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ANFIS Models for Fault Detection and Isolation in the Drive Train of a Wind Turbine

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Abstract – *The paper aims to improve the fault detection and isolation process in wind turbine systems by developing intelligent systems that can effectively identify and isolate faults. Specifically, the paper focuses on the drive train part of a horizontal axis wind turbine machine. The proposed fault diagnostic strategy is designed using an adaptive neural fuzzy inference system (ANFIS), which is a type of artificial neural network that combines the advantages of both fuzzy logic and neural networks. The ANFIS is used to generate residuals that occur after faults have been detected, and to determine the appropriate thresholds needed to correctly detect faults. The simulation results show that the proposed fault diagnostic strategy is effective in detecting faults in the drive train part of the wind turbine system. By using intelligent systems such as ANFIS, the fault detection process can be automated and streamlined, potentially reducing maintenance costs and improving the overall performance and efficiency of wind turbine systems.*

Keywords: *Wind Turbine, Drive Train, Fault Detection, ANFIS, Residual, Estimation*.

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I. Introduction

Recently, many types of wind turbine systems have been developed and installed to power production. However, the operation long time becomes more challenging for the wind turbines because they are exposed to environmental facts. To maintain their safety, much research has been proposed to maintain their availability [1, 2]. A new approach based on ultrasonic was used on two real blades to detect the elimination of it [3], Among the most commonly used methods, are those based on data where they are used to generate residuals for diagnosis of various faults [4, 5], a model of a nominal power 4.8 MW wind turbine was developed and a set of actuator and sensor faults is proposed in paper [6]. A method based on intelligent technical has used fuzzy and neural networks to derive a nonlinear dynamic connection between the measured input-output parameters and the presumed fault signal [7]. Kalman filter as an observer with artificial neural networks has been proposed for the diagnosis of the blade pitch system fault for wind turbines and floating wind turbines in papers [8, 9]. A deep convolutional network for feature learning and classification based on SCADA measurements is proposed for sensor fault detection [10]. Hence, a new intelligent method of diagnosing faults via deep learning called Ce-CNN (as a convolutional neural network) has been proposed for the diagnosis of bearing faults in the wind turbine [11]. It has a good advantage in generalization ability, not only a good precision of classification. The model can balance the depth and width of the network, and thus control the growth of parameters and calculations. A new algorithm for diagnosis, sensor, and actuator diagnosis is solved, by integrating analysis techniques into fast multi-linear principal components with Fourier transform and uncorrelated is presented in [12]. The use of the principal component analysis (PCA) technique to classify the faults in the wind turbine is investigated in [13]. The SVM method is combined with a model-based observer for the diagnosis of faults actuator and sensor in the wind turbine benchmark [14]. An effective fault diagnosis structure is proposed for the pitch system part of a wind turbine benchmark [15]. The elaborated structure is based on the physical redundancy of sensors and actuators to generate the appropriate residuals between all measurements. Then a crisp logic technique is used to classify actuator and sensor faults [16]. A fault detection scheme for a wind turbine based on the Takagi–Sugeno interval observer, a set of interval observers is used to detect the sensor fault [17].

The objective of this paper is to propose a fault diagnosis system based on intelligent techniques as equivalent models using an adaptive neural network-based fuzzy inference system (ANFIS) as an output estimator to detect and isolate faults in a wind turbine system. ANFIS is used for generating residuals and as a decision system for the detection and classification of the occurred failures in the drive train part.

II. Description of the Wind Turbine

The function of the wind turbine is to generate electrical energy from the wind energy. The three blades of the turbine exploit the wind to produce kinetic energy in the two shafts. The wind turbine is composed mainly of four components as depicted in Fig. 1: pitch system, drive train, converter with its generator, and control [6, 18]. Each part is modeled as follows: the module temperatures, calibrated platinum sensors with ±0.5 °C measurement accuracy, and 0.1 °C resolution, placed on the backside center of each module are used. The data recorded by the system included environment temperature, module temperature, total insolation, operating current and voltage, wind speed, and total output power. The data captured starts in March 2012 and ends in May 2015. However, the point of focus in this research was the year 2014 since it provided the greatest amount of data as compared to the other years.

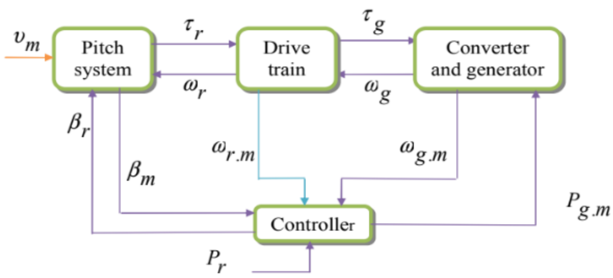


Figure 1. Wind turbine structure

- Pitch System Model: It is the process of adjusting the angle of the turbine blades to optimize power output. Where a hydraulic motor is employed for each blade. The pitch system is defined by a second-order closed-loop transfer function [18] between the measured pitch angle β_m and its reference β_{ref} as shown in eq. 1.

$$\frac{\beta_m}{\beta_{ref}} = \frac{\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2} \tag{1}$$

ζ: is the dumping factor equal to 0.6, ωn is the natural frequency equal to 11.11 rad/s.

- Drive Train Model: It's like a locomotive for the turbine. It consists of two shafts (low-speed shaft and high-speed shaft) for increasing the speed of the rotor to the generator. The state space model is:

$$\begin{bmatrix} \dot{\omega}_{r(t)} \\ \dot{\omega}_{g(t)} \\ \dot{\theta}_{\Delta(t)} \end{bmatrix} = A_{dt} \begin{bmatrix} \omega_{r(t)} \\ \omega_{g(t)} \\ \theta_{\Delta(t)} \end{bmatrix} + B_{dt} \begin{bmatrix} \tau_{r(t)} \\ \tau_{g(t)} \end{bmatrix} \tag{2}$$

The output of the state space is:

$$Y_{dt} = \begin{bmatrix} \omega_{r(t)} \\ \omega_{g(t)} \\ \theta_{\Delta(t)} \end{bmatrix} \tag{3}$$

- Generator with Converter: Its role is to convert the mechanical energy generated from rotating the shaft into electrical energy. It is modeled by a transfer function of the first order:

$$\frac{\tau_g(s)}{\tau_{g.r}(s)} = \frac{\alpha_{gc}}{s + \alpha_{gc}} \tag{4}$$

Where τ_{rg}: the reference torque of the generator is, α_{gc} is a parameter model. The produced power is defined as:

$$p_g(t) = \eta_g \omega_g(t) \tau_g(t) \quad (5)$$

Where the generator function efficiency $\eta_g = 0.98$.

- Controller: Its role is to generate appropriate control actions to maintain the output of 4.8 MW during its period of operation by a suitable wind speed. The employed controller type is a proportional integrator (PI), which works in two intervals for various wind speeds.

III. Brief on ANFIS Model

Adaptive Network Based Fuzzy Inference System (ANFIS) is a hybrid system between the fuzzy inference system (FIS) and artificial neural network (ANN) [19, 21]. This system as depicted in Fig. 2 has the advantages of the two approaches, the powerful knowledge representation of FIS and the learning capacities of ANN. So, the hybrid ANFIS system exploits these characteristics to generate an optimal FIS using the available data on the studied process. As the name suggests Adaptive network, the neural network adapts to the input and output values of the system, because the network contains a group of nodes, a node that operates on itself to generate an output signal to another node via the input signal, where the function of each node changes depending on the general behaviour of the network. Each layer of this ANN defines an operation of FIS [19, 20, 21]. ANFIS is composed of five layers: The first layer for fuzzification, the second layer to calculate the degree of activation, the third layer for normalization, the Fourth layer to calculate rule outputs based on the consequent parameters, and finally the fifth layer for computing the overall output of the FIS.

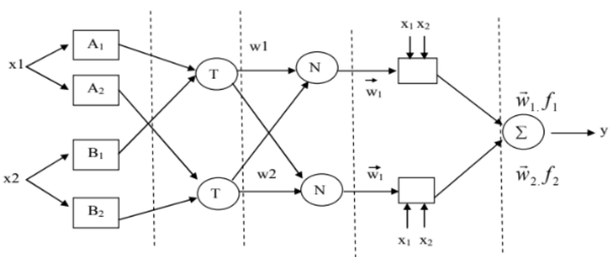


Figure 2. ANFIS architecture

Proposed Fault Diagnosis Strategy

In this section, we will present and explain the proposed fault diagnostic strategy in this paper, based on an equivalent model of the ANFIS system for the drive train part of a wind turbine benchmark. The proposed structure is illustrated in Figure 3, where the simulated wind turbine is based on the benchmark model of Odgaard [18]. This fault detection and isolation strategy is tested on the drive train part in order to detect occurred system faults. As depicted in Figure 3.

The ANFIS model is trained and elaborated as an equivalent model of the wind turbine machine. This intelligent system is used to generate residuals as mentioned in the form of step (1). Then, in the second step, a set of ANFIS models have been employed to decide and detect the occurred faults. In this calculation stage, the diagnosis structure must determine the existence of faults. The parameters of tested system faults in the simulated scenario are presented in Table. 1. In this paper, we will simulate faults in the generator speed (ω_g) and rotor speed (ω_r) for the drive train as a modification in the efficiency from η_{dt} =0.97 to η_{dt2}=0.3.

The proposed diagnosis structure is based on three steps: Output Estimation using an equivalent model based on Neuro-Fuzzy system, Residual Generation, and Residual Evaluation.

Table. 1 Fault scenario

System Fault	Type	Symbol	Time Interval
ω_g	Change dynamic	$\Delta\omega_g$	[2000s-2200s]
ω_r	Change dynamic	$\Delta\omega_r$	[2000s-2200s]

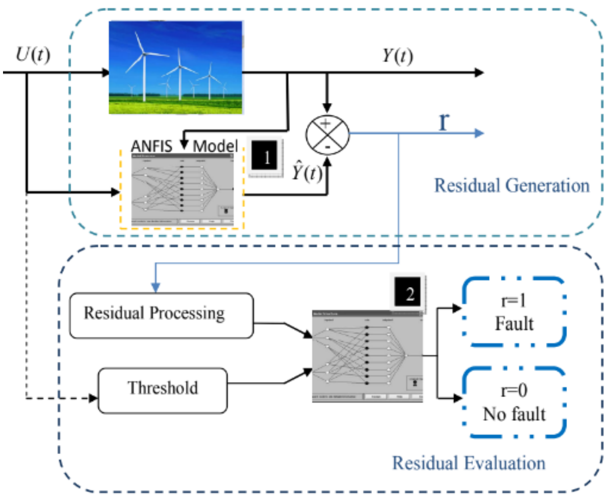


Figure 3. Structure of the diagnosis approach based on ANFIS models

1) ***Output Estimation***: an ANFIS system is used as an equivalent model to ensure the output of the system without fault, while the model is not affected by the

system damage and its output is always without fault.

2) Residual Generation: as shown in figure 3, in this step, the obtained residual by comparing the output of the system (Y_t) and the equivalent model system ($\check{Y}_t$), each difference between them is a residual, the following equation at each time

$$r_{1,2} \in \Re^{1*1} = Y_{1,2} \in \Re^{1*1} - \hat{Y}_{1,1} \in \Re^{1*1} \quad (6)$$

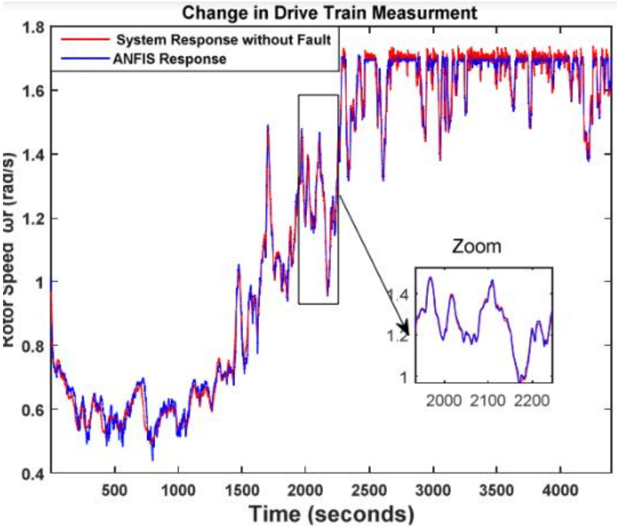
3) Residual Evaluation: After obtaining the residuals, another ANFIS is used with a fixed threshold to detect the fault. When the signal exceeds this threshold, it is considered a fault, else, it doesn't consider a fault.

IV. Results and Discussions

In this section, we will present the obtained simulation results of the proposed diagnosis structure (shown in Figure 3) for the drive train system. The developed framework is tested on the wind turbine benchmark measurements [6, 18]. Firstly, the simulation results will be displayed without faults and then it will be studied with faults to demonstrate the ability of the designed ANFIS models to detect faults.

IV.1. Dynamic without Fault for (ωr) and (ωg)

In the case of the system without fault, in Figures 4 and 5 the speed of the rotor and the generator denoted (ωg) and (ωg), and the calculated residuals are presented respectively. Figure 4 (a) shows the output of the rotor Y̌t. The capture zoom at the interval time speed (Yt) and the estimated output by the equivalent model [2000s-2200s] show that both signals are very similar. Whereas, Figure 4 (b) presents the obtained residual as calculated using eq.6. This result shows a good estimation of the output signal at a rotor speed.



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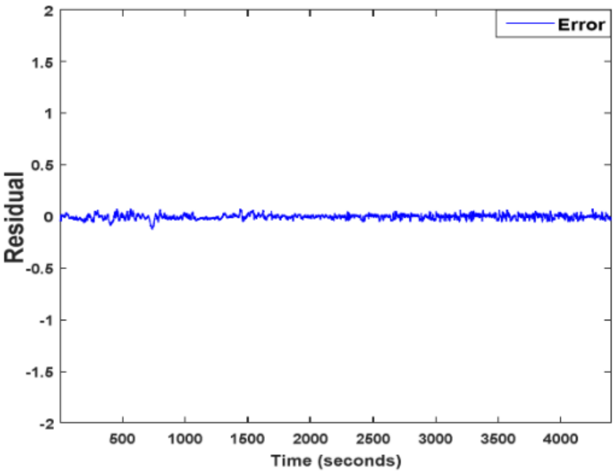
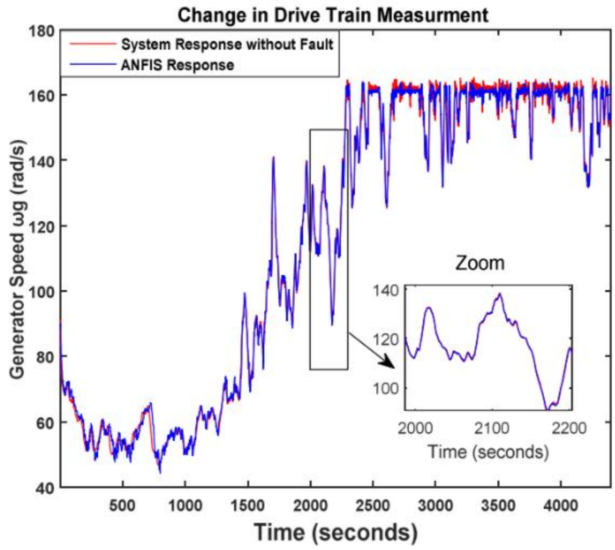


b

Figure 4. Rotor speed without fault (ωr) and the residual

The second output of the drive train as a speed generator denoted (ω_g) and the estimated output of the equivalent model ANFIS are presented in Figure 5(a). It's clearly shown the similarity of the two responses, which demonstrates the ability of the designed ANFIS model to perceive the output. This is depicted in the capture zoom, which shows that both signals are identical at the interval time [2000s-2200s]. Figure 5(b) presents the residual between both outputs.



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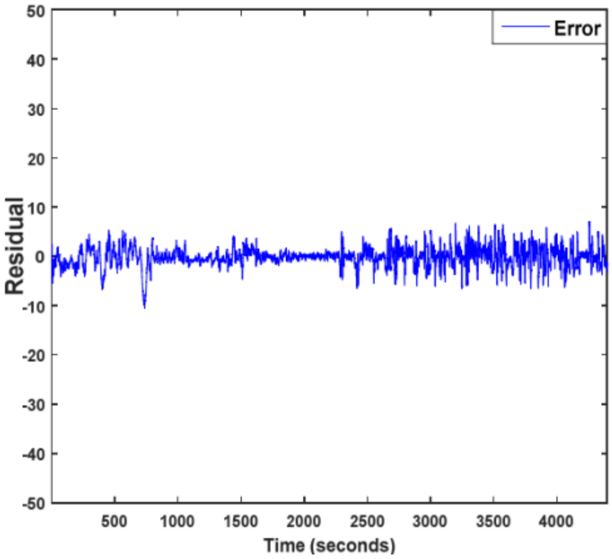

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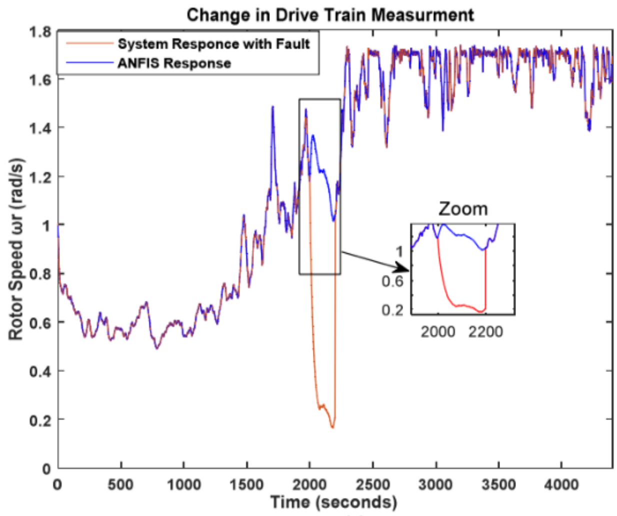
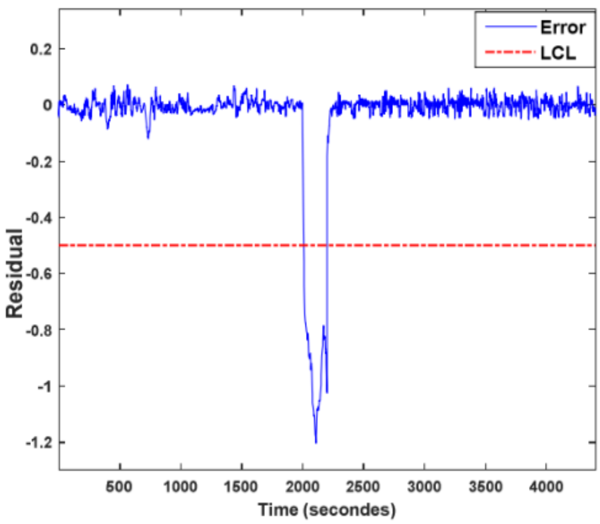
Figure 5. (a) Generator speed without fault (ω_r), (b) Generated residual



(a)



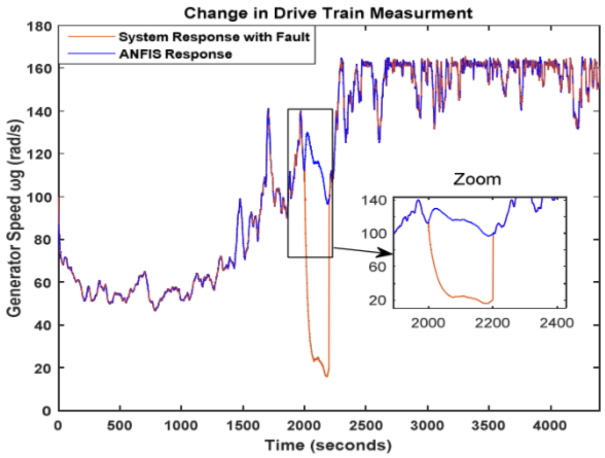
(b)

Figure 6. (a) Generator speed with the fault (ωr), (b) Generated residual

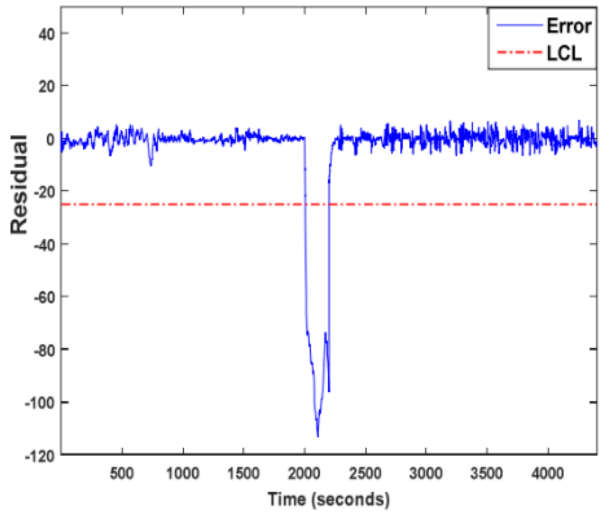
IV.2. Dynamic with Fault for (ωr) and (ωg)

The fault that occurred in the drive train was caused by the increased level of drive train vibrations that can be simulated by changing the parameter from η_{dt} = 0.97 to η_{dt2}=0.3 affected by both output generator speed (ω_g) and the rotor speed (ω_r). Figure 6(a) shows both outputs of the rotor speed (ω_r) as an output Y(t), Y̌(t). The occurred fault in the rotor speed is presented and the output of the equivalent model denoted capture zoom presents the fault that happened at the interval time [2000s-2200s] at a period time of 200s. Figure 6(b) presents the obtained residual.

The same fault occurred in the generator speed (ω_g) at the same time [2000s-2200s]. Figure 7(a) illustrates the capture zoom of the fault that happened in the generator speed during 200s. Whereas, Figure 7(b) shows the residual and the lower defined threshold.



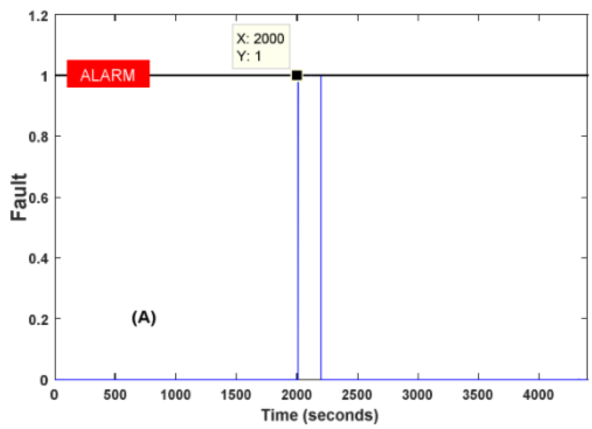
(a)



(b)

Figure 7. (a) Generator speed with the fault (ω_r), and (b) the residual

Figures 8 (a, b) present detection of a fault in rotor speed and generator speed respectively at the same interval time [2000s-2200s] during a period of 200s.



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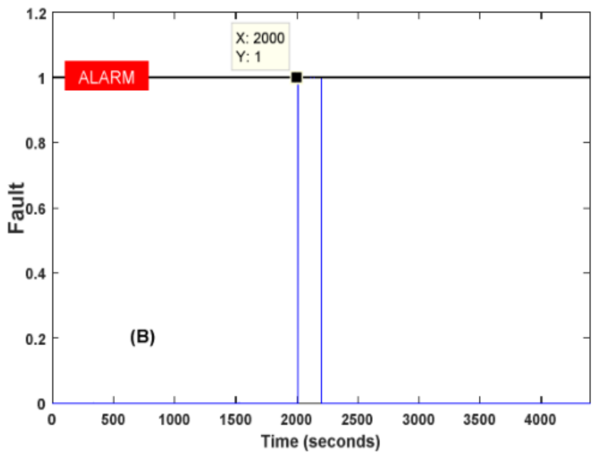

b

Figure 8. (a) Detection of faults in the rotor speed (ω_r) and (b) Generator speed (ω_g)

V. Conclusion

In this paper, a powerful and efficient fault diagnostic strategy is proposed for the drive train part of the horizontal axis with three blades wind turbine machine. The elaborated structure is based on the development of an equivalent model of the drive train using the ANFIS approach. This hybrid model can generate residuals resulting from the occurrence of faults in the studied system. A fixed threshold is determined by another intelligent system to detect the fault that occurred in the drive train sub-system, especially in generator and rotor speeds. The obtained simulation results demonstrate the ability of this diagnosis strategy to detect faults in the drive train correctly.

In future work, all faults in the wind turbine will be tested and investigated using this type of approach as Intelligent equivalent models.

Declaration

- The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.
- The authors declare that this article has not been published before and is not in the process of being published in any other journal.
- The authors confirmed that the paper was free of plagiarism.

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