Wind Turbine Blade Mass Imbalance Detection Using Artificial Intelligence

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Abstract

Wind power has been increasingly used to electricity generation since its energy cost is becoming closer to conventional non-renewable sources. Although the useful lifetime expectancy of wind turbines being typical of 20 years, they can fail much earlier due to unexpected components failures, especially gears and blades. A precision prediction of the useful lifetime of the wind turbine components certainly reduces costs and downtime of the machine. The objective of this paper is to develop an intelligent Condition Monitoring System (CMS), using a platform Turbsim/FAST/Simulink for simulations of a 1.5 MW wind turbine at normal operations and fault operation due to blade mass imbalance. Those results are compared using machine learning techniques for indicating the occurrence of faults, in order to facilitate predictive maintenance. This paper presents promising indicators that to coupling wind turbine aeroelastic numeric simulations with machine learning techniques is a feasible methodology in CMS. A smart fault detection system can be a useful tool for the development of predictive O&M practices that maximize the profitability of wind energy assets and reduce the LCOE of wind power.

Key-words: Wind Power, FAST, Machine learning, Rotor imbalance.

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Introduction

As wind energy production continuously grows all over the world, the already installed wind turbines have to keep running. New Energy Update analysis projects that the number of turbines between 10-15 years of age globally is set to double from the current volume of 40,000 to almost 80,000 by 2020 (NewEnergyUpdate, 2018). This report raises the importance of operation and maintenance (O&M) practices for producers and Wind farm owners, since the numbers of wind turbines aging, is starting to be expressive. High costs have made maintenance management for wind turbines to receive more attention, to avoid unpredicted failures, have scheduled operations for the availability of parts and tools for repairing needs and achieve reduced downtime. During the life cycle of a wind turbine, the blades are exposed to harsh environments, dealing with rain, hailstone, ice, among other phenomena that can cause erosion and fatigue, especially by the fact that operational speeds are generally high. Since the blades are one of the most critical components in terms of failure (Leite et al., 2018), it is wise to identify and have a prognosis as earlier as possible of progressive failures, such as rotor imbalance.

The rotor imbalance can have several causes, such as the center of mass difference between blades (blade mass imbalance), uneven aerodynamic forces at the blades (such as pitch error or aerodynamic efficiency loss along the blade), wind shear, yaw misalignment. The imbalance is undesired and can cause more significant moments and motions to others wind turbine components and parts, leading to earlier exhaustion and faults to those components. It can also cause torque fluctuations and power fluctuations (Zhao et al., 2017). Therefore, understand the blade mass imbalance phenomena and its causes and effects is of foremost importance to the wind energy industry.

Ideally, the blade mass imbalance would be studied testing blades of real wind turbines in a field experiment. However, it is hard to develop and have a proper wind turbine for research and study, and many researchers have attempted to work with numerical simulations and the so-called digital twins retrieving excellent results (Myrent et al., 2014) (Keegan et al., 2014) (Chen and Tsai, 2014). While the information age rises, hardware and software are improving, and the use of computers for simulations has reached a new level, with highly validated tools that help in terms of precision and reduces the computational costs, like Fatigue, Aerodynamics, Structure, and Turbulence (FAST) from National Renewable Energy Laboratory (NREL).

Lately, in the discussion about O&M costs and efficiency, machine learning has been widely used and researched for better and faster results in terms of fault detection and condition-based maintenance (Mazidi et al., 2017) (Bangalore and Tjernberg, 2015). This kind of data processing is capable of work with and handle big amounts of information that humans would not be able to.

This paper presents the effects of simulated blade mass imbalance based on IEC 61400-13, the wind turbine fundamental load quantities and the detection of its occurrence with a machine learning method known as Support-Vector Machine (SVM). The NREL Computer-Aided Engineering (CAE) tool FAST was used for simulations, while TurbSim was used for generating wind series read by FAST. Results were processed and plotted with Python package matplotlib. A Robust Model Adaptive Collective Controller developed by (Morim et al., 2018) was used for both region 2 (maximum power point tracking) and 3 (blade pitch speed controller) of operation. The wind turbine fundamental loads quantities showed to be considerably affected by rotor blade mass imbalance, thus, leading effects to all other wind turbine components as expected and the neural network being able to detect the faults.

This paper is organized as follows: in Section 1, the methods and tools used are described. Section 2 presents the results and discussions about the simulations and Section 3 concludes the paper with the main findings and implications.

1 Methods

1.1 FAST Simulations

FAST (Fatigue, Aerodynamic, Structure, and Turbulence) is a CAE tool developed by NREL for simulations of the coupled dynamic responses of wind turbines. It has been validated a few times (Guntur et al., 2016) and is widely used due to its reliability, giving an output of more than 200 parameters of a simulated wind turbine.

The specific aim of this paper was to analyze the rotor imbalance due to mass difference between turbine blades, then FAST V8 and ElastoDyn module were employed.

The wind series input files for FAST were generated using TurbSim. Turbsim is a stochastic, full-field, turbulence simulator from NREL that provides numerical simulations of a full field wind flow, primarily for use with InflowWind/AeroDyn-based simulation tools (Jonkman, 2009)). For this paper, wind series were generated using as an inflow of 12 m/s and 5% turbulence intensity as input for all cases. Figure 1 shows FAST interface with its modules. SubDyn, HydroDyn, and BeamDyn are not enabled for this case.

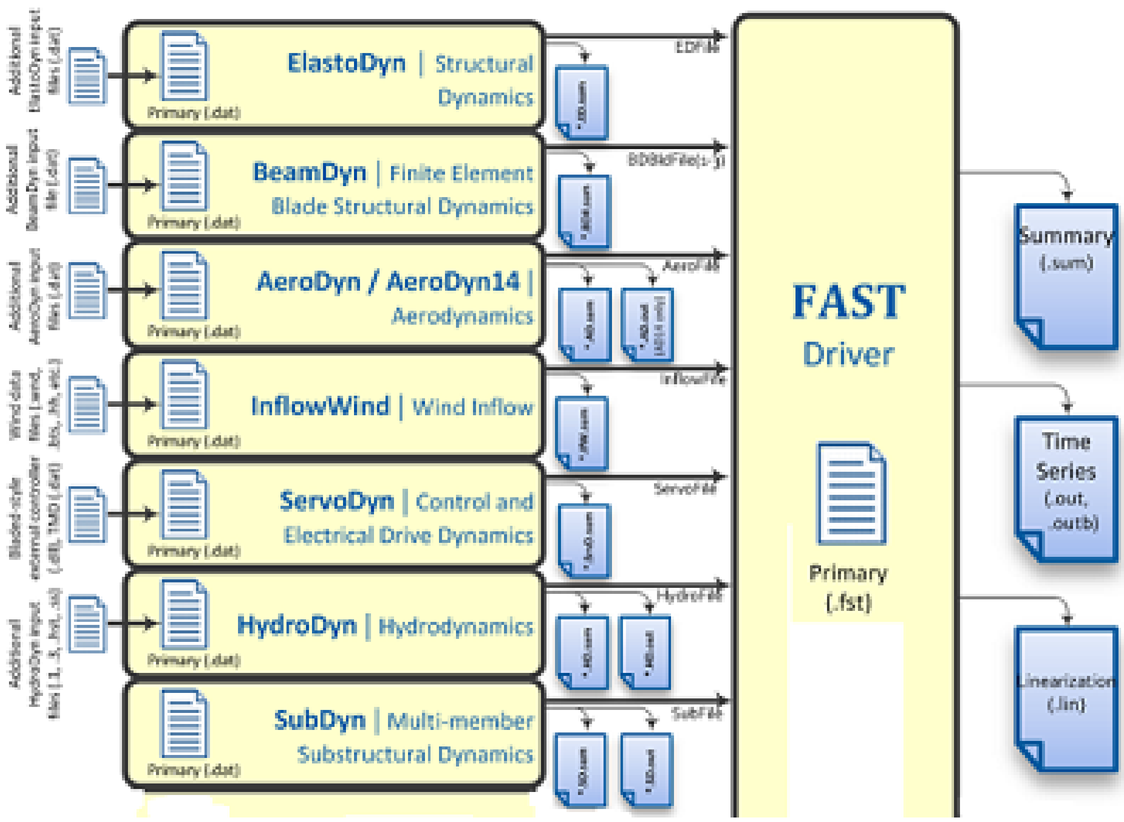

Figure 1 – Fast interface. Source: Jonkman et al. (2005)

To reach the specific aim of this paper, a platform that allows Turbsim/FAST/Simulink was developed for simulating vibration signals of the wind turbine for different fault scenarios, as Figure 2.

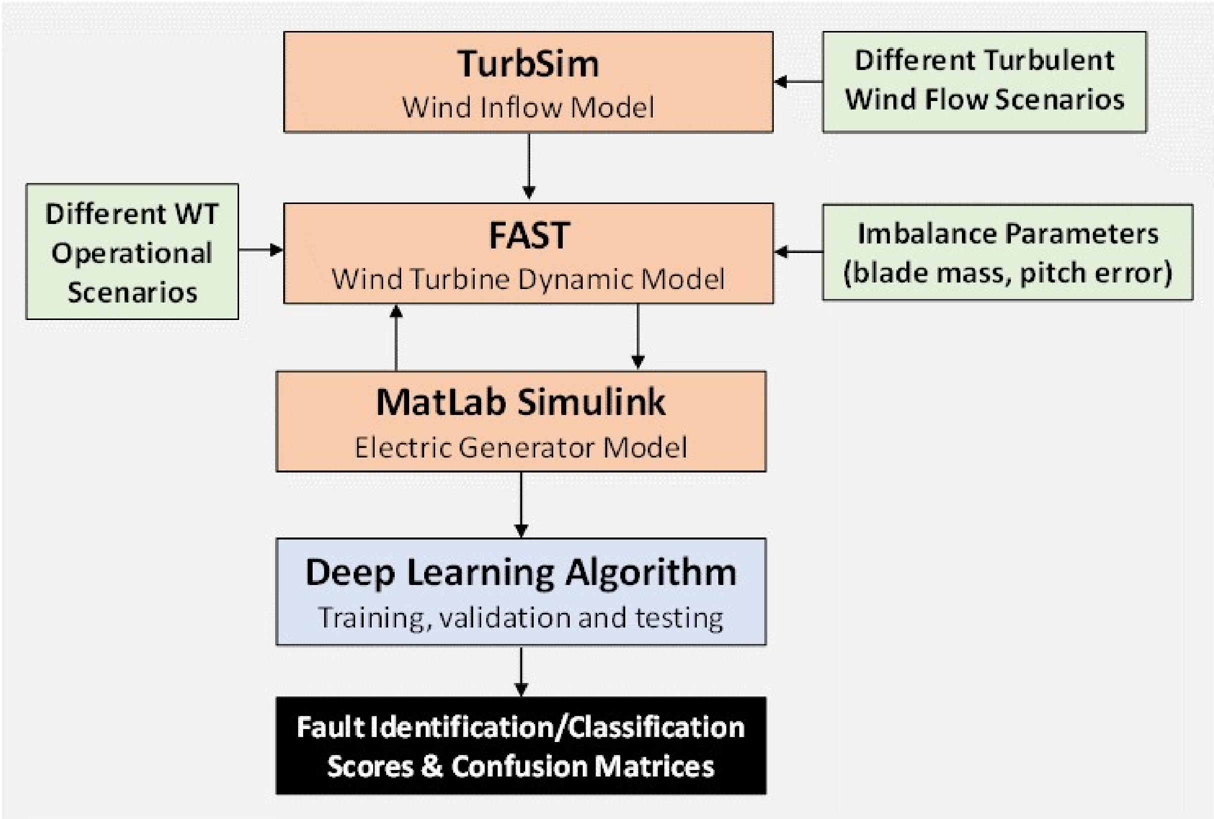

Figure 2 – Fast-Simulink interface. Source: author

For simulations, as mentioned, a Robust Model Reference Adaptive Controller developed by Morim et al. (2018) was used in the FAST-Simulink interface to control (during both power operation region (regions 2 and 3). The 1.5 MW turbine was developed, implemented and distributed along with FAST V8 by NREL in the software folder. Table 1 shows some of the contents of the turbine and its parameters.

Table 1 – Features of wind turbine simulated

Characteristics of the Wind Turbine	
Rated Power	1.5 MW
Control	Variable speed, collective pitch
Rotor Orientation, Configuration	Upwind, three blades
Rotor Diameter	70 m
Hub Diameter	3.50 m
Hub Height	84 m
Rated Rotor Speed	20.463 rpm (0.34 Hz)

1.2 Mass imbalance

As a rotatory machine, the wind turbine should be statically and dynamically balanced to avoid undesired loads on the main shaft that could propagate throughout the complete structure. The governing structural equation of motion is given by

$$\mathbf{M}\ddot{\mathbf{x}} + \mathbf{D}\dot{\mathbf{x}} + \mathbf{K}\mathbf{x} = \mathbf{f}_e(t) \tag{1}$$

where $\mathbf{M}$,$\mathbf{D}$ and $\mathbf{K}$ are the structural mass (and inertia), damping and stiffness matrices, the vector $\mathbf{x}$ contains the displacements of all degrees of freedom, and $\mathbf{f}_e$ is a vector containing the external forces. The FAST software solves this equation, and the loads are computed from the resulting displacements, velocities, and accelerations. The assembly of the matrix $\mathbf{M}$ considers not only the mass but also the mass inertia components of each structural part. Considering the simplified 3-bladed rotor, shown in Figure 3, is expected that the total mass and center of gravity position should be the same for all blades, so that

$$m_1 \cdot r_1 = m_2 \cdot r_2 = m_3 \cdot r_3 \tag{2}$$

and

$$J_1 = J_2 = J_3 \tag{3}$$

where m_i indicates the blade mass, r_i the distance from the center of gravity to the rotor axis, and J_i indicates the relation between blade mass inertia and the rotor axis given the blade's center of gravity.

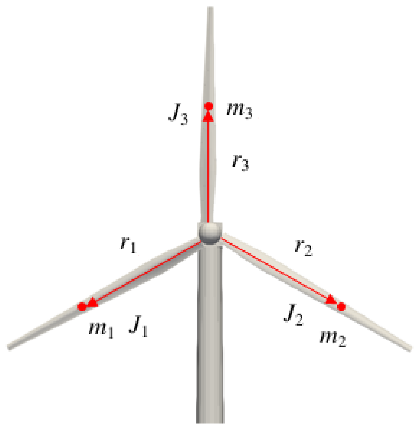

Figure 3 – Three-bladed rotor showing blade total mass m_i at the blade center o mass, located at a distance r_i from the shaft.

However, the blade mass inertia related to the rotor axis also should be the same. The mass inertia depends on the mass distribution along the blade, and even if the center of gravity and total mass remain the same, the inertia might be different, due to composite lamination imprecision, for example. The resulting blade inertia around its center of gravity, when modeling the complete rotor, is redefined with the axis, and the resulting value can be obtained with the Steiner Theorem:

$$J_{a,i} = J_i + m_i r_i^2 \tag{4}$$

where $J_{a,i}$ is the blade inertia taken to the rotor axis. It is seen then, that any change in the center of gravity position affects the rotor structural inertia matrix through the square of the distance between them.

Evaluating the structural equation of motion considering a small out-of-balance mass m_R, placed at a distance r_R from the shaft axis, then the norm of the resulting force in the plane of rotatory motion is proportional to the rotational speed (see Inman (2013))

$$F_R = m_R \cdot r_R \cdot \omega^2 \tag{5}$$

This effect can be simulated via FAST by manipulating Elastodyn blade file. This module has an input that refers to the mass density span of the blade. By modifying just one blade mass-density span, a different center of mass position is computed, as well as the resulting mass inertia terms. For this study, blade mass changes of 1% and 2% were applied to a single blade of the turbine mentioned before.

1.3 Measured parameters

As mentioned before, FAST can output more than 200 parameters (Jonkman et al., 2005), so it is necessary to base the simulations outputs in a strategic reference. IEC 61400-13 has some measurements requirements of fundamental loads for model validation of wind turbines, and those data were required within the FAST outputs. Fundamentals loads are the basic loads on critical locations of the wind turbine, and the loading in all relevant structural components of it can be derived from them (IEC, 2016), as shown in Table 2.

Table 2 – Fundamental load quantities

Load quantities	
Blade root flatwise bending moment	1 blade mandatory
Blade root edgewise bending moment	1 blade mandatory
Rotor tilt moment	Mandatory
Rotor yaw moment	Mandatory
Rotor torque	Mandatory
Tower base normal	Mandatory
Tower base lateral moment	Mandatory

Wind turbines with rated power greater than 1.5 MW and a rotor diameter greater than 75 m have additional requirements, as shown in Table 3. The similarity of blade behavior is verified through a second blade measurement.

Table 3 – Fundamental load quantities for wind turbines with 1.5 MW rated power or more

Load quantities	
Blade flatwise bending moment distribution	2 blades mandatory
Blade edgewise bending moment distribution	2 blades mandatory
Blade root flatwise bending moment	2 blades mandatory
Blade root edgewise bending moment	2 blades mandatory
Blade torsional frequency and damping	Recommended
Pitch actuation loads	One blade mandatory
Tower top acceleration in normal direction	Mandatory when used for controller feedback
Tower top acceleration in lateral direction	Mandatory when used for controller feedback
Tower mid normal moment	Recommended
Tower mid lateral moment	Recommended
Tower top normal moment	Mandatory
Tower top lateral moment	Mandatory
Tower torque	Mandatory

This work does not show the results for all of them, but of a few relevant. When dealing with rotor imbalance, we expect that the all structure of the wind turbine should be affected, mainly rotor tilt and yaw moments, and tower top moments and accelerations presented a greater sensibility. Also, most of the control strategies focus on those loads for reference signals, so it would be practical to include the fault effects on them.

2 Results and Discussion

Figures 4-9 presents the simulation results for the proposed wind turbine with one of the blades with a mass of 99% and 102% of the value from the other two blades. The parameters showed are the same as the ones mentioned above: rotor moments and tower top acceleration and moments.

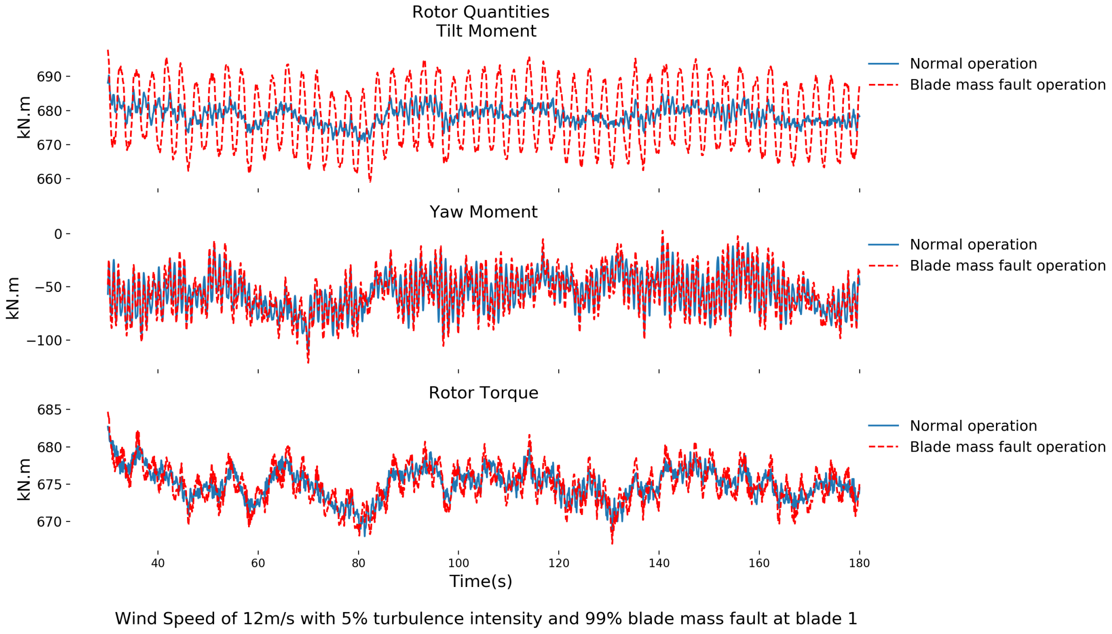

Figure 4 – Rotor yaw, tilt and torque time series

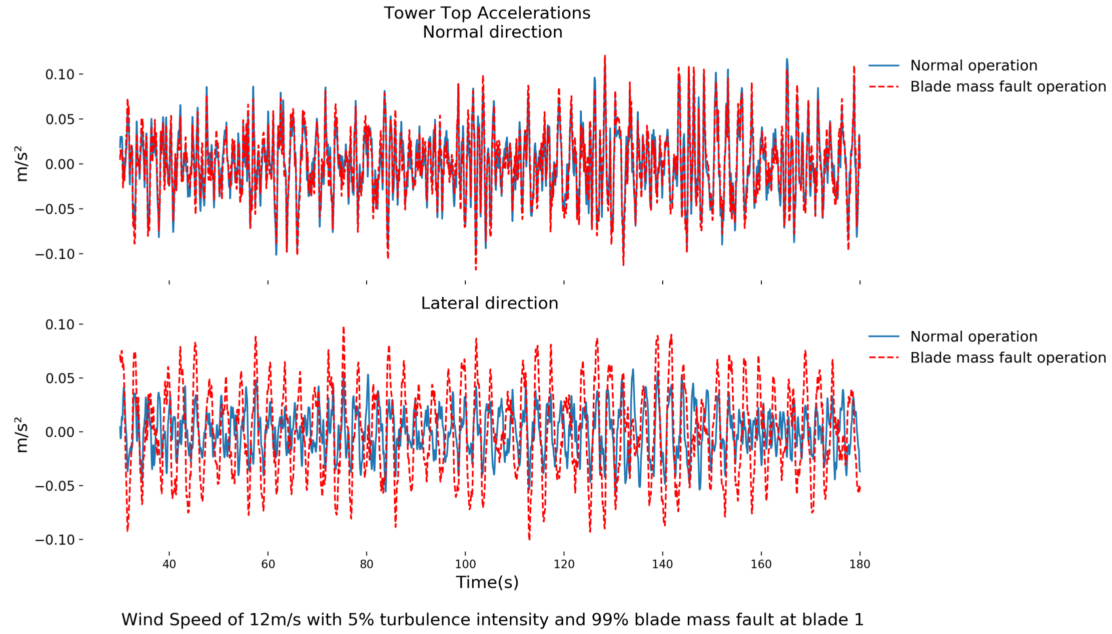

Figure 5 – Tower top accelerations: Normal and Lateral directions time series

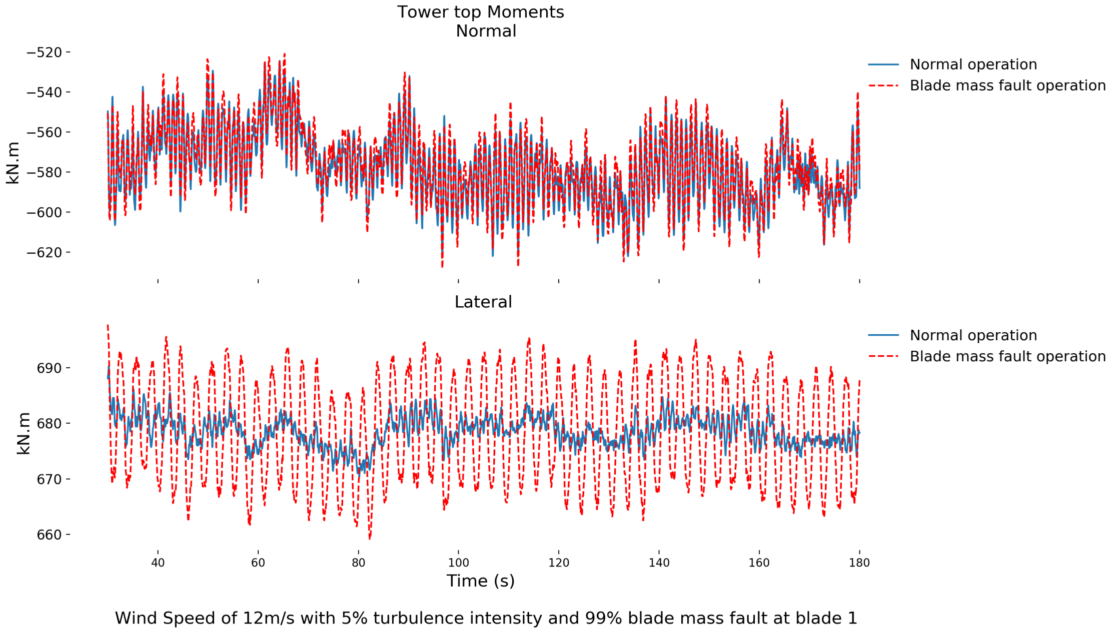

Figure 6 – Tower top moments: Normal and Lateral time series

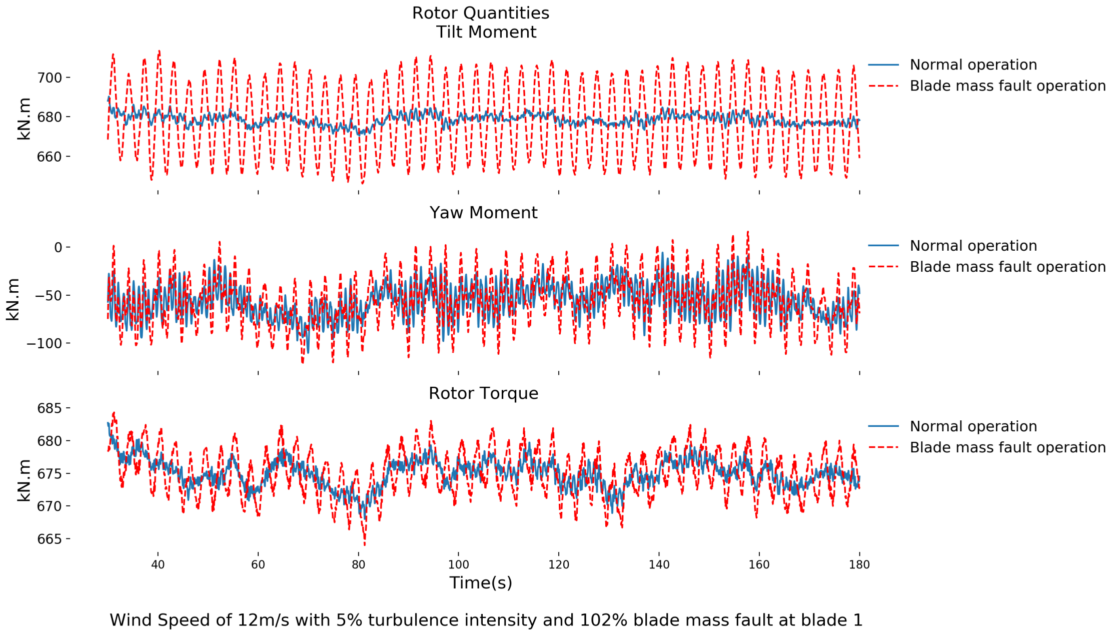

Figure 7 – Rotor yaw, tilt and torque time series

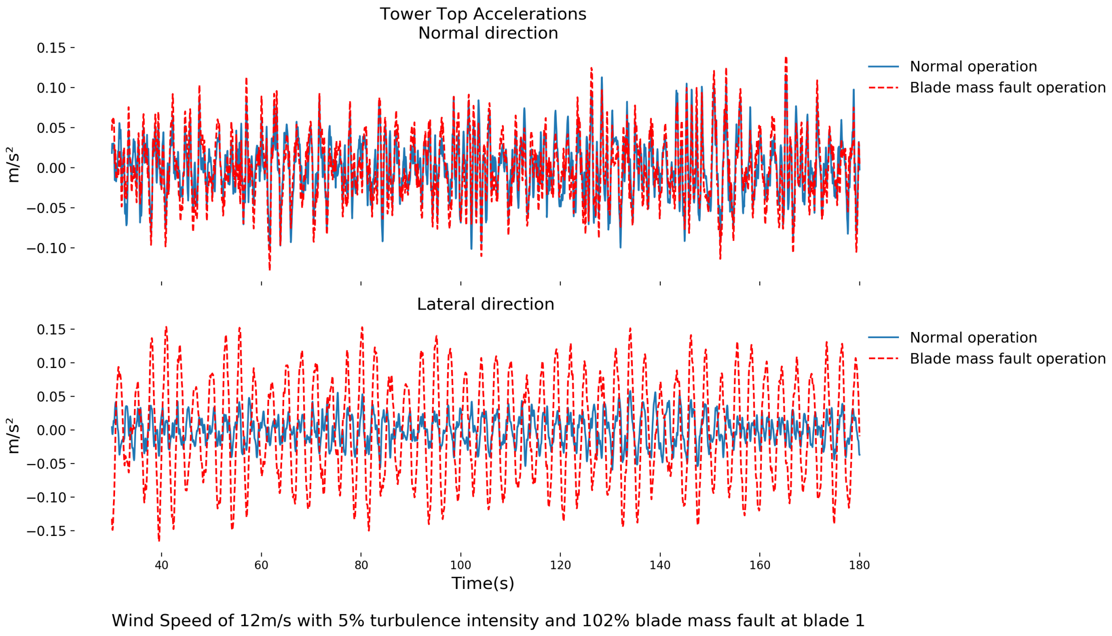

Figure 8 – Tower top accelerations: Normal and Lateral directions time series

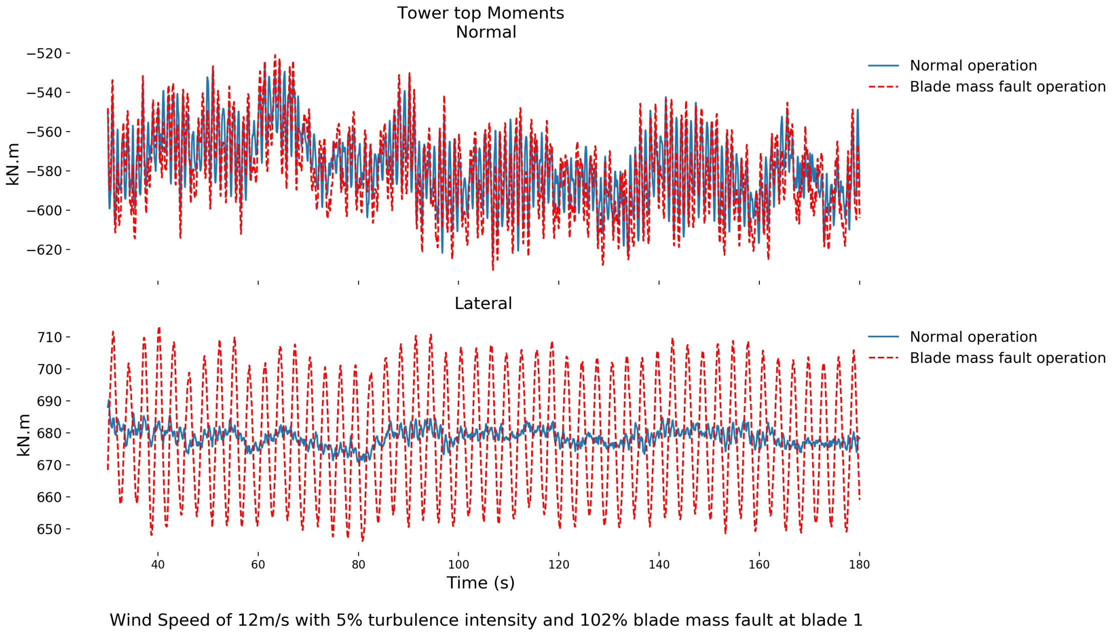

Figure 9 – Tower top moments: Normal and Lateral time series

From the time series simulation results, it is possible to notice how expressive the blade mass fault is for the chosen parameters rotor tilt, yaw and torque moments, tower top moments and accelerations. Applying a Fast Fourier Transform (FFT) to the time series, it gets even more clear hand an extra component around 0.3 Hz in all the parameters for blade mass fault operation emerge, as shown in Figures 10-15.

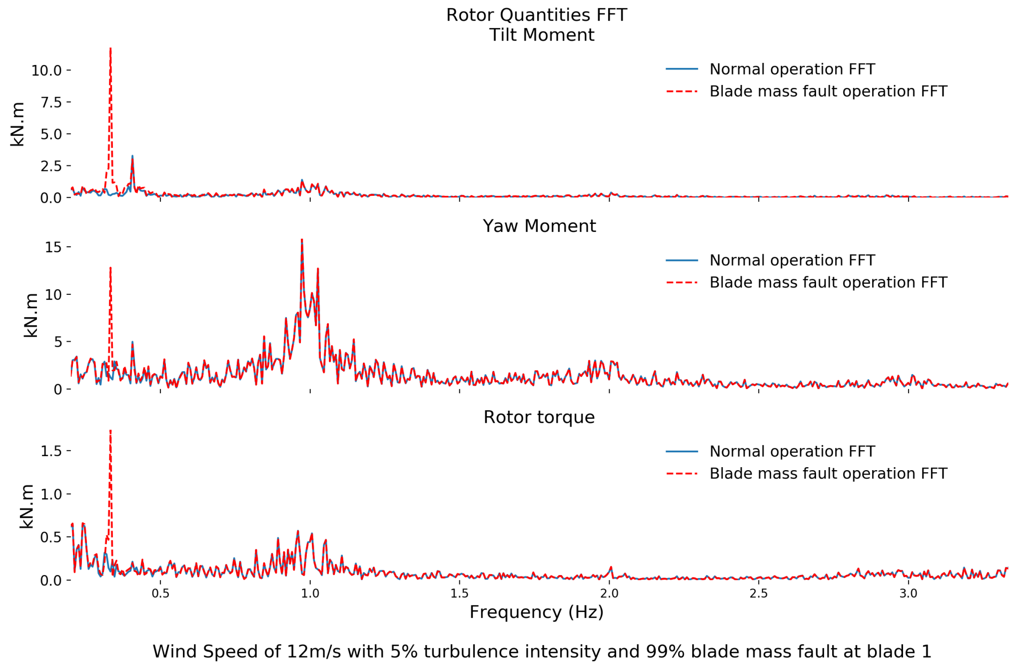

Figure 10 – Rotor yaw, tilt and torque FFT

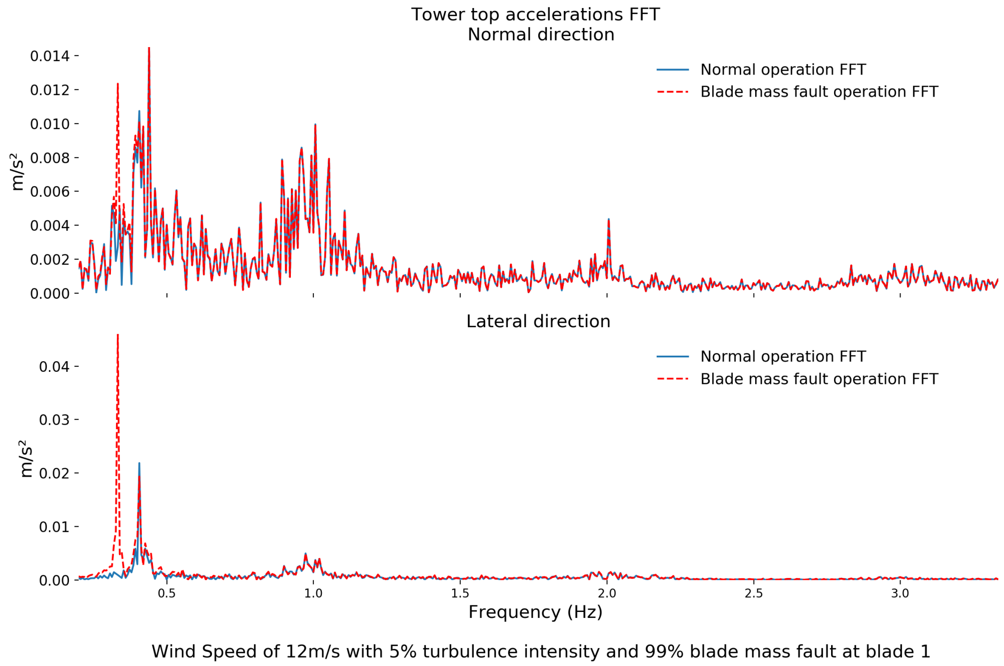

Figure 11 – Tower top accelerations FFT: Normal and Lateral direction

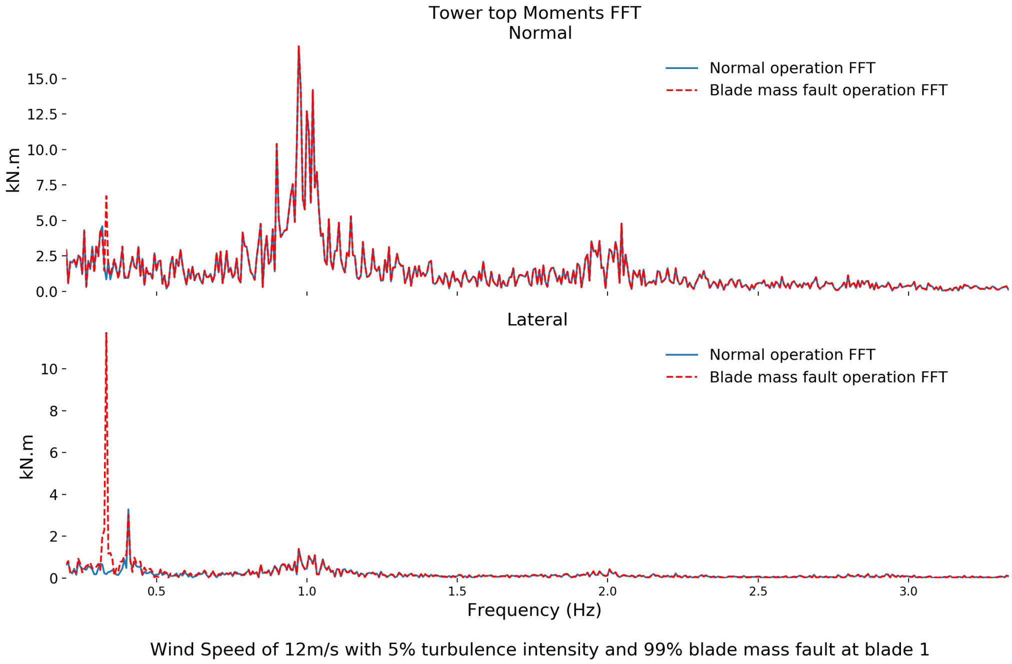

Figure 12 – Tower top moments FFT: Normal and Lateral

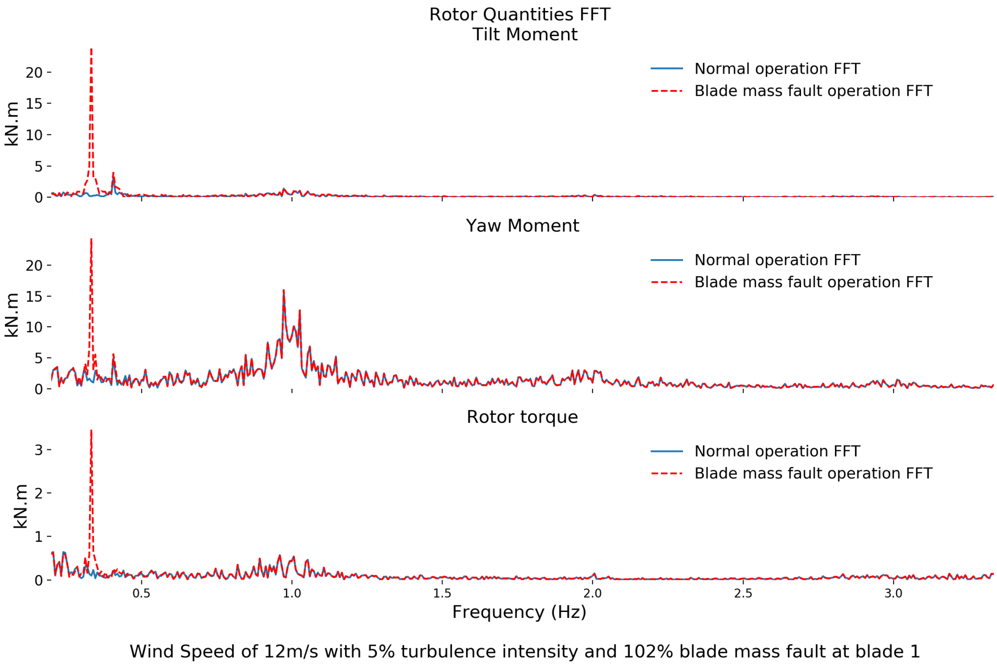

Figure 13 – Rotor yaw, tilt and torque FFT

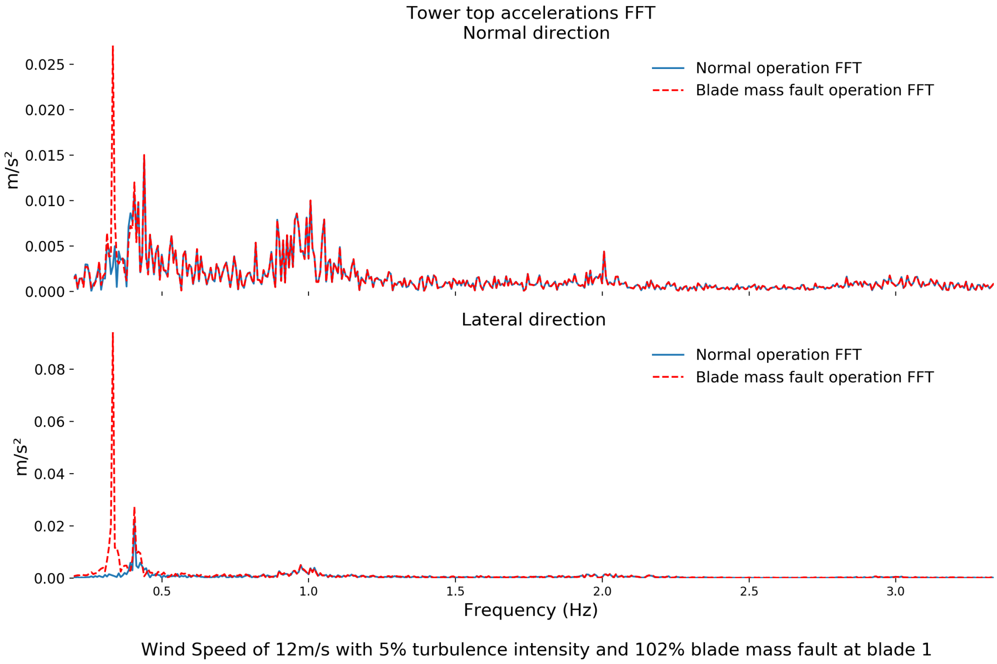

Figure 14 – Tower top accelerations FFT: Normal and Lateral direction

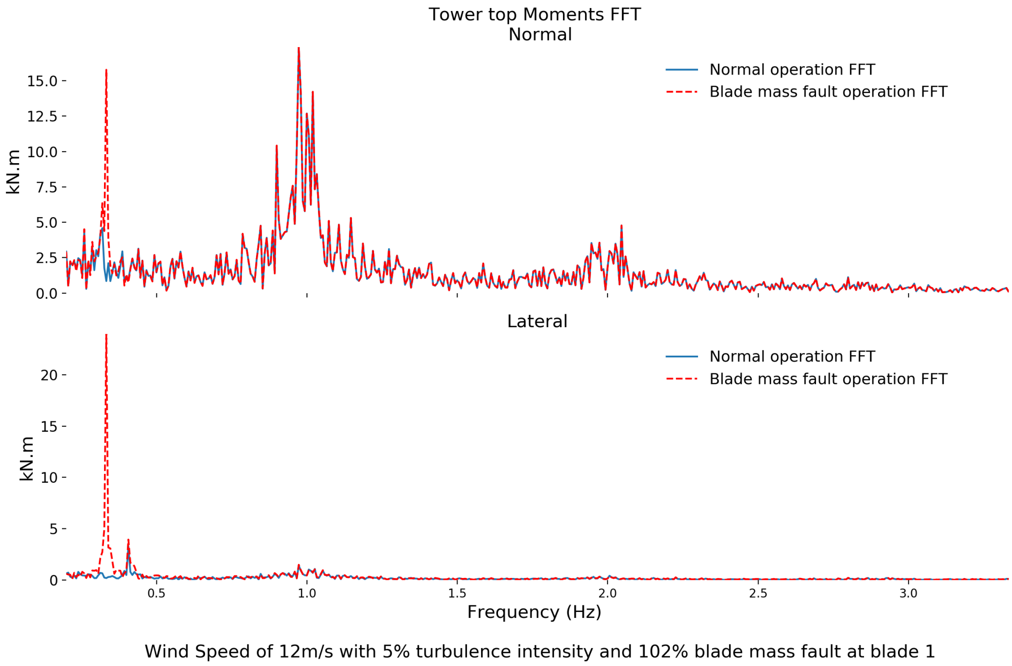

Figure 15 – Tower top moments FFT: Normal and Lateral

As it is possible to observe in Figures 10-15, clearly there is a signature signal in all of the quantities outputs. So, for this case, in particular, a simple machine learning method would be capable of identifying this signature from the blade mass imbalance. Therefore, a Support-Vector Machine (SVM), a neural network used for pattern detection is proposed. SVM was initially created for binary classification (Scholkopf and Smola, 2001), and for this study, it is used to detect the blade mass imbalance from another fundamental quantity of the wind turbine, the rotor speed. Since the outputs listed before showed a pattern of behavior due to blade mass imbalance, it is expected that the rotor speed may have this harmonic component at 0.3 Hz either.

The SVM neural network was trained with 200 preprocessed data samples of the rotor speed, with a hundred being with 5% blade mass fault operation and a hundred with normal operation. The preprocessing applied was a Power Spectral Density (PSD) to the time series data of the rotor speed. The rotor speed data acquisition was of 200 Hz and a window sample-time of 30 seconds was used. All of the simulations were performed with stochastic winds of 15 m/s of speed and 5% of turbulence intensity, during a ten minutes period. Figure 16 and Figure 17 shows the preprocessing applied to the data.

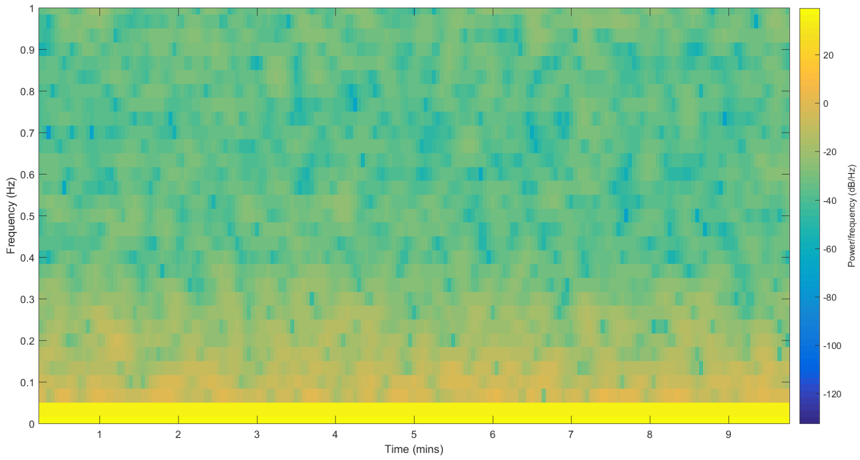

Figure 16 – Rotor Speed Spectogram: Normal operation with 15 m/s wind speed and 5% turbulence intensity

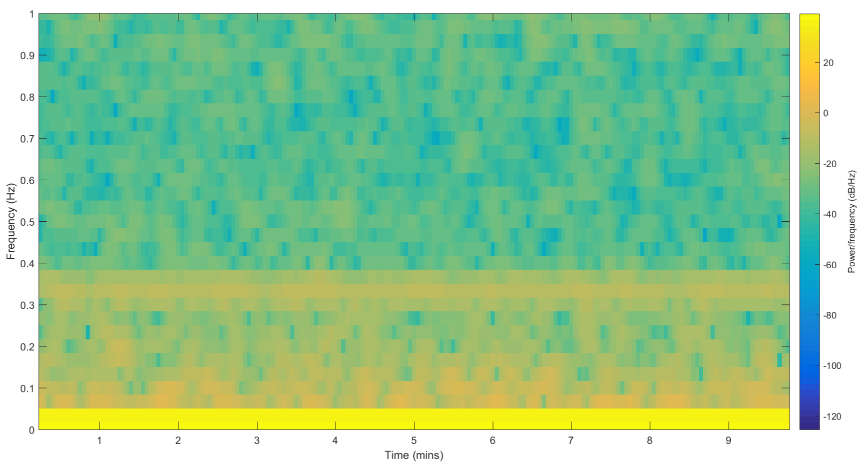

Figure 17 – Rotor Speed Spectogram: Fault operation with 5% bladed mass fault, 15 m/s wind speed and 5% turbulence intensity

To build the SVM, the kernel from the *sklearn* library was used, and it is known as Radial Basis Function (RBF). The C parameter of the training function related to the error penalty used was 10, and this value was achieved from the test. The Gamma parameter used corresponding to the kernel function was 0.1, also took from testing. It is also relevant to notice that this parameter can not have a high value, because it causes the network to overfit the data.

The accuracy of the network developed was of 99%. The confusion matrix obtained from the training data set reveals that 100% of the normal operation data was correctly classified, while 98% of the imbalance operation data was also correct. From this point, 48 simulations data points were applied to test the neural network, with 24 simulations of normal operation and 24 with fault operation, with random wind speeds of 8-16 m/s and 1-7% of turbulence intensity. The developed neural network achieved 24 right predictions of normal operation and 23 of fault operation. Next section bring the conclusions

3 Conclusion

This paper described a framework Turbsim/FAST/Simulink to evaluate the wind turbine imbalance conditions in a wind turbine. This framework can simulate different wind flow scenarios and fault conditions, and it was possible to notice the blade mass effects in the numerical simulation results.

As conclusion, it was possible to apply a technique using SVM neural network to the rotor speed data to detect blade mass imbalance, providing relevant results with an accuracy of the network developed of 99%, with normal operation 100% correctly detected and imbalance operation 98% correctly detected, considering stochastic winds of 15 m/s of speed and 5% of turbulence intensity.

It is possible to notice from these results that the combination of aeroelastic models and machine learning can improve the area of CMS and the reliability of wind energy production, and this paper encourages further studies in larger turbines using the framework proposed and in real turbines in an experimental wind turbines test field.

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