Optimal Maintenance Management of Offshore Wind Farms

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Keywords: binary decision diagrams, fault tree analysis, maintenance management, wind turbines, offshore

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Nowadays offshore wind energy is the renewable energy source with the highest growth. Offshore wind farms are composed of large and complex wind turbines, requiring a high level of reliability, availability, maintainability and safety (RAMS). Firms are employing robust remote condition monitoring systems in order to improve RAMS, considering the difficulty to access the wind farm. The main objective of this research work is to optimise the maintenance management of wind farms through the fault probability of each wind turbine. The probability has been calculated by Fault Tree Analysis (FTA) employing the Binary Decision Diagram (BDD) in order to reduce the computational cost. The fault tree presented in this paper has been designed and validated based on qualitative data from the literature and expert from important European collaborative research projects. The basic events of the fault tree have been prioritized employing the criticality method in order to use resources efficiently. Exogenous variables, e.g., weather conditions, have been also considered in this research work. The results provided by the dynamic probability of failure and the importance measures have been employed to develop a scheduled maintenance that contributes to improve the decision making and, consequently, to reduce the maintenance costs.

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Optimal Maintenance Management of Offshore Wind Farms

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Abstract: Nowadays offshore wind energy is the renewable energy source with the highest growth. Offshore wind farms are composed of large and complex wind turbines, requiring a high level of reliability, availability, maintainability and safety (RAMS). Firms are employing robust remote condition monitoring systems in order to improve RAMS, considering the difficulty to access the wind farm. The main objective of this research work is to optimise the maintenance management of wind farms through the fault probability of each wind turbine. The probability has been calculated by Fault Tree Analysis (FTA) employing the Binary Decision Diagram (BDD) in order to reduce the computational cost. The fault tree presented in this paper has been designed and validated based on qualitative data from the literature and expert from important European collaborative research projects. The basic events of the fault tree have been prioritized employing the criticality method in order to use resources efficiently. Exogenous variables, e.g., weather conditions, have been also considered in this research work. The results provided by the dynamic probability of failure and the importance measures have been employed to develop a scheduled maintenance that contributes to improve the decision making and, consequently, to reduce the maintenance costs.

Keywords: offshore; wind turbines; maintenance management; fault tree analysis; binary decision diagrams

1. Introduction

The renewable energy industry is in continuous development to achieve the energy framework targets established by governments [1]. Nowadays, the most developed countries are focused on improving the technology for offshore wind energy. The main advantages of the offshore wind farms are [2]:

- The wind power captured by wind turbines (WTs) is more than onshore.
- The size of offshore wind farms can be larger than onshore.
- The environmental impact for offshore is less than in onshore.

The main disadvantages are:

- It is more complex to evaluate the wind characteristics.
- Larger investment costs. The offshore installation cost is 1.44 million €/MW, where the onshore is 0.78 million €/MW [3].
- Operation and maintenance (O & M) tasks are more complex and expensive than onshore. The offshore O & M costs tasks are from 18% to 23% of the total system costs, being 12% for onshore wind farms [4].

The objective of this paper is to develop a novel maintenance management approach in order to establish a proper strategy for the maintenance task by using a predictive maintenance method based on statistical studies. This approach provides information about the WTs with high fault probability, a ranking of components of WTs to repair or replace according to the state of the system over the time, and when those maintenance tasks must be carried out. An adequate maintenance planning to ensure the right operation of an offshore wind farm is required. For this purpose, different techniques and methods of condition monitoring (CM) are employed for detection and diagnosis of faults of WTs [5]. Most of the research papers consider the CM in WTs referred to blades [6], gearboxes [7], electrical or electronic components [8] and tower [9]. CM leads to improve RAMS and to increase the productivity of wind farms.

2. CM Applied to WT

The main components of WTs are illustrated in Figure 1. WTs are usually three-blade units [10]. Once the wind drives the blades, the energy is transmitted via the main shaft through the gearbox to the generator. At the top of the tower, assembled on a base or foundation, the housing or nacelle is mounted and the alignment with the direction of the wind is controlled by a yaw system. There is a pitch system in each blade. This mechanism controls the wind power and sometimes is employed as an aerodynamic brake. Finally, there is a meteorological unit that provides information about the wind (speed and direction) to the control system.

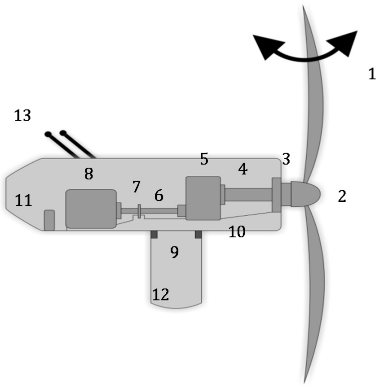

Figure 1. Components of the wind turbine (WT) where: 1—pitch system; 2—hub; 3—main bearing; 4—low speed shaft; 5—gearbox; 6—high speed shaft; 7—brake system; 8—generator; 9—yaw system; 10—bedplate; 11—converter; 12—tower; 13—meteorological unit.

CM systems are composed of different types of sensors and signal processing equipment applied on the main components of WTs such as blades, gearboxes, generators, bearings and towers. The choice and location of the right type and number of sensors are a key factor. The acquisition of accurate data is critical to determine the occurrence of a fault and to address the solution to apply. Nowadays, different techniques are available for CM: vibration analysis [3,11], acoustic emission [3,12], ultrasonic testing techniques [13,14], oil analysis [15], thermography [3,13] and other methods [16].

The first step of the CM process is the choice of an adequate technique for data acquisition, including electronic signals with the measurement of the required conditions, e.g., sound, vibration, voltage, temperature, speed. Then, a correct signal processing method is applied, e.g., fast Fourier transform, wavelet transforms, hidden Markov models, statistical methods and trend analysis. Fault detection and diagnosis (FDD) involves both CM techniques and the signal processing methods.

The frequency of occurrence, *i.e.*, the probability of failure, of an event is necessary to study in order to improve the application of CMS for WTs [17]. This paper employed the Fault Tree Analysis (FTA) technique to calculate the probability of failure of the WT. FTA is a graphical representation of logical relationships between events. A Binary Decision Diagram (BDD) has been used to provide an alternative to the traditional technique in order to reduce the computational cost. BDD is an approach that determines the probability of failure of a system by examining the probability of failure of the components. The BDD method does not analyses the FTA directly. The Boolean equation represents the main event to analyse, e.g., the wind turbine failure, and it is obtained by BDDs that come from the fault tree. The ordering algorithm for the construction of the BDD has a crucial effect on its size, and therefore the computational cost. The algorithms are heuristics, and this is the reason that in this paper has been considered several in order to compare the results, being: Top-down-left-right, Depth First Search, AND, Breath First Search, and Level.

Finally, in order to optimize the resources, e.g., human, material, economic resources, *etc.*, proper and accurate prioritization of the basic events, based on importance measurement, has been done according to the criticality method [18]. The information provided by the aforementioned method leads to establish an optimal maintenance management for offshore wind farms, considering both endogenous and exogenous variables.

3. FTA and BDD

A Fault Tree (FT) is a graphical structure formed by the causes of a certain type of failure mode (Top Event) and the failure mode of the components (basic events) connected by logical operators such as AND/OR gates [19]. The probability vector **p** represents the failure probabilities of the basic events q_i, $i \in \{1, \ldots, n\}$, being n the total number of events [20,21].

Then, the system failure probability Q_{sys} can be obtained via FTA according to **q**:

$$\mathbf{q} = \begin{pmatrix} q_1 \\ \vdots \\ q_n \end{pmatrix}$$

Complex systems analysis produce thousands of combinations of events (minimal cut sets) that would cause the failure of the system and are used in the calculation of Q_{sys} [21]. The determination of these minimal cut sets can be a large and time-consuming process, even on modern high speed computers. When the FT has many minimal cut sets, the determination of the exact failure probability of the top event also requires a high calculation costs. For many complex FTs, this requirement may be beyond the capability of the available computers. Therefore, some approximation techniques have been introduced with a loss of accuracy.

The BDD method does not analyze the FT directly. The conversion of the FT to a BDD make possible to calculate the probability of the top event by determining the Boolean equation of the top event. The conversion process from FT to BDD presents several problems, e.g., the ordering scheme chosen for the construction of the BDD has a crucial effect on its resulting size. A wrong ordering scheme may result in large BDD that presents high computational costs [19]. In order to improve the resource deployment in an existing system, proper and accurate ranking of the basic events is necessary [23,24]. Some prioritizations of the basic events of the FT have been considered in this paper. For further details of FTA and ranking methods, consultation of references [18,25] is recommended. BDDs have been successfully used in the literature as an efficient way to simulate FTs. BDDs were introduced by Lee [26], and further popularized by Akers [27], Moret [25] and Bryant [22]. These decision diagrams are composed by a data structure that can represent a Boolean function [28].

A BDD is a directed acyclic graph representation (**V**, **N**), with vertex set **V** and index set **N**, of a Boolean function where equivalent Boolean sub-expressions are uniquely represented [29]. A directed acyclic graph is a directed graph, *i.e.*, to each vertex v there is no possible directed path that starts and finishes in v. It is composed of some interconnected nodes with two vertices. Each vertex is possible to be a terminal or non-terminal vertex. Each single variable has two branches: 0-branch corresponds to the cases where the variable has not occur and it is graphically represented by a dashed line (Figure 2); on the other hand, 1-branch cases are those where the event is being carried out and corresponds to the occurrence of the variable, and it is represented by a solid line (Figure 2). It allows to obtain an analytical expression depending on the probability of failure of the basic events and the topology of the FT. Paths starting from the top event to a terminal 1 provide a state in which the top event will occur. These paths are named cut sets.

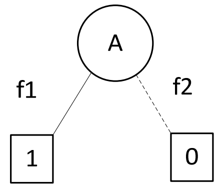

Figure 2. Binary Decision Diagram (BDD).

ITE (If-Then-Else) conditional expression is employed in this research work as an approach for the BDD's cornerstones, based on the approach presented in reference [30]. Figure 2 shows an example of an ite done in a BDD that is described as: "If event A occurs, Then f_1, Else f_2" [31]. The solid line always belongs to the ones and the dashed lines to the zeros, explained above.

The following expression is obtained from Figure 2, considering Shannon's theorem:

$$f = b_i \cdot f_1 + \overline{b}_i \cdot f_2 = ite\,(b_i, f_1, f_2)$$

The size of the BDD, equivalent to CPU runtime, has a strong dependence on the ordering of the events. Different ranking methods can be used in order to reduce the number of cut sets, and consequently, to reduce the computational runtime. Note that there is no method that provides the minimum size of BDD in all cases. The following methods have been considered in this paper: Top-down-left-right, Depth First Search, AND, Breath First Search, and Level. The AND method has chosen for ranking the events because it provides the best results in this case. For further information about BDDs readers are recommended to see references [20,22,26,27].

The quantitative analysis also takes into account the importance of each basic event within the global system. With this purpose, different importance measures (IMs) are considered in this paper. IMs are used in reliability and risk analysis to quantifying the impact of single component on a system failure [32]. In order to determine the importance of a component, it is necessary to consider all the related basic events as a group [33]. A complete importance analysis of all groups is therefore impractical for large systems, and it is necessary to focus on the most important groups of components [34]. In this work Birnbaum and Criticality IMs are presented.

Birnbaum IM introduced, for an event k, a measure of importance based on the fault probability of the system caused by the failure of the component k [35]. The priority of the event k is given by its Birnbaum IM and is calculated as follows:

$$I_k^{Birn} = \frac{\partial Q_{sys}}{\partial q_k}$$

where q_k is the failure probability assigned to the k event, and Q_{sys} is the probability of the top event. A drawback related to the Birnbaum IM is that it does not consider the failure probability of the k event and, therefore, a high importance can be assigned to rare events.

Criticality IM [18], in contrast to Birnbaum, takes into account the failure probability of a certain component. It rectifies the drawback presented in Birnbaum IM, balancing the values obtained. It is defined as:

$$I_k^{Crit} = \frac{q_k}{Q_{sys}} \cdot \frac{\partial Q_{sys}}{\partial q_k} = \frac{q_k}{Q_{sys}} \cdot I_k^{Birn}$$

where I_k^{Crit} is the Criticality IM of the k event, $q_k$is the probability assigned to the k event and Q_{sys} is the top event probability. Criticality IM provides a different perspective than the Birnbaum IM, even though both are connected providing a measurement of the criticality of each components. Therefore, the Criticality IM has been employed in the following sections to carry out a simulation as realistic as possible.

4. FTA for WTs

A study of failure modes and effects analysis (FMEA) for WTs in 2010 (RELIAWIND project) collected the causes of failure and failure modes of a specific WT of 2MW with a diameter of 80 m [35]. Some causes of failures (or root causes) are summarized in [36]. These main causes of the failures can be due to environmental conditions (e.g., lightning, ice, fire, strong winds, *etc.*) or to defects, malfunctions or failures in the components of the WT (e.g., braking system failure, or be struck by blade, *etc.*) [37,38]. The causes of failures (or root causes) of the components of a wind turbine can be summarized as follows [35,39]: structural (design fault, external damage, installation defect, maintenance fault, manufacturing defect, mechanical overload, mechanical overload–collision, mechanical overload–wind, presence of debris); wear (corrosion, excessive brush wear, fatigue, pipe puncture, vibration fatigue, overheating, insufficient lubrication); electrical (calibration error, connection failure, electrical overload, electrical short, insulation failure, lightning strike, loss of power input, conducting debris, software design fault). Some of the principal component failure modes of WTs are [35,39]: mechanical (rupture, uprooting, fracture, detachment, thermal, blockage, misalignment, scuffing); electrical (electrical insulation, electrical failure, output inaccuracy, software fault, intermittent output); material (fatigue, structural, ultimate, buckling, deflection).

In this work, the construction of the illustrative FT has been focused on a three blades, pitch system and geared WT. The turbine has been divided into four major groups of elements for a better FTA: The foundation and tower; the blades system; the electrical components (including generator, electrical and electronic components), and; the power train (including speed shafts, bearings and a gearbox). The elements of the FT are connected by AND and OR gates, and their fault probability is unknown. The failures considered in this paper are set by an exhaustive review of the literature and the support of experts from the NIMO and OPTIMUS FP7 European projects [40,41].

Table 1 shows a summary of the failures from the literature taken into account for this paper. It can be seen that gearboxes, generators, blades and electric and control systems have been extensively studied in the literature, but there are not many references about other components such as brakes, hydraulic and yaw systems.

Table 1. Failures of the main elements of a WT.

Foundation and Tower Failure	Structural fault [17,38,42–45]	
	Yaw system failure [46]	
Critical Rotor Failure	Blade failure	Structural failure [17,34,47–53]
		Pitch system failure [54,55]
		Hydraulic system fault [50,56]
		Meteorological unit failure [50,57]
	Rotor system failure	Rotor hub [42,46]
		Bearings [45–47]
Power Train Failure	Low speed train failure [17,46,48]	
	Critical gearbox failure [7,46,53,58–62]	
	High speed train failure	Shaft [6,46,58]
		Critical brake failure [6,56]
Electrical Components Failure	Critical generator failure [6,46,58,60,63–65]	
	Power electronics and electric controls failure [17,56,58,60]	

The following sub-sections show the events or components considered to build the FT presented in Appendix 1. This FT is built from the different sub-trees that correspond to the four main parts of a WT aforementioned (see also the first column of Table 1). The components and faults that are involved in system failures are obtained from the NIMO and OPTIMUS European Projects. The interrelation between these faults is also done considering the literature. The FT in Appendix 1 is composed by the following four main sub-trees:

- g001 corresponds to a "Foundation and Tower Failure" described in Section 4.1.
- g002 corresponds to a "Critical Rotor Failure" depicted in Section 4.2.
- g003 corresponds to a "Power Train Failure" showed in Section 4.4.
- g004 corresponds to a "Electrical Components Failure" presented in Section 4.3.

4.1. Foundation and Tower

The tower supports the nacelle that is located at a suitable height in order to minimize the influence of turbulence and to maximize the wind energy. The tower is assembled by thin-wall cylindrical elements welded together along their perimeters in three sections that are joined by bolts. This is done in order to enable the transportation of the large structural elements to the wind farm where they need to be assembled [66]. The base section of the tower is installed on a reinforced concrete foundation comprising a square base [67].

Structural defects associated with the tower, foundation, blades and hub, in the form of fatigue cracks, delamination *etc.*, can initiate and evolve with time [44]. The main causes for structural failures are fatigue induced crack initiation and propagation, extreme wind speeds and distribution, extreme turbulences, maximum flow inclination and terrain complexity [39], and also the fire, ice accumulation or lightning bolt strikes. Material fatigue [38] (tower-based fatigue damage has been shown to decrease significantly when using active pitch for the blades [40,43]), impact of blades on the tower, faulty welding and failure of the brakes [45] are the main representative failure modes.

The literature shows that the major faults found on WT towers are: cracks in the concrete base, corrosion, gaps in the foundation section, loosen studs joining the foundation and the first section, loosen bolts joining first/second and second/third sections and welding damages [38].

On the top of the tower, the yaw system turns the nacelle in an optimum angle with respect to the wind direction. Powered by electrical or hydraulic mechanisms (this paper the electrical is considered), the yaw systems can fail due to the failure of the yaw motor or the meteorological unit [46] resulting in a wrong yaw angle. Structural failures could appear when the yaw motor is damaged or it does not have power supply, in addition to extreme wind speed or turbulences and some structural faults. These structural failures can cause the collapse of the tower [38].

4.2. Blade System

The rotor is located inside the nacelle. The blades are attached to the rotor shaft by the hub and they are mounted on bearings in the rotor hub. The blades are the components of the WT with the highest percentage of failures and downtimes [68,69]. Ciang *et al.* reviewed damage detection methods [70] in 2008, considering in particular the blades [42]. The rotor hub supports heavy loads that can lead to faults such as clearance loosening at the blade root, imbalance, cracks and surface roughness [46]. Bearings between blades and hub can be damaged by wear produced by pitting, deformation of outer face and rolling elements of the bearings [46], spalling and overheating [56]. Cracks can appear due to the fatigue [56]. Faults in lubrication and corrosion of pins are typically the main failure cause of bearings.

The blades faults are predominantly related to structural failures, e.g., strength [47] and fatigue of the fibrous composite materials. Other faults, e.g., cracks, erosions, delamination and debonding, could appear in the leading and trailing edges of the blades [48,69]. Delamination and debonding or cracks are found in the shell [49,50], and also in the root section of the blades [51]. The tip deflections (a structural failure of the blade [46]) increase drag near the end of the blades [53].

A common fault of the blades is associated with the failure of the pitch control system [54]. In pitch-controlled turbines, the pitch system is a mechanism that turns the blade, or part of the blade, in order to adjust the angle of attack of the wind. Turbulence of wind is an important cause for pitch system faults [71]. Pitching motion can be done by hydraulic actuators or electric motors. The hydraulic system leads stiffness of bearings, a little backlash and a higher reliability than the electric motors [52]. The hydraulic system can suffer from possible defects such as leakages, overpressure and corrosion [56].

The weather station or meteorological unit provides information about some characteristics of the wind (direction and speed) to the control system of the WT. The main failures found in the WT weather station are related to the vane and the anemometer faults [57]. These can be the cause of a wrong blade angle [50,55].

4.3. Generator, Electrical and Electronic Components

The generator, electrical and electronic components are installed inside the nacelle. The high speed shaft drives the rotational torque to the generator, where the mechanical energy is converted to electrical energy. This conversion needs a specific input speed, or a power electronic equipment to adapt the output energy from the generator to the characteristics of the grid.

Faults in generators can be the result of electrical or mechanical causes [65]. The main electrical faults are due to open-circuits or short-circuit of the winding in the rotor or stator [58] that could cause overheating [46]. Many research works have demonstrated that bearings, rotors and stators involve a high failure rate in WTs [63]. The bearing failures of the generator are usually caused by cracks, asymmetry and imbalance [72]. The rotor and stator failures can be produced by broken bars [64], air-gap eccentricities and dynamic eccentricities, among other failures [58]. Rotor imbalance and aerodynamic asymmetry can have their origin in the non-uniform accumulation of ice and dirt over the blades system [58]. Short-circuit faults, open-circuit faults and gate drive circuit faults are the three major electrical faults of the power electronics and electric controls in WTs [58]. Corrosion, dirt and terminal damage are the main mechanical defects [56]. The group formed by generator, electrical system and control system, has a relevant rate of failures and downtime in WTs.

4.4. Power Train

The power train, or drive train, is installed in the nacelle and is compound by the low speed train, the gearbox and the high speed train. Through the main bearing, the rotor is attached to the low speed shaft that drives the rotational energy to the gearbox. The rotational speed of the rotor is generally between 5 and 30 rpm, and the generator speed is from 750 to 1500 rpm, depending on the type and size of generator. A gearbox is mounted between the rotor and the generator in order to increase the rotational speeds. The gearbox output is driven to the generator through the high speed train. A mechanical brake powered by a hydraulic system is usually mounted in the high speed train as a secondary safe breaking system.

The low speed train failure includes main bearing [56] and low speed shaft defects. Severe vibrations can appear due to impending cracks in any component, or to the mass imbalance in the low speed shaft [58]. The gearbox failure is one of the most typical failures [53]. There are many studies about gearboxes in the literature because their failure causes significant downtimes in the system [73]. The most common faults were found in gear teeth and bearings due to lubrication faults [58], e.g., contamination due to defective sealing [54] or loss of oil [60], wear or fatigue damage which can generate pitting, cracking, gear eccentricity, gear tooth deterioration, offset or other potential faults [46,53].

Overheating can appear in shafts due to the rotational movement of the high speed train. The wear and fatigue, that can initiate cracks [46] and mass imbalance [58], are the principal source of failures in the high speed shaft. The main failure causes of brakes are overpressure or oil leakages [6], cracking of the brake disc and calipers [56].

5. Maintenance Management Approach

The maintenance management proposed in this paper aims to maximise the RAMS of the offshore wind farms optimising the resources such as human or material, conditioned to exogenous variables, e.g., weather conditions [74]. This approach is based on the probability of failure of each WT. The operation of the WT will be focused on a set of components collected by a FT (see Appendix 1). The fault probability of any component is simulated by a statistical function of failure probability over the time (see Appendix 2). Then, the failure probability of a WT is set by the Boolean expression obtained from the BDD. Therefore, according to the resources, the maintenance task will be done in the WTs that present more fault probability over a threshold set. It will lead to predict any preventive/predictive maintenance task over the time. The importance measurements will determine the components that need a maintenance task. A low probability threshold is set to determine if the fault probability of the WT is under control or not. The importance measurement is calculated with the Criticality IM method. The downtime can be defined as the period of time that is required to carry out the corresponding maintenance task. Each event of the fault tree has associated one maintenance task with a specific downtime. The downtime depends on endogenous and exogenous variables. Figure 3 shows the flowchart of the procedure maintenance management.

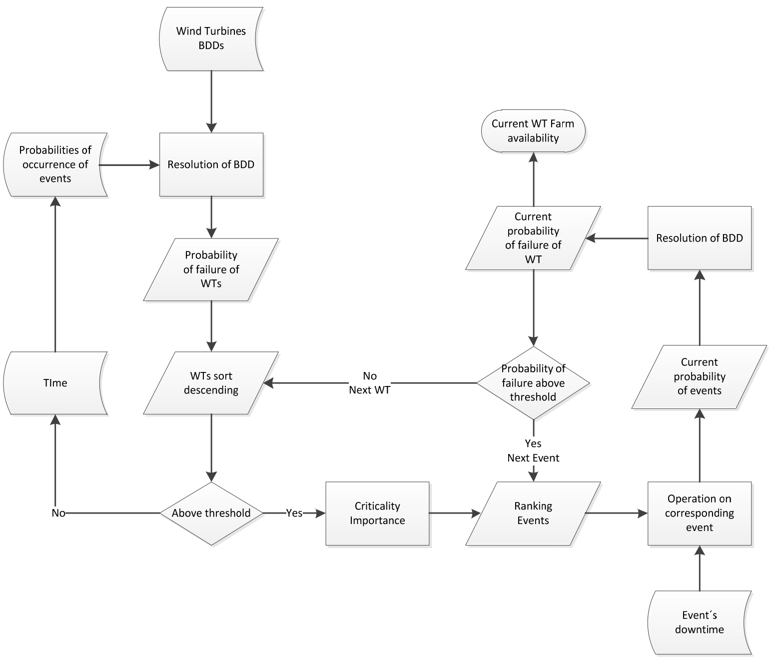

Figure 3. The maintenance management procedure.

6. Case Study

An offshore wind farm composed by 20 WTs has been taken into account. The offshore wind farm has been designed taking into account considerations from expert of the NIMO and OPTIMUS research projects. It has been designed in order to demonstrate and validate the approach proposed in this paper. The WTs are the same type, with the same FT, given in Appendix 1. Different mathematical models have been defined for each event (see Appendix 2). These models have been based on time-dependent probability functions to describe the behavior of events over the time. These probability models are not intended to match exactly the real behavior of the events because there is no dataset to validate it, therefore it they have been set by the aforementioned expert. For example, the event e006 corresponds to the corrosion of the foundation or tower, where a linear increasing probability have been assigned to this event, this is due to the salinity that is assumed to be constant over the time. The main novelty lies in the procedure to elaborate qualitatively and quantitatively a preventive maintenance planning process based on the knowledge of the WTs and on statistical data that, for example, could be collected through condition monitoring systems [75,76]. The probability functions employed are:

I *Constant probability*

In this model the probability of the event is constant over the time:

$$q(t) = K, (K \in \mathbb{R}/0 \leqslant K \leqslant 1)$$

II *Exponential increasing probability*

In this model, the probability function assigned is:

$$q(t) = 1 - e^{-\lambda t}, (\lambda \in \mathbb{R}/\ \lambda \geqslant 0)$$

where λ determines the rising velocity of the probability.

III *Linear increasing probability*

In this model, the probability function is:

$$q(t) = \begin{cases} mt \; mt < 1 \\ 1 \; mt \geqslant 1 \end{cases} ; \forall \, m > 1$$

where m determines the rising velocity of the probability.

IV *Periodic probability*

This model represents those components that need to be replaced, repaired, and zeroed in a periodical way. In this model, the events have a periodic behavior following the next expression:

$$q(t) = 1 - e^{-\lambda(t - n\alpha)}, n = 1, 2, 3$$

where λ is a positive parameter and determines the rising velocity of the probability, and α is a parameter that defines the size of the time period.

Figure 4 shows the probability of the events of one WT over the time taken into account the probability function assigned to each event. The simulation has been carried out for 600 samples, where each sample can be considered as a period of one day. The objective is to propose an algorithm able to collect stochastic information of the failure probability of a complex system.

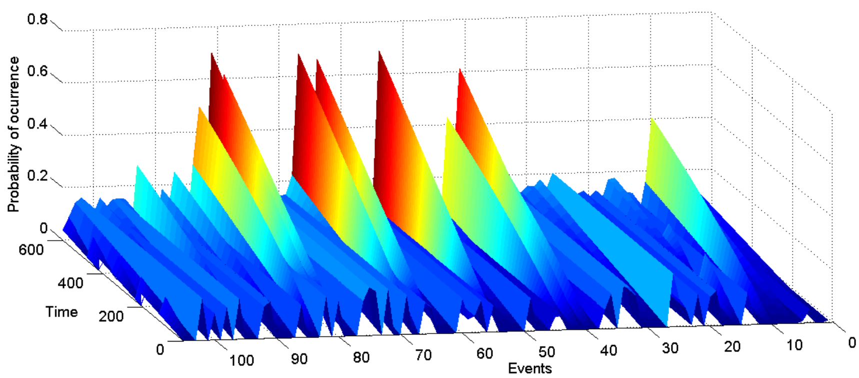

Figure 4. Occurrence probabilities of events.

Considering the last probabilities obtained for each event and the analytical expression of the system failure provided by the BDD, the probability of failure for all WTs of the offshore wind farm can be achieved. Figure 5 presents the failure probability of each WT over the time. The probability of failure for each WT is different among them and over the time, because the values of the parameters that represent the occurrence function of each event are not exactly the same.

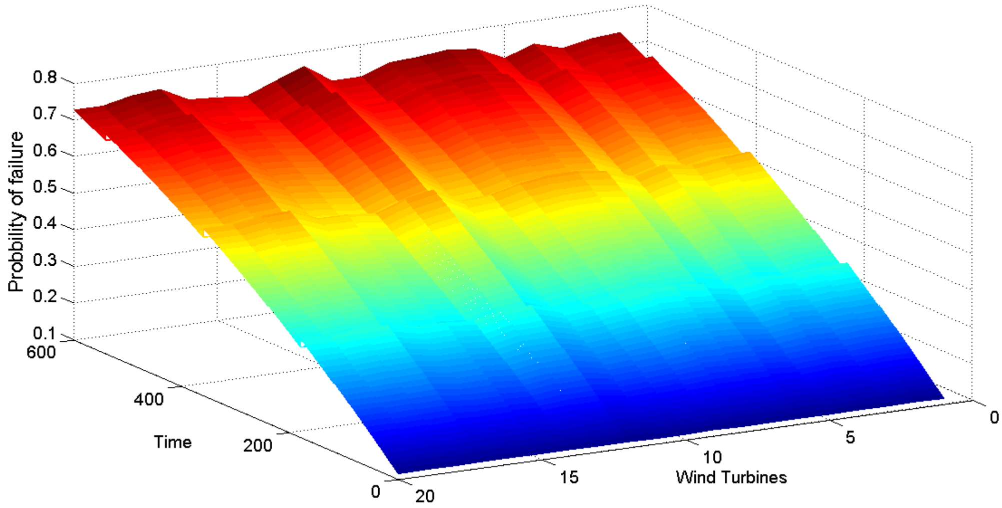

Figure 5. Probabilities of failure of each WT over the time.

The components that require any maintenance task have been set by the importance measurements, specifically by the Criticality IM method. Figure 6 shows the criticality importance of the events of all WTs considered in this case study in a period of time (in this case the study has been considered for a total of 600 days).

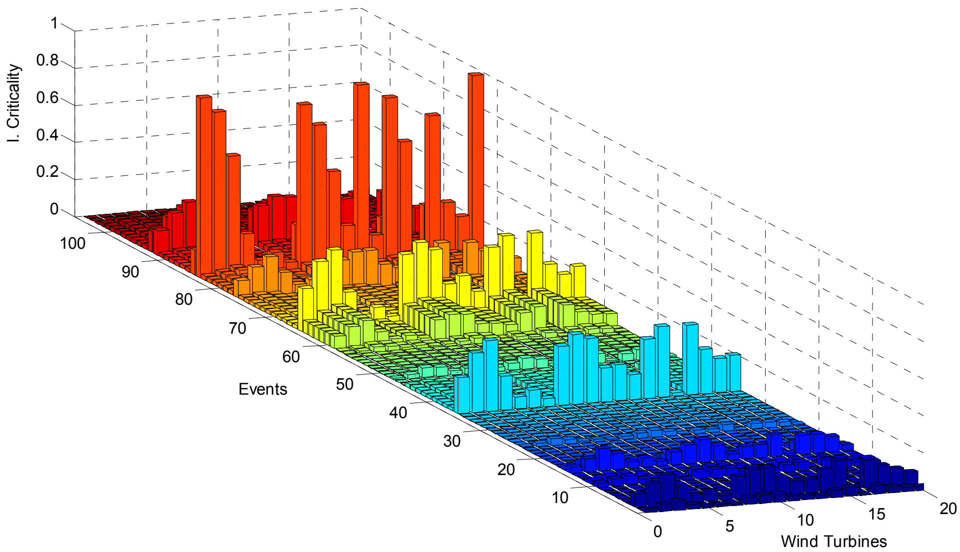

Figure 6. Criticality importance of the events in a given time.

7. Results

The exogenous conditions such as maintenance budget, human and material resources and weather conditions will determine the downtimes, together with the time required to carry out any maintenance task. Figure 7 shows the fault probability over the time of a WT considering different maintenance polices. An upper probability threshold of 0.20 has been established to suggest when the maintenance must be started. Moreover, a lower threshold of 0.15 has been set indicating when the maintenance should be finished. The availability of resources will lead to attend to one or several WTs at the same time.

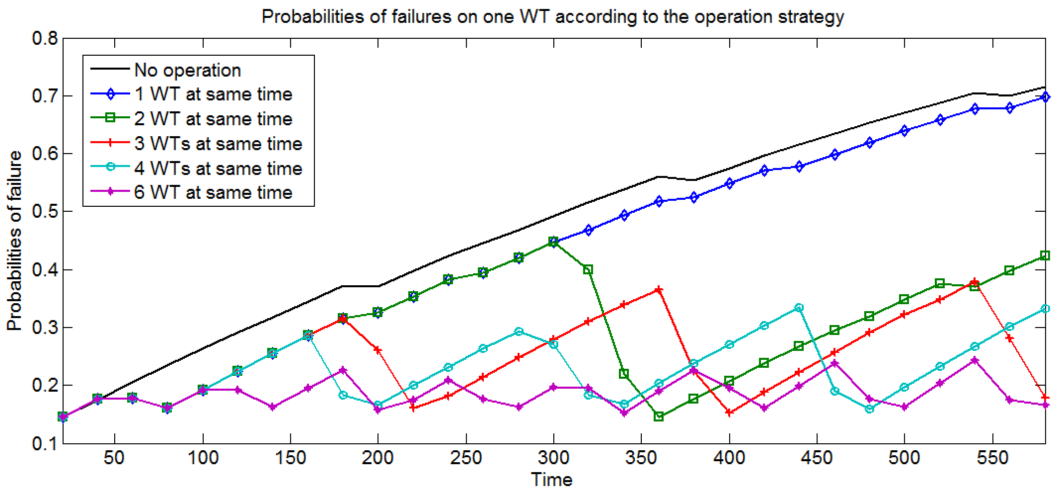

Figure 7. Probabilities of failure of a WT.

The average fault probability of the offshore wind farm according to the resource employed is illustrated in Figure 8. The probability decreases when the potential of maintenance tasks is bigger. In this case study, the average fault probability of the offshore wind farm decreases faster when it is attended at the same time two instead of one WT, than four instead of three WTs. The main conclusion is that a correct resources use could optimize the average fault probability of the offshore wind farm.

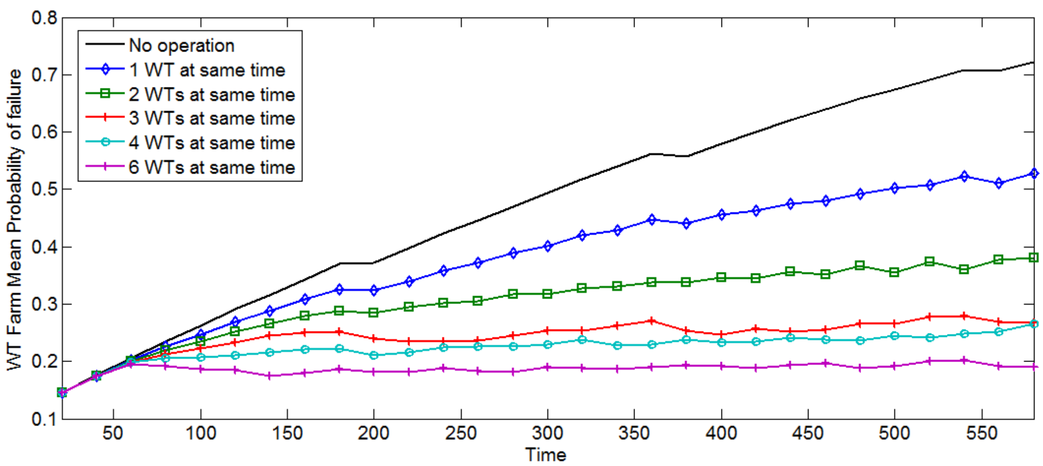

Figure 8. Average fault probability of the offshore wind farm.

The boxplots of Figure 9 show the behavior of the offshore wind farm for different maintenance management policies. The approach lead to control the average probability of failure by a correct maintenance police, and the boxes to be smaller, *i.e.*, presenting a homogeneous probability distribution in all WTs.

The maintenance management performance for offshore wind farms is subject to several uncertainties related to the randomness of exogenous conditions, e.g., weather conditions [77]. Therefore, the approach presented requires weather forecasting. Weather forecasting depends on the temperature, dew point, wind velocity, pressure, visibility, cloud height and quantity [4]. In addition, the state of the sea, the wind and the wave heights need to be considered. There are some probabilistic models based on historical wave height data that are used to determine the conditions of the sea in a certain moment, e.g., the Markovian wave height model [78], forecasting of safe sea-state using finite elements method and artificial neural networks [79], short-term predictions based on nonlinear deterministic time series analysis [80], Gaussian processes [81], resampling methods, parametric models, *etc.*

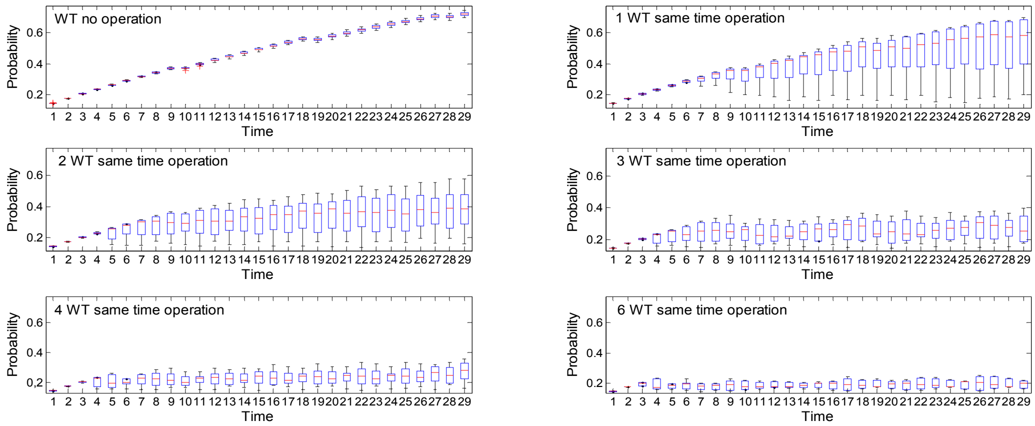

Figure 9. Boxplot of the fault probability of the offshore wind farm for WT operated at the same time.

The maintenance task will be carried out when certain permission value is reached. This dimensionless value, which varies from 0 to 1, will be given by a weighting of the weather conditions and external permissions. It has been simulated in this paper and validated by experts. Figure 10 shows the maximum allowed value assigned to each event. The maximum allowed valued is randomly generated for this case. It is due to the goal of this study is to clarify how the proposed methodology should be applied, taking into account that the method is close to the reality only from the qualitative point of view. This value is compared with a predicted value given randomly in this paper in order to consider the stochastic of the system. If the value assigned to the task is bigger than the predicted value, the maintenance task must be carried out, in other case, it must be necessary to wait for a suitable value from the forecasting.

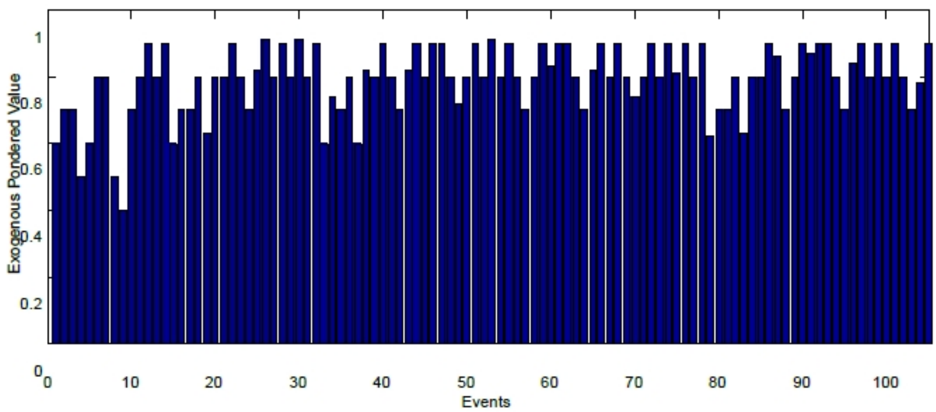

Figure 10. Maximum allowed exogenous pondered value for each maintenance tasks.

Figure 11 shows a randomized forecasting value of the weather conditions given for each day (sample) evaluated in the example. This figure can be used to determine the tasks that can be performed according to the exogenous variables. For example, in the 100th day (green circle) there is a value of 0.2 (this value is a ponderation between temperature, dew point, wind velocity, pressure, visibility, *etc.*), *i.e.*, any maintenance task can be carried out because this value is lower than all the maximum allowed exogenous pondered values. However, in the 300th day (red circle) none of the tasks can be carried out because the value is higher than the allowable value in all the cases.

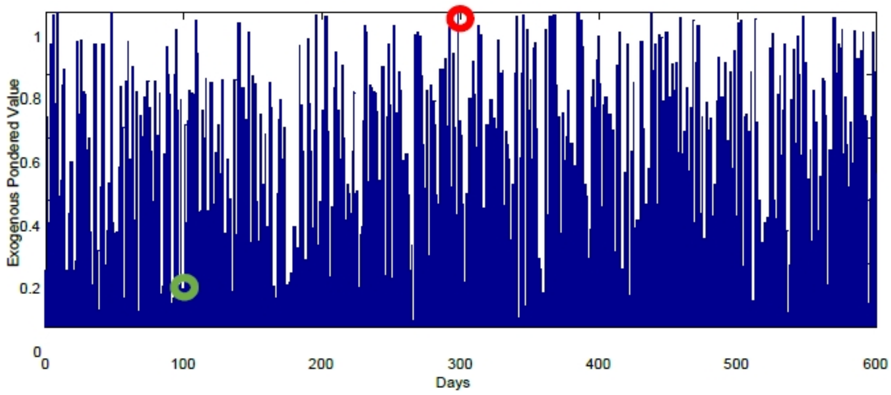

Figure 11. Representative exogenous pondered value forecasting per day.

Figure 12 represents the weather influence on the distribution of the failure probabilities of the WTs over the time. Different weather scenarios have been taken into account randomly in order to evaluate the weather conditions and the influence to the maintenance tasks.

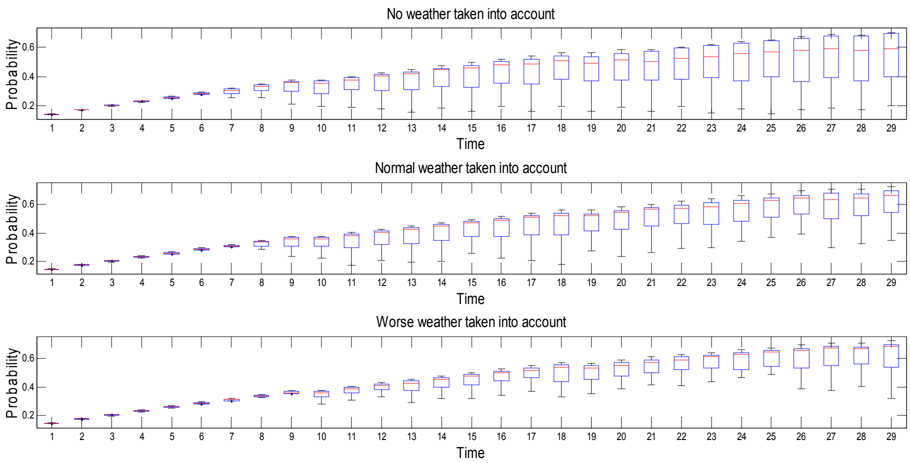

Figure 12. Influence of exogenous variables on the state of the offshore wind farm.

In the top boxplot of Figure 12, the weather conditions have not been taken into account. In the second one, the weather forecasting presented in Figure 11 has been considered. In the last one boxplot, an adverse weather conditions have been established. The presence of adverse weather conditions makes to increase the average fault probability of the offshore wind farm, and the size of the boxes of boxplot decreases because the maintenance tasks that can be done are minimum.

8. Conclusions

The offshore wind energy is being supported by the international community. Offshore wind farms employ large and complex wind turbines that generate more power electricity than onshore. The farms are located in places with difficulty to access that depends of the weather conditions. These conditions have leaded the development of robust remote condition monitoring system in order to increase the RAMS of the offshore wind farms.

This paper presents the BDD in order to evaluate qualitatively the FTA of a WT. The approach is based on the fault probabilities of each component of the WT, that depend of a statistical function of probability of occurrence over the time. The fault probability of the WT has been set by the Boolean expression obtained by the BDD. An optimal ranking of the events has been done for minimising the computational cost.

The IMs have been employed in order to facilitate the improvement of the maintenance management and the resources deployment in an offshore wind farm, where a proper and accurate prioritization of the basic events has been elaborated according to Criticality IM method.

The maintenance management approach proposed in this paper maximise the RAMS of the offshore wind farm, optimising the resources as human, materials, *etc.* The maintenance task will be carried out in the WTs that present more fault probability over a threshold. It will lead to establishment of preventive/predictive maintenance tasks over time. A low probability threshold has also been set to determine when the fault probability of the WT is under control. The time to carry out a maintenance task has been established by the downtime associated to each failure. The downtime depends on the time to repair or replace the component, human resourcesstate of the sea, *etc.*

It has been demonstrated that the average fault probability of the offshore wind farm decreases more when two instead of one WT can be attended at the same time than between four instead of three. The main conclusion is that there is a reasonable amount of resources that allow controlling the average fault probability of the offshore wind farm, and this method can be used to calculate this value.

The weather conditions have been also considered. The average fault probability of the offshore wind farm increases when there is a presence of adverse weather conditions. The adverse weather increases the gap between the failure probabilities of the different WTs that compose the wind farm because the maintenance tasks that can be done are minimum.

The dynamic analysis proposed in this paper can be used to improve the maintenance planning using the fault probability of the system over the time. The fault probability and the IMs determine when the maintenance tasks must be carried out and to set the tasks over the events.

The qualitative data used in this paper is gathered from several research projects and the results have been validated by experts involve in the research projects. The main novelty of the paper is the procedure to analyse endogenous and exogenous data using graphical tools.

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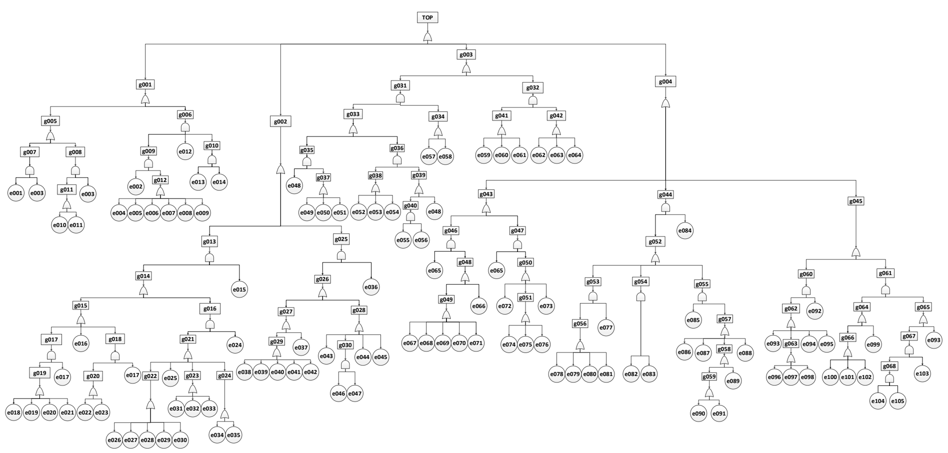
Author Contributions: Alberto Pliego, Fausto García and Jesús Pinar conceived and designed the experiments; Alberto Pliego, Fausto García and Jesús Pinar performed the experiments; Alberto Pliego, Fausto García and Jesús Pinar analyzed the data Alberto Pliego, Fausto García and Jesús Pinar contributed reagents/materials/analysis tools; Alberto Pliego, Fausto García and Jesús Pinar wrote the paper.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix 1. FT for a Wind Turbine



Appendix 2. Events and Probabilistic Models

Fault Tree 1 Foundation and Tower Failure				Probabilistic Model Assignment
Intermediate Event	**Code**	**Final Event**	**Code**	
Yaw System Failure	g005	Yaw motor fault	e001	Constant
Critical Structural Failure	g006	Abnormal Vibration I	e002	Linear Increasing
yaw motor failure	g007	Abnormal Vibration H	e003	Linear Increasing
Wrong Yaw Angle	g008	Cracks in concrete base	e004	Constant
Structural Failure (Foundation and tower)	g009	Welding damage	e005	Constant
No electric power for yaw motor	g010	Corrosion	e006	Linear Increasing
Metereologhical Unit Failure	g011	Loosen studs in joining foundation and first section	e007	Linear Increasing
Structural Fault (Foundation and tower)	g012	Loosen bolts in joining different sections	e008	Linear Increasing
		Gaps in the foundation section	e009	Exponential Increasing
		Vane damage	e010	Exponential Increasing
		Anemometer damage	e011	Exponential Increasing
		High wind speed	e012	Periodic
		No power supply from generator	e013	Constant
		No power supply from grid	e014	Constant
Fault Tree 2 Critical Rotor Failure				**Probabilistic Model Assignment**
Intermediate Event	**Code**	**Final Event**	**Code**	
Critical blade failure	g013	High wind speed	e015	Periodic
Blade Failure	g014	Blade Angle asymmetry	e016	Exponential Increasing
Pitch System Failure	g015	Abnormal Vibration A	e017	Exponential Increasing
Critical structural Failure (Blades)	g016	Motor failure	e018	Exponential Increasing
Hydraulic system Failure	g017	Leakages	e019	Constant
Wrong Blade Angle	g018	Over pressure	e020	Constant
Hydraulic system Fault	g019	Corrosion	e021	Exponential Increasing
Metereologhical Unit Failure	g020	Vane damage	e022	Constant
Structural Failure (Blades)	g021	Anemometer damage	e023	Constant
Leading and traililling edges	g022	Abnormal Vibration B	e024	Constant
Shell	g023	Root Cracks	e025	Constant
Tip	g024	Cracks	e026	Constant
Rotor System Failure	g025	Erosion	e027	Exponential Increasing
Rotor System Fault	g026	Delamination in leading edges of blades	e028	Exponential Increasing
Bearings (Rotor)	g027	Delamination in trailing edges of blades	e029	Exponential Increasing
Rotor Hub	g028	Debonding in edges of blades	e030	Exponential Increasing
Wear	g029	Delamination in shell	e031	Exponential Increasing
Imbalance	g030	Crack with structural damage	e032	Constant
		Crack on the beam-shell joint	e033	Constant
		Open tip	e034	Constant
		Lightning strike	e035	Periodic
		Abnormal Vibration C	e036	Constant
		Cracks	e037	Constant
		Corrosion of Pins	e038	Exponential Increasing
		Abrasive Wear	e039	Exponential Increasing
		Pitting	e040	Linear Increasing
		Deformation of face & rolling element	e041	Linear Increasing
		Lubrication Fault	e042	Linear Increasing
		Clearance loosening at root	e043	Exponential Increasing
		Cracks	e044	Constant
		Surface Roughness	e045	Constant
		Mass Imbalance	e046	Exponential Increasing
		Fault in Pitch adjustment	e047	Exponential Increasing

Appendix 2. *Cont.*

Fault Tree 3 Electrical Components Failure				Probabilistic Model Assignment
Intermediate Event	**Code**	**Final Event**	**Code**	
Critical Generator Failure	g031	Abnormal Vibration G	e048	Exponential Increasing
Power Electronics and Electric Controls Failure	g032	Cracks	e049	Constant
Mechanical Failure (Generator)	g033	Imbalance	e050	Exponential Increasing
Electrical Failure (Generator)	g034	Asymmetry	e051	Exponential Increasing
Bearing Generator Failure	g035	Air-Gap eccentricities	e052	Linear Increasing
Rotor and Stator Failure	g036	Broken bars	e053	Linear Increasing
Bearing Generator Fault	g037	Dynamic eccentricity	e054	Linear Increasing
Rotor and Stator Fault	g038	Sensor T error	e055	constant
Abnormal Signals A	g039	T above limit	e056	Periodic
Overwarming generator	g040	Short Circuit (Gen)	e057	Constant
Electrical Fault (PE)	g041	Open Circuit (Gen)	e058	Constant
Mechanical Fault (PE)	g042	Short Circuit	e059	Constant
		Open Circuit	e060	Constant
		Gate drive circuit	e061	linear increasing
		Corrosion	e062	Periodic
		Dirt	e063	Periodic
		Terminals damage	e064	linear increasing

Fault Tree 4 Power Train Failure				Probabilistic Model Assignment
Intermediate Event	**Code**	**Final Event**	**Code**	
Low speed train Failure	g043	Abnormal Vibration D	e065	Constant
Critical Gearbox Failure	g044	Cracks in main bearing	e066	Constant
High speed train Failure	g045	Spalling	e067	Linear Increasing
Main Bearing failure	g046	Corrosion of Pins	e068	Linear Increasing
Low speed shaft failure	g047	Abrasive Wear	e069	Constant
Main Bearing fault	g048	Deformation of face & rolling element	e070	Linear Increasing
Wear main bearing	g049	Pitting	e071	exponential increasing
Low speed shaft fault	g050	Imbalance	e072	Constant
Wear low shaft	g051	Cracks in l.s. shaft	e073	Linear Increasing
Gearbox Fault	g052	Spalling	e074	Constant
Bearings failure(Gearbox)	g053	Abrasive Wear	e075	Constant
Lubrication fault	g054	Pitting	e076	Constant
Gear Failure	g055	Abnormal Vibration F	e077	Linear Increasing
Wear bearing gearbox	g056	Corrosion of Pins	e078	Exponential Increasing
Gear Fault	g057	Abrasive Wear	e079	Linear Increasing
Tooth Wear	g058	Pitting	e080	Constant
Offset	g059	Deformation of face & rolling element	e081	Linear Increasing
High speed shaft Failure	g060	Oil Filtration	e082	Constant
Critical Brake Failure	g061	Particle Contamination	e083	Exponential Increasing
High speed structural damage	g062	Overwarming gearbox	e084	Linear Increasing
Wear high shaft	g063	Abnormal Vibration E	e085	Periodic
Brake Fault	g064	Eccentricity	e086	Constant
Abnormal Signals B	g065	Pitting	e087	Linear Increasing
Hydraulic brake system Fault	g066	Cracks in gears	e088	Exponential Increasing
Abnormal Signals C	g067	Gear tooth deterioration	e089	Exponential Increasing
Overwarming brake	g068	Poor design	e090	Periodic
		Tooth surface defects	e091	Constant
		Abnormal Vibration J	e092	Constant
		Cracks in h.s. shaft	e093	Linear Increasing
		Imbalance	e094	Periodic
		Overwarming	e095	Exponential Increasing
		Spalling	e096	Constant
		Abrasive Wear	e097	Linear Increasing
		Pitting	e098	Constant
		Cracks in brake disk	e099	Exponential Increasing
		Motor brake fault	e100	Constant
		Oil Leakage	e101	Linear Increasing
		Over pressure	e102	Constant
		Abnormal speed	e103	Linear Increasing
		T sensor error	e104	Periodic
		T above limit	e105	Periodic

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