearly invisible on residuals which can be unseen as a result of coupled disturbances. However, incipient faults progress gradually to cause severe hazard on the system, which should be diagnosed as early as possible so that necessary actions can be taken to avoid any further damage of the systems. Wind turbines generally have two typical types of faults which are abrupt faults and incipient faults.

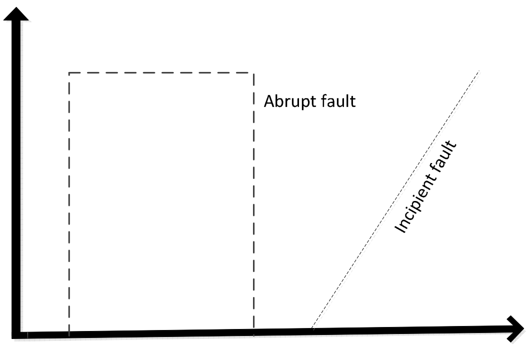

Fig. 1 Types of Fault description

Disturbances always exist in real-time systems which make it challenging for fault diagnosis [7]. In order to make the residual signal sensitive to the faults but robust against the disturbances, different optimization techniques can be utilized to minimize the effects from disturbances, but maximize the faults sensitivity on residual [8]–[11].

As one of the advanced soft computing procedures of artificial intelligence, genetic algorithm (GA) is inspired by Darwin's theory of evolution and driven by the survival of the fittest. The GA optimisation was well addressed by [12] and further research results were reported during last the two decades. Currently, GA has been widely used in all the science communities due to its ability for seeking a global optimal solution. This motivates us to employ the GA techniques to improve the fault detection performance. In this paper, GA optimization will be utilized for the robust fault diagnosis of wind turbine systems subjected to multiple faults, including the types of incipient and abrupt faults.

The paper is organized as follows. Following the introduction in Section I, is the wind turbine model and the principle of fault diagnosis is addressed in Section II. The application of genetic approach is described in part III. Simulation results and analysis are addressed in Section IV. The paper is ended by the conclusion in Section V.

II. Wind Turbine Model and Principle of Fault Diagnosis

A. Wind Turbine Model

A 5MW wind turbine subjected to faults and disturbances is described as $x \in \Re^n$ is the state vector, $u \in \Re^m$ is the input of the system, $y \in \Re^p$ is the measured output and $f \in \Re^h$ is a fault vector $d \in \Re^l$ represents the unknown disturbance where $A, B, C, B_f, B_d M, D, D_f$ and D_d are known matrices with appropriate dimensions. The state $\boldsymbol{x(t)}$, input $\boldsymbol{u(t)}$ and output $\boldsymbol{y(t)}$ vectors are represented by:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + B_f f(t) + B_d d(t) \\ y(t) = Cx(t) + Du(t) + D_f f(t) + D_d d(t) \end{cases} \tag{1}$$

The 5MW model is characterized below, the parameters and symbols are described by [4] in Table I:

$$x = \begin{bmatrix} \beta \\ \theta_K \\ \omega_{wt} \\ \omega_{m,} \\ i_{dr} \\ i_{qr} \end{bmatrix} = \begin{bmatrix} \text{pitch angle} \\ \text{angular speed position} \\ \text{wind turbine speed} \\ \text{generator speed} \\ \text{d - axis rotor current} \\ \text{q - axis rotor current} \end{bmatrix} \tag{2}$$

$$u = \begin{bmatrix} \beta_d \\ T_{wt,} \\ T_e^c \\ v_{dr} \\ v_{qr} \end{bmatrix} = \begin{bmatrix} \text{pitch angle} \\ \text{wind turbine torque} \\ \text{electrical control torque} \\ \text{active control rotor volt ages} \\ \text{reactive control rotor volt ages} \end{bmatrix} \tag{3}$$

$$y = \begin{bmatrix} \beta \\ \omega_{wt} \\ \omega_m \\ T_e \end{bmatrix} = \begin{bmatrix} \text{pitch angle} \\ \text{wind turbine speed} \\ \text{generator speed} \\ \text{electromag netic torque} \end{bmatrix} \tag{4}$$

The matrices of the wind turbine model are given as:

$$A = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & \frac{-1}{n_g} & 0 & 0 \\ 0 & \frac{K_s}{J_T} & \frac{-C_s}{J_T} & k_1 & 0 & 0 \\ 0 & k_2 & k_3 & k_4 & 0 & 0 \\ 0 & 0 & 0 & -i_q & \frac{-R_r}{\sigma L_r} & k_5 \\ 0 & 0 & 0 & k_6 & -k_5 & \frac{-R_s}{\sigma L_r} \end{bmatrix}, \quad B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{1}{J_T} & 0 & 0 & 0 \\ 0 & 0 & \frac{-1}{J_G} & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$B_f = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \quad B_d = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & k_7 \end{bmatrix}$$

where,

$$k_1 = C_s / J_T n_g, \quad K_c = 0.8383 \quad k_2 = K_s / J_G n_g \quad k_3 = C_s / J_G n_g,$$
$$k_4 = -C_s / J_G n_g^2, \quad k_5 = \omega_s - \omega_m, \quad k_6 = \left(i_d + L_m V_{sq}\right) / L_s \omega_s$$
$$k_7 = -\sqrt{3} n_p L_m V_s K_c / \sigma L_r \quad \theta = \omega_{wt} - \omega_m / n_g,$$

$$D = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad D_d = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \quad D_f = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

TABLE I
MONITORED PARAMETERS DESCRIPTION AND SYMBOLS

Symbol	Quantity	Unit
σ	Leakage coefficient	[.]
n_g	Drive train gear ratio	[.]
J_G	Moment of inertia of a generator	[.]
K_s	Torsion stiffness of the drive train	[Nm/rad]
C_s	Torsional damping coefficient of the drive train	[Nm/(rad/s)]
ω_S	Synchronous speed	[rad/s]
R_s	Stator resistance	[p.u]
R_r	Rotor resistance	[p.u]
L_s	Stator inductance	[p.u]
L_r	rotor inductance	[p.u]
L_m	Mutual inductance	[p.u]
i_d, i_q	Stator current	[p.u]
β	Pitch angle	[º]
β_d	Desired pitch angle	[º]
T_{wt}	Mechanical torque	[Nm]
T_e	Electrical torque	[Nm]
T_e^c	Control torque	[Nm]
V_{dr}, V_{qr}	Control rotor voltages	[p.u]
ω_{wt}	Wind turbine speed	[m/s]
ω_m	Generator speed	[rad/s]
V_s	Stator voltage	[p.u]
η_g	Efficiency of the generator	[·]

B. Principle of Fault Diagnosis

The observer-based fault detection filter can be described by $r \in \Re^p$ is the residual vector which is regarded as fault indicator, $\hat{x}$ and $\hat{y}$ are the estimates of the state and output of the system respectively. The matrix $W \in \Re^{p \times m}$ is the residual weighting factor as defined in (5):

$$\begin{cases} \dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + K(y - \hat{y}) \\ \hat{y}(t) = C\hat{x}(t) + Du(t) \\ r(t) = W(y(t) - \hat{y}(t)) \end{cases} \tag{5}$$

The residuals are designed in such a manner to be near zero (or within a limit) in normal operation of the process, but with a derivation from zero (a limit) in the event of a fault. Fault detection scheme is depicted in Fig. 2.

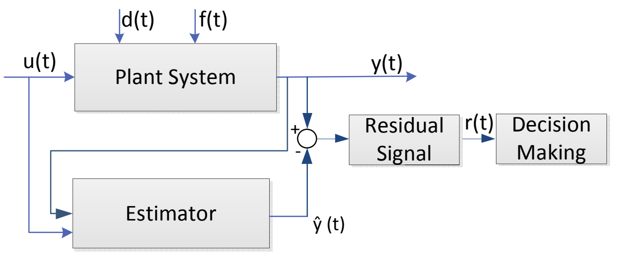

Fig. 2 Fault detection scheme

Actually, even when there is no fault in a system, the residual $r(t)$ is not zero due to the existence of the disturbance and noises. Therefore, the robust residual signal can be used to detect faults according to natural threshold logic:

$$\begin{cases} \|r(t)\| \le f_T, & faulty-free \\ \|r(t)\| > f_T, & give \quad alarm \end{cases}$$

where f_T is the threshold value.

The objective of this method is to apply a robust observer to make the transfer disturbance function $G_d(s)$ as small as possible but transfer fault function $G_f(s)$ as large as possible. Establishing the relationship from $d(s)$ and $f(s)$ to the residual gives:

$$r(s) = G_f(s)f(s) + G_d(s)d(s) \tag{6}$$

where

$$\begin{cases} G_f(s) = C(sI - A + KC)^{-1}(B_f - KD_f) + D_f \\ G_d(s) = C(sI - A + KC)^{-1}(B_d - KD_d) + D_d \end{cases} \tag{7}$$

The design of a robust fault detection filter is to select gain matrix ***K*** which must guarantee the stability of the observer using the artificial intelligence GA, such that the followings are satisfied:

- Stability: All eigenvalues of $A-KC$ lie within the left-hand open complex plane, which is denoted by desired poles $\lambda_i(i = 1,......., n_r, n_{c-c})$ with corresponding eigenvectors.
- Sensitivities to faults: To improve the response of the system behavior to fault regardless of disturbance in the system by maximizing the norm of $G_f(s)$.
- Robustness against disturbances: To decrease the effect of process disturbances on the residual by minimizing the norm of $G_d(s)$.

As a result, to seek this optimal residual signal, the multi objective constrained optimization problem needs to be a solved using genetic algorithm. Eigenstructure assignment gives parameters freedom to effectively design the generated gain observer to make the residual robust against disturbances and sensitive to the process faults of the wind turbine control system.

III. Application of Genetic Algorithm (GA) Approach

The eigenstructure assignment is a technique used to allocate the entire eigenstructure (eigenvalues and left or right eigenvectors) of a linear system through feedback control law, which is further extended for the observer gain design and fault detection and diagnosis [3], [6]-[8]. The eigenvalues and eigenvector of the observer dynamics can be described as $(A - KC)$ is the assign matrix of eigenvalues system, qi are the i_{th} right eigenvector corresponding to the i_{th} eigenvalues of λ_i as in [3]:

$$q(A^T - K^T C^T) = \lambda_i q_i \ . \tag{8}$$

These design parameter vector are chosen to improve the sensitivity and the robustness of the closed-loop matrix system respectively.

The eigenvalues can be indicated in predefined points or regions allowing the residual responses. The eigenvalues can be selected as real and complex values, such as n_{real} real eigenvalues are closed loop observer poles of $\lambda_i(i = 1, \cdots, n_{real})$, and n_{c-c} complex-conjugate eigenvalues $\lambda_{j,re} \pm j\lambda_{j,im}(j = 1, \cdots, n_{c-c})$ have to be chosen by designer earlier the design procedure to meet the stability criteria and one can have

$$n = n_{real} + 2n_{c-c} \ . \tag{9}$$

Hence, eigenstructure assignment system is chosen to give parameterization of observer K , the appropriate gain matrix is $K \in \Re^{n \times p}$ which must achieve the stability of the observer:

$$K = \left[WQ^{-1}\right]^T \tag{10}$$

The assignment of eigenvalues is in regions rather than at precise points which raises the design freedom. The design parameter matrix and the corresponding column vector whose elements can be determined randomly.

$$V = \left[v_{1,..............}, v_n, v_{c-c}\right]^T \in \Re^{n \times n} \ ,$$
$$W^T = \left[w_{1..............}, w_n, w_{c-c}\right] \in \Re^{p \times n}$$

The matrix W are the eigenvalues of the closed loop gain, V is chosen to be the left eigenvector matrix and its inverse corresponding values of eigenvalues of W mutually equal-sided to diverse eigenvalues where v_i corresponds to the eigenvalue of λ as the chromosome population expressed in a vector form.

$$\alpha = \left[\lambda_1, \lambda_2, \lambda_3 ....., \lambda_n, \lambda_{c-c} q_1^T, q_2^T, q_3^T ... q_n^T, q_{c-c}^T\right]$$

The total sum of the parameters is $\alpha = n + n \times p$

The fitness is chosen to find the global solution by evaluating fitness function is defined as $J_2 = \left\| G_d(s) \right\|_{s=jw_d}$ represent the robustness against disturbance to be minimized and $J_1 = \left\| G_f(s) \right\|_{s=0}$ indicates the sensitivity to faults to be maximized as designated in (11).

$$P = \frac{J_2}{J_1} \tag{11}$$

The constraints function is the eigenvalues to be within the open left-hand complex plane for continuous system, that is, the residual dynamics must be stable.

IV. Simulation Results and Analysis

The process disturbance injected to the 5MW wind turbine system is defined as follows:

$$d(t) = 0.001\sin(12\pi t) \tag{12}$$

A. Sensor Faults Robust Detection

Sensor faults can be described as the case when $B_f = 0$, while $D_f = I$ in (1).

The best fitness values generated by the GA evolution progress are shown in Fig. 3, where the population and generations are both set as 100.

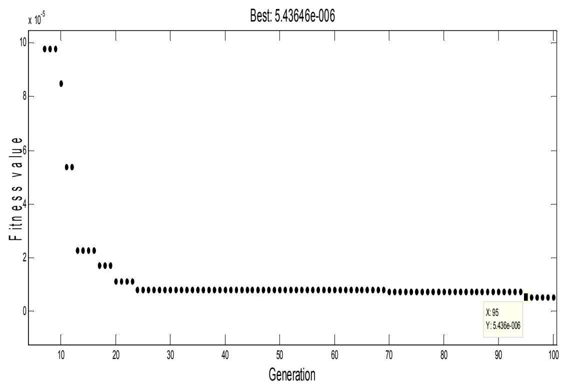

Fig. 3 The best fitness values by GA

The optimal observer gain K_{GA} is produced as:

$$K_{GA} = \begin{bmatrix} -8.0685 & 20.2109 & -102.9554 & -0.0001 \\ -1.0134 & 1.8971 & -8.9383 & 0.0000 \\ -8.3254 & 16.5511 & -77.1626 & -0.0000 \\ -0.0069 & 0.0134 & -0.0628 & 0.0000 \\ -0.4642 & 0.9522 & -4.3656 & -0.0046 \\ 23.2720 & -44.1216 & 208.5145 & -0.0001 \end{bmatrix} \tag{13}$$

In order to make the comparison, an observer gain by using the ordinary pole assignment method is given as:

$$K_{\text{PLACE}} = 10^3 \times \begin{bmatrix} 0.0004 & -0.0000 & 0.0000 & 0.0000 \\ 0.0000 & 0.0986 & 2.9480 & -0.0000 \\ -0.0000 & 0.0014 & 0.0001 & 0.0000 \\ 0.0000 & 0.0001 & 0.0060 & -0.0000 \\ -0.0000 & -0.0000 & 2.4992 & -0.0000 \\ -0.0000 & -0.0000 & 0.0017 & 0.0000 \end{bmatrix} \tag{14}$$

where the pre-assigned desired closed poles for sensor faults are: p=[-3 -3.436 -1.42 -1.4 -1.205 -4.835]

1. Incipient Sensor Faults

The sequence of the ramp sensor faults are assumed to be in the following form:

$$f_{s1} = \begin{cases} 0.01t & t \geq 10 \\ 0, & t < 10 \end{cases} \tag{15}$$

$$f_{s2} = \begin{cases} 0.01t & t \geq 20 \\ 0, & t < 20 \end{cases} \tag{16}$$

$$f_{s3} = \begin{cases} 0.01t & t \geq 30 \\ 0, & t < 30 \end{cases} \tag{17}$$

$$f_{s4} = \begin{cases} 2t & t \geq 40 \\ 0, & t < 40 \end{cases} \tag{18}$$

It is noted that the ramp rate of the fourth sensor fault is 200 times than that of the ramp rates of the first three sensor faults. The reason can be found in the figure of the system output responses (see Fig. 4). From Fig. 4, one can see the fourth sensor output is obviously larger than the other sensor outputs. Therefore the fourth sensor output is insensitive to a small sensor fault, which makes the fault diagnosis for the fourth sensor fault more challenging than diagnosing the first three sensor faults.

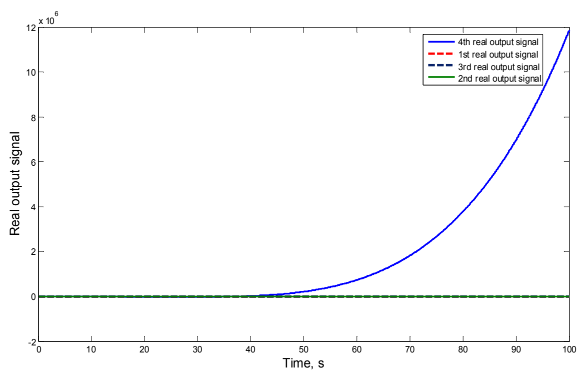

Fig. 4 Real output signal of 5MW wind turbine

The residual signals of the ramp faults are shown in Fig. 5 by using the GA-based optimal observer gain and the observer gain by using the non-optimization pole-assignment method. One can see the evident magnitude changes at 20s, 30s, and 40s are detected by using the GA optimal gain, and the change at 10s is also detected although it is not very visible without the aid of a zoom-in figure. It is also noticed that the residual signal by using pole-place assignment method (see the dash line in Fig. 5) can only detect the fault that occurs at 40s. As a result, the GA based fault detection method provides better detection performance as the effect from the disturbance is attenuated successfully.

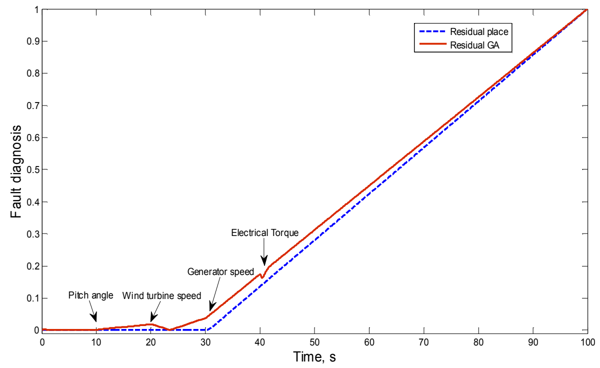

Fig. 5 Incipient sensor residuals by using the optimal and non-optimal observer gains, respectively

2. Abrupt Sensor Faults

The first three sensor step faults are assumed to happen at 10s, 20s, and 30s respectively with the same amplitude 0.01, and the fourth sensor fault is assumed to occur at the 40s with the magnitude 100, by noticing that the forth sensor output is much larger than the first three sensor faults shown by Fig. 4. By using the GA-based optimal observer gain and the pole-assignment non-optimal observer gain, the fault detection residual curves are shown by Fig. 6.

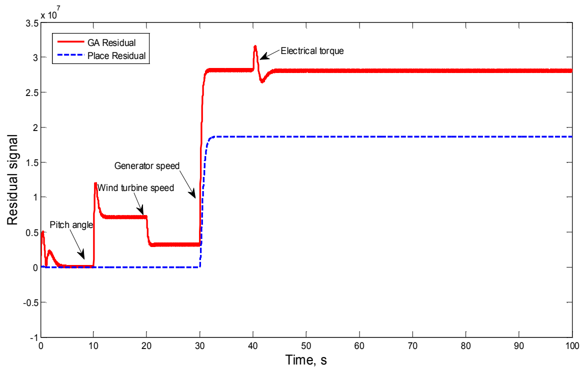

Fig. 6 Abrupt sensor residuals by using the optimal and non-optimal observer gains, respectively

From Fig. 6, one can see the abrupt faults occurring at 10s, 20s, 30s, and 40s have been successfully detected, by using the optimal observer gain K_{GA}. However, by using the pole-assignment based observer gain K_{PLACE}, only the fault happening at 30s is detected while other abrupt sensor faults are not detected. As a result, the GA-based fault detection method has a better fault detection performance against process disturbances.

B. Actuator Faults Robust Detection

Equation (1) represents wind turbine plant, the actuator fault known matrices is assumed to be $B_f = B$ and $D_f = 0$, one can concentrate on the fault detection for actuator faults. The evolution of the best fitness functions is shown in Fig. 7, where the population and generation are both selected as 100.

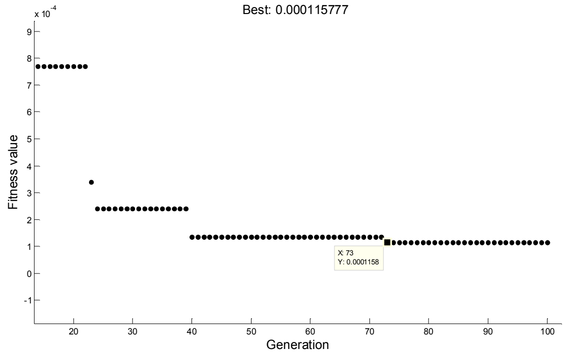

Fig. 7 The best fitness values by GA

The optimal GA-based observer gain is calculated as:

$$K_{GA} = \begin{bmatrix} 17.3343 & -20.2396 & 107.3839 & 0.0002 \\ -3.6151 & 4.6556 & -26.8440 & -0.0000 \\ 6.9315 & -5.8983 & 41.1725 & 0.0001 \\ 0.0005 & 0.0015 & -0.0039 & 0.0000 \\ 0.4301 & -0.5593 & 3.4449 & -0.0046 \\ 8.8256 & -21.6733 & 107.4305 & 0.0001 \end{bmatrix} \tag{19}$$

In order to make the comparison, one use the same K_{PLACE} as in (14) with assume desired closed poles are for actuator faults are P= [-3 -3.436 -1.42 -1.4 -1.205 -4.835]

1. Incipient Actuator Faults

The five actuator faults are assumed to be:

$$f_{a1} = \begin{cases} 0.01t & t \geq 10 \\ 0, & t < 10 \end{cases} \tag{20}$$

$$f_{a2} = \begin{cases} 100000t & t \geq 20 \\ 0, & t < 20 \end{cases} \tag{21}$$

$$f_{a3} = \begin{cases} 0.01t & t \geq 30 \\ 0, & t < 30 \end{cases} \tag{22}$$

$$f_{a4} = \begin{cases} 0.01t & t \geq 40 \\ 0, & t < 40 \end{cases} \tag{23}$$

$$f_{a5} = \begin{cases} 0.01t & t \geq 50 \\ 0, & t < 50 \end{cases} \tag{24}$$

It is noticed that the input system coefficient of the second system input is 1 million times smaller than the coefficients of the other system input signals. Therefore the second actuator fault is extremely difficult to detect. In (21), the slope rate of the second actuator fault is selected as 100000, which is 1 million larger than the slop rate of the first actuator fault.

However, the signal intensities of the first and second actuator faults which are actually added to the system dynamics have the same order.

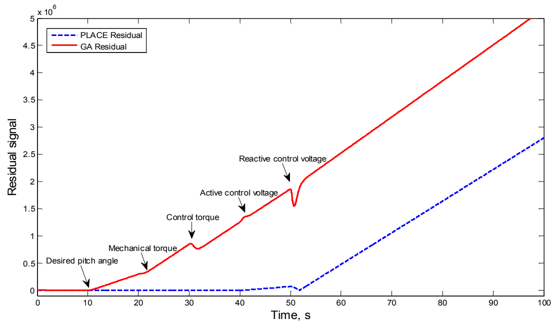

Fig. 8 Incipient actuator fault detection residuals by using the optimal and non-optimal observer gains

From Fig. 8, on can see the sequential actuator incipient faults that occur at 10s, 20s, 30s, 40s and 50s are all detected by using the GA-based optimal fault detection filter. However, the non-optimal fault detection filter can only detect the actuator fault that occurs at 50s. Therefore, GA-based fault detection method has given a better solution.

2. Abrupt Actuator Faults

The first, third, fourth and fifth actuator step slope fault magnitude is designated as 0.01 at t=10s, 30s, 40s and 50s respectively, while the magnitude of the second actuator fault occurring at 20s is assumed to be 100000 due to the weak intensity of the second input signal to the system dynamics.

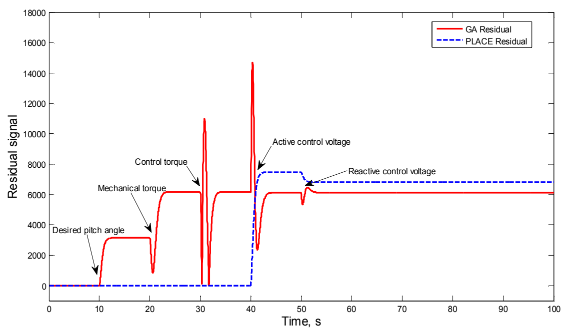

Fig. 9 Abrupt actuator fault detection residuals by using the optimal and non-optimal observer gains

From Fig. 9, the sequential actuator abrupt faults are successfully detected by using the optimal residual; however, the non-optimal residual can only recognize the fourth and fifth actuator step faults. As a result, the GA-based fault detection method is in advantageous position compared with the ordinary pole-assignment based fault detection method.

V. Conclusion

Due to the complexity of the wind turbine model, the actuator input signal intensities are in different order, which makes it challenging to detect all the actuator faults simultaneously. Similarly, the intensities of the output systems are not in the same order, the fault detection for the sequence of the sensor faults is difficult. In this paper, a GA based fault detection filter is designed, which has shown an effective detection performance for both incipient faults and abrupt faults against process disturbances. It was noticed that it is not always possible to successfully detect all the faults in one scale or one set-up for the 5MW wind turbine system due to the diversity of the input and output signal intensities. Potential solutions may be the fault isolation techniques [13] [14] and fault estimation methods [15], of which the relevant researches are under the way.

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