System for detecting pathologies in wind turbines by means of use of digital and artificial intelligence techniques

Guillermo Alandí^{1,*}, Julia I. Real¹, Miriam Labrado¹, and Laura Morera²

(1) Institute of Multidisciplinary Mathematics, Universitat Politècnica de València, 46022, València (Spain)

(2) Instituto Tecnológico y de Energías Renovables, S.A., Polígono Industrial de Granadilla, s/n 38600 Granadilla de Abona, Santa Cruz de Tenerife (Spain)

1 Introduction

Wind turbine maintenance operations account for 10-20% of the total cost of energy generated due to failures and defects that require costly repairs. These failures are mainly caused by weather variability, which affects mechanical loads and modes of operation, the complexity and number of wind turbine systems, and the increasing size of wind turbines, which increases loads and stresses on the structure and foundations.

Wind turbine failures show early signs that current solutions are trying to detect to reduce costs and prevent further damage. With the growth in turbine capacity, downtime and repair costs also increase. Therefore, the industry is looking for reliable solutions that detect, diagnose, and anticipate problems at an early stage, improving decision making and enabling planned and optimised maintenance to reduce costs.

In response to this need, this work arises where the main objective is to create an innovative integral monitoring system for wind turbines, capable of identifying, diagnosing, and predicting the evolution of defects in its main components, such as the rotor, multiplier, generator, tower and foundations. This system will be based on the use of non-intrusive sensors distributed throughout the wind turbine and will include two key innovations. One will be monitoring the state of the drive train by analysing the electrical signature of the generator with a Neural Network, and the other option is monitoring the state of the wind turbine structure by means of a pathology detection system with another Neural Network.

2 Methods

The system is based on the use of two techniques to diagnose the state of all the main elements of a wind turbine:

* Guillermo Alandí guialma3@upv.es

2.1 Electrical Signature Analysis for POWER TRAIN (rotor, multiplier, and generator)

The ESA technique is because the electrical output of a generator (current) can be expressed as a function of the rotational speed of the rotor, therefore, it carries the signature of any generator failure as a function of the rotational speed of the rotor. It also carries the signature of any drive failure that affects the rotational speed transmission faults that affect the rotational speed.

- Rotor: mass imbalance and main bearing failure.
- Multiplier: failure in bearings and gears.
- Generator: failure in bearings, stator and rotor windings.

The functionality will consist of:

- 1. Employ current sensors connected to the output of the doubly fed electrical generator (DFIG).
- 2. Perform demodulation of the electrical output of the generator to extract shaft speed information.
- 3. For each defect typology, apply a mathematical treatment until obtaining the signal amplitude as a function of the shaft speed [1].
- 4. To the signal obtained, perform the continuous wavelet transform (CWTS), together with a Neural Network, to identify/classify the pathologies. The wavelet transform decomposes the signal into different scales and creates a fingerprint of the signal, which can be analysed, compared and classified using image recognition methodology [2].

Figure 1. Diagram of the diagnostic process of the wind turbine drive train elements.

2.2 Mathematical finite element model (FEM) for the STRUCTURE (tower and ambience)

For the structure (tower and foundation) an analysis of the vibration of the tower, the displacement between the tower and the foundation, and the deformations in the foundation will be used to obtain the dynamic responses of the structure through a mathematical finite element model (FEM). This system will be properly calibrated and validated through the vibration, displacement and deformation records obtained with the sensors used and the boundary conditions such as dead loads (dead weight), variable loads (wind and other climatic agents) and mechanical and geometrical characteristics.

• **Tower:** cracks and fatigue in the cylindrical structure and problems in the joints between the different tower segments

• **Foundation:** appearance of cracks and increase of the relative separation between the tower and the foundation.

The FEM will make it possible to introduce each of the pathologies described above and to know the dynamic response of the structure to these changes. This process will allow the creation of a database with the dynamic responses of each of the pathologies and, using a Neural Network, detect if there is a defect in the structure while the wind turbine is still in operation.

Figure 2. Diagram of the diagnostic process of the wind turbine structure elements.

The work system will consist of the following components:

• **Hardware and Communication Subsystem:** This subsystem will record and transmit the necessary information from both the drive train and the tower and foundation. For the drive train, it will use current sensors connected to the generator output. For the tower and foundation, a series of sensors such as accelerometers, linear displacement sensors, and strain gauges will be developed to measure deformations. Information transmission will employ two types of communication: short-range, likely wired, and long-range, likely via 4G or 3G networks.

Figure 3. Arrangement of a total of 6 current sensors [3] between the 6 phases of the rotor and the stator

• **Software Subsystem**: This will be responsible for processing the data recorded by the hardware subsystem. It will consist of various algorithms that analyse current [4], vibration, displacement, and deformation records to detect possible defects in the drive train, tower, or foundation of the wind turbine. Developing a Digital Twin of the wind turbine elements will be crucial for simulating different scenarios and calibrating the algorithms. Additionally, Artificial Intelligence techniques, such as Neural Networks, will be employed to detect and predict the evolution of defects.

Figure 4. Angular domain conversion and current signal pre-treatment algorithms based on [5]

• **Cloud-based Digital Platform:** This platform will host all the algorithms and mathematical models developed in the software subsystem. It will feature multiple visualization interfaces and access from different devices.

Figure 5. Descriptive diagram of the solution.

3 Results

Firstly, a hardware system for current, acceleration, deformation and displacement data acquisition has been developed. For this purpose, a series of PCBs have been designed (see [Figure 6\)](#page-3-0) and manufactured (see [Figure 7\)](#page-4-0) to meet the technical specifications.

Figure 6. Design of (a) current sensor, (b) accelerometer, (c) strain gauge, and (d) acquisition system.

Figure 7. Manufacture and tests of (b) accelerometer, (c) strain gauge, and (d) acquisition system.

Secondly, the development of the FEM model of the wind turbine structure has begun and can be seen in [Figure 8.](#page-4-1) Once the dimensions have been specified, it will be necessary to calibrate the model to obtain the Twin Model. To do this, the information obtained from the sensors will be used and the dynamic properties of the FEM model will be matched with those of the real structure. Once this is done, we will have a numerical model (Digital Twin) that faithfully represents the behaviour of the real wind turbine (Real Twin).

Figure 8. FEM model of the wind turbine structure.

4 Conclusions

The development of an innovative monitoring system for wind turbines aims to significantly reduce maintenance costs, which currently account for 10-20% of the total energy generation cost. This system addresses primary failure causes such as weather variability, mechanical loads, and the increasing complexity of turbine systems.

The monitoring system incorporates advanced techniques like Electrical Signature Analysis (ESA) and the Finite Element Model (FEM). ESA monitors the drive train components, including the rotor, multiplier, and generator, by analyzing the electrical output and using neural networks to detect potential failures. This method is effective in identifying issues such as mass imbalances, bearing failures, and gear defects. On the other hand, the FEM focuses on the structural integrity of the tower and foundation, using vibration, displacement, and deformation data to detect defects. This model, calibrated with real-time sensor data, allows for accurate identification of structural pathologies through neural networks.

The system integrates hardware and communication subsystems, including sensors for current, acceleration, displacement, and strain. These sensors gather data and transmit it via both wired and wireless networks. The software subsystem processes this data using sophisticated algorithms and digital twin models, leveraging artificial intelligence to predict and diagnose defects.

Additionally, a cloud-based platform hosts the algorithms and models, providing remote access and real-time monitoring capabilities. This platform enhances decision-making processes and facilitates planned, optimized maintenance schedules.

References

[1] Shahriar, M. R. (2017). Electrical signature analysis-based condition monitoring of wind turbine drivetrain (Doctoral dissertation, Queensland University of Technology).

[2] Guo, S., Yang, T., Gao, W., & Zhang, C. (2018). A novel fault diagnosis method for rotating machinery based on a convolutional neural network. Sensors, 18(5), 1429

[3] Artigao, E., Koukoura, S., Honrubia-Escribano, A., Carroll, J., McDonald, A., & Gómez-Lázaro, E. (2018). Current signature and vibration analyses to diagnose an in-service wind turbine drive train. Energies, 11(4), 960

[4] Zhang, P., & Neti, P. (2014). Detection of gearbox bearing defects using electrical signature analysis for doubly fed wind generators. IEEE transactions on industry applications, 51(3), 2195-2200.

[5] Apostoaia, Constantin & Scutaru, Gheorghe. (2006). A Dynamic Model of a Wind Turbine System