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A Review on the State of the Art for Failure Diagnosis and Prognosis Techniques for Wind Conversion System.

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ABSTRACT

Due to gradual depletion of fossil energy resources and the increasingly serious issue of environmental pollution, the scale of renewable energy has been increasing. The demand for wind energy has made it a top competitor as a renewable energy resource. But with all this said, Wind Turbines (WT) manifest many faults along the drive train from the blades to the converter. Some are more prominent than others and more frequent. Three types of major failures are common; failure in electrical subsystems, failure in mechanical subsystems and failures in structural subsystems. This paper is a technical state of the art review as part of a research for WT fault classification. The first highlight of this review covers the WTs critical failures as well as detection algorithms. The second highlight will go into the details of the state of the art and future development of prognosis methods and data analysis techniques that are based on well-built algorithms for remaining useful life calculation and predictions. As a conclusion, the optimal choice is a data collection and diagnosis using stator current signatures, analysed by a discrete wavelet transform with feature extraction optimized by a genetic algorithm, like an Artificial Bee Colony.

KEYWORDS

Wind Turbines (WTs); Faults Diagnosis; Condition Monitoring; Downtime; Gearbox; Bearings, Root Causes, Data processing, Artificial Intelligence.

1. INTRODUCTION

Due to gradual depletion of fossil energy resources and the increasingly serious issue of environmental pollution, the scale of renewable energy has been increasing. Multiplied worldwide demand for energy has made wind energy a forerunner as a renewable energy source [1]. In Europe, the aim is to achieve 20% of renewable power generation by 2020, in accordance with Kyoto protocol [2]. In The USA, three cities are currently running on 100% renewable energy. The first two U.S. cities to reach the goal were Burlington, Vermont and Greensburg, Kansas. Aspen is the third as of September 2015. A new study done between Stanford University and U.C Berkeley is the first of its kind to outline how each of the 50 states can achieve such a transition by 2050, which saw a 39% reduction in total end-use power demand that year. WTs are power plants that are usually located in isolated areas where there is lack of power from the local grids. These systems are usually unmanned [3]. Being exposed to the elements of nature, WT are subjected to different weather conditions which include high winds, lightning, extreme heat and cold, sleet and snow. These external variables cause WTs to have highly intermittent operation and intense mechanical stress thus causing subsystems to fail [4]. In this case, WT system reliability will become a major concern in the future thus leading to the need of highly performing fault diagnosis and Condition Monitoring Systems (CMS) [5, 6].

Data collection can come from WT's main components, like the drive train which includes the shaft, main bearing, generator and gearbox. The type of collected data affects the type of data analysis techniques to be used. Stator current signature analysis is gaining popularity for detection mechanical and electrical faults and can be a solution for sensor faults and failures within mechanical systems. Induction machines fault diagnosis techniques based on Stator currents spectrum analysis for fault diagnosis have gained intense interest in the past decades. Many researchers have conducted extensive studies regarding this issue and came up with results which have demonstrated the validity of this method as a fault monitoring technique. In some papers, it has been explained and highlighted that faults in the drivetrain can inject additional components in the stator current spectrum in particular around the supply frequency value, and modulate the current signals of the generator. In this case, the development of these methods is helpful for deciphering this data and having much useful information for classification and later prediction of faults. The motivation for this review is as an evaluation research for detecting and classifying WT faults, to finally choose the most optimal detecting method, coupled with a solid feature gathering and signal processing method.

The paper in hand acts as a literature review on the different faults that manifest in WTs, as well as for the state of the art of the techniques of detection, classification analysis and prediction of said faults. It's divided into six sections. Section 2 describes the structure and types of a WT. In order to have a better understanding of the failures affecting a WT, Section 3 presents a general overview of the different failures that affect WT subsystems as well as their effect on energy production. Section 4 will go over the several condition monitoring and fault detection methods to determine the most appropriate ones. Section 5 and 6 detail the different data analysis, classification and prediction algorithms. Conclusions are given in Section 7 where the optimal choice is made.

2. WIND TURBINE STRUCTURE, COMPONENTS AND TYPES

2.1 WT Structure configuration

WTs are intricate electromechanical systems that have the ability to extract the kinetic power of the wind and convert it into electricity [1, 7] as presented in Figure 1. Rotor blades are constructed to extract the maximum power from the wind. The Wind power formula is stated as following [8, 9]:

$$P_M = C_P\ (\lambda, \beta). P_W \quad (1)$$
$$P_W = \frac{1}{2}.\pi. R^2. V^3. \rho_{AIR} \quad (2)$$

Where P_W and P_M represent the wind power and the mechanical power of the wind respectively, CP is the performance coefficient of the turbine, R designates the rotor radius, V represents the wind speed and ρ_{AIR} the air density. The equation above clearly shows that the mechanical power is directly proportional to the wind power multiplied by the performance coefficient factor $C_P\ (\lambda, \beta)$ which is dependent on λ and β. λ is the tip speed ratio of the blade tip speed to the wind speed and β represents the pitch angle of the blade in degrees. C_P Is at a maximum when β=0 and λ=8.1. By introducing the torque coefficient C_m, the mechanical torque T_{mec} can be determined in the following relations [8, 9]:

$$C_m = {C_p}/{\lambda} \quad (3)$$
$$T_{mec} = \frac{1}{2}.\pi. R^2. C_m. V^3. \rho_{AIR} \quad (4)$$

The typical range of rotational speeds for multi-MW WTs is between 10-14 rpm.

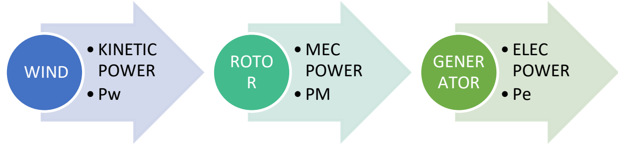

Figure 1: Energy conversion scheme of WTs [8]

2.2 WT Components

In all modern WTs, the number of blades is three. The main sections of a WT are shown in Figure 2. The system is made of three main sections, Structural, Mechanical and Electrical. The Mechanical and Electrical sections include rotor blades, brakes and hydraulic system, a gearbox (or no gearbox for direct drive WTs), yaw system, a generator, a power control system (converter), and a transmission system (transformer) for connection to the power grid [7, 10].

The power collected by the rotor blades is of low speed and high torque. To convert this power to electrical power, a gearbox and generator as well as a power electronic interface is needed. The gearbox increases the speed of the turbine main shaft to adapt to the generator's higher speed, while the generator does the conversion from mechanical to electrical power. Electronic converters and a transformer make the connection to the grid possible. This power conversion system is all mounted on a tower or mast with concrete foundation and enclosed in a nacelle, which comprise the Structural section. Each of the above mentioned sections can be broken down to many subassemblies or subsystems [11]. Table 1 summarizes the complete structure of a wind turbine with its various subsystems.

2.3 Types of WTs

WTs are of two main configurations, fixed speed and variable speed. Nowadays, WT are inserted with Induction generators or Permanent magnet generators. Early WTs were fixed speed and with ratings less than 1 MW. The type of generator used was standard squirrel-cage induction generator, directly connected to the grid with a multistage gearbox. These types were in production until the end of the 1990's. Due to the fixed speed WTs' many shortcomings, many improvements were introduced. Below are mentioned the most critically issues that fixed speed WTs faced:

- Stopping in emergencies. This was difficult due to presence of only air mechanical brakes,
- Noise,
- Mediocre power quality,

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- The necessity of a reactive power compensator to eliminate the reactive power drawn by turbine generators from the utility grid,

A better technology started to become in use; the variable speed WT. These WTs are known to achieve maximum aerodynamic efficiency over a wide range and to continuously adjust by accelerating and decelerating to the speed range of the wind. Contrary to a fixed speed system, a variable speed system keeps the generator torque nearly constant. It is also designed to reduce stress on mechanical components, mainly the shaft and the gearbox, while maximizing power capture and minimizing audible noise [10, 12].

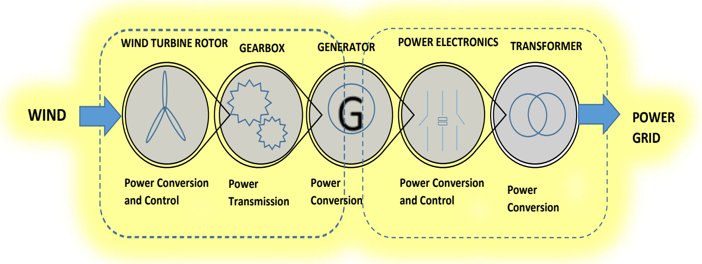

Figure 2: Main sections of a Wind Conversion System [8]

Table 1: WT Subassemblies [8]

Electrical Subassemblies	Mechanical Subassemblies	Structural Subassemblies
▪ Generator ▪ Electrical Controls system ▪ Power Converter ▪ Grid and electrical system ▪ System transformer	▪ Rotor and blades assembly ▪ Mechanical brake ▪ Main shaft ▪ Gearbox ▪ Yaw system ▪ Hydraulics ▪ Pitch control system	▪ Tower ▪ Nacelle ▪ Concrete foundation

3. FAILURE IN WIND TURBINES

Concerning WT faults, many statistical analysis that were undertaken showed that the availability and reliability of WTs depend on many factors like size, age, weather conditions, location, wind speed, and failure rates of subassemblies factors. As per E.Chavarria et al. [11] and Hahn et al. [13], manufactures design WTs to operate for a period of 20 to 25 years. E.Chavarria et al. [11], performed a 15 years research on different rated WTs, to study the frequency of WTs failures with respect to increasing operational age. The results showed that the number of incidents for each WT per operational year tend to be higher for higher rated turbines. According to other surveys and studies conducted in [14-17], the frequency of failures in WTs vary with the scale and type. Their findings is summarized in Fig 3 show that with the trend in WTs manufacturing going towards higher rated capacity systems and newer, less mature technologies like direct drive technology, the reliability decreases and initial failure rates are projected to increase. Ahmad et al [18], Amirat et al [19] and Hahn [20], all discussed the three fundament failure patterns of WT mechanical systems throughout its operating life, which are represented by the reliability of the system as operating years (time) in function of failure rate. This is called the bathtub curve. Stenberg and al. [21] based their study on WT performance and failure data collected for 72 WTs in Finland by the Technical Research Centre of Finland. Failure statistics from these 72 WTs were collected for years 1996 to 2008. Figure. 4 represents the number of faults caused by technical failure per turbine per operating years. It clearly shows that, as the system ages, the deterioration phase becomes faster and the system reaches a wear-out period. Due to the complex nature of a WT system and the existence of many subsystems within the main system, different types of failure can occur. Some happen more frequently than others and some are critical enough to cause downtime on energy production.

Failures in WTs system are either due to design and manufacturing causes, O&M (Operations and Maintenance) practices and environmental impact [22]. Many authors have studied the distribution of failure rates between subassemblies of the WTs and downtimes of each components. Ribrant [4] studied the number of failures in comparison to the downtime per component, for four consecutive years, in a Swedish plant. He concluded that most failure rates are related to the electrical and power control systems where as the most downtime is related to gearbox which can reach up to 256 hours per failure and 6,057 hours downtime per year and control system failures which can reach up to 184.6

hours per failure and 5,724 hours average downtime per year.

Alwine [22] collected the statistics of 1200 WTs generator repairs on differently rated machines of less than 1MW, between 1 and 2 MW and more than 2 MW and mapped the results out for component type in function of percentage of failure occurrence rate. His statistics showed that the cumulative percentage of failures happens on the bearings and comparison with study being done at Durham University proved that failure in bearings was the main root cause of failure for wind generators (in blue) and industrial rotating electrical machines (in red) , as is reflected in Figure 5. According to a report issued by [23], 63.1% of failures consequences result in plant shutdown, for the same period. In addition, it is noticed that the failure frequency varies with the wind speed.

For wind speeds above 12 m/s, the failures are bound to occur about twice as high as the frequency of wind classes [24]. Investigations done for wind farms in three European countries who are major contributors in the wind power industry, have highlighted how critical gearboxes failures are with respect to failure rates and mean down time. These finding are in concurrence with the results in [4] and [22].

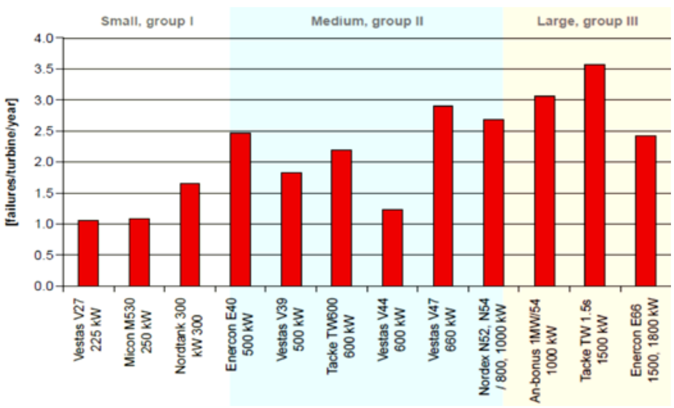

Figure 3: Distribution of failure frequencies between different turbine types [11]

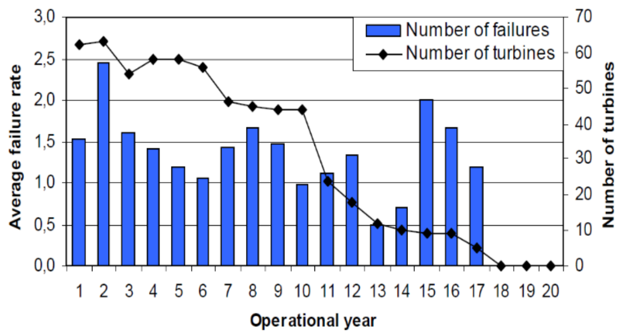

Figure 4: Reliability in function of Operational Years [18]

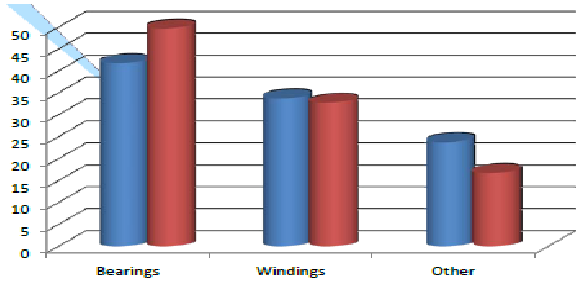

Figure 5. Comparison of root cause failures in both wind and industrial generators [19].

Mothanna. A.Aziz and al. [24] also mentioned that critical failures affect the rotor blades, even though being rare with respect to failures in other parts of the mechanical system. These types of failures can occur in higher rates in hostile environment.

Another important finding is that smaller and older turbines have a lower frequency of failures compared to bigger sized wind turbines [25]. Studies have been done on the two types of WTs, the direct drive turbines and the indirect drive to compare the failure rates. Since the gearbox is a main characteristic of indirect drive WTs, a supposition that the indirect drive machine is then more susceptible to gearbox failures. Results based on system annual efficiency and cost, show the total opposite, where direct drive WTs have a higher failure rate on the electrical system (both the electrical level and power converters level) than the gearbox failure rates in their indirect drive counterparts, while generator failure rates are nearly twice as recurrent [26,27], thus the real benefits of direct-drive WTs over geared ones are still inconclusive, and more data collection from operating direct drive systems need to be collected over a number of years for comparison.

Based on statistical surveys, Crabtree [28] inducted on European Wind Turbines, in comparison of failure rates and downtime for different WT subassemblies, he concluded that gearbox downtime cause the highest percentage in power production lose that any other subassembly.

Minghao Zhao and al. [29] investigated the fault mechanism of icing on rotor blades. In the study, it is shown that icing has a detrimental effect on the aerodynamics of the blades, since the accumulation of ice changes the geometry as well as cause the misalignment of the rotor centre of rotation which creates excessive vibration.

3.1 Failures Modes in the Electrical Subsystems

The major number of failures in a WT happen in the electrical system and are due to control system failures, sensor failures and grid connection faults. Electronics controls in the WT account to about 1% of the total WT cost only, whereas their failure rates is 13% and the downtime caused by the failures is 18%. The rate of failure of grid connection faults add up to 17.5% with a 14.3% downtime and sensor faults to 14.5% with a 5.4% of downtime [4].

Effective diagnosing of power electronics is hard, even with the advancement of diagnostic techniques because the time lapse between the fault appearing and a catastrophic failure is very small [30]. Many studies have concluded that the main reason behind power electronic faults in WT is the defected semiconductors. In wind generation systems, the three level Neutral Point Clamped (NPC) technology is widely used among the multi-level converter technology and is part of a back to back converter topology [31]. The type of converter is comprised of a grid side topology and a generator side topology, where grid-side is known as the NPC inverter and the generator side is known as the NPC converter [32, 33].

As interest in increased system reliability has become the focus of all studies in the WT field in order to minimizes downtime and ensure low cost of energy production. The NPC power converter switch faults are further studied to improve the system reliability. The generator side converter is affected by short circuited switch faults and open switch faults.

- In the short circuited switch faults, a very high current that is above rated value will flow in the closed switches, causing serious failures and even breakdowns to the system.
- Open switch faults are caused by thermal cycling. This causes a high collector current which forces the current pattern distortion, and can generate a torque ripple in the system in addition to secondary failures in other system parts that can propagate breakdown in many sections of the system.

The grid side inverter, like the generator side converter, is also affected by short circuit faults, as well as, thermal loading faults due to grid related faults [34].

- When a short circuit happens in the grid, there will be a voltage dip that will be detected by the grid side inverter through the AC bus.
- Thermal loading causes overheating in the inverters components (switches and diodes), above the normal operating temperatures.

The other electrical component of the WT which has a relatively high downtime is the generator, about 9% per year with a frequency of failure per year of 5% [4]. WT generators are subject to failures in bearing mainly as well as in the stator and rotor among others.

In induction machines, about 40% failures are related to bearings, 38% in the stator and 10% to the rotor. Faults in induction machines are the reason for the manifestation of the phenomena such as harmonics in the air-gap flux and phase currents, excessive heating in the winding, increased torque pulsation, decreased average torque and increased losses thus a significant reduction in efficiency [35]. Strong vibration creates looseness inside the generator. Looseness can cause insulation deterioration, resulting in windings short circuits, arcing currents, and partial discharge.

The most critical of faults inside a generator manifest in the stator winding, this is mainly caused by magnetic wedge loss. Magnetic wedge loss happens in over speeding conditions when coils become loose and can knock the wedges out of place. The loss of these wedges can also let loose conductive dust that can migrate through the stator to the windings. These particles are affected by the electrical field and can clump into larger particles and fly onto the windings. They can heat up causing arcs that can burn holes in the insulation and into ground wall causing spectacular ground faults. This eventually can lead to a fire in the generator [36]. It is also very interesting to see that generator failures begin with the manufacturing process thus choosing the manufactures and spare part suppliers is very important to insure the longevity of the system. In addition to that, maintenance plays a very crucial role that can affect the life of a WT.

Generator failures are categorized into four failure root causes, design causes, maintenance causes, operational causes, and environmental causes.

1) Design causes:
    a) Loose components,
    b) Poorly crimped lead connections,
    c) Inadequate collector ring/brush performance,

d) Rotor lead failures,
e) Inadequate Electrical insulation

2) Maintenance causes
 a) Heat related failures due to problems in cooling systems,
 b) Collector ring contamination,
 c) Bearing electrical and mechanical failures,
 d) Rotor lead damages due to bearing damages,
 e) Lost rotor wedges,
3) Operational causes
 a) Over-speed conditions,
 b) Inadequate grounding system,
 c) Voltage irregularities,
 d) Wrong converter rating (mismatching),
 e) Stator connection short circuits,
 f) Magnetic wedge loss,
4) Environmental causes
 a) Wind Loading,
 b) Icing,
 c) Lightning/ Electric storms,
 d) Moisture,
 e) Thermal cycling
 f)

A summary of failures and downtimes of electrical components are presented in Figure 6.

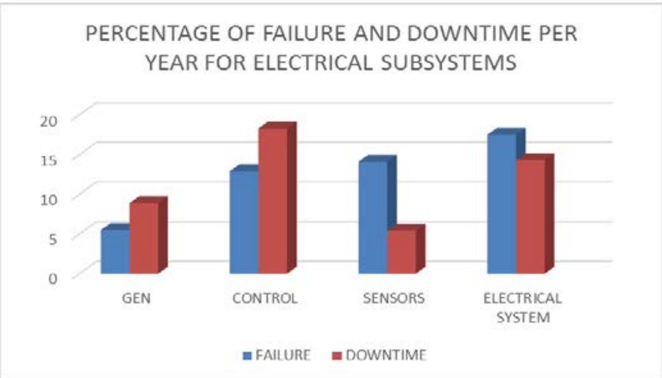

Figure 6: Electrical subsystems percentage of failure rates and downtime per year.

3.2 Failures Modes in Mechanical subsystems

The extreme environmental conditions which WTs operate in include very changing temperatures, dust and humidity, changing air pressure and unpredictable loads caused by gust. Mechanical failures in a WT usually manifest in the drive train (main shaft, main bearings and gearbox). Wind turbine drive trains are susceptible to severe wear and tear conditions, fractures caused by high cyclic fatigue and corrosion which is caused by misalignment and over loads [37]. These manifestations lead to increased failures in the machine and component malfunction and damage. In addition to the faults manifesting in the gearbox and bearings, many faults appear in rotor blades, yaw system, brakes, and hydraulic system and pitch actuators as part of the faults in the mechanical system. Several studies and surveys across Europe and the USA have highlighted how significant gearboxes failures are on the overall WT, with a failure rates per year of 10% and mean down time per year of 19.4% in WTs [4]. Most gearbox failures are known to appear in the first five years of use, and have yet to reach the twenty year design life goal. Gearboxes are known to be one of the most expensive parts of a WT, therefore, in addition to loss of power from downtime caused by gearbox failure, the price of the gearbox adds to the cost of wind energy production. Wind farms still suffer multiple gearbox repairs in the operational life of their WTs as well as these repairs being highly expensive, and this is despite all efforts to improve gearbox designs.

1) Gearbox and Bearings faults: The NREL (National Renewable Energy Laboratory) Gearbox Reliability Collaborative has answered many question related to gearbox failures. “Most gearbox failures do not begin as gear failures or gear-tooth design deficiencies. The observed failures appear to initiate at several specific bearing locations under certain conditions, which may later advance into the gear teeth as bearing debris and excess clearances cause surface wear and misalignments.“ [38].Deterioration of bearing rollers generally starts with an occurrence called micro pitting, which consists of microscopic cracks in the roller surface

This happens when the oil film that separates the roller from the races breaks down. As these cracks accumulate the bearing roller starts to shed its surface, creating small hard steel particles that can contaminate the oil and are very small to be filtered out. Even in a properly designed and lubricated gearbox, oil film breakdown can occur during transient events that can cause concentrated loading and skidding of the bearing rollers on the races [39]. These events are called torsional reversals and include the below mentioned events. These transient events might be infrequent but they can be very severe:

- Grid loss and Grid faults,
- Generator short circuits,
- High wind shutdowns and other emergency stops,
- Vibration,
- Wind gusts,
- Control system malfunctions,
- Crowbar events.

Torsional reversals cause the load zone of the bearings to skew at almost a 180º angle. Concentrated loads on the askew rollers can break through the oil film [39, 40]. The common failure modes that happen in the gearbox gears and bearings of a WT are listed in Table 2.

2) Rotor Blades faults: Blades have a high failure occurrence per year, of 13.4% and a downtime incurred by those failures of about 9% per year [4]. Extreme weather conditions, like high wind loads lighting strikes and icing are mostly responsible for loss of structural of integrity of rotor blades. Failure of gearbox and brakes is another indirect reason for faults in the blades [41]. Even though rare to occur, a list of faults of rotor blades are mentioned below and detailed.

a) Fire due to lighting strikes, where combustible material in the turbine ignites causing fires to break out which are fanned by the continually rotating blades until they are completely burned out and disintegrated. Large pieces of debris falling from the height of the turbine result in damage of nearby property and sometime fatalities.

b) Icing is another serious problem for turbine blades. Mostly icing is a concern in arctic regions where large chunk of ice fall are flung off the blades onto surrounding areas. For operational turbines, the ice debris on the blades changes the blade aerodynamics and is known to reduce mean power by 25%. The phenomenon of icing debris build-up can also cause serious excessive vibrations on the turbine which leads to blade high load fatigue and change in bending moment. Reports stated that in southern Sweden a farm was stopped for over 7 weeks during the best operating period due to icing [29, 42].

c) Another serious fault on the rotor blade is the rotor mass imbalance which is a direct result of debris build-up. This deviates or misaligns the centre or rotation of the blades causing excessive vibrations. Usually fault detection systems depend a lot on information gathered from vibration signals [42-43]. It is important to monitor the condition of wind turbine's vibration and detect the fault of mass unbalance out of vibration signals to avoid any catastrophic failure.

d) Failures in blades due to brake failures and gearbox fault can happen. They are systems needed to shut down the system during high winds for safety reasons and to extract useful energy from the wind at low speeds, respectively. If either system were to fail, the blades are able to rotate at many times its normal speed. The tips of a blade rotating out of control could be travelling at very high speeds (nearly 1000 mph) and can be detached with an enormous amount of kinetic energy and be flung hundreds of meters away.

e) The blades are made of fibre glass impregnated with resin. They have good mechanical strength and have reduced weight. However, they are brittle: resin ages and layers peel, sudden impacts (like birds, bats and lightning) can cause delamination and fibre breaks. [24]

3) Hydraulic system faults: This system is known to have a high failure rate with respect to the mechanical components of the WT, higher than the very critical gearbox, with a failure rate per year of 13%, but usually the faults that manifest are dealt with relatively fast making the downtime percentage per year about 4% [4]:

f) Common problems are failures in pumps and oil leakages.

g) Old turbines tend to have problems with the hydraulic system which have resulted in a mean value of more than 5 % in the sixteenth operational year.

h) Valve failures can cause over speed and the inability to shut the system down due to wind.

i) Leakage of hydraulic fluid can cause pollution to crops and trees.

4) Pitch Actuator faults: Faults related to blade pitching come mostly appear due to failures in the hydraulic system. Pitching mechanism can fail also due to sensory faults and bearings faults. The amount of downtime caused by this type of failure is minimal.

5) Brakes failure: There are two different kinds of brakes in a wind turbine: Aerodynamic brake, called rotor tip brakes, and mechanical brakes. Brake failure in any of the blades is very dangerous since it can cause an event called runaway turbine

which is the result of over speeding of the blades. This fault can propagate a series of events in the nacelle and the hub making them imbalanced. Consequently, the blade will hit the tower and slice it, thus make it collapse with everything on it and sending the disintegrated blades to be ejected to far distances.

a) These two types of breaks have different types and causes of failures then, they are treated differently from each other.

b) As per report analysis and statistics on 7 WT in Finland over 15 years, [21], failures in the mechanical brake have caused 2603 hours of downtime which is about 1.2% of WT failure rates/year and failures with the tip brake have caused 13383 hours of downtime. Tip brake failures are extremely rare about but if they happen can be a cause of a lot of downtime. This is becoming an old method of breaking as pitching mechanism and is being adapted in the newer model turbines. In the older still operational turbines, these brakes become faulty in the old age of the turbine.

6) Yaw motor failures: Yaw motor failure is one of the most common reasons for downtime in WT of about 13% yearly and also the reason for the largest value of downtime in the eleventh operational year, due to long waiting period for a new motor. The failure frequency per year is also considerable and it amounts to 6.7% of failures that manifest in a WT yearly [4].

Some icing problems are also connected to the yaw system. Figure. 7 clearly shows the failure rates and downtimes of mechanical subcomponents. Figure 8. Summarizes and shows the different subsystems compared to each other in function of failure rates and downtimes per year of operation.

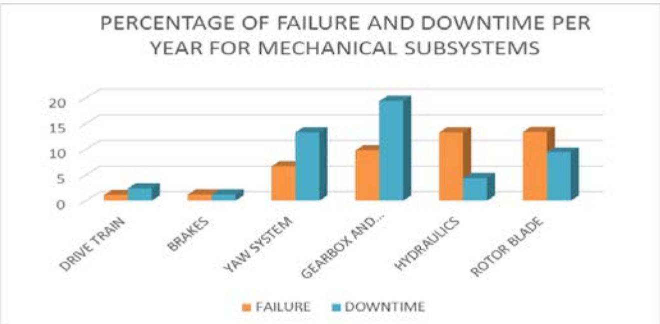

Figure 7: Mechanical subcomponents percentage of failure rates and downtime per year

Table 2: Gearbox Failure Modes common to WTS

GEAR DAMAGE	FAILURE ROOT CAUSES
Micro pitting	• Improper tooth grinding • Contaminated lubricant by hard, sharp-edged particles
Tooth Cracking	• Due to inclusions and metal debris from other failed components causing tooth stress and breakage. • Operational overload
Spalling	• Hertzian Fatigue • Contaminated lubricant by hard, sharp-edged particles and poor lubrication. • Over rolling of debris • localized stress due to misalignment
High cycle bending fatigue (Top failure)	• Due to Cyclic stress being less than the material yield strength hard, sharp-edged particles and poor lubrication.
Fretting corrosion (Top failure)	• Deterioration of contacting gear tooth surfaces caused by minute vibratory motion • Poor Lubrication.
BEARINGS DAMAGE	**FAILURE ROOT CAUSES**
Spalling	• Hertzian Fatigue • Contaminated lubricant by hard, sharp-edged particles and poor lubrication. • Over rolling of debris localized stress due to misalignment
Roller cracks	• Localized stress.
Scuffing (Top failures)	• Transfer of material from one bearing surface to another due to welding and tearing
Abrasion (Top failures)	• Contamination of lubricant by hard, sharp-edged particles. • Poor lubrication can promote wear between rollers.
Oil leakage	• Bad Maintenance
High oil temperature	• Vibration • Overload • Failure in other components
	•

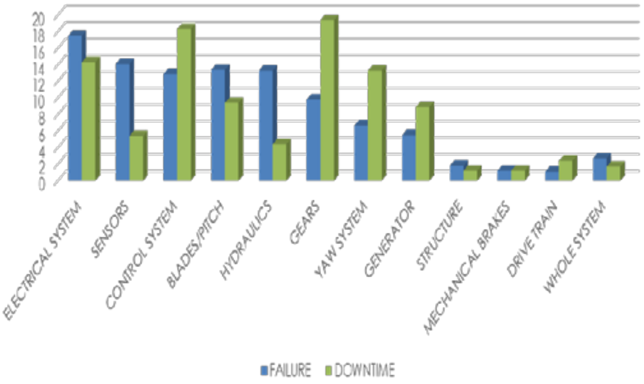

Figure 8: Subsystem failure rate and downtime summary.

3.3 Failures Modes in Structural subsystems

Faults in Tower structure and nacelle are usually caused by extreme weather conditions and by other failures in WT components.

1) A tower can fracture and collapse after being struck by blade. This can be during very high winds or in case of collapse of blade for many reasons. This causes the collapse of nacelle and all the WT components within the nacelle structure.
2) Nacelle and rotor severed from tower during a storm following problems with control system.
3) Metal fatigue.
4) Over speeding runaway turbine which is caused by failure of brake system can cause the collapse tower and nacelle as well as everything in the nacelle to the ground.
5) Hurricanes can topple to whole turbine as well as pull out the concrete foundation.

4. CONDITION MONITORING

WTs are usually installed in rural isolated areas or in sea areas off shore. This makes them not easily accessible for maintenance. In general, maintenance or replacement of faulty parts in a WT usually includes the cost of lifting equipment such as cranes as well as specialized crews which can create additional cost on the already expensive cost of spare parts, and the cost of loss of power generation due downtime created by the failure.

Therefore, research in the domain of fault diagnostics and condition monitoring of wind turbines has been gaining a lot of attention in the past decade. Not many articles are found in the literatures reviews concerning wind turbine condition monitoring and fault diagnosis [14, 19, 28, 47-53]. Some methods are listed below.

4.1 Comparison of Maintenance Approaches.

In WT systems, maintenance can be classified into predictive which are performed before a failure happens and corrective are performed after it happens. In general, Maintenance can be:

- Corrective maintenance, or run to failure.
- Preventive maintenance (schedule-based);
- Predictive maintenance (condition-based).

In the case of preventive maintenance, prevention cost can be quite high, but because failures will rarely happen, the repair costs will be low. In other words, preventive maintenance is expensive. With corrective or reactive maintenance, repairs will be expensive due to the fact that many failures will occur but prevention cost will be low. An intelligent mix between both strategies can improve the system reliability while reducing the maintenance cost. The estimated annual contribution of the corrective and scheduled condition-based maintenance to annual O&M cost is represented in Figure 9.

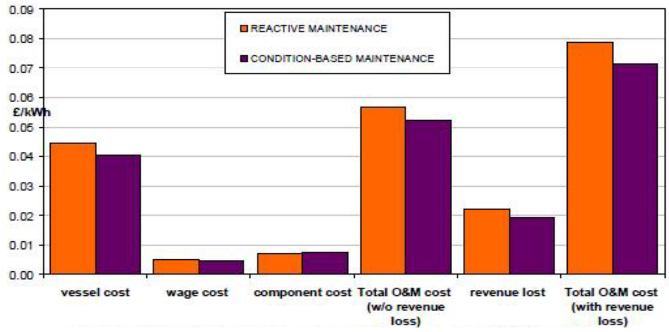

Figure 9: Cost of Energy in Relation to Type of Maintenance [65]

4.2 Condition Monitoring Techniques.

The Techniques are highlighted below and their usage is explained.

1) Vibration Analysis: is the most common technology used for condition monitoring of rotating equipment. The types of sensors used depend on the frequency range, relevant for the monitoring. For WTs, it is applicable for monitoring rollers and bearings of the gearbox, the main bearing and the generator bearings. Position transducers, velocity sensors, accelerometers, and spectral emission energy sensors are used for low, middle, high, and very-high-frequency ranges, respectively [3]. Due to the very big number of sensors, this approach can become very expensive as well as highly prone to sensor failures and false alarms.

Reviews on different methods like vibration measurements in the time and frequency domains, sound measurements, the shock pulse method and the acoustic emission technique have been studied [43,44].

2) Oil analysis: monitors the oil quality for contamination and moister, and safeguarding the components that are being lubricated for unusual characteristics. Oil analysis is mostly executed by taking oil samples off line. On-line analysis is also available now when access is limited. In many cases online debris analysis is becoming favourable in cases where faults can propagate very quickly. This type of approach will increase accuracy in detection and system reliability. Online detection technologies are generally three types: pressure drop sensing, electromagnetic sensing and optical debris sensing [45].
3) Thermography: used for monitoring and failure diagnosis of electronic and electric components. Heat generated (hot spots) from loose or bad contacts or degenerated components is detected. This method is generally not sufficient because component temperature can also be influenced by the surroundings. Therefore, it is nearly never used as a primary method of diagnosis but often as a secondary monitoring method. Nowadays, infrared cameras are being used to create images of cracks on rotor blades by visualization of blade temperature. This method can pinpoint cracks efficiently as well as impending threat of damage [46].
4) Visual Inspection: or observation can serve as a supplement to other monitoring techniques. It includes audible sound detections, and sensory detection of heat and vibration as well as inspection for malformations. This technique is used to monitor all visible components in a WT like rotor blades, nacelles, bearings, generators, yaw drive, etc.… This monitoring method depends a lot on the extensive experience of the inspector thus it is highly subjective and prone to personal errors.
5) Optical Fibre Monitoring: Optical fibre sensors are a very promising technology but still very expensive. Optical Fibre monitoring will have to wait some more years to become a cost effective method of monitoring. They might become very utile in detecting damage in rotor blades since they can be installed inside the blades and are not affected by any exterior conditions.
6) Electrical Stator Current Monitoring: Most wind turbine condition monitoring techniques require to collect signals from numerous mechanical sensors which are costly and difficult to implement in already installed wind turbines [3]. Electrical sensors installed inside and on the generator are being recommended by many authors in recent literature as they are easy to implement compared to the mechanical ones and they are non-evasive [47-50]. The measurement of the stator current of the generators can lead to the detection of both electrical failures and mechanical failures in the drive train, by looking at the harmonics in the stator current created by propagating faults. Stator current analysis has many advantages with respect to other detection and monitoring methods. In most cases, current and voltage signals can be acquired by extremal measuring devises like voltage and current transformers, during the machine operation. They are also non-invasive methods that require no sensors which in their own, sum up to 14% of faults that WTs suffer from. [52-55]. Electrical resistance can be used to detect defects in certain structural components of WTs. Since stiffness in the structures can cause a change in electrical resistance, any sudden variation can help detect fatigue damage. This method is still laboratory confined and theoretical [56].
7) Strain Measurements: usually used to predict the life time and high stress levels of the blades. Strain gauge sensors installed on the blade send out signals that are interpreted with signal processing algorithms. Geibal and al. [57] show in their study how strain gauge sensors can monitor load on the WT blades.
8) Acoustic Emission (AE) Monitoring: It functions through sensors which are glued by low attenuation flexible glue to the component. They “listen” for any abnormal sound, or audible noise. This method is considered more robust for low-speed operation of WT when compared vibration analysis. AE is more capable of identifying early faults in bearings of the gearbox. Primary cause of acoustic emissions in WTs are cracks propagating in metal and it has been successful in predicting early faults more efficiently than some methods such as vibration analysis method. Many authors have demonstrated the ability of AE fault detection in radially loaded ball bearings at different speed ranges, in monitoring bearings and gearboxes and for detecting damage in blades of a WT. [43, 58-59].

9) Shock Pulse Method (SPM): This method is a quantitative method that detects shocks that occur when a bearing ball comes in contact with debris or strikes a damaged area in the raceway. Piezoelectric Transducers a type of vibration sensors detect these signals which are compared against normalized shock values to give an alarm in case of fault [60].
10) Radiographic Inspection: Radiographic imagery or X-ray is advantageous for its accuracy in locating damage or cracks in WT blades and other internal structural components. X-rays are efficient in detecting very small cracks in the laminate of WT blades [61].
11) Ultrasonic monitoring (UT): The propagation of UT waves through the surface and subsurface of blades and tower allow the location of a defect also the type of this defect detected can be estimated, thus providing a reliable method of determining the material properties of WT components. UT is used to make images of the inner structure of a blade as well as for inspecting the multi-layered structure and pinpointing defects such as delamination. UT imagery can help find the shape of the defect as well as its dimension [62, 63]. Signal processing methods used to further interpret imagery by UT are time frequency transforms and wavelet transforms. [64].
12) Performance Monitoring: Power values, rotor rotational speed, wind speed and angle of blade are related to each other. These relations can be used to detect early signs of failures in WTs. Authors have studied the effect of flickering of voltage and power with turbulent wind as others have studied power and torque generated with wind time series taken in the field as measured by an anemometer.

5. DATA PROCESSESING TECHNIQUES

Various data processing techniques such as algorithms and models have been developed to analyse and interpret data to extract useful information for further diagnostic and prognostic purpose. Data processing techniques depend on the type of data collected. It can be value type data, waveform data or multidimensional data. Data processing for waveform or multidimensional data like imagery is called signal processing. Since Signals from WTs are usually non stationary due to the various loads applied on the system, precise data analysis is very important to have a reliable condition monitoring system. Many data processing methods have been reviewed in literature. The process of extracting information from any raw signal is called feature extraction. In the sections below, we will highlight the most used methods for signal processing and feature extraction in WT condition monitoring and diagnosis. In Table 3, the most widely used are listed.

5.1 Time and Frequency analysis techniques

Various data processing techniques such as algorithms and models have been developed to analyse and interpret data to extract useful information for further diagnostic and prognostic purpose. Data processing techniques depend on the type of data collected. It can be value type data, waveform data or multidimensional data [66]. Data processing for waveform or multidimensional data like imagery is called signal processing. Since Signals from WTs are usually non stationary due to the various loads applied on the system, precise data analysis is very important to have a reliable condition monitoring system. Many data processing methods have been reviewed in literature. The process of extracting information from any raw signal is called feature extraction. In the Sections below, will be highlighted the most used methods for signal processing and feature extraction in WT condition monitoring and diagnosis. Signal processing techniques for vibration data and acoustic data are called waveform data analysis. They can be either analysed in the time domain or in the frequency domain or in the time-frequency domain together.

5.2 Time domain analysis

Time domain analysis is the simplest of the three techniques mentioned. The time domain approach is based on the discrete time signal itself being directly analysed by filtering or averaging convolution or correlation.

It requires the computation and comparison of the statistical features available from the vibration data by which particular faults can be classified and identified. It calculates time domain features like peak to peak intervals, mean (μ), variance (σ2), Root Mean Square (RMS), Kurtosis (Kt), Skewness (Sn), and normalized central moments of higher order. This method is commonly used for analysing gear and bearing fault signals [48]. To calculate derivatives that are in random or arbitrary order, applying the Fast Fourier Transformation (FFT) on a time signal and then deriving it in frequency domain and then using inverse FFT to reconstitute the time signal is an efficient method.

5.3 Frequency domain analysis

Frequency domain analysis sometimes called spectral analysis. Frequency analysis is typically used for monitoring and diagnosis of gearboxes and machines that have roller bearings. Main failure manifests in the degradation of bearings, and this will exhibit an increase in characteristic frequencies related to the bearings. This method is widely used over time domain analysis for its ability to isolate certain frequency components that are of interest. The most used and conventional in spectral analysis is the power spectrum by means of Fast Fourier Transform (FFT) and the methods are:

1) Power spectrum: this uses the Fast Fourier Transform (FFT) which is a special case of discrete FT. It is employed to search for periodic peaks in the power spectrum [67]
2) Envelope Method: mainly consists of a band-pass filter followed by a demodulation and a fast Fourier transformation. To include resonance frequency, a band-pass filter should be used to focus on a range of frequencies which must be wide enough. For example the Hilbert transform is a type of envelope analysis that has been used for machine fault detection and diagnosis [68]. Other useful spectra for signal processing include Cepstrum. This spectrum analysis method has the ability to detect harmonics in power spectrum [69].

5.4 Time–frequency analysis

Time–frequency analysis uses more systematic band pass filter that are sharper and can provide a filtering of a wider range of oscillation frequencies, thus providing a more exact feature extraction from fault signals.

Time frequency analysis can be implemented using Wavelet Transform, Short Time Fourier Transform and Wigner-Ville distribution [70-71]. For variable-speed wind turbine operation, wavelet analysis has been recently accepted for feature extraction, as compared to faster Fourier transform (FFT) and envelop analysis tools developed earlier [66].

1) Wavelet Analysis Methods uses functions that assigns a frequency to each component by dividing the system to different scale components. It is a signal processing method in the time-frequency domain. It is isolated with respect to time and spatial location as well as isolated of frequency. The technique has been employed in different applications, but its use in fault diagnostics and monitoring of machines is still young. It decomposes a fault signal into a wavelet levels and issues a time-frequency rendition of that signal. Due to the finite length and the irregularity of shape of wavelets, this method has been proven to be successful in analysing transitory signals. Wavelet transform are still the most useful in predicting faults in the bearings and gearbox as well as predicting some generator faults. Wavelet transform come in three forms [70]:

a) Continuous Wavelet Transform (CWT): This technique gives information with regard to the correlation between the mother wavelet and the signal, which is being analysed in both time domain and frequency domain.
b) Discrete Wavelet Transform (DWT): In practice, one deals with discrete or sampled signals and DWT is mostly used. This transform permits a methodical decomposition of the signal into its sub band levels. Since each faults affects the system differently, in case of stator currents, the wavelet transform contributes a superior approach for features extraction, which contributes a solid premises for the extracting of the next feature.
c) Empirical Mode Decomposition (EMD) is used to decompose a nonlinear and non-stationary signal into a finite number of intrinsic modes without prior knowledge of the signal. This method is useful in detecting frequencies. Demodulation methods came into the light and they are becoming state of the art. Most electrical machine faults lead to stator current modulation in terms of amplitude and frequency.
d) These signature manifest in faults like bearings, gearbox, broken rotors and shaft misalignment.

Various authors have studied fault diagnostic methods and condition monitoring techniques for machinery, in general and for WT in particular. Vibration measurement is a very typical choice of monitoring method for gearbox. Spectrum analysis is also a popular choice. Earlier, authors like Hameed.Z et al [48] and C.Hatch [72], have developed the FFT and the envelop methods. In later years, Time-Frequency analysis and in particular wavelet transforms has been widely accepted for feature extraction in cases of variable speed WT operation. Huang and al. [73] studied gearbox fault classification using wavelet neural network based on vibration spectrum analysis.

S.Yang et al. [74], presented a study for gearbox faults classification as well as a neural network based diagnostic method. W.Yang et al. [51], used discrete wavelet transform (DWT) to deal with the noise-rich signals from wind turbine measurements, also the authors used electrical signal analysis to identify mechanical faults on the drive train and for gear eccentricity. D.J.lekou et al. [75], studied the usage of vibration monitoring in parallel with Acoustic Emission (AE), temperature data and rotational speed data to monitor WT health.

The statistic study proved that AE data is a very reliable indicator that damage exists and to what extent the severity of the damage is during dynamic operation of wind turbine. Authors like M.R.Wilkinson et al. [76], studied the utility that the torque measurement has for drive train fault detection. When a fault happens inside the rotor, a shift in the torque-speed ratio may occur. By using this information detection of rotor faults like rotor imbalance is made possible. Also an important method of fault detection in gearbox bearings is based on the finite element simulation. Chen et al. [77] used wavelet transforms on the output signals of a finite element simulation which was set up to diagnose the stress level of roller bearings in a WT gearbox. Doguer and Strackeljan [78] studied the vibration structure generated by small roller bearings defects and applied suitable time domain features to extract 32 features from the time signal. Two test rigs were set up. Their method proved to be useful in cases of high order derivatives.

Generators are the main cause of faults in WT, whereas gearboxes are the main cause of downtime. Induction generators are the most popular currently in the WT industry and 40% of their faults are related to bearings, while 38% and 10% are related to stator and rotor respectively. Induction machines manifest many fault phenomena which include but are not limited to rotor unbalance, increased torque pulsations and decreased torque, harmonics in phase current etc.

Some authors studied the recent advancement of condition monitoring on rotating machinery in general and on WT generators in particular Lu et al. [32] and . Amirat et al. [19] reviewed the recent advancements in rotating machinery condition monitoring systems. S.Watson et al [49] were interested in the power output of the generator of a WT and experimented on a condition monitoring system using wavelets. Khaled B et al. [50] studied a condition monitoring system based on electrical torque pulsation measurements for a WT generator. Shorted winding coil is a very critical electrical fault which affects the generator synchronous reactance and which propagates rapidly where immediate action should be taken. W.Yang et al. [53] diagnosed the shorted coil by applying mechanical and electrical signatures. Current, voltage and power proved to be effective in detecting shorted winding coil as well as the torque speed signatures. But winding coil defects are very fast in comparison to other mechanical faults so accuracy and response time is a matter to be addressed when dealing with diagnosis of such defects.

Wilkinson et al. [76] detected shorted coil by using the shaft speed through wavelet analysis. E. Al-Ahmar et al. [54] Conducted a study based on DFIGURE (Double fed induction generator), using a specific discrete wavelet transform. Popa et al [34] conducted an experimental study on fault diagnosis of a DFIGURE. S.Watson and Xiang [79] used the power signal of the generator to detect rotor misalignment and bearing faults, also applying both FFT and wavelet analysis. The results showed the utility of their method in detecting faults earlier on.

S.Watson and Dorrell [80] as well as other authors [81-83] have suggested the use of the stator current to obtain induction machine condition. The machine faults are related to current harmonics because the relation between them is well established. These authors studied stator-winding faults, rotor bars fault, static and dynamic eccentricity and bearing faults. Benbouzid [84] introduced a feature extraction technique for a motor's signature, for prediction of its health. The harmonic content of motor currents and the instantaneous power are used to predict the health. A bispectrum, high-resolution spectrum and wavelet transform as a medium tools for motor fault detection are used and compared. Their study can be used as guidelines for selecting the most appropriate diagnosis tool for motor diagnosis.

Benbouzid [84] and Najjari [85] have used Park's vector patterns for detecting machine supply faults, such as voltage imbalance and single phasing. Sam [86] and Sarkar [87] applied wavelet transform for condition monitoring of three-phase induction motor. The harmonics of the stator current, have a relation with the motor health conditions.

Two difficulties appeared; the fluctuation in the machine speed and supply frequency. Their experiment showed that the application of wavelet transform for the detection of twice slip frequency in the stator current was unsuccessful The other subsystems of the drive train which include rotor blades, pitch control and hydraulic system also manifest faults. Strain measurement is a typical method for studying the integrity of rotor blades.

G.Geibal and al. [88] show in their study how strain gauge sensors can monitor load on the WT blades. Similarly, M. Volanthen [89] and L. Boger et al [90], used strain measurement methods with fibre optics. Authors like T.Buono et al [91] studied the utility of AE sensors for fault detection, while Yuzi et al [92] studied detection by shock pulse method through piezoelectric impact sensors. Maintaining Blade pitch control is important for the healthy operation. Pitch control is usually run by hydraulic actuators and electric motors. While both are very useful, hydraulic actuators are more robust in extreme aerodynamic loading situations. Pitching angle is very important, any asymmetry in it will lead to complete shutdown. Y. Kong and Z. Wang [93] created a dynamic model for the hydraulic pitch mechanism in the case of variable speed WT. They used the control signal of the pitch system for fault detection in the valve.

6. PATTERN RECONGNITION TECHNIQUES

Faults diagnostics of machinery depend on pattern recognition of information which can be done manually by highly trained personnel. This can be done with graphical tools such as spectrum graphs, wavelet phase graphs, power spectrum and phase spectrum graphs, etc.… but human error is always an issue. This makes automatic pattern recognition highly desirable. Signals can be classified according to the extracted information and features of these signals. Statistical, Artificial Intelligence (AI) diagnostic methods and model-based diagnostic methods will be emphasized below.

6.1 Statistical Approach

Statistical approach is a common method of fault diagnostics is to detect whether a specific fault is present or not based on the available condition monitoring information without intrusive inspection of the machine.

1) <u>Statistical Process Control (SPC)</u>. This is a conventional method that works in separating the historical data of each machine life cycle into two zones: stable zone and failure zone. The principle behind this method is to measure the deviation between normal operating conditions that are represented by a reference signal and the current signal to see whether the current signal is within the control limits or not.
2) <u>Cluster Analysis</u>: this is a multivariate analysis method. This approach groups signals into categories of faults based on the similarity of their extracted features. Results of a cluster analysis is a number of different groups with similar signals within the same group. Grouping signals depends on certain similarity distance measures between two signals. Some of these distance metrics are Euclidean distance, Mahalanobis distance, Kullback–Leibler distance and Bayesian distance [94-96].
3) <u>Hidden Markov Model (HMM)</u>: is a tested model for condition monitoring data and analysing it. The model is made up of two stochastic processes: a Markov chain with finite number of states describing an underlying mechanism and an observation process depending on the hidden state.

6.2 AI Approach

AI techniques have been increasingly applied to machine diagnosis and have shown improved performance over conventional approaches. In practice, however, it is not easy to apply AI techniques due to the lack of efficient procedures to obtain training data and specific knowledge, which are required to train the models. So far, most of the applications in the literature just used experimental data for model training. In literature, the below listed are the most popular AI techniques for machine diagnosis.

1) <u>Artificial Neural Networks (ANN)</u>: is a computational model which consists of a network of parallel interconnections that mimic the structure of the human brain. It is made up of simple processing elements or neurons that comprises a node and a weight. ANN is “trained” to learn about an unknown function by observing the input and output and then adjusting its weights. A principle benefit ANN model is its ability to diagnose signals that are fuzzy. The main limitation in ANN is the difficulty in the training process as well as the physical interpretation of the trained model.

2) Evolutionary algorithms (EA): which are mainly genetic algorithms and they copy the natural evolutionary process of a population. They have proved their success in machine fault diagnosis. They include the likes of artificial ant and bee colonies. The Artificial Bee Colony (ABC) algorithm is a swarm intelligence approach which duplicates the intuitive deportment of foraging honey bees. The first studies done on ABC algorithm were testing the performance against other well-known algorithms like the Genetic Algorithm (GA), Differential Evolution (DE), and Particle Swarm Optimization (PSO),
3) Expert systems (ES): use domain expert knowledge in a computer program to perform reasoning for problem solving. This comes in contrast to ANNs which learn knowledge by observation of data with known inputs and outputs. ESs consist of many reasoning methods but the main ones are model-based, case-based and rule-based reasoning methods. ES have a main limitation with the reasoning. This phenomenon is called combinatorial explosion which refers to the computation problem caused when the number of rules increase exponentially as the number of variables increases.

6.3 Model Based Approach

This approach is based on the mathematical model of the machine to be monitored. Methods of residual generation such as Kalman filter and parameter estimation are dependent on residual signals which indicate presence of a fault in a machine. These approaches are very effective in comparison to model free methods when based on accurate model design.

J. Ma and C.J .Li [97] have used hypothesis testing for fault diagnosis. This testing method can be described based on two hypothesis problems; a null hypothesis H0: Fault X is present, against an alternative hypothesis H1: Fault X is not present. Test statistics are constructed in order to be able to decide whether to accept the null hypothesis H0 or not. Fugate et al. [98] discussed the use of SPC in fault detection. In his book, A.R. Webb [99] highlights many cluster methods for determining signal groups. C.K Mechefske [100] studied a commonly used algorithm in machine fault classification. It is called "nearest neighbour algorithm" and it works in combining two groups that are the closest into one new group. It then calculates the "nearest neighbour" distance between two separate groups. Q. Sun et al. [101] spoke about pattern recognition and how to determine the boundary distance between two adjacent groups by using a discriminant function.

Many authors used different types of distance measures or distance metrics in their literature. Pan et al. [102] are proposing an extended symmetric Itakura distance for signals represented in time–frequency distributions. Ding et al. [103] in their work were studying a new distance metric for machine fault diagnosis called the quotient distance. A technique called support vector machine (SVM) is usually employed to optimize a boundary curve in the sense that the distance of the closest point to the boundary curve is maximized [104].

The HMM described earlier is also a very useful method in fault diagnosis and has been studied by many authors in literature. In recent studies, M. Ge et al. [105] and Z. Li et al. [106] both considered an HMM with hidden states having no physical meaning for each machine condition (normal and faulty). They then used the trained HMMs to decode an observation with an unknown machine condition. Y.Xu and M. Ge [107] offered an HMM based intelligent fault diagnosis system. D. Ye et al. [108] introduced a new application of a two-dimensional HMM based on time–frequency analysis. The application of ANNs in machine fault diagnosis has been studied by many researchers. Many models are available.

The most widely used ANN in machinery fault diagnosis is the Feedforward neural network (FFNN) structure with Back Propagation (BP) training algorithm [79, 109-111]. In earlier years a special case of FFNN was applied for pattern recognition and classification in machine fault diagnosis. Nejjari and Benbouzid [84-85], studied a FFNN with a BP training algorithm to test the machine condition by testing the patterns of the park vectors, the authors experimental result claim the reliability of this method.

Z. He et al. [112] studied the application of a multilayer feedforward network. B.A Paya et al. [113] applied FFNN as a diagnosis method for rotating machines using wavelets. B. Samanta et al. [114] applied time frequency domain features with

FFNN to diagnose bearings. W.R Becraft and P.L Lee [115] developed an AI system for the fault diagnosis in industrial scale chemical process plants. Another type of neural network is cascaded correlation neural network (CCNN). CCNN have some advantages in comparison with FFNN.

The main difference is that the network structure and the number of nodes need not be determined at the initial stage. Also CCNN is preferable with online training. J.K Spoerre [116] used CCNN for the classification of bearings fault and proved the reliability and accuracy of this technique in diagnosing faults by using minimum knowledge about the networks structure. Neural networks can be one of two types; supervised and unsupervised.

The ones that are mentioned above are supervised. Supervised neural networks are trained using sets of experimental data for known faults. Unsupervised neural networks teach themselves from new information and do not depend on external input.

TABLE 3: Typical Methods of Data analysis

Data Analysis Technique	**Commonly Used Method**	**Faults Analyzed.**
Time and frequency analysis techniques		
Time domain	Fast Fourier Transform (FFT)	Analyzing gear and bearing fault signals
Frequency domain	Power spectrum	Monitoring and diagnosis of gearboxes and machines that have roller bearings
Time-Frequency domain	Wavelet transform	Bearings and gearbox faults, generator faults like shortened coil by use of shaft speed.
Pattern Recognition Techniques		
Statistical analysis	Cluster Analysis	Electric machine faults
Artificial Intelligence	Artificial Neural Network (ANN) Expert Systems (ES) Neural/Fuzzy or Fuzzy/Neural	Electric machine faults and generator maintenance Bearing fault Induction motor faults
Model-based	Kalman filters	Faulty physical parameters of DFIG.

R.M Tallman et al. [117] were interested in applying unsupervised self-training neural networks for the electrical machine faults classification. Various researchers have become interested to fuse Fuzzy logic with neural networks as well as Neural Network with EA and ESs for better decision making.

She et al. [112] discussed the fuzzy relationships between symptoms and causes of faults. They also reviewed the high nonlinearity between the input and the output of the network. S. Mitre and S. Pal [118] looked into the application of the fuzzy version of the multilayer perceptron. Buckley and Hayashi [119] describe the construction of a hybrid neural net that is identical computationally to a fuzzy logic expert system. Ahmed and Kothari [120] have reviewed traditional mathematical techniques for generator maintenance as well as various advanced diagnostic methods, such as ESs, fuzzy logic, and EAs for generator maintenance.

An example was presented in [121] for the application of fuzzy logic in the classification of frequency spectra representing several bearing faults. Depold and Gass [122] studied the combined application of both neural networks and ESs in gas turbine diagnostics.

Liu et al. [123] applied fuzzy logic and ESs to build a fuzzy ES for bearing fault detection. Yang et al. [124] applied a case-based ES combined with an ART-Kohonen neural network to enhance fault diagnosis. Their study showed that this approach outperformed the map-based system with respect to classification rate. Penman and Yin [125] discussed the feasibility of using unsupervised neural network for condition monitoring of three phase induction motor. They used the Kohenen's feature map. Vibration harmonics are inputs. The condition of the machine was reflected by watching the outputs. The conclusion for their study was that accuracy in fault diagnosis using an unsupervised neural networks is less than when applying a supervised, but it is more convenient for automatic diagnostic due to the fact that it doesn't depend on external data and can teach itself. Goode [126] and Chow [127] have presented in two papers the methodology of extracting heuristic knowledge from neural/fuzzy system based incipient faults of induction motors. These authors were able to use the quantitative information obtained from the neural network to provide qualitative information concerning the health of a machine. The faults of the bearing and the stator winding of a single phase induction motor are considered and the authors based the machine diagnosis on the current and speed of the rotor.

Bennouna et al. [128-130] conducted various studies based on the model-based approach with residual analysis. They showed that this method has an advantage in identifying the faulty physical parameters in a DFIGURE generator which unlike signal signatures are not dependent on the load conditions. But it was in [130] that in case of a nonlinear system like a generator with variable speed, linearization is necessary because the analysis was based on a linear system assumption. Durovic et al. [131] like Bennouna el al. [128-130] had the same idea of identifying abnormally manifested physical parameters and conducted another model-based diagnosis study on DFIG wind turbine. The faults considered were winding unbalance and excitation unbalance on either the stator or rotor. They constructed a test rig with a 4-pole and 30-kW wound-rotor machine, coupled to a converter-controlled DC machine and their results were verified with experimentation.

Authors like Karaboga et al. [132-133], emphasized the importance of how genetic algorithms like the artificial bee colony can optimize system feature extractions using the natural selection by conducting a comparison between various methods.

7. CONCLUSION

WT have made a huge advancement in technology in the recent years and the increasing number of WT installed in farms that are connected to power grids require a very reliable operation. But even with increased popularity, WTs still suffer from failures in the different levels of their assembly. As illustrated in Figure 8 of this paper, the main failure issues for WT are related to the gearbox, the generator and the electronic control system, which are the elements that cause the most downtime to the whole WT system.

These failures are interrelated because, defects in generator and control system, among other defects can propagate to cause torsional reversal in the bearings of the gearbox that can cause severe to gearbox itself.

Failures in the Sensors are known to be frequent and are cause of 14% of total system failures. Grid related faults can also affect the grid side converter causing short circuit failures to propagate into the control system and then into the generator. O. Beniuga et al. [134 -135] have studied and assessed the effect of grid disturbances on WT converters and the methods of protection. In fact, authors like Peter Fogh Odgaard and al. [65-66], who are addressing these matters in an interesting manner, proposed a complete WT model as a test benchmark and performed many severe fault scenarios to study the best fault detection and isolation technique, and also extended their studies to a benchmark wind farm model to further study the faults that are better monitored at a farm level.

From the above bibliography review, fault detection methods for WT drive trains were mainly based on vibratory analysis and acoustic analysis which till this day are the go to and most reliable. But they are based on the collection of data through a large number of sensors that themselves can become faulty. It is interesting to combine the stator current signature analysis method with different pre-processing methods like Neural Networks that can be equally successful and even better.

It is clear that the most successful data processing methods and widely used ones are based on the time-frequency analysis. DWT in the time-frequency domain helps extract features from stator currents in the various faulty conditions, but the issue is that there is a very large number of features that can affect the calculation time directly. To overcome this matter, AI methods of data analysis have shown a superior ability to detect faults such as ANN function with less computation time and with no need for prior knowledge of system model parameters. ANN are a sophisticated machine learning technique that are applied to solve problems of classification as well as predictions.

For a future extension of this he study which is a part of a PhD research, a model of an advanced ANN algorithm to deal with the fault diagnosis and classification problem, optimized with an ABC algorithm to select significant features prior extracted by a DWT, and that are carrying the best information in order to optimize the ANN will be done. Such an ANN-ABC hybrid technique looks very promising. The future research will be implemented in a way where several severe faults will be simulated on the drive train and generator of WT equipped with DFIG. The stator current signal will be measured and containing the fault harmonics will be analysed by DWT. As a result of that, fault data matrix will be extracted and used for training and testing the ANN. A precise method for diagnosis and classification of faults by confusion table methods will help prove the hypothesis that the ABC has the ability to isolate the signals with the most important features, thus decreasing the number of useless features yielding less computation time and producing a better classification for the ANN.

REFERENCES

1. Z. Daneshi-Far, G. A. Capolino, H. Henao, “Review of Failures and Condition Monitoring in Wind Turbine Generators”, XIX International Conference on Electrical Machines - ICEM 2010, Rome., pp. 1-6
2. M. Pappalardo, “Diversification of wind electricity generation for creating a French industrial development (in French)”, presented at ASE Conference, Paris, France, 2010.
3. P. Tchakoua, R. Wamkeue, M. Ouhrouche, F. Slaoui-Hasnaoui, T. Andy Tameghe, and G. Ekemb, “Wind Turbine Condition Monitoring: State-of-the-Art Review, New Trends, and Future Challenges”, Energies 2014, 7, pp. 2595-2630.
4. J. Ribrant, “Reliability Performance and Maintenance,“A Survey of Failures in Wind Power Systems”, Master’s Thesis, School of Electrical Engineering, KTH Royal Institute of Technology, Stockholm, Sweden, 2005–2006.
5. H. Arabian-Hoseynabadi, H. Oraee, P.J. Tavner, “Failure Modes and Effects Analysis (FMEA) for wind turbines”, Electrical Power and Energy Systems 32 , 2010, pp. 817–824.
6. S. Nasr et N. Moubayed, “ Etude comparative entre éolienne à axe horizontal et éolienne à axe vertical “, Bulletin of the Polytechnic Institute of Jassy, Tome VII, Fascicule 5, 2011, pp. 145-157.
7. H. Al-Sheikh, O. Bennouna, G. Hoblos et N. Moubayed, “Study on power converters used in Hybrid Vehicules with Monitoring and Diagnostics Techniques” ,17th IEEE Mediterranean Conference (MELECON 2014), Beirut, Lebanon, 13-16 April 2014, pp. 103-107.
8. A. Beainy, N. Moubayed, C. Maatouk et F. Kaddah, “Decision on Failure Diagnosis and Condition Monitoring technique for Wind Conversion Systems”, the 41st Annual Conference of IEEE Industrial Electronics Society (IECON 2015), Yokohama, Japon, Novembre 9-13, 2015, pp. 5148-5155.
9. A. Beainy, N. Moubayed, C. Maatouk et F. Kaddah, “Méthodes de Diagnostic et de Pronostic Pour Les Défaillances de L'Éolienne” , Les 3ème Journées Franco-Libanaises (JFL3 2015), Beyrouth, Liban, Octobre 29-31, 2015.
10. S. K. Bisoyi, R.K.Jarial, R.A.Gupta, “A Review Of The State Of The Art Of Generators And Power Electronics Converter Topologies For Wind Energy Conversion System”, International Journal of Emerging Technology and Advanced Engineering Volume 3, Special Issue 3: ICERTSD 2013, Feb 2013, pp. 283-291.
11. E.Chavarria, E.; Hahn, B.; van Bussel, G.J.; Tomiyama, T. “Reliability of wind turbine technology through time”. J. Sol. Energy Eng. 2008, 130, pp. 6-13.
12. A. El-Ali, N. Moubayed et R. Outbib, « L’éolienne : Historique, composants et principe de fonctionnement », IEEI’08, 2nd International Symposium on the History of the Electrical Engineering and of Tertiary-Level Engineering Education, 3-5 Octobre 2008, IASI – Roumanie, Vol. 4, pp. 13-20
13. B.Hahn, M. Durstewitz.; K. Rohrig. “Reliability of Wind Turbines. In Wind Energy”; Springer: Berlin/Heidelberg, Germany, 2007; pp. 329–332
14. P.J. avner, J. Xiang, F. Spinato, “Reliability analysis for wind turbines”. Wind Energy 2007, 10, pp. 1–18.
15. F.Spinato, PJ Tavner, G.J.W Van Bussel,.; E Koutoulakos. “Reliability of wind turbine subassemblies”. IET Renew. Power Gener. 2008, 3, pp. 387–401.
16. H.Guo, S.Watso, P.jTavner, J Xiang, “Reliability analysis for wind turbines with incomplete failure data collected from after the date of initial installation”. Reliab. Eng. Syst. Saf. 2009, 94, pp. 1057–1063.
17. K. Fischer, F. Besnard, L. Bertling, “Reliability-centered maintenance for wind turbines based on statistical analysis and practical experience.” IEEE Trans. Energy Convers. 2012, 27, pp. 184–195.
18. R. Ahmad, S. Kamaruddin,. “An overview of time-based and condition-based maintenance in industrial application”. Comput. Ind. Eng. **2012**, 63, pp. 135–149
19. Y. Amirat, M.E.H Benbouzid, B Bensaker, R Wamkeue, “Condition Monitoring and Fault Diagnosis in Wind Energy Conversion Systems: A Review”. In Proceedings of the IEEE International Electric Machines & Drives Conference, IEMDC ’07, Antalya, Turkey, 3–5 May 2007;Volume 2, pp. 1434–1439.
20. B. Hahn, “Reliability Assessment of Wind Turbines in Germany”. The 1999 Europeen Wind Energy Conference, Nice, France, March 1999, 1–.tenberg, H Holttinen.,”Analysing Failure Statistics of Wind

Turbines in Finland", European Wind Energy Conference, April , 2010, Warsaw, Poland, pp.20-23

21. K. Alewine' " Wind Turbines Generator Failure Modes," Presentation for Shermco Industries; 2011.
22. Fraunhofer-Institute for Wind Energy and Energy System Technology, Germany, " Energy Wind Report", 2013.
23. M. A. Aziz, H. Noura, A. Fardoun, "General review of fault diagnostic in wind turbines", 18th Mediterranean Conference on Control & Automation, Congress Palace Hotel, Marrakech, Morocco, June 2010, pp. 23-25.
24. P. J. Tavner, F. Spinato,, G. Van Bussel, E .Koutoulakos, "Reliability of different wind turbine concepts with relevance to offshore application," European Wind Energy Conference (EWEC2008), Brussels, Belgium, April 2008, pp. 21-24
25. P. J. Tavner, G. Van Bussel, F. Spinato, "Machine and converter reliabilities in wind turbines," in Proc. 2006 IET 3rd International Conference on Power Electronics, Machines and Drives, pp. 127-130.
26. H. Polinder, F. F. A. Pijl, G-.J. Vilder, and P. J. Tavner, "Comparison of Direct-Drive and Geared Generator Concepts for Wind Turbines, " IEEE Transactions on Energy Conversion, vol. 21, n° 3, , Sept. 2006, pp. 725-733.
27. C.J Crabtree, Y Feng; PJ Tavner. "Detecting Incipient Wind Turbine Gearbox Failure: A Signal Analysis Method for On-line Condition Monotoring". In Proceedings of European Wind Energy Conference (EWEC 2010), Warsaw, Poland, 20–23 April 2010; pp. 154–156.
28. M. Zhao, D. Jiang, S. Li, "Research on Fault Mechanism of Icing of Wind Turbine Blades" State Key Laboratory of Control and Simulation of Power System and Generation Equipment, 2009; pp. 1-4.
29. L. Solero, "Power Electronic converters devoted to stand-alone wind energy generating systems", EPE Journal, Vol. 12, Nº 2, mai 2002, pp. 43-48.
30. R. Spée, S. Bhowmik," Novel control strategies for variable speed doubly fed power generation systems", Renewable Energy, Vol. 6, Nº 8, pp. 907-915, Mars 1993.
31. J.S Lee, K.-Beum Lee, F. Blaabjerg "Open-Switch Fault Detection Method of an NPC Converter for Wind Turbine Systems", IEEE Transactions On Industry Applications, 2013, pp. 325, 335.
32. B. Lu, Y. Li, X. Wu,; Z Yang, "A Review of Recent Advances in Wind Turbine Condition Monitoring and Fault Diagnosis". In Proceedings of the IEEE Power Electronics and Machines in Wind Applications, PEMWA 2009, , USA, 24–26 June 2009, pp. 1–7.
33. K. Ma, M. Liserre, F. Blaabjerg,"Operating and Loading Conditions of a Three-Level Neutral-Point-Clamped Wind Power Converter Under Various Grid Faults", IEEE Transactions On Industry Applications, Vol. 50, No. 1, January/February 2014, pp. 520-530.
34. L. M. Popa, B.B. Jensen, E. Ritchie, and I. Boldea, "Condition monitoring of wind generators," in Proc. IAS Annu. Meeting, vol. 3,2003, pp. 1839-1846.
35. O. Wasynczuk, D.T. Man et J.P. Sullivan, "Dynamic behavior of a class of wind turbine generators during random wind fluctuations", IEEE Transactions PAS, Vol. 100, Nº 6, 1981, pp. 2837 – 2845
36. M. Nie, L. Wang, "Review of condition monitoring and fault diagnosis technologies for wind turbine gearbox", 2nd International Through-life Engineering Services Conference, 2013, pp. 287-290.
37. W. Musial, S., B. McNiff, "Improving Wind Turbine Gearbox Reliability," National Renewable energy Laboratory, European wind Energy Conference paper, 2007, ref: NREL/CP-500-41548, pp. 1-18
38. D. Heidenreich, Chief Engineer, Wind Products and D. Herr, Wind Products Manager, PT Tech Inc, "Why Wind Turbine Gearboxes Fail", 2013, AVAILABLE ONLINE http://www.aerotorque.com/images/company_assets/F538C9D0-9954-49D1-A425-05493F7E7EB4/PTTechWhitePaper2013_d4b0.PDF
39. S. Sheng, M. McDade, R. Errichello, "Wind Turbine Gearbox Failure modes, a brief", ASME/STLE 2011International Joint Tribiology Conference, 2011, NREL/PR-5000-53084, pp.. 133-148
40. A. B.Borcehrsen, J. A. Larsen, J. Stoustrup" Fault Detection and Load Distribution for the Wind Farm Challenge", Proceedings of the 19th IFAC World Congress, 2014 , PP. 4316-4321.
41. A. Stenberg, H. Holttinen, "Analysing failure statistics of wind turbines in Finland", proceedings of the EWEC 2010, warsaw poland..
42. N. Tandon, B.C Nakra, "Vibration and acoustic monitoring techniques for the detection of defects in rolling element bearings; a review". The Shock and Vibration Digest, 1992, 24(3), 3-11
43. N. Tandon, N., A. Choudhury, "A review of the vibration and acoustic measurement methods for detection of defects in rolling element bearings". Tribology International, 1999, 32(8),469e480
44. A. Hamilton, F. Quail, "Detailed state of the art review for the different on-line/in-line oil analysis techniques in context of wind turbine gearboxes". J. Tribol. 2011, 133, doi:10.1115/ 1.4004903.
45. L.Dolinski, M. Krawczuk, "Damage detection in turbine wind blades by vibration based methods", 7th international conference on modern practice in stress and vibration analysis. Journal of Physics: Conference Series, 2009. 181, 012086
46. B.N Madsen,"Condition Monitoring of Wind Turbines by Electric Signature Analysis". Master's Thesis, Technical University of Denemark, Copenhagen, Denmark, October 2011
47. F.P García, A.M Tobias, J.M Pinar, M Papaelias, "Condition monitoring of wind turbines", Techniques and methods. Renew. Energy 2012, 46, 169–178.
48. Z. Hameed, Y.S Hong, Y.M Cho, Y.M.; Ahn, S.H.; Song, C.K. "Condition monitoring and fault detection of wind turbines and related algorithms: A review". Renew. Sustain. Energy Rev. 2009, 13, 1–39.
49. S. Jonathan Watson, B. J. Xiang, W. Yang, P. J. Tavner, C. J. Crabtree, "Condition Monitoring of the Power

Output of Wind Turbine Generators Using Wavelets" Ieee Transactions On Energy Conversion, Vol. 25, No. 3, September 2010; 715-721.

50. K. B. Abdusamad, D.W. Gao, Y. Li, "Condition Monitoring System Based on Effects of Electrical Torque Pulsations of Wind Turbine Generators" PES General Meeting | Conference & Exposition, 2014 IEEE; pp. 1-5.
51. W. Yang, P.J Tavner, and M. Wilkinson, "Wind turbine condition monitoring and fault diagnosis using both mechanical and electrical signatures," in Proc. 2008. IEEE International Conference on Advanced Intelligent Mechatronics; 1296-1300.
52. R.F Orsagh, H. Lee,. M. Watson, C.S Byington, "Power, J. Advance Vibration Monitoring for Wind turbine Health Management"; Impact Technologies, LLC: Rochester, NY, USA, 2006.
53. W. Yang, P. J. Tavner, M. R. Wilkinson, "Condition monitoring and fault diagnosis of a wind turbine synchronous generator drive train," IET Renewable Power Generation, Vol. 3, n°1, 2009; 1-11,.
54. E. Al-Ahmar, M. Benbouzid, Y. Amirat, S. Ben Elghali, "DFIG based wind turbine fault diagnosis using a specific discrete wavelet transform," in Proc. 2008. IEEE International Conference on Electrical Machines (ICEM'2008); 1-6.
55. D.C Seo, J.J Lee, "Damage detection of CFRP laminates using electrical resistance masurement and neural network". Composite Structures, 1999, 47, 525-530
56. G. Giebel, G. Oliver, M. Malcolm, B. Kaj, "Common access to wind turbines data for condition monitoring.", In Proceedings of the 27th Riso international symposium on material science ;157-164. Denmark: Riso National Laboratory
57. C.C Tan, "Application of acoustic emission to the detection of bearing failures". In Proceedings tribology conference, Brisbane, 1990 , 110-114.
58. N. Tandon, G.S.Yadava, K.M Ramakrishna, "A comparison of some condition monitoring techniques for the detection of defect in induction motor ball bearings". Mechanical Systems and Signal Processing 2007, 21(1), 244-256
59. J. Wei, J. McCarty," Acoustic emission evaluation of composite wind turbine blades during fatigue testing". Wind Engineering 2003, 17(6), 266-274
60. N.Tandon, B.C Nakra,"Comparison of vibration and acoustic measurement techniques for the condition monitoring of rolling element bearings". Tribology International, 1992, 25(3), 205e212.
61. R.Raisutis, E. Jasiunien, R.Sliteris, A. Vladisauskas, "The review of nondestructive testing techniques suitable for inspection of the wind turbines blades". Ultragarsas (Ultrasound), 2008, 63(1), 26-30.
62. J. Knezevic, "Reliability, maintainability and supportability engineering: A probabilistic approach". London, 1993, UK: McGraw-Hill.
63. R.Raisutis,E. Jasiunien, E. Zukauskas," Ultrasonic NDT of wind turbines bladesusing guided waves", 2008. In Ultrasound (vol. 63(1), 7-11. Kaunas: Technologija.
64. C.S Tsai, C.T Hsieh, S.J Huang, S. J., "Enhancement of damage detection of wind turbines". IEEE Transactions on Energy Conversion 2006, 21(3), 776-781
65. P. F. Odgaard, J. Stoustrup, Michel Kinnaert, "Fault-Tolerant Control of Wind Turbines:A Benchmark Model", IEEE Transactions On Control Systems Technology, Vol. 21, NO. 4, July 2013, pp. 1168-1182
66. P. F. Odgaard, J. Stoustrup,, "Fault Tolerant Wind Farm Control - a Benchmark Model", 2013 IEEE International Conference on Control Applications (CCA) Part of 2013 IEEE Multi-Conference on Systems, Hyderabad, India, August 28-30, 2013, pp. 412-417
67. L. Pratyusha , S. Priya , VPS Naidu, "Bearing Health Condition Monitoring: Time Domain Analysis", IJAREEIE, Vol. 3, Special Issue 5, December 2014, pp. 75-82.
68. V. Wowk, "Machinery Vibration: Measurement and Analysis", McGraw-Hill, New York, 1991.
69. M.A Minnicino, H.J. Sommers," Detecting and quantifying nonlinearity using the Hilbert transform" in, Health Monitorong and Smart Nondestrcutive Evaluations of Structural and Biological Systems III, vol.5394, Bellingham, 2004, pp. 419-427.
70. C.M. Harris, A.G. Piersol, "Harris' Shock and Vibration Handbook", McGraw-Hill, NewYork, 2002.
71. M. Boufenar, S. Rechak, M. Rezig, "Time-Frequency Analysis Techniques Review and their Application on RollerBearings Prognostics", Proceedings of the Second International Conference on Condition Monitoring of Machinery in Non-Stationary operation (CMMNO'2012), published by Springer 2012, pp. 239-246.
72. C. Hatch, "Improved wind turbine condition monitoring using acceleration enveloping," Orbit, 2004, pp. 58-61.
73. Q. Huang, D. Jiang, L. Hong, Y. Ding, "Application of wavelet neural networks on vibration fault diagnosis for wind turbine gearbox," Lecture Notes in Computer Science, vol. 5264 LNCS, PART 2, Advances in Neural Networks, [Proc. 5th Int.Symposium on Neural Networks, 2008, pp. 313-320.
74. S. Yang, W. Li, C. Wang, "The intelligent fault diagnosis of wind turbine gearbox based on artificial neural network," Proc. 2008 Int. Conf. on Condition Monitoring and Diagnosis, pp. 1327-1330
75. D. J. Lekou, F. Mouzakis, A. Anastasopoulos, D. Kourousis,"Emerging techniques for health monitoring of wind turbinegearboxes and bearings," in Proc. EWEC 2009, Scientific Track –Operation and Maintenance, Marseille, France, March 16-19, 2009
76. M. R. Wilkinson, F. Spinato, P. J. Tavner, "Condition monitoring of generators and other subassemblies in wind turbine drive trains", in Proc. 2007 IEEE International Symposium on Diagnostics for Electric Machines, Power Electronics and Drives, September. 2007, pp. 388-392
77. C. Chen, C. Sun, Y. Zhang, N. Wang, "Fault diagnosis for largescale wind turbine rolling bearing using stress

wave and wavelet analysis," in Proc. 8th Int. Conf. on Electrical Machines and Systems, vol. 3, 2005, pp. 2239-2244.

78. T. Doguer ,J. Strackeljan, "Vibration Analysis using Time Domain Methods for the Detection of small Roller Bearing Defects", SIRM 2009 - 8th International Conference on Vibrations in Rotating Machines, Vienna, Austria, 23 - 25 February 2009, pp. 1-12
79. S. J. Watson and J. Xiang, "Real-time condition monitoring of offshore wind turbines," in Proc. EWEC 2006, Paper #BL-3
80. S.J. Watson, G.D. Dorrell, "The use of finite element methods of improve techniques for the early detection of faults in three-phase induction motors", IEEE Trans. Energy Converssion, 1999, pp. 655-660
81. C.M. Riley, B.K. Lin, T.G. Habetter, R.R. Schoen, "A method for sensor-less on-line vibration monitoring of induction machines",IEEE Trans. Ind. Appl. 34 (6), 1998, pp. 1240-1245.
82. R.R. Schoen, et al., "A new method of current based condition monitoring in induction machines operating under arbitrary load conditions", Electr. Mach. Power Sys.,1997, pp. 141-152
83. G.B. Kliman, J. Stein, "Methods of motor current signature analysis", Electr. Mach. Power Sys, 1992, pp. 463-473
84. M. Benbouzid, H. El, "A review of induction motors signature analysis as a medium for fault detection", IEEE Trans. Ind. Electron. 2000, pp. 984-993
85. A. Nejjari, M. Benbouzid, H. El, "Monitoring and diagnosis of induction motors electrical faults using a current Park's vector pattern learning approach", IEEE Trans. Ind. Appl., 2000, pp. 730-735
86. Y.S. Sam, A. Ho, Innes, R.A. Langman, "Stator current frequency analysis for the condition monitoring of induction motors Part II: variable supply frequency", J. Electr. Electron. Eng. PAS-17, 1997, pp. 57-70.
87. A.K. Sarkar, G.J. Berg, "Digital simulation of three phase induction motors", IEEE Trans. Power Appar. Sys. 1970, pp. 1031-1036.
88. Giebel..G, Oliver.G, Malcolm.M, Kaj, B;" common access to wind turbine data for condition monitoring" In proceddings of the 27th Riso International Symposium on material science; p.p-157-164.
89. M. Volanthen, "Blade and rotor condition monitoring using bladeload measurement data", in Proc. 2007 Non-Grid-Connected Wind Power Systems, Shanghai, 2007, pp. 468-473.
90. L. Boger, M. H. G. Wichmann, L. O. Meyer and K. Schulte, "Load and health monitoring in glass fibre reinforced composites with anelectrically conductive nanocomposite epoxy matrix", CompositesScience and Technology, vol. 68, June 2008. no. 7-8, pp. 1886-1894.
91. T. Bouno, T. Yuji, T. Hamada, and T. Hideaki, "Failure forecast diagnosis of small wind turbine using acoustic emission sensor," KIEE Int. Trans. Electrical Machineary and Energy ConversionSystems, vol. 5-B, 2005, no. 1, pp. 78-83.
92. T. Yuji, T. Bouno, and T. Hamada, "Suggestion of temporarily for forecast diagnosis on blade of small wind turbine", IEEJ Trans. Power and Energy, 2006, vol. 126, no. 7, pp. 710-711.
93. Y. Kong and Z. Wang, "Modelling and analysing the hydraulic variable-pitch mechanism for a variable-speed wind turbine," Wind Engineering, vol. 31, no. 5, Oct. 2007, pp. 341-352.
94. H. Ding, X. Gui, S. Yang, "An approach to state recognition and knowledge-based diagnosis for engines", Mechanical Systems and Signal Processing 5 (1991), pp.257–266.
95. W.J. Staszewski, K. Worden, G.R. Tomlinson, "Time–frequency analysis in gearbox fault detection using the Wigner–Ville distribution and pattern recognition", Mechanical Systems and Signal Processing 11, 1997, pp. 673–692.
96. S.K. Goumas, M.E. Zervakis, G.S. Stavrakakis, "Classification of washing machines vibration signals using discrete wavelet analysis for feature extraction", IEEE Transactions on Instrumentation and Measurement 51, 2002, pp. 497–508.
97. J. Ma, C.J. Li, "Detection of localized defects in rolling element bearings via composite hypothesis test", Mechanical Systems and Signal Processing 9, 1995, pp. 63–75.
98. M.L. Fugate, H. Sohn, C.R. Farrar, "Vibration-based damage detection using statistical process control", Mechanical Systems and Signal Processing 15, 2001, pp. 707–721.
99. A.R. Webb, "Statistical Pattern Recognition", Wiley, West Sussex, England, 2002.
100. C.K. Mechefske, J. Mathew, "Fault detection and diagnosis in low speed rolling element bearing. Part II: The use of nearest neighbour classification", Mechanical Systems and Signal Processing 6, 1992, pp. 309-316
101. Q. Sun, P. Chen, D. Zhang, F. Xi, "Pattern recognition for automatic machinery fault diagnosis", Journal of Vibration and Acoustics, Transactions of the ASME 126, 2004, 307-316
102. M.-C. Pan, P. Sas, H. Van Brussel, "Machine condition monitoring using signal classification techniques", Journal of Vibration and Control, 2003, pp. 1103-1120
103. H. Ding, X. Gui, S. Yang, "An approach to state recognition and knowledge-based diagnosis for engines", Mechanical Systems and Signal Processing 5, 1991, pp. 257,-266
104. M. Guo, L. Xie, S.-Q. Wang, J.-M. Zhang, "Research on an integrated ICA-SVM based framework for fault diagnosis", in: Proceedings of the 2003 IEEE International Conference on Systems, Man and Cybernetics, vol. 3, Washington, DC, USA, 2003, pp. 2710–2715
105. M. Ge, R. Du, Y. Xu, "Hidden Markov model based fault diagnosis for stamping processes", Mechanical Systems and Signal Processing 18, 2004, pp. 391–408.
106. Z. Li, Z. Wu, Y. He, C. Fulei, "Hidden Markov model-based fault diagnostics method in speed-up and speed-down process for rotating machinery", Mechanical Systems and Signal Processing 19, 2005, 329–339.

107. Y. Xu, M. Ge, "Hidden Markov model-based process monitoring system", Journal of Intelligent Manufacturing , 2004, pp. 337–350.

108. D. Ye, Q. Ding, Z. Wu, "New method for faults diagnosis of rotating machinery based on 2-dimension hidden Markov model", in: Proceedings of the International Symposium on Precision Mechanical Measurement, vol. 4, Hefei, China, 2002, pp. 391–395.

109. M.J. Roemer, C. Hong, S.H. Hesler, "Machine health monitoring and life management using finite element-based neural networks", Journal of Engineering for Gas Turbines and Power—Transactions of the ASME 118, 1996, pp. 830–835.

110. E.C. Larson, D.P. Wipf, B.E. Parker, "Gear and bearing diagnostics using neural network-based amplitude and phase demodulation", in: Proceedings of the 51st Meeting of the Society for Machinery Failure Prevention Technology, Virginia Beach, VA, 1997, pp. 511–521.

111. B. Li, M.-Y. Chow, Y. Tipsuwan, J.C. Hung, "Neural-network-based motor rolling bearing fault diagnosis", IEEE Transactions on Industrial Electronics 2000, pp. 1060–1069

112. He, Z., Wu, M., & Gong, B, "Neural network and its application on machinery fault diagnostics". IEEE International Conference on Systems Engineering 1992, pp. 576–579

113. B.A. Paya, I.I. Esat, M.N.M. Badi, "Artificial neural network based fault diagnostics of rotating machinery using wavelet transforms as a preprocessor", Mechanical Systems and Signal Processing, 1997, pp. 751–765.

114. B. Samanta, K.R. Al-Balushi, "Artificial neural network based fault diagnostics of rolling element bearings using time-domain features", Mechanical Systems and Signal Processing, 2003, pp. 317–328

115. W.R Becraft, P.L Le, "An integrated neural network/expert system approach for fault diagnosis". Computers and Chemical Engineering, 1993, 1001–1014.

116. J.K. Spoerre, "Application of the cascade correlation algorithm (CCA) to bearing fault classification problems", Computers in Industry, 1997, pp. 295–304.

117. R.M. Tallam, T.G. Habetler, R.G. Harley, "Self-commissioning training algorithms for neural networks with applications to electric machine fault diagnostics", IEEE Transactions on Power Electronics, 2002, pp. 1089–1095

118. S. Mitra, S.K Pal,. "Fuzzy multi-layer perceptron, inferencing and rule generation". IEEE Transactions on Neural Networks, 1995, pp. 51–63

119. J.J Buckley, Y. Hayashi, " Hybrid neural nets can be fuzzy controllers and fuzzy expert systems". Fuzzy Sets and Systems, 1993, pp. 135–142

120. A. Ahmad, D.P. Kothari, "A review of recent advances in generator maintenance scheduling", Electrical Machinery Power Systems (1998) pp. 373-387

121. C.K. Mechefske, "Objective machinery fault diagnosis using fuzzy logic", Mechanical Systems and Signal Processing, 1998, pp. 855–862

122. H.R. Depold, F.D. Gass, "The application of expert systems and neural networks to gas turbine prognostics and diagnostics", Journal of Engineering for Gas Turbines and Power, 1999, pp. 607–612

123. T.I. Liu, J.H. Singonahalli, N.R. Iyer, "Detection of roller bearing defects using expert system and fuzzy logic", Mechanical Systems and Signal Processing 10 (1996) pp. 595–614

124. B.S. Yang, T. Han, Y.-S. Kim, "Integration of ART-Kohonen neural network and case-based reasoning for intelligent fault diagnosis", Expert Systems with Applications , 2004, pp. 387–395

125. J. Penman, C.M. Yin, "Feasibility of using unsupervised learning artificial neural networks for the condition monitoring of electrical machines", IEEE. Proc. Electr. Power Appl. 141 (6) (1994), pp. 317-322

126. P.V. Goode, M.Y. Chow, "Using a neural/fuzzy system to extract heuristic knowledge of incipient faults in induction motors Part I: methodology", IEEE Trans. Ind. Electron. 42 (2) (1995), pp. 131-138.

127. P.V. Goode, M.Y. Chow, ""Using a neural/fuzzy system to extract heuristic knowledge of incipient faults in induction motors Part II: application", IEEE Trans. Ind. Electron. 42 (2) (1995), pp. 139-148

128. O. Bennouna, N. Heraud, H. Camblong, and M. Rodriguez, "Diagnosis of the doubly-fed induction generator of a wind turbine," Wind Engineering, vol. 29, no. 5, Sept. 2005, pp. 431-448

129. O.Bennouna, N. Heraud, M. Rodriguez, and H. Camblong, "Data reconciliation and gross error detection applied to wind power", Proc. Inst. Mechanical Engineers, Part I: Journal of Systems and Control Engineering, vol. 221, no. 3, pp. 497-506, 2007.

130. O. Bennouna, N. Héraud, H. Camblong, M. Rodriguez and M. A.Kahyeh1, "Diagnosis and fault signature analysis of a wind turbine at a variable speed", Proc. Inst. Mechanical Engineers, Part 2: Journal of Risk and Reliability, vol. 223, no. 1, pp. 41-50, 2009.

131. S. Durovic, S. Wiiliamson, W. Yang, and P. Tavner, "Condition monitoring artifacts for detecting winding faults in wind turbine DFIGs," in Proc. EWEC 2009, Scientific Track – Wind Turbine Electrical Systems & Components, Marseille, France, March 16-19, 2009.

132. D. Karaboga, B. Basturk, B, "A powerful and Efficient Algorithm for Numerical Function Optimization: Artificial Bee Colony (ABC) Algorithm". Journal of Global Optimization, Volume: 39, Issue: 3, 2007, pp. 459-171.

133. D. Karaboga, B. Akay, B, "A comparative study of Artificial Bee Colony algorithm. Applied Mathematics and Computation", Volume 214, 2007 Issue 1, Pages 108-132.

134. O. Beniugă, M. Leca, R. Beniuga, "Assessment of Influence of Grid Disturbances on Wind Turbine DFIG Converters",Proceedings of the 2016 International Conference and Exposition on Electrical and Power Engineering, ISBN: 978-1-5090-6128-0, pp.693-696

135. O. Beniuga, R. Beniuga, "Wind Farms' Grid Connection And Protection Requirements For Sustainable Development",Proceedings

of International Conference "Energy Of Moldova – 2016. Regional Aspects Of Development" 29 September – 01 October, 2016 - Chisinau, Republic of Moldova, ISBN 978-9975-4123-5-3 pg. 478 – 481.