

DESIGN THINKING ON FAULT DIAGNOSIS OF FLOATING WIND TURBINE GENERATOR USING ARTIFICIAL INTELLIGENCE

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Abstract - Floating wind turbines are the centerpiece of offshore floating power generation and an important means of developing offshore wind resources. In few years, artificial intelligence technology has achieved great results in many fields, and equipment fault diagnosis is also much important. Since the working environment of the floating fan is bad and far from the land, a failure of the floating fan generator can have very serious consequences. Based on the research results of AI technology, this article focuses on the application of AI technology in fault diagnosis of floating wind turbines and proposes a fault diagnosis intelligent system framework. According to the research of expert systems and artificial neural networks, the floating fan generator failure diagnosis technology is proposed, and the artificial neural network model and the reasonable failure receive the diagnostic reasoning flow.

Key Words: artificial intelligence; component; neural network; fault diagnosis; floating wind turbine.

1. INTRODUCTION

The generator is the heart of the offshore floating wind turbine, and its proper performance is the foundation for the wind turbines proper operation. Because the floating fans are situated in the water and are unattended, the unit frequently fails due to the poor operating environment, making the intelligent generator fault detection system extremely vital. Overload, bearing fracture, line ageing, and other common generator defects are all too common. When a malfunction arises that cannot be corrected in a timely manner, the light will force the unit to shut down, while the heavy will burn the entire unit, resulting in huge financial losses. Furthermore, failure of one component might influence other components or even the complete wind turbine in extreme circumstances. It is significant in light of all of these facts. Using this technology, it will greatly help the physically challenged and elderly people to control the appliances easily. A mobile application along with Vuforia Server will help the users to control a switch by simply pointing their mobile camera to it from a distance. Different virtual switches will appear like on and off when the camera is pointed to image target, thus allow the user to control different appliances easily and conveniently. Instead of normal switches, 2D buttons will appear on the screen which gives a familiar interface to the user. When the user touches the button information will be transfer to the Blynk server and instruction is forwarded to the microcontroller and the controller turns the device on or off according to the user operation.

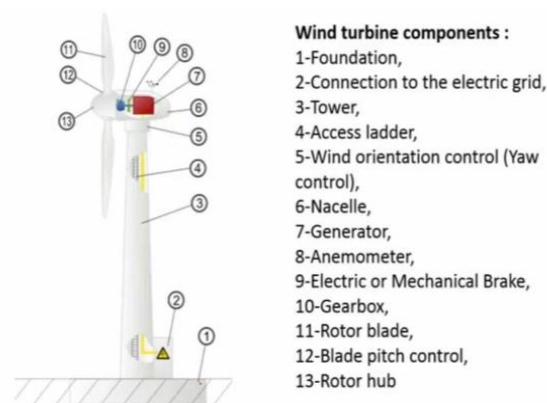


Fig -1: Wind Turbine Components

1.1 ARTIFICIAL INTELLIGENCE TECHNOLOGY

Artificial intelligence technology is to study and make computers simulate normal human activities (such as learning, thinking, etc.). In the fault diagnosis of the floating wind turbine generator, by building the expert knowledge system database artificial intelligence technology can carry out fault diagnosis of the generator in advance. Through continuous learning of neural networks, the data of faults in expert knowledge systems can be recorded, and then continuous learning and evolution can be achieved. The artificial intelligence system can improve the efficiency and accuracy of fault diagnosis of wind turbine generators.

1.2 ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (NNs) are simplified simulations of the neurological systems of living organisms. A neural network (NN) is a data processing system made up of a large number of simple, densely interconnected processing components (artificial neurons) in a form inspired by the cerebral cortex's organization. The interconnected neural computing parts have the potential to learn and hence accumulate knowledge, allowing for event prediction areas .where NNs can be used in forecasting, pattern recognition, optimization, control systems and image processing

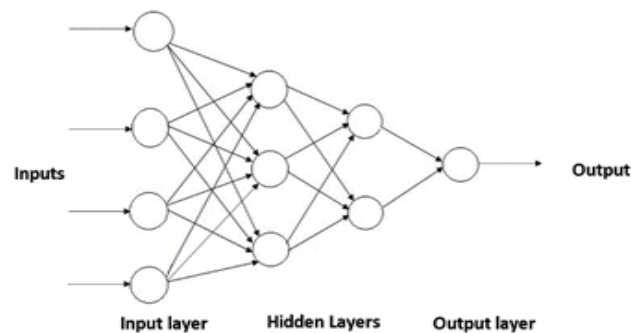


Fig -2: Neural Network

2. LITERATURE SURVEY

Hue, Liu Xiu-wen ,Bian Jing-yu.[1].“The Application of Artificial Intelligence Technology in the Fault Diagnosis of Floating Wind Turbine Generator”.

Qi-Ping Yang, Meng-Qun Li, Xue-Yun Mu, Jun Wang.[2].“Application of Artificial Intelligence (AI) in Power Transformer Fault Diagnosis”.

YirongLiu,Zidong Wu, Xiaoli Wang. [3]. “Research on Fault Diagnosis of Wind Turbine Based on SCADA Data”.

Xiaojia Kong, Tongle Xu, Junqing Ji, Fanghao Zou, Wei Yuan,Leian Zhang. [4]. “Wind Turbine Bearing Incipient Fault Diagnosis Based on Adaptive Exponential Wavelet Threshold Function With Improved CPSO”.

Hameed, Z,Hong, Y.S,Cho, Y.M,Ahn, S.H,Song, C.K. [5].“Condition monitoring and fault detection of wind turbines and related algorithms”.

Bill Chun PiuLau,EdenWai Man Ma,MichaelPecht. [6]. “Offshore Wind Turbine Failures and Fault Prognostic Methods”.

Par Marklund,Kim Berglund. [7].“Bearing monitoring in the wind turbine drive train a comparative study of the FFT and wavelet transforms”.

M Nithya,S.Nagarajan,P. Navaseelan. [8].“Fault detection of wind turbine systems using neural networks”.

Acho, L.; Rodellar, J.; Tutivén, C.; Vidal, Y. [9].“Passive Fault Tolerant Control Strategy in Controlled Wind Turbines”.

3. HARDWARE

The hardware components and materials that we used in the system are Battery, Power Supply, Temperature Sensor, Vibration Sensor, Speed Sensor, PIC 16F877.

3.1 Battery

A battery is an implement that converts chemical energy into electrical energy. Battery is composed of one or more electrochemical cells, which are composed of two half cells connected in series by the conductive electrolyte. Voltaic cells are connected in series with one or more.

3.2 Power Supply

The power supply should be +5V no transistors exceeding 10mV. The voltage should be suitably tuned to get high / enough contrast for the display in pin 3.

A module must not be installed or removed in a live circuit. The power supply of the ground terminal must be congruously isolated so that no voltage is induced to it. The module must be isolated from the rest of the circuitry to prevent stray voltages from flickering display.

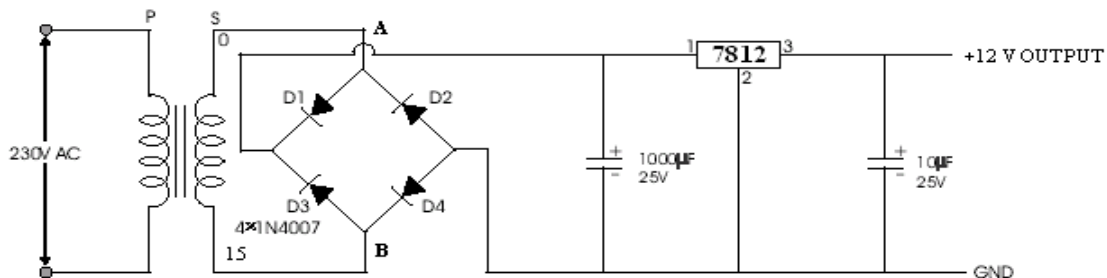


Fig -3: Circuit Diagram

3.3 Temperature Sensor

A temperature sensor is a utensil, customarily a resistance temperature detector or a thermocouple. It uses an electrical signal to deliver temperature measurements in a legible form. A thermometer is the most cardinal type of temperature meter, and it is used to determine how balmy or cold. In the geotechnical profession, temperature meters are used to monitor concrete, soil, structures, water, bridges, and structural changes caused by seasonal variations.

3.4 Vibration Sensor

Vibration sensors detect vibration using piezoelectric accelerometers. They're used to quantify variable accelerations or speeds, as well as typical vibrations. Process control systems, aerial navigation, and undersea applications are examples of applications where vibration sensors are used. The piezoelectric plate is a type of sensor used to detect mechanical vibrations. The mechanical vibration is converted to an electrical signal by a piezoelectric plate. The transformed electrical signal has a voltage range of a few mill volts.

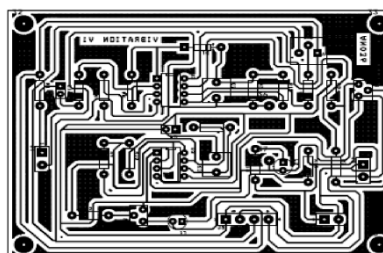


Fig -4: Piezoelectric Sensor

3.5 Speed Sensor

A speed sensor is often installed on the side of a wheel axle or the axle of a traction motor and driven by a pin pushed into the axle. When this mounting method is used, the speed sensor gear's centre almost always differs from the axle's centre. The influence of the eccentricity of the speed sensor gear has been investigated.

3.6 PIC 16F877

Microchip's PIC 16F877 is one of their latest microcontrollers. Due to its economical price, wide variety of applications, good quality and easy availability, this controller is widely used for experimental and current applications. It is suitable for a variety of applications including machine control, measuring devices, research, etc. The PIC 16F877 has all the components found in current microcontrollers.

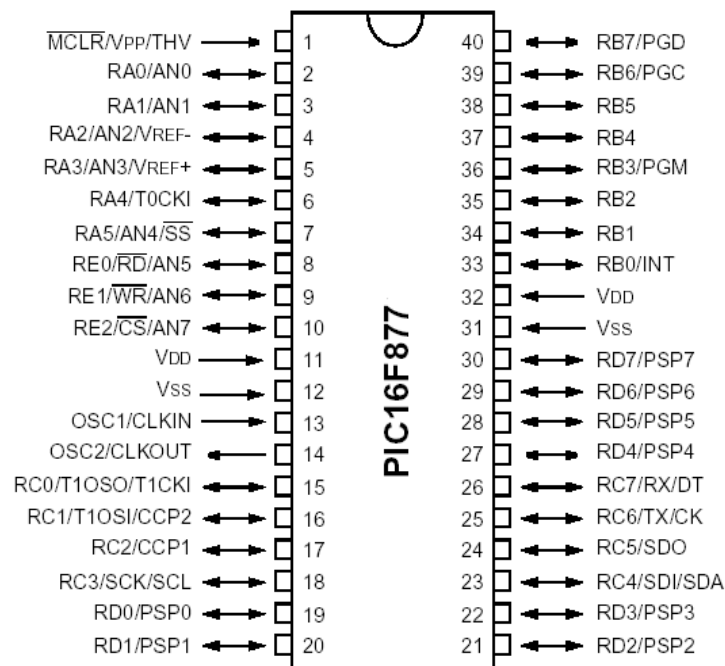


Fig -5: PIN Diagram of 16F877

DEVICE	PROGRAM FLASH	DATA MEMORY	DATA EEPROM
PIC 16F877	8K	368 Bytes	256 Bytes

Table -1: Specification

4. EXISTING SYSTEM

Wind turbines are programmed to deliver consistent active and reactive power for a set length of time in order to contribute to the power grid. We compare the performance of three forms of separate active and reactive power control for horizontal axis wind turbines in this paper: the direct method with a (PI) and a Fuzzy Logic controller, as well as the indirect method control with power feedback.

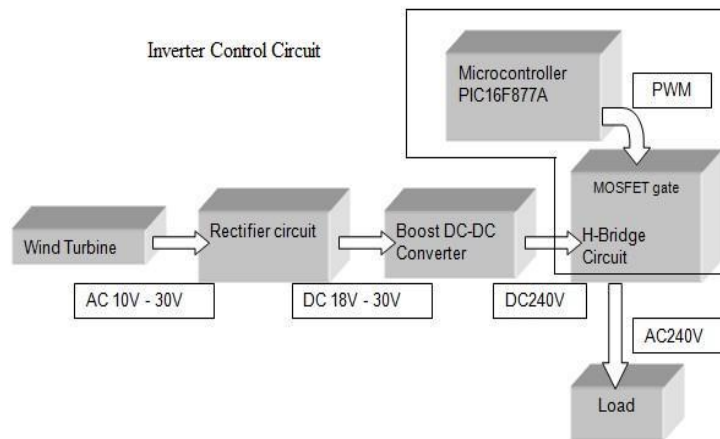


Fig -6: Inverter Control Circuit for SCADA

4.1 BOOSTER CONVERTER

A boost converter can only increase the value of the output voltage to the point where the output voltage is greater than the input voltage. The boost converter circuits will step-up the low DC voltage to a high DC voltage. The basic circuits of a boost converter use power MOSFETs. When the power supply is ON, the circuit operates and the current flows by way of the inductor, L, and it will store the energy. The stored energy in the inductor will be taken out to load if the power supply is turned OFF.

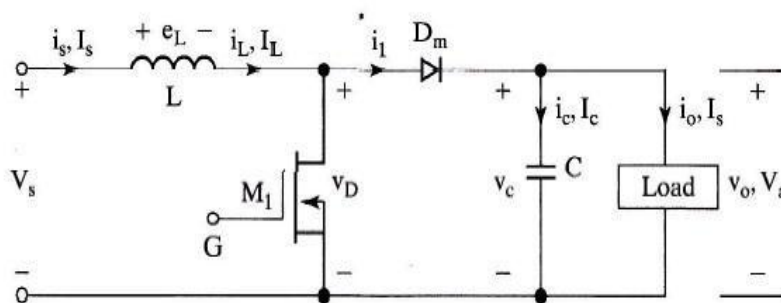


Fig -7: Booster Converter Circuit

4.2 BASIC OF FUZZY LOGIC CONTROLLER

The fuzzy logic system is simple to learn, develop, and use, and it outperforms other types of controllers. By performing basic rules guiding the system's behavior, a fuzzy logic controller is developed into an automatic way of modifying the language of control steps. By mixing multiple ways of thinking at a higher level of abstraction, fuzzy logic permits the modeling of complex systems based on knowledge and experience. For the control algorithm that affects the system variables and a rule table, fuzzy logic variables are described. The gain is calculated by dividing the input voltage by the average output voltage value.

4.3 METHODOLOGY

The methodology for this project follows these steps:

- Develop and design the boost converter circuit
- Based on the literature.
- Design and enlarge the Fuzzy Rules for the Fuzzy
- Logic Controller based from the gain response

- Graph.
- Restoring the boost converter with/without the FLC
- Integrated for transient response based from
- Different input voltage levels.

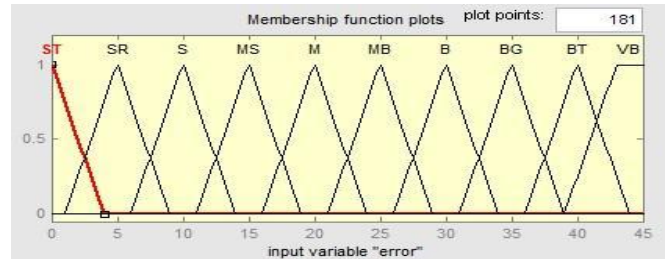


Fig -8: Wind Speed

4.4 Disadvantages

It describes the design and development of a fuzzy logic controller boost DC-DC converter for renewable energy. Based on comparison simulation results, using the MATLAB SIMULINK is the most convenient way to design the circuit. This project is responsible with the design and simulation of boost DC-DC converter with application of fuzzy logic controller. The performance for this project can be increased by reducing the voltage ripple on the output voltage. To maintain a constant output voltage by designing the boost converter of the switching regulator within an acceptable regulation.

5. PROPOSED SYSTEM

The generator is the core of the offshore floating wind turbine, and the ordinary operation of the generator is the idea of the ordinary operation of the wind turbine. The floating enthusiasts are hooked up inside the sea and unattended. Because of the horrific operating surroundings, the unit regularly fails, so the sensible generator fault detection machine is especially essential. Overloads, bearing fractures, line aging, and other common faults occur frequently in generators. Once the fault happens and cannot be treated in time, the light will cause a shutdown, and the heavy will burn the entire unit, causing full-size economic losses.

5.1 Fault Diagnosis Based on Artificial Neural Network

Artificial neural network is composed of several neurons, which have the functions of association, reasoning and memory. The data information from the fault sensors in the floating wind turbine generator is collected first, then the characteristic function is constructed, and the constructed characteristic function is used to process these data, yielding the output value of the first calculation result, which is then used as the input value of the second calculation, and so on, until the final calculation result is output. The final result is then compared to a pre-determined threshold function. The result will be output directly if it fits the conditions. It will be returned to the feature function's construction for recalculation if it does not fulfill the requirements.

Because of high production costs of WTs, Computer-Aided Engineering (CAE) has become fundamental to the wind energy industry because of its ability to get reliable and accurate simulations and results in the preproduction stage. The software that was used for the development of the project was Open FAST, which is an open-source WT simulation tool designed by the NREL that computes the coupled dynamic response of WTs.

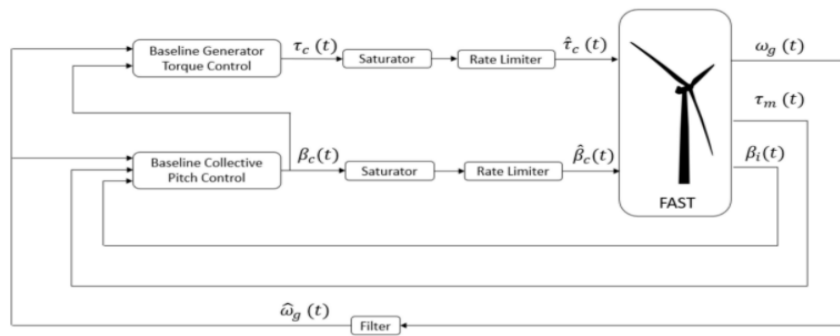


Fig -9: Fast used in Control System

5.2 FAULT DETECTION AND TOLERANT CONTROL DIAGRAM

To effectively introduce fault-tolerant control of a SCADA solution without getting into the particular control loops, the subsequent architecture was proposed.

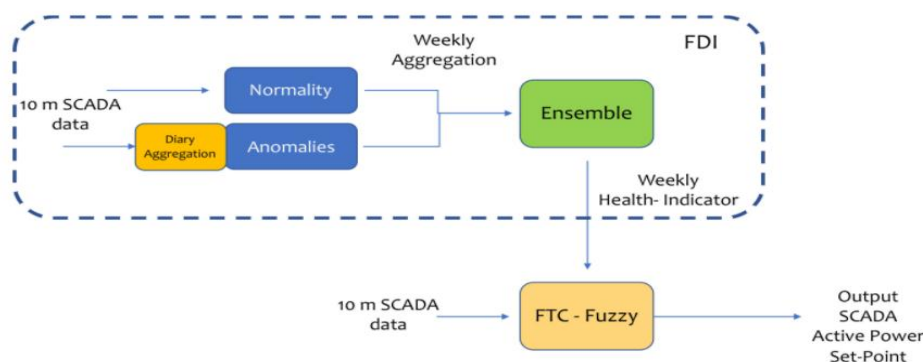


Fig -10: High Level Architecture

The main blocks conforming to this Passive FTC were the Fault Detection Block and the Fault-Tolerant Control. The input was the quality 10 min SCADA data, usually acquired using an Open Platform Protocol (OPC). For the fault diagnosis, we proposed a solution combining Normality (Regression) Models and Anomalies using ensemble learning. The fault diagnosis output was weekly health indicators that fed the symbolic logic.

The inputs were health indicators (on a weekly basis) and 10 minute SCADA data. The 10 min SCADA data was wont to fine tune the output during the weekly operation.

5.3 HEALTH INDICATORS

An unmonitored health indicator was used to determine the initial failure state. These indicators were collected weekly to enable early stage error detection. Here it was used as an input to a fault tolerant control strategy. The health indicator consisted of a regression algorithm and an anomaly algorithm. We then used ensemble learning to combine these two indicators to improve sensitivity and accuracy.

6. SOFTWARE

The MPLAB IDE is an integrated development environment that provides development engineers with the flexibility to develop and debug firmware for various Microchip devices. The MPLAB IDE is a Windows-based Integrated Q Development Environment for the Microchip Technology Incorporated PIC microcontroller (MCU) and aspic digital signal controller (DSC) families. In the MPLAB IDE, you can:

- Create source code using the built-in editor.

Assemble, compile, and link your source code using a variety of language tools. The MPLAB IDE comes with an assembler, linker, and librarian. The C compiler is available from Microchip and other third parties. Monitor the programmer flow in real time with a simulator like MPLAB SIM or an emulator like MPLAB ICE to debug the executable logic. A third-party emulator that runs on the MPLAB IDE is also available

- Take timing measurements.
- View variables in Watch windows.

7. CONCLUSION

The SCADA system is commonly used to detect issues in wind turbine systems, although it takes a lot of labor and time. Artificial intelligence (AI) is utilized to improve the program's efficiency and power. The Naive Bays method is a sophisticated machine learning approach for fault analysis. Naive Bays classifiers are a subset of simple "probabilistic classifiers" found on Bays' theorem and strong feature independence conjecture. They're one of the most basic Bayesian network models, but when combined with kernel density estimation, they can achieve higher levels of accuracy. As a result, internal and circuit defects can be identified in a short amount of time.

This research offers an intelligent fault diagnostic method based on an artificial neural network and an expert system to increase the accuracy of fault diagnosis of offshore floating wind turbine generators. According to the pre-built database and reasoning framework, the diagnosis system analyses and calculates the data collected from the sensor. In comparison to the traditional fan generator fault diagnosis system, it can effectively improve the fault diagnosis efficiency and accuracy of the floating fan generator system, as well as feed the diagnosis results back to the user in real time, greatly improving equipment maintenance efficiency and lowering equipment maintenance charge.

8. REFERENCE

- [1] Renewable Energy Institute, "Statistics Global Energy". Available online: <https://www.renewable-ei.org/en/statistics/international/> (accessed on 12 August 2021).
- [2]. Sheng, S. Report on Wind Turbine Subsystem Reliability—*A Survey of Various Databases*; National Renewable Energy Laboratory: Golden, CO, USA, 2013.
- [3]. Reder, M.D.; Gonzalez, E.; Melero, J.J. Wind turbine failures-tackling current problems in failure data analysis. In *Journal of Physics: Conference Series*; IOP Publishing: Bristol, UK, 2016; Volume 753, p. 072027.
- [4]. Faulstich, S.; Hahn, B.; Tavner, P.J. Wind turbine downtime and its importance for offshore deployment. *Wind Energy* 2011, *14*, 327–337.
- [5]. Statista .2021. Available online: <https://www.statista.com/statistics/268363/installed-wind-power-capacity-worldwide/> (accessed on 12 August 2021).
- [6]. Gao, Z.; Liu, X. An overview on fault diagnosis, prognosis and resilient control for wind turbine systems. *Processes* 2021, *9*, 300.
- [7]. Hart, E.; Clarke, B.; Nicholas, G.; Amiri, A.K.; Stirling, J.; Carroll, J.; Dwyer-Joyce, R.; McDonald, A.; Long, H. A review of wind turbine main bearings: Design, operation, modeling, damage mechanisms and fault detection. *Wind Energy Sci.* 2020, *5*, 105–124.
- [8]. Rashid, H.; Khalaji, E.; Rasheed, J.; Batunlu, C. Fault Prediction of Wind Turbine Gearbox Based on SCADA Data and Machine Learning. Proceedings of the 10th International Conference on Advanced Computer Information Technologies (ACIT) Advanced Computer Information Technologies (ACIT), Deggendorf, Germany, 16–18 September 2020.

- [9]. Habibi, H.; Howard, I.; Simani, S. Reliability improvement of wind turbine power generation using model-based fault detection and fault tolerant control: A review. *Renew. Energy* 2019, *135*, 877–896.
- [10]. Acho, L.; Rodellar, J.; Tutivén, C.; Vidal, Y. Passive Fault Tolerant Control Strategy in Controlled Wind Turbines. In Proceedings of the 3rd Conference on Control and Fault-Tolerant Systems (SysTol), Barcelona, Spain, 7–9 September 2016.
- [11]. Pozo, F.; Vidal, Y. Wind turbine fault detection through principal component analysis and statistical hypothesis testing. *Energies* 2016, *9*, 3.
- [12]. Hosseinzadeh, M.; RajaeiSalmasi, F. Analysis and detection of a wind system failure in a micro-grid. *J. Renew. Sustain. Energy* 2016, *8*, 043302.
- [13]. Zaher, A.S.A.E.; McArthur, S.D.J.; Infield, D.G.; Patel, Y. Online wind turbine fault detection through automated SCADA data analysis. *Wind Energy* 2009, *12*, 574–593.
- [14]. Gibert, K.; Marti-Puig, P.; Cusidó, J.; Solé-Casals, J. Identifying health status of wind turbines by using self organizing maps and interpretation-oriented post-processing tools. *Energies* 2018, *11*, 723.
- [15]. Beretta, M.; Julian, A.; Sepulveda, J.; Cusidó, J.; Porro, O. An Ensemble Learning Solution for Predictive Maintenance of Wind Turbines Main Bearing. *Sensors* 2021, *21*, 1512.
- [16]. Odgaard, P.F.; Stoustrup, J. A benchmark evaluation of fault tolerant wind turbine control concepts. *IEEE Trans. Control Syst. Technol.* 2014, *23*, 1221–1228.
- [17]. Vidal, Y.; Rodellar, J.; Acho, L.; Tutivén, C. Active Fault Tolerant Control for Pitch Actuators Failures Tested in a Hardware-in-the Loop Simulation for Wind Turbine Controllers. Proceedings of the 23rd Mediterranean Conference on Control and Automation (MED), Torremolinos, Spain, 16–19 June 2015.
- [18]. Badihi, H.; Zhang, Y.; Hong, H. Wind turbine fault diagnosis and fault-tolerant torque load control against actuator faults. *IEEE Trans. Control Syst. Technol.* 2014, *23*, 1351–1372.
- [19]. Casau, P.; Rosa, P.; Tabatabaeipour, S.M.; Silvestre, C. Fault detection and isolation and fault tolerant control of wind turbines using set-valued observers. *IFAC Proc. Vol.* 2012, *45*, 120–125.
- [20]. Kim, J.; Yang, I.; Lee, D. Control allocation based compensation for faulty blade actuator of wind turbine. *IFAC Proc. Vol.* 2012, *45*, 355–360.