

Equivalent model based on Neural Network for Detection and Isolation of Generator Faults of a Wind Turbine

Zemali Zakaria¹, Cherroun Lakhmissi¹, Nadour Mouhamed^{1*}

¹Laboratory of Applied Automatic and Industrial Diagnostics (LAADI), University of Djelfa, Algeria

*Corresponding author; Email: m.nadour@univ-djelfa.dz

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ABSTRACT

This paper introduces an intelligent approach to fault diagnosis in horizontal wind turbines using an equivalent model designed by a neural network, focusing specifically on generator faults. The effectiveness of the model is demonstrated by analyzing generator faults and comparing the actual process output with the neural network's equivalent model, which is quantified by calculated residuals. A decision block is integrated to determine the severity and timing of the fault. The results obtained highlight the system's proficiency in fault identification, offering insights into its capability to detect and respond to faults within horizontal wind turbines, particularly emphasizing generator-related issues.

I. Introduction

The field of renewable energy has experienced substantial progress, driven by a multitude of power generation technologies. Among these, wind turbine systems (WTs) have become notable contributors to the generation of electricity [1]. WTs generate electrical energy by harnessing the kinetic energy of the wind. Nevertheless, the continuous functioning of these systems is hindered by environmental factors [2]. Frequent malfunctions observed in wind turbines include sensor inaccuracies, actuator malfunctions, gear and brake failures, generator issues, blade defects, and structural weaknesses [3].

Enhancing WTs reliability requires early and effective problem detection to reduce expensive downtime. Preventive actions are crucial for ensuring the safety of this key energy source, including planned short-term outages for fault management [4]. Comparably, instantaneous fault surveillance is necessary to recognize and resolve problems immediately, optimizing power production while maintaining operational integrity [5]. The criticality of fault detection is highlighted by the fact that fault-induced variations in actuator or sensor readings might interfere with the system's overall closed-loop control [6, 7].

In recent years, a variety of approaches have been used to investigate the fascinating research subject of WTs fault identification [4, 8, 9, 11]. Model-based and data-based approaches are the two general groups into which these techniques are divided. The latter employs statistical analysis of past data to find patterns, whereas the former depends on thorough system modeling [9]. Two approaches were combined to diagnose the 10 MW floating offshore WT. A model-based technique was employed to identify problems with the actuators and sensors. On the contrary, signal-based systems identify issues with mooring lines [2]. The defect diagnosis technique (FIS) rendered conventional fuzzy inference systems obsolete by employing non-singleton fuzzy logic. This study employed Supervisory Control and Data Acquisition (SCADA) on a functioning WT to detect and quantify the severity of early issues [3].

In order to improve the rates at which faults are detected, novel methodologies have been suggested, including fuzzy logic techniques that leverage neural network constraints [4]. By employing simulation-based benchmarking and exhaustive WT models, fault detection can be assessed across a range of scenarios [5]. Further contributions include Kalman filter estimators for residual generation in WT pitch systems [7] and effective defect detection methods employing precise logic structures [6]. Furthermore, cutting-edge methodologies, including the convolutional neural network Ce-CNN, exhibit encouraging potential in the realm of bearing defect diagnosis [8]. Recent studies have explored fault identification using multi-linear principal component analysis [9, 10] and Kalman filter observers combined with artificial neural networks [13], showcasing a diverse range of methodologies for fault diagnosis in WT systems. The Principal Component Analysis (PCA) approach has been used to categorize problems in the WT. It is constructed using a spectrogram and a convolution neural network, and fault detection in sensors and actuators uses a multi-classifier fusion approach. The results of this research are compared to those obtained using other techniques [12]. For fault identification in the offshore WT's hydraulic pitch system, Kalman filter observer and Artificial Neural Networks (ANN) are used [13-16].

This study aims to present a reliable fault diagnosis method based on the neural network equivalent model as an output for detecting and adequately isolating defects in a WT system, specifically focusing on actuator faults in the generator. The structure of this study is outlined as follows: Section 2 provides an overview of fundamental components and mathematical models constituting the Benchmark. Section 3 delves into the neural network framework. Section 4 elucidates the proposed fault diagnosis framework and processes. Section 5 presents and discusses simulation findings for fault detection. Finally, Section 6 concludes the study.

II. Research Method

II.1. Wind Turbine Model

In the upcoming sections, we will describe the model of the WT machine used. It is a three-blade horizontal turbine, as depicted in Fig.1, that consists of a generator with a converter, a driving train, and a pitch system. The concept is to convert the kinetic energy contained in the wind into electrical power.

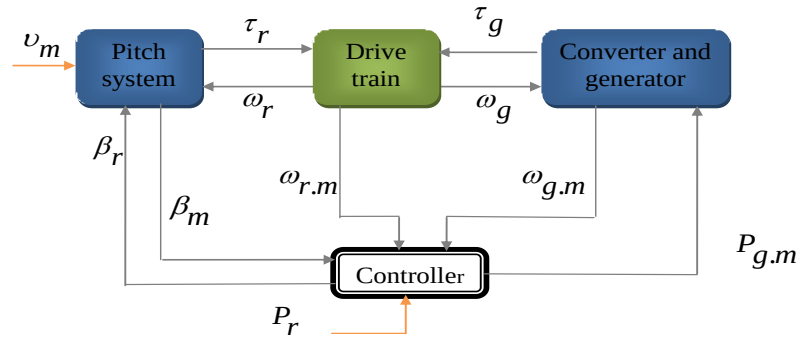


Figure 1. Wind turbine components

1) Model of the Pitch System

The pitch mechanism of the WT is powered by a hydraulic piston servo, which is responsible for rotating the blade to a specific angle β_m . This rotational movement is governed by the observed pitch angle β_m and a second-order closed-loop transfer function, along with its reference β_{ref} (see Equation 1) [5]. In the WT system, the controller mandates β_{ref} as the closed-loop input, while the measurement β_m , obtained as the output of this loop, is utilized to adjust the internal pitch actuator controller [5, 6]. The Transfer Function (TF) describing all WT blades conforms to Eq. 1:

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

Where:

β_{ref} represents the reference angle of the blade imposed by the controller, β_m represents the current angle value of the blade, ζ the damping factor equal to 0.6, ω_n the natural frequency = 11.11 rad/s.

2) Drive Train

The drive train is an essential component frequently compared to a locomotive in the wind turbine system. The primary purpose is to control the rotational speed of the rotor, which is linked to the generator through the blades. This regulation guarantees effective electricity production from the wind energy harnessed by the turbine.

The drive train is represented in state space as follows:

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

The state space's output is:

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

3) Generator and Converter

The generator serves the essential function of converting mechanical energy from the wind turbine into electrical energy [5]. It plays a pivotal role in the overall energy conversion process within the wind turbine system. The generator can be represented by a first-order transfer function (TF), as shown below:

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

Where:

$\tau_{g,r}$ is the torque generator reference, α_{gc} is the generator and converter parameter model. The function representing the power replicated by the generator is shown in Eq. 5 :

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

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

4) Controller

The controller is of utmost importance as it protects the turbine from potential harm caused by high wind velocities while simultaneously ensuring a steady output of electricity, which is typically aimed at 4.8 MW [5]. By utilizing a Proportional Integrator (PI) of the type, the controller functions at two discrete time intervals by the current wind velocities. The controller employs active control measures within the velocity range of [3-12.5 m/s] to optimize energy production and guarantee that the generator functions optimally to achieve the intended output level. By taking this proactive measure, the energy output is increased to the optimal level, thereby

optimizing the use of the wind resources that are currently available. When wind velocities increase to the range of [12.5-25 m/s], the controller modifies its approach to maintain the generator's uninterrupted operation. Instead of actively manipulating energy production, the controller regulates the generator's operation to ensure a steady and consistent electricity supply. The controller's adaptable operation allows the wind turbine system to efficiently adjust to fluctuating wind conditions, all the while preserving operational stability and optimizing energy production.

II.2. NEURAL NETWORKS

Artificial neural networks (ANNs) are computational models that are inspired by the form and function of the human brain's neural network. They imitate the behavior of organic neurons, allowing for complicated computations and pattern recognition tasks. In this study, the artificial neural network (ANN) architecture includes an input layer with six neurons representing the input variables, specifically the power generator reference ($\tau_{g,r}$). The output layer consists of a single neuron that represents the power generated by the generator (τ_g) [14]. This configuration enables the neural network to process incoming data and produce predictions or outputs based on previously learned relationships between input and output variables.

The global equation of a neural network with one hidden layer (10 neurons), sigmoid activation, and 1 output can be expressed as:

$$y = \sigma(w^{[2]} \cdot \sigma(w^{[1]} \cdot x + b^{[1]}) + b^{[2]}) \quad (6)$$

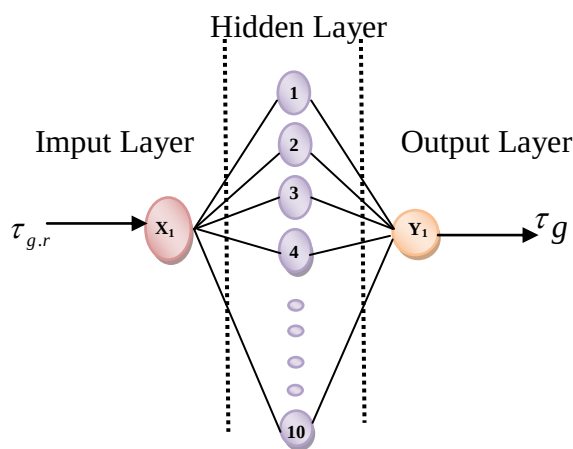


Figure 2. Structure of Neural network

Table 1. Model Architecture of Neural network

Input layer	Hidden layer	Activation function	Output Layer
One Input x1	One (10 neurons)	Sigmoid	One Output (Y ₁)

II.3. DIAGNOSIS APPROACH

This section presents and discusses the developed neural network model-based diagnostic technique for the WT-generating system. Following an evaluation of significant actuator failures, the suggested method for conducting fault diagnostic activities is illustrated in Fig.3. The WT simulation utilizes Odgaard's model [5], serving as a benchmark to simulate the proposed failure of the generator actuator. Adjustments to the parameters of the transfer function model are made accordingly. Fig.3 outlines the construction of the fault diagnosis method, which relies on residual generation through analysis of the neural network model's residual output to identify the presence of faults. The parameters of the actuator failures occurring in the simulated scenario are detailed in Table 1.

In this section, we will elucidate the suggested steps for diagnosis and provide a comprehensive overview of the methodology employed to detect and analyze faults within the WT-generating system.

$$\tau_g = \tau_g + 2300 \quad (6)$$

Table 2. Scenario Fault

Actuator Fault	Fault	Symbol	Interval Time
B2	F1	$\Delta\tau_g$	[2000s-2150s]

The suggested diagnostic structure is comprised of three phases for detecting potential actuator defects in the generator actuator: Estimation using Model NN, Residual Generation, and Residual Evaluation as follows:

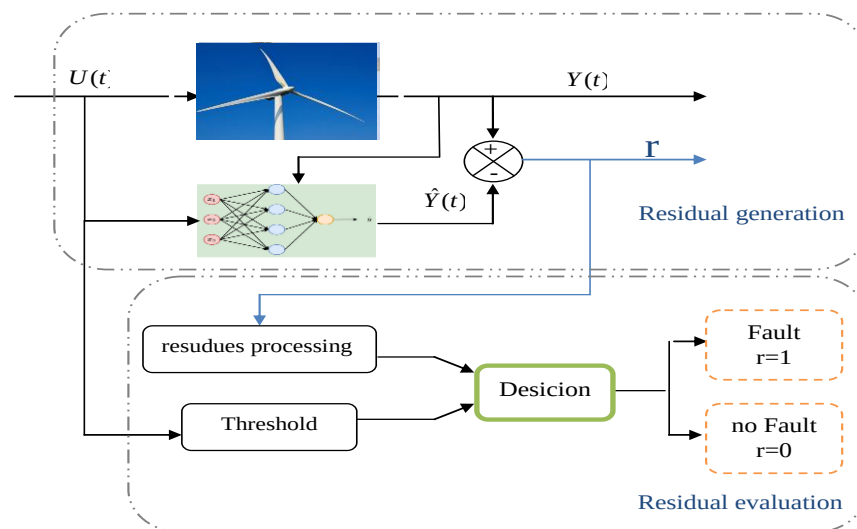


Figure 3. Structure of Diagnosis Approach

- Estimation using a model based on NN:

The objective of using the A model based on neural networks is to estimate the system's output and identify the fault since the output of the Model NN does not include the defect that exists in the system, ensuring that the problem is discovered in the system.

- Residual generation:

As can be seen in the image, the residual is calculated by comparing the system's output with the observer's output. Since both the observer and the system get the same input, any difference between the two outputs is considered a residual.

- Residual evaluation:

After getting the residuals, a threshold with a constant value is derived from the residuals' value. In this instance, there are one upper and lower threshold UCL values for residuals since the residual has one positive value. The objective is to identify the error field such as when the signal surpasses the threshold, it is deemed a defect, and when it does not, it is not deemed a fault.

III. RESULTS AND DISCUSSIONS

The proposed diagnosis structure for identifying actuator defects in the wind turbine (WT) generator system is validated by the simulation results presented in this section. The efficacy of the proposed neural network (NN) model is assessed in both typical operating conditions (i.e., without actuator faults) and faulty conditions. The power generated by the system, the prediction errors (residuals), and the defect detection mechanism are illustrated in the figures cited in this section (Fig4 and Fig5).

III.1. System Response Under Normal Conditions

The results under normal operating conditions (i.e., without actuator faults) are shown in Fig. 4. In the case of a system that works perfectly without fault, Fig. 4 shows the generator speed given by the generator and the calculated residual. Fig.4(a) depicts the power given by the generator denoted (τ_g). In contrast, Figure 4(b) illustrates the error determined between the process response ($Y(t)$) and the estimated value using the neural network ($\hat{Y}(t)$) as described in eq. 6.

1) Power Output Response:

The power output from the generator closely follows the system's anticipated behavior, as illustrated in Fig. 4(a). In Fig. 4(a), we present a zoom that shows the generator power (τ_g). There is no fault in the interval time [2000s-2150s], ensuring that the generating system actuator operates appropriately and without issue. The system that is in control produces the intended ($\tau_{g,r}$) efficiency. In the absence of a fault, the error as residual is always zero, with a small number of false alarms. The generator operates without deviations in the time interval [2000s–2150s], as evidenced by a zoomed-in region of the power output. It is considered a typical case occurring in all simulated periods. Displays the effectiveness of the estimate utilized to block. This confirms that the NN model accurately predicts the generator's response, thereby capturing the system dynamics under normal conditions.

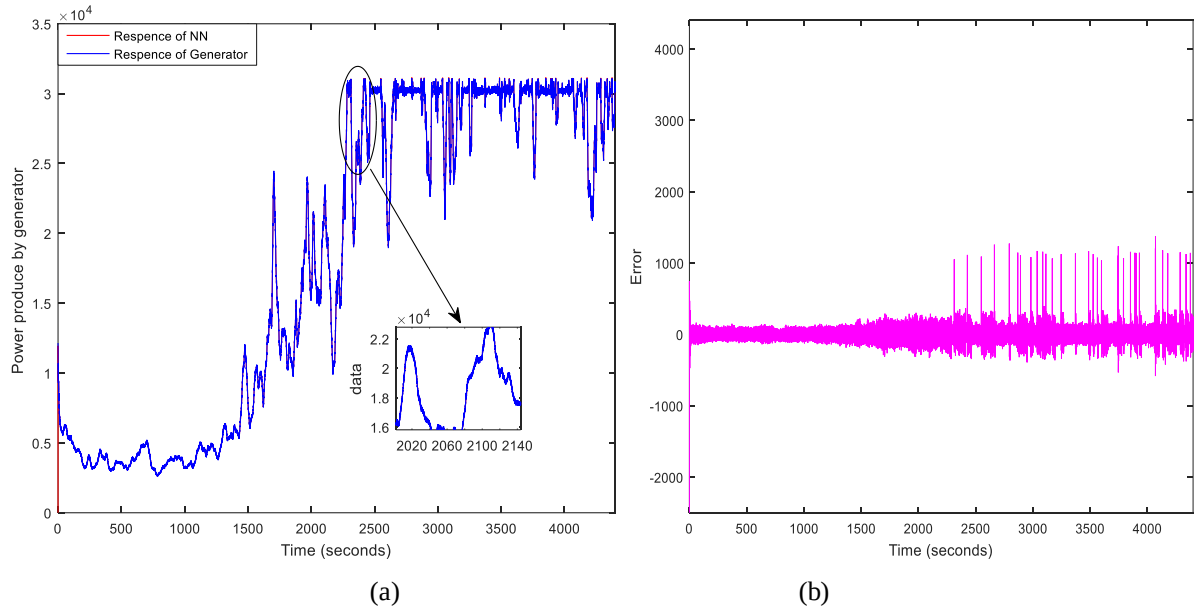


Figure 4. Generator power and residuals under normal conditions

(a) the generator's output of power indicated (τ_g)

(b) the residual without fault

2) Error Residual Analysis:

Fig. 4(b) shows the residuals (errors) between the actual generator power and the NN model's predictions. The residuals remain close to zero throughout the entire simulation period, with only a few minor fluctuations that may be attributed to noise or minor discrepancies in the prediction model. These minor false alarms are well within acceptable thresholds and do not signify any significant issues in the system. This consistent performance highlights the NN model's capability to estimate the generator's state under healthy conditions.

III.2. System Response Under Faulty Conditions

The proposed diagnosis method exhibits its capacity to detect abnormal system behavior when actuator faults appear. The residuals and responses of the generator system in the presence of defects are illustrated in Fig. 5.

1) Power Output Deviation :

The NN model's predicted response clearly deviated from the actual power output of the generator, as illustrated in Fig. 5(a). The presence of this deviation suggests that an actuator fault has occurred. The model's capacity to identify dynamic changes in the generator's behavior is further illustrated by a zoomed-in region of the power output within the interval [2000s–2150s], which emphasizes the distinctions between the two curves.

The first defect is reproduced as a dynamic change and slow torque control, which implies severe issues or slow, suboptimal power output. This error may be stated by altering an unwanted increase in generation capacity. Fig. 5(a) depicts the responses of the Power generated by the generator represented by (τ_g) $Y(t)$ and the predicted value using the neural network-based model ($\hat{Y}(t)$). A distinction between the two curves can be seen in the zoom obtained for these two replies.

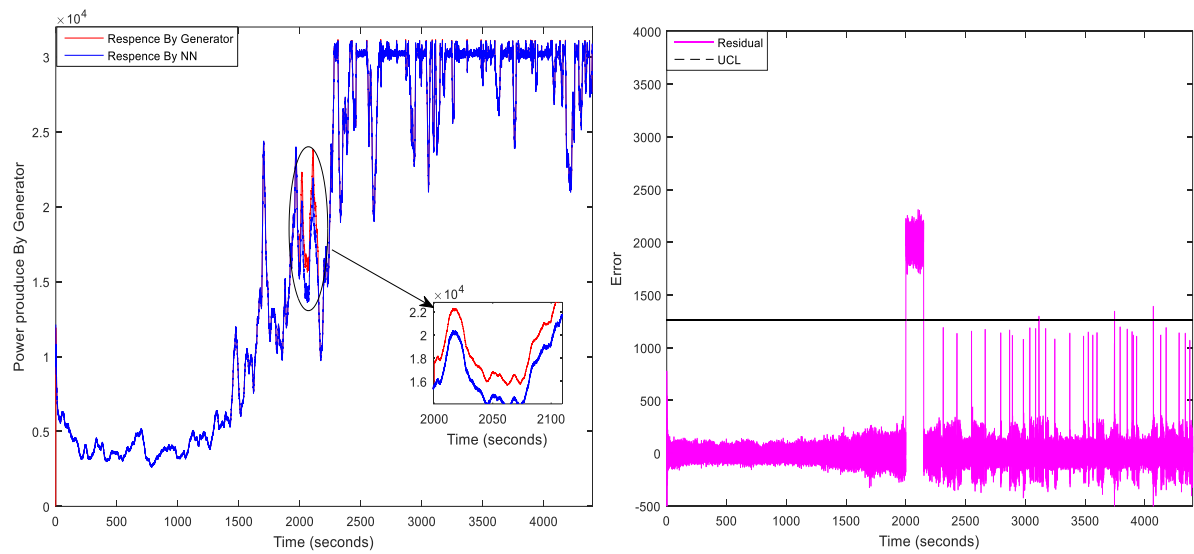

 Figure. 5(a). The power produced by the generator with fault denoted (τ_g)

Figure. 5(b). The residual fault

2) Residual Analysis:

The residuals during the defective condition are depicted in Fig. 5(b), which demonstrates a substantial increase in error in comparison to the normal condition. This plainly indicates the existence of a defect, as the error peaks within the time interval [2000s–2150s]. The residual values exceed the empirically determined threshold boundaries, which confirms the presence of an actuator defect. Although the system occasionally generates spurious alarms, they are infrequent and do not significantly impact the overall defect detection performance.

This is shown in Fig. 5(b), which depicts the residual as an error of power production with a small number of false alarms. It is considered a typical case. The two responses are denoted ($Y(t)$ and $\hat{Y}(t)$). The error is detected in an interval time of [2000s-2150s]. It quantifies the difference between the actual system's reaction and the NN model's estimated output.

III.3. Fault Detection Performance

The identified actuator defects during the interval [2000s–2150s] are illustrated in Fig. 6, which summarizes the fault detection performance. The results indicate that the diagnostic structure based on NN is capable of detecting defects within a relatively brief period of time (150 seconds) after they have occurred. Although some false alarms are present, they are negligible and within the permissible range for practical applications. The defect detection framework's ability to identify actuator malfunctions in real time is illustrated by this performance.

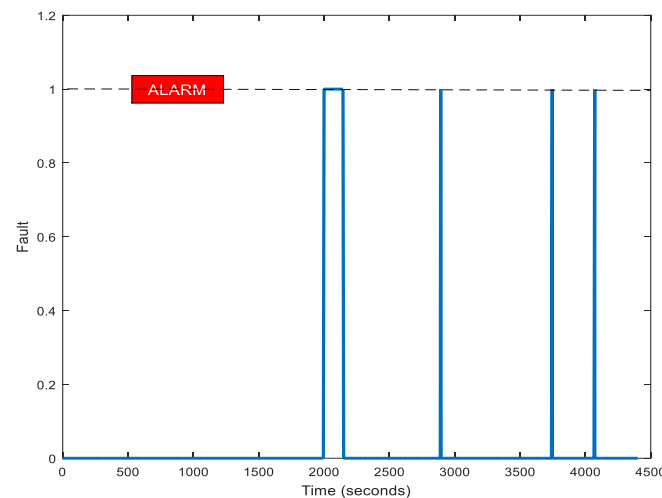


Figure. 6. Detection of actuator fault

III.4. Discussion

The efficacy of the proposed NN-based fault detection framework is validated by the results depicted in Figs. 4, 5 and 6. Under typical circumstances, the system exhibits robust predictive capabilities, with minimal errors and negligible false alarms. The NN model effectively detects deviations in the generator's power output and generates a dependable residual signal for defect detection under malfunctioning conditions.

The NN model's accuracy in capturing system dynamics is confirmed by the comprehensive insights into the system's response over specific intervals provided by the zoomed-in analyses in Figs. 4 (a) and 5 (a). In addition, the empirical threshold boundaries employed in Fig. 5(b) for fault detection are demonstrated to be effective in distinguishing between normal and defective operating conditions.

The necessity of improving the threshold selection method to improve the accuracy of defect detection is emphasized by the occurrence of false alarms in specific situations. In order to mitigate the occurrence of false alarms while maintaining a high level of sensitivity to defects, future research may examine sophisticated filtering methods or adaptive thresholding approaches.

IV. Conclusion

This paper suggests a defect diagnosis method for the generator system of the three-blade horizontal-axis WT that is both efficient and reliant on a neural network model. The methodology entails the comparison of the network-based model's output with that of the original system to produce residues in the event of a malfunction in the original model. Faults can be reliably identified by establishing a residual threshold. The reliability and effectiveness of the proposed NN-based diagnosis structure for detecting actuator defects in wind turbine generators are confirmed by the simulation results. The methodology guarantees system reliability and facilitates timely maintenance interventions by offering a precise and resilient framework for real-time fault detection.

In the future, this neural network-based model will be expanded to incorporate and investigate a variety of issues that are encountered in WT systems. Additionally, the investigation of equivalent models, particularly those of an outer type, may provide enhancements in WT behaviour and increase the effectiveness of their diagnosis duties. Contributing to the advancement of renewable energy technologies, these advancements have the potential to improve the overall performance and reliability of WT systems.

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