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Modeling of fault detection and isolation in pitch control of wind energy conversion systems via digital twins

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***Abstract*— There is a growing trend in renewable energies for wind harvesting and power generation. As new offers for the energy sector continue to rise up, the operation and maintenance team plays a vital role in increasing the availability and decreasing downtime of wind turbines subassemblies, based on conditional monitoring of their assets. This paper developed an approach for fault detection and isolation of the pitch control system on a direct drive permanent magnet synchronous generator using dynamic modeling and digital twins. The work presents two models of wind turbines, whose conditions were replicated in a multi-domain simulation software and the analyses were conducted under rotor constant speed. One concept represents a wind turbine model with a fault in pitch system, while the other is a healthy replica or a virtual model. Through the difference between three observable variables, namely: active power, angular speed and pitch angle, it was possible to isolate and classify each type of fault in the pitch system in wind turbines.**

***Keywords* — wind turbine, fault detection, fault isolation, digital twin, pitch control.**

I. INTRODUCTION

A system prone-to-fault that results in poor power regulation comes from pitch control. Accelerometers and actuators account for 19% of the failure rate in wind energy conversion systems [1]. When combined with other systems, they contribute about 30% to 60% of the total operating and maintenance costs due to unplanned maintenance [2].

Pitch control faults can overheat the generator winding and permanent magnets, generate excessive wear on gears and main bearing rings, and can also tolerate a delayed response to abrupt wind changes [3]. The detailed fault mechanisms will be displayed along the paper.

Fault alarms with SCADA data are limited and do not cover all possible fault types. Therefore, mathematical models are used to reproduce complementary fault signatures. However, simulation software hides internal modeling processing. Consequently, a digital twin approach for fault detection and isolation becomes feasible by creating fault signatures and dynamic modeling.

Some papers have proposed fault diagnosis using the digital twin approach. According to [4], the authors used a residual vector containing oxygen excess ratio, stock voltage, current and compressor speed to detect and isolate faults in proton exchange membrane fuel cells (PEMFC), according to predetermined threshold residuals. In compliance to [5], the authors used digital twins to predict battery energy storage system state of charge (SOC). They determined the SOC from equations and real parameters, then applied long short-term memory (LSTM) and gated recurrent unit (GRU) neural network for prediction. The authors compared different neural network architectures based on MSE metrics. Finally, in conformity with [6], digital twins, which comprised SCADA dataset and wind turbine virtual replica in MATLAB, predicted the behavior of the replica by means of neural networks. Consequently, this work aims to develop a fault model for a wind energy pitch system that can detect and classify faults using digital twins, employing a residual approach.

This paper is divided into five sections. The second section presents the basic fundamentals for modeling wind turbines, presenting the main equations for modeling the blade, PI controller, drivetrain and permanent magnet synchronous generator. The third section brings a description of faults in speed sensors, actuators and electric motors. The digital twin model for fault detection and isolation were developed. The fourth section presented the main results of the simulation of the general model and the replica, followed by the last section with the main conclusions of the work.

II. GENERAL BACKGROUND ON WIND ENERGY CONVERSION SYSTEMS MODELING

This section presents the mathematical formulation to develop models of wind turbine main systems, such as: blade, PI controller, drivetrain and a direct drive permanent magnet synchronous generator. A description of faults and digital twins were exposed.

A. Blade modeling

The wind kinetic energy that is converted into available power is given bellow:

$$P_{av} = 0.5\rho\pi R^2 v_w^3 \qquad (1)$$

In such equation ρ is the air density, R is the rotor radius and v_w is the wind speed [7-8].

However, a typical wind turbine is capable of extracting 0.593 from this energy, the maximum value given by the Betz limit. This fraction called performance coefficient (C_p) is built upon pitch angle (β) and tip-speed ratio (λ) [9]. Therefore, mechanical power extracted from wind as means to generate electricity is modeled according to:

$$P_m = 0.5\rho\pi R^2 v_w^3 C_p(\lambda,\beta) \tag{2}$$

An analytical approach well established in the literature models the behavior of the performance coefficient and this approach is presented below [10].

$$C_p(\lambda,\beta) = 0.5\left(\frac{116}{\lambda_i} - 0.4\beta - 5\right)e^{-21/\lambda_i} \tag{3}$$

Performance coefficient is based on a λ_i factor then it is expressed by the following equation:

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} \tag{4}$$

Equation 5 exhibit tip-speed ratio, a quotient between blade linear velocity and the incoming wind speed, where ω_r is the rotor speed of the wind turbine.

$$\lambda = \omega_r R / v_w \tag{5}$$

The typical behavior of the performance coefficient is illustrated in Fig. 1. The performance coefficient, based on Eq. 3 and 4, has a maximum value of 0.41 when the ratio between velocities is 7.9 and the pitch angle is set to 0°. For pitch angles higher than zero, the performance coefficient diminishes for different values of the tip-speed ratio, moving away from the optimal value of the tip-speed ratio.

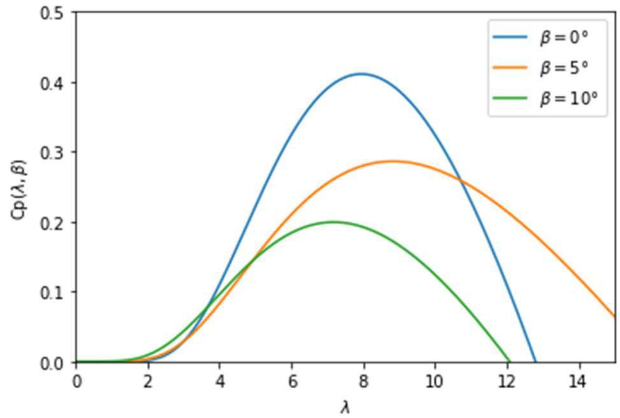

Fig 1. Performance coefficient for different blade pitch angles.

Wind turbines operate at a wide range of wind speeds, generally between 3m/s and 25m/s. For each wind speed a balance between pitch angle and rotor speed is realized to meet power demand and maintain wind turbine availability. Fig. 2 presents the control zones of the wind energy conversion systems, taking into account the wind speed and the generated power.

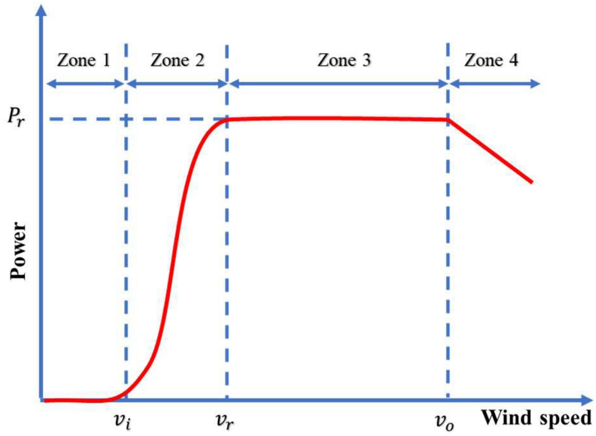

Fig 2. Wind turbine operating control mode for four different zones.

In zone 1, there is not enough wind speed to generate power, so the turbine remains disconnected from the grid until a minimum speed is reached [11]. In zone 2, the rotor begins to generate energy from a minimum wind speed, called cut-in speed. The power generated varies according to wind speed. Hence, control algorithms are useful for the extraction of maximum power. The literature lists a few algorithms: tip-speed ratio control, optimal torque control, power signal feedback and perturbation and observation control [12-13]. Constant rotor speed denotes zone 3. Pitch control fits rotor speed to maintain rated power and does not compromise mechanical systems [14]. At zone 4, wind turbine systems shut down to protect their assemblies from structural overloading and mechanical failures.

Zone 3 is the main object of study in this article. Constant rotor angular speed is achieved by pitch control. A controller fits blade pitch angle to maintain constant speed even for different wind speeds.

B. PI Controller

A PI controller is used to model the blade's angle of attack control mechanism. The combination of proportional and integrative constants helps to model rotor speed control, maintaining the integrity of the mechanical system and stabilizing the operation of the wind turbine in steady state. PI controller which outputs pitch angle is presented bellow under u(t) function:

$$u(t) = K_p e(t) + K_i \int e(t)dt \tag{6}$$

The PI controller aims to adjust the actual rotational speed to the rated rotational speed, minimizing the error between them. This fitting is made through the pitch angle, exposed by the function u(t) [15].

C. Wind turbine drivetrain

The drivetrain is modeled after a dynamic torque analysis of the system. One mass model for direct drive low-speed wind turbines is capable of modelling drivetrain behavior.

The relationship between the rotor (T_m) and generator (T_g) torque is expressed below [16], taking into account the equivalent moment of inertia on drivetrain:

$$J\dot{\omega}_r = T_m - T_g \tag{7}$$

D. Synchronous generator

Fig. 3 shows the equivalent circuit of a permanent magnet synchronous generator, following the rotary reference of the quadrature (q) and direct (d) axis [17].

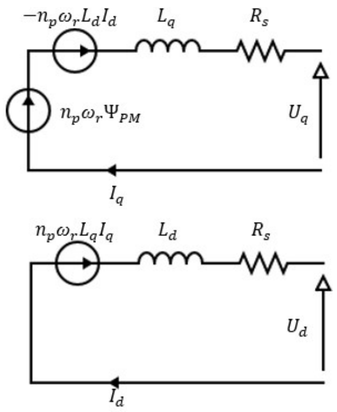

Fig 3. Equivalent circuit for a permanent magnet generator, represented by a dq0 frame.

The voltages and currents in the stator winding along the direct and quadrature axis are represented, respectively, as U_d, U_q, I_d and I_q. Both circuits show stator resistance (R_s) and the armature L_q and L_d. On the quadrant axis there is the back electromotive force, induced by the stator winding through the permanent magnet flux (Ψ_{PM}). Both the armature reaction and the electromotive force of the permanent magnet are proportional to the angular speed of the rotor (ω_r) and the number of pole pairs (n_p). The stator voltages in the direct and quadrature axis are given respectively below:

$$U_d = R_s I_d + L_d \frac{dI_d}{dt} - n_p\omega_r L_q I_q \tag{8}$$

$$U_q = R_s I_d + L_d \frac{dI_d}{dt} - n_p\omega_r \left(L_d I_d + \Psi_0\sqrt{3/2}\right) \tag{9}$$

Active power generated based on a dq0 frame is exhibited next:

$$P = \frac{3}{2}(U_d I_d + U_q I_q + 2U_0 I_0) \tag{10}$$

Tab. 1 exhibits the parameters used to model the behavior of the wind energy conversion system.

TABLE I. WIND TURBINE PARAMETERS

Parameter	Value	Unit
Rated power	2000	kW
Rated speed	18	rpm
Rotor diameter	120	m
Rotor and generator inertia	16700000	kgm²
Stator resistance	0.001	ohm
Number of pole pairs	200	
Inductance on q and d axis	0.5	mH

III. MAIN FAULT MODELING

This section describes the main faults in pitch control, considering speed sensor and pitch angle. Finally, an approach based on digital twins for fault detection and isolation is presented.

A. Sensor faults

Pitch faults can be caused by an incorrect reading of the rotor angular speed sensor. Sensor' faults are classified as: drift (a progressive change in signal over the time), bias (a step signal), scaling or offset (a signal amplification) and loss of signal or null value. Null value and offset signal were considered in this paper [17-18]. PI controller senses an incorrect reading dealing as an input, then a wrong pitch angle is generated, making the system unstable and unhealthy [19].

B. Pitch faults

In literature there are two types of pitch systems on wind turbines: hydraulic actuators and electric motors. Hydraulic actuator faults are associated with low pressure in hydraulic supply system and high air content in the oil. Low pressure is caused by a leakage in the hose or a blocked pump. However, air content is difficult to control and difficult to avoid on hydraulic actuators [19].

In electric motors, failures are related to short circuits on the motor's winding, brake damage, bearing jams, lubricant starvation, cooling fan errors, and overheating caused by oil leakage from the gearbox. Oil could leak from the gearbox into slip rings creating an insulating fluid film which causes pitch signal intermittence. Issues to feather the blade is also induced by a fault in a battery that supplies energy to the motor [20]. The faults mentioned above avoid the rotor from maintaining a constant speed, generating fluctuations in the generated power.

C. Digital twins for fault detection and isolation

There are two main concepts of digital twins proposed in literature. The first concept consists of a system embedded with available physical models to mirror the life of its corresponding twin [21]. The second concept argues that it is a system comprising three components: a physical product in a real space, a virtual product in a virtual space and its interconnection among them [22].

Two wind energy conversion systems are created in AMESim 17, a multidomain dynamic modeling which shrinks submodels into multiport blocks that are connected by a two-way flow of information [23]. A general model simulates a physical wind turbine in real space prone to faults. The second is a virtual model or a replica that is in a healthy state. Both models carry the same mathematical formulation proposed on section A, except for the general model that has an inserted fault.

Fig. 4 presents an illustration between the two models and its data flow. Mean wind speed fed both models, which returns blade pitch angle, active power and rotor speed. Data flowing through models is automatic, real time and calculates a difference between observable variables to detect faults.

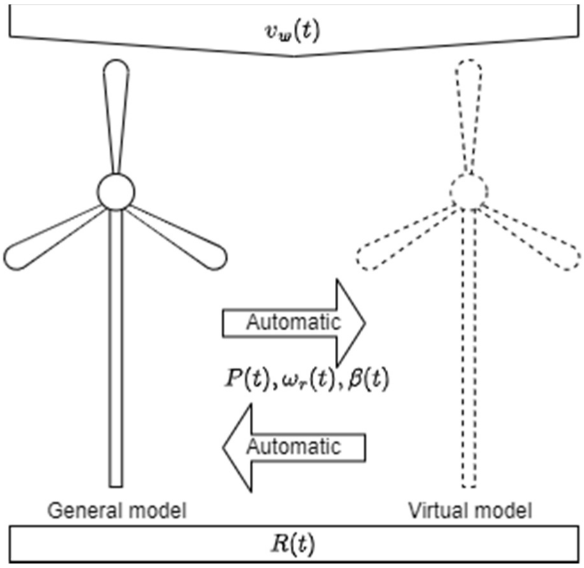

Fig 4. Wind turbine digital twins modeling.

The formulations proposed in section II elucidate mathematical models for application in digital twins, useful for building a pitch fault detection model. Three variables namely active power, rotor speed and pitch angle are evaluated to determine the outputs of the general model, y(t). All three variables are arranged in a transposed vector according to:

$$y(t) = [P(t)\ \omega_r(t)\ \beta(t)\ ]^T \tag{11}$$

Wind speed supplies both replica and general model and estimates the same variables to detect nonconformities with the general model. The expected outputs for virtual model, ŷ(t), were expressed hereafter:

$$\hat{y}(t) = [\hat{P}(t) \quad \hat{\omega}_r(t) \quad \hat{\beta}(t)]^T \tag{12}$$

Variables from the virtual model output are represented by a circumflex accent and have the same meaning as the general model.

For fault detection it was necessary to find out the residuals R(t), which were given by the difference between the measured real-time output of the general model and the output extracted from the virtual model and is represented below:

$$R(t)=y(t)-\hat{y}(t) \tag{13}$$

In fault detection methods based on digital twins a nonconformity is detected if the residual is greater than a threshold value τi. When R(t) is less than a threshold value, the system operates in a healthy state, else a faulty state at the system appears. Hence, a faulty conditional (FC) appears as stated below to classify whether or not there is a fault.

$$FC = \begin{cases} 0, & if\ |R(t)| < \tau_i \\ 1, & else \end{cases} \tag{14}$$

A healthy system has a faulty conditional equal to 0 and 1 to indicate a fault.

A complete fault diagnosis is achieved by fault isolation i.e., after fault detection pitch control diagnosis system classifies the fault. Tab. 2 exhibits three faults involving pitch control in wind turbines and how to model them. The F_1 fault is a null signal inserted into the sensor' general model and it is modeled as a zero angular speed. The F_2 fault is a half reading of the rotor speed, while F_3 fault is 50% of the integrative constant of the general model.

TABLE II. WIND TURBINE PITCH CONTROL FAULTS

Fault	Fault name	Modeling	Effect
F_1	Rotary speed sensor fault	Gain = 0	Sensor' null rotary speed
F_2	Rotary speed sensor fault	$\omega_r/2$	Sensor' rotary speed bellow replica's rotary speed.
F_3	Actuator delay	k_i*50%	Long time to achieve rated power

IV. SIMULATION RESULTS

The results in this section are based on multi-domains to assemble a variable-pitch wind energy conversion system. The graphical representation of the blocks is shown in Fig. 5.

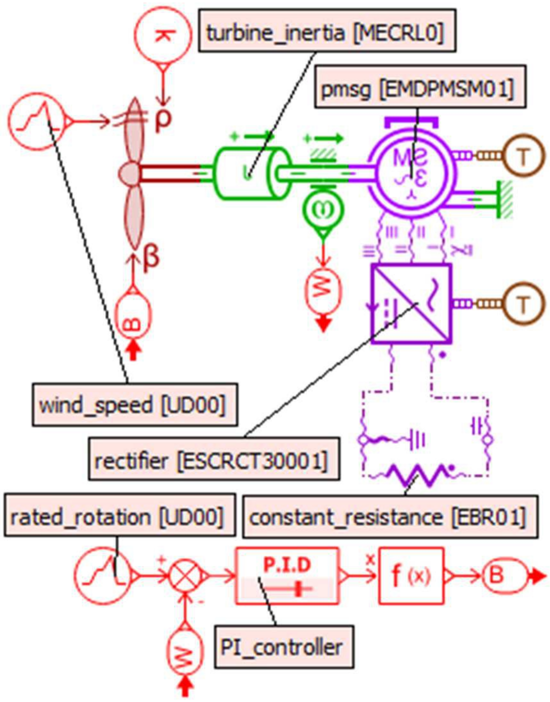

Fig 5. Wind turbine model deployed on AMESim.

Based on the previous illustration, the system has a turbine, an inertia, speed sensor, PI controller, generator, rectifier and a resistive load. The wind turbine has four ports, whose inputs are wind speed, pitch angle (β), air density (ρ) and shaft angular velocity and returns mechanical torque on the shaft. The wind speed input signal is continuous and has an average value of 12m/s. Air density is defined by a constant on the order of 1.225 kg/m³.

Turbine inertia, which has two ports, takes as input the torque from turbine and generator, then returns angular rotation to both. A speed sensor gives the same transmission of power due to causality between the blocks. Then, the speed sensor sends a signal to the pitch angle control in the PI controller. The parameters of the speed sensor with gain and offset were changed to simulate faults in the pitch control.

In the PI controller, the plant value is based on the output signal of the speed sensor and the setpoint is given by the rated speed of 18rpm. The proportional and integrative constants are of the order of 0.007 and 0.04 and a fault in the system response is given by an increment in the integral part.

The permanent magnet synchronous generator has six ports. One port is related to the transmission of power of temperature and heat flow. Other two ports feature angular speed input and torque output on the rotor and stator. However, a zero-rotation block is placed on the stator port. Then, the three-phase wires receive voltage and return current.

The rectifier receives three-phase currents then returns voltage on the alternate current side. At the direct current side, the rectifier receives voltage and returns direct current to the resistor, which presents voltage and current flows.

In the model proposed, the wind turbine starts from zero speed then stabilizes under the rated speed of 18rpm and 2MW over the 500s of simulation. Faults were inserted at the beginning of the modeling and three analyses were performed for each fault individually.

Fig. 6 depicts the residuals of fault 1. A zero reading on the speed sensor causes the residue to stabilize at its own rated speed in Fig. 6b, and the active power of the general model is much higher compared to the virtual model. In practice, the turbine rotates above rated speed. Fig. 6c shows pitch angle residuals. A peak is found due to the stabilization on 0° of the general model, which does not correspond to a 0° stabilization for the virtual model. Next, the virtual model stabilizes itself at an angle higher than the general model. The general model reaches 0º to track the maximum extraction of wind energy.

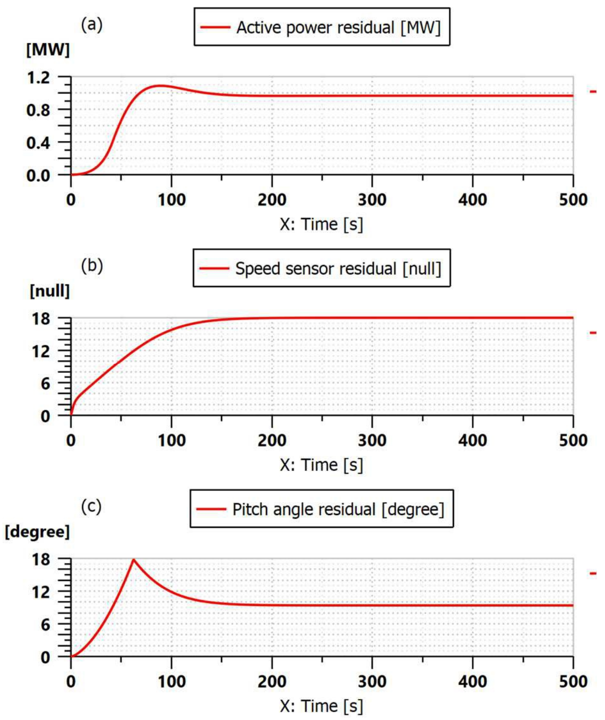

Fig 6. Residuals obtained for fault 1: (a) active power, (b) speed sensor and (c) pitch angle residuals for a null rotary speed on sensor' signal.

Fig. 7 shows a fault in sensor speed which corresponds to an offset in sensor' speed reading on general model. In Fig. 7b the residual of the speed sensor is null, however, in practice, the turbine has half the speed of the virtual model. Already in Fig. 7c, the residual of the pitch angle is different from zero, because the pitch angle of the general model is higher than the replica, reducing the rotary speed of the general model. The reduction of rotor speed contributes to the residual active power in Fig. 7a, also reducing the power generated in the general model.

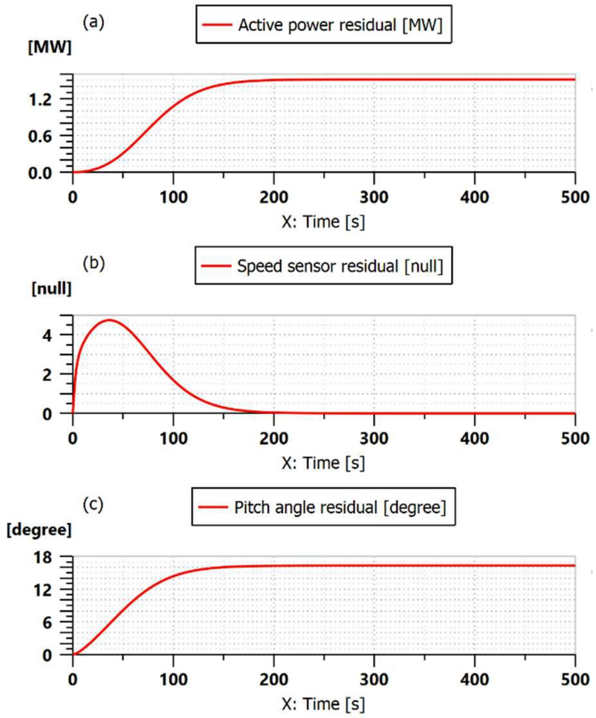

Fig 7. Residuals obtained for fault 2: (a) active power, (b) speed sensor and (c) pitch angle residuals for a half rotary speed offset on sensor' signal.

Fig. 8 shows a delay fault of either the actuator or the electric motor. The behavior of the residuals is given in a similar way. In Fig. 8c the pitch angle slowly stabilizes rotor rotation speed over the 500s. It takes a long time for the general model to stabilize at a rated speed, which is only achieved around 360s as illustrated in Fig. 8c. In the same way as in Fig. 8a, active power has a delay to reach rated power.

Each isolated fault demonstrated a different behavior among the three residual variables analyzed. Tab. 3 summarizes the behavior of failure modeling in wind turbines, taking into account faults in the speed sensor and pitch angle.

TABLE III. CHARACTERISTICS OF THE RESIDUAL BEHAVIOR AFTER SIMULATIONS

Fault	Residual characteristic
F_1	Angular speed equal to nominal speed.
F_2	Active power and pitch angle are different from zero, but speed sensor equals to zero after stabilization.
F_3	Long stabilization towards zero value to all three variables.

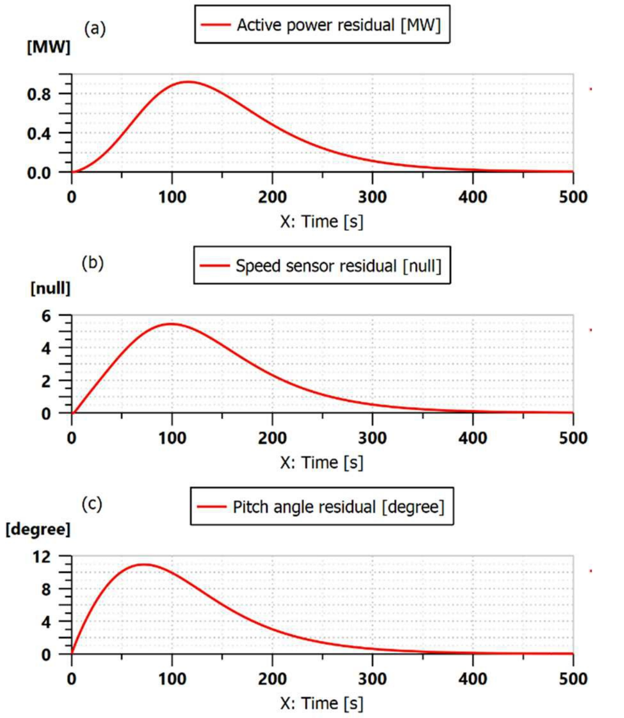

Fig 8. Residuals obtained for fault 3: (a) active power, (b) speed sensor and (c) pitch angle residuals for a delay in pitch actuator or motor to track rated power.

V. Conclusions

In this work a digital twin approach for fault diagnosis in pitch control of wind turbines was introduced. An approach was presented for digital twins, where the behavior of active power, rotor speed, and pitch angle were assessed through residual vectors. With this approach, the modeling flow could be controlled, and three signature faults were created: a null value and an offset value in the speed sensor, and a delay in the actuator.

The subsequent research involves replicating this analysis within the power optimization zone and employing a knowledge-based system for complete fault diagnosis: detection, isolation and failure mode identification.

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