Failure prognostic schemes and database design of a software tool for efficient management of wind turbine maintenance

Yashwant Sinha[1], John A Steel[1]
[1]School of Engineering, Robert Gordon University, Garthdee, Aberdeen AB10 7GJ, UK
Corresponding Author: y.sinha1@rgu.ac.uk, **Phone**: (+44 1224) 262422

Abstract
Wind Turbines require numerous and varied types of maintenance activities throughout their lifespan, the frequency of which increases with years in operation. At present the proportion of maintenance cost to the total cost for wind turbines is significant particularly for offshore wind turbines (OWT) where this ratio is ~35%. If this ratio is to be reduced in-spite of adverse operating conditions, pre-mature component failures and absence of reliability database for wind turbine components, there is a need to design unconventional maintenance scheme preferably by including novel failure prediction methodologies. Several researchers have advocated the use of Artificial Neural Networks (ANN), Bayesian Network Theory (BNT) and other statistical methods to predict failure so as to plan efficient maintenance of wind turbines, however novelty and randomness of failures, nature and number of parameters involved in statistical calculations and absence of required amount of fundamental work required for such advanced analysis have continued to maintain the high cost of maintenance. This work builds upon the benefits of condition monitoring to design methods to predict generic failures in wind turbine components and exhibits how such prediction methods can assist in cutting the maintenance cost of wind turbines. This study proposes using a dedicated tool to assist with failure prediction and planning and execution of wind turbine maintenance. The design and development of such an all-inclusive tool will assist in performing administrative works, inventory control, financial calculations and service management apart from failure prediction in wind turbine components. Its database will contain reference to standard management practices, regulatory provisions, staff details and their skillsets, service call register, troubleshooting manuals, installation guide, service history, details of customers and clients etc. that would cater to multiple avenues of wind turbine maintenance. In order to build such a software package, a robust design of its database is crucial. This work lists prerequisites for choosing a physical database and identifies the benefits of relational database software in controlling large amounts of data of various formats that are stored in such physical databases. Such a database would be an invaluable resource for reliability studies, an area of interest for both academic researchers and the industry that are identifying avenues to economise wind turbine operations.

Keywords: wind turbines, failure prediction, condition based maintenance, artificial neural network, Bayesian network, maintenance tool, database, offshore wind turbines, efficient maintenance, reliability database

1. Introduction

Early failure detection is critical in planning for maintenance and preventing failure. However for Wind Turbines, that is a prominent source of electrical energy in many countries having both onshore and offshore variants, failure prediction is full of challenges. Partly, this is due to the large number of components in wind turbines (an offshore wind Turbine contains >10,000 components) that gives rise to thousands of root causes and failure combinations (10,000 components if on an average fail due to 5 root causes in 5 different types, this would give a total of 250,000 root cause and failure combinations). As an example, root causes of failures for wind turbine generator are varied and result in electrical faults, stator and rotor faults, fault in power electronic devices, sensors and associated circuits, etc. Common failures in wind turbine gearbox are pitting, spalling, tooth breaking, bearing ring and bearing roller failures[1,2], etc. that arise from loss of lubricants, excessive vibration in some loose components etc. Similarly failure in turbine hub can occur from cracks, misalignment of blades, prolonged interaction with wind, dust and ice build-up, etc. whereas failure in blades can occur due to unbalanced masses, aerodynamic asymmetry and misalignment[3]. Failure in the main shaft can occur due to fatigue, misalignment, expansion, friction, wind turbulence, cavitation, inherent defects[4] etc. whereas common failures in the electrical system are short and open circuits, fused, burning, malfunction of electronic and electrical parts[5,6], sensor and controllers failures etc. Many of these failure occur due to design and manufacturing faults[7,8,9,10,11]. Similarly there are many other types of failures in wind turbine components[12,13,14,15,16,17,18,19].

Failure prediction for wind turbine components is also challenging as historically rotating machineries were largely used under controlled conditions for which reliability data exists, however their operation under stochastic conditions, like offshore weather and onshore windy terrains, is new and not well understood. The confidentiality surrounding wind turbine component failures has made it difficult to build a reliability database that has further made it difficult to study such failures and design methods to predict failures and use existing prediction methods. It is important that as a first step a generic framework for studying failures and reliability studies is built that can later be expanded to meet site or turbine specifications. Design of such a reliability database has been proposed by Sinha (2015)[20].

A major benefit of failure prediction is the lead time to failure that gives time to optimise activities, a practice that can control costs by availing best suited resources at most economical prices and avoiding purchase of high cost items on short notices. This is of particular interest to offshore wind turbine (OWT) operators due to their higher maintenance and operating costs as compared to onshore wind turbine (OnWT) operators (maintenance cost to total cost ratio for OWT and OnWT are ~35% and ~15%[21,22]respectively). Using failure prediction, an offshore vessel of correct capacity can be hired to meet the specific requirement of maintenance rather than paying higher amount for bigger offshore vessels for urgent requirements. Offshore transportation being very costly, can cost thousands to tens of thousands of pounds per day[23], any saving made on this can be a big overall saving. As OWT have distinct advantages over OnWT[24,25,26] and as their maintenance is costlier than OnWT maintenance cost, in this work, whenever a discussion is done about cutting costs, the work will take case scenario of OWT. However challenges associated with controlling high cost of wind turbine maintenance is not only related to predicting failures. They are multifaceted and involve costs and difficulties associated with management of transportation, inventory (spares), skilled and unskilled manpower, health and safety, cost of offsetting safety risks, cost of maintenances deferment, etc. The cumulative financial impact of these challenges has resulted in elevating the Levelised Cost of Energy (LCoE) that for OWT and OnWT are ~ £130/MW and ~£110/MW (for >5MW OnWT) respectively[27], whereas for coat, petroleum, and biomass etc. LCoE is < £100/MW. Thus methods that are developed to control the maintenance cost of OWT and OnWT would invariably indorse this business. In order to cater to these requirements, there is a need for a tool that can assist in performing these functions and cater to the requirements of company-wide departments.

In order to take advantage of the lead time provided by failure prediction and accurately plan for CBM style maintenance, there will a requirement to work with company-wide departments, external regulators and service providers. This will require both time and expenditure. However a tool that is designed and developed to meet such requirements would greatly assist maintenance planners. Such a tool would be a great asset in establishing the root cause of failure and hence to plan appropriate maintenance. For example in rotating parts, like shaft, that fails due to fatigue and cracking, establishing fatigue to be the cause of failure would need to be justified by the higher than normal speed of shaft during operation, a data that would need evidence from speed monitoring of the shaft. Alternatively if misalignment of shaft had caused failure, evidence would be needed for variation in its inclination angle over a period of time. Again this is something that would need monitoring data as evidence. Similarly a shaft that fails due to its internal defects would release higher amount of energy over a period of time before failing when compared to a normal shaft. Numerous such failures need to be studied to determine the true root cause of failure[28,,29,30,31,32,33,34,35,36,37,38] in a wind turbine, a number that cannot be managed manually. Hence there is need of a tool that can provide assistance in management of wind turbine maintenance. Some prerequisites for such a tool were discussed by Sinha et al. (2013)[39]. Such a tool would be different from the available tools that are generally designed to monitor wind turbine components or detect failure, like WAsP, WindPRO, SCADA and WANSYS. This novel tool would largely assist with integration of multitude of information, right from automatic failure detection, to anticipating date for next maintenance, to calculating cost of implementing next maintenance, to providing reference to stored information, like regulatory provisions, personal management, call register etc., and right to the administrative aspect of planning maintenance[40,41,42]. This work discusses about the usefulness of designing a robust database for such a tool, its prerequisites and advantages.

SECTION A

A1. Planning for a CBM maintenance

Condition Based Maintenance (CBM) is a scheme where maintenance is planned when components of a machine starts to show signs of malfunction, not necessarily a complete failure. CBM has assisted in reducing downtime, lower spares requirements and economise machine maintenance in several industries[43,44,45,46] and this work aims to utilise the benefits of CBM to predict failures in wind turbine components. In this scheme the operation of machine components are monitored using properties like vibration[47,48], acoustics[49,50], strain[51,52], shock[53,54], ultrasonic waves[55,56], viscosity and composition of lubricating oil[57,58], electrical parameters[59,60], performance parameters[61,62,63], radio waves[64], temperature[65], electrical signals[66,67,68] and others parameters[69,70]. Failures in components are then detected by studying these outputs and comparing it to standard results. Once some abnormalities are detected these components are classed as failing and so preventive maintenance is planned. Many supplementary techniques are also used to assist in decoding failures in components, like the use of Fast Fourier Transformation[71], Time-Frequency Representation, Time Scale Decomposition[72], AM/FM technique[73] etc. to analyse electrical signals[74,75]. The information obtained from monitoring is also useful for designing reliable component[76,77,78] and reduce component failure. Supervisory Control and Data Acquisition (SCADA) systems, like Wind Power Dashboard, CONCERTO, Wind Net[79,80] etc. are modules that collect condition monitoring signal from wind turbine controller and transmits it to remote locations where these signals are studied and failures are detected. A Wind Turbine controller collects signal and data from sensors attached to the monitored components and either stores it locally or sends it via a transmitting medium or instruments like SCADA system to remote offices. As sensors need to function correctly for monitoring of components and proper operation of wind turbines, it is important that these sensors are also proactively maintained and checked for any malfunction. To give an example of the role of sensor in wind turbine operation, the outputs of wind vane are used to orient and align the nacelle and blades of wind turbines in the direction of the incoming wind. If due to faulty sensors, this is not done actively, this might result in failures to creep in associated components. Hence, by making use of existing sensors, CBM cuts down cost of special instruments that are useful for failure detection, such as in the case of inspection methods. However cost of sensors, its implementation and periodic services adds to the overall cost to wind turbine maintenance[81,82,83] and so a trade-off is often established between cost and benefits when deciding upon what and how many components are to be monitor in the wind turbines[84].

To demonstrate an example of CBM based maintenance planning, let us assume the case of many OWT operating alongside each other in the offshore site. This has been shown in Figure 1. Further let us assume that continuous monitoring of OWT results in the detection of failures in the sub-systems, assemblies, subassemblies and components of various OWT. These failures can be uniquely represented by codes as shown in Figure 1. All such failures and faults in various OWT are compiled in a list called a Failure and Fault List (FFL). Now, based on the policy to decide and plan for maintenance, resources are assembled and maintenance is executed. FFL is useful in deciding on the type and quantity of resources that would be required for any maintenance manoeuvre.

As CBM provides lead time to failure, any staff training or specialised resources can be procured in given time. Any learning from maintenance execution is incorporated in the future trainings.

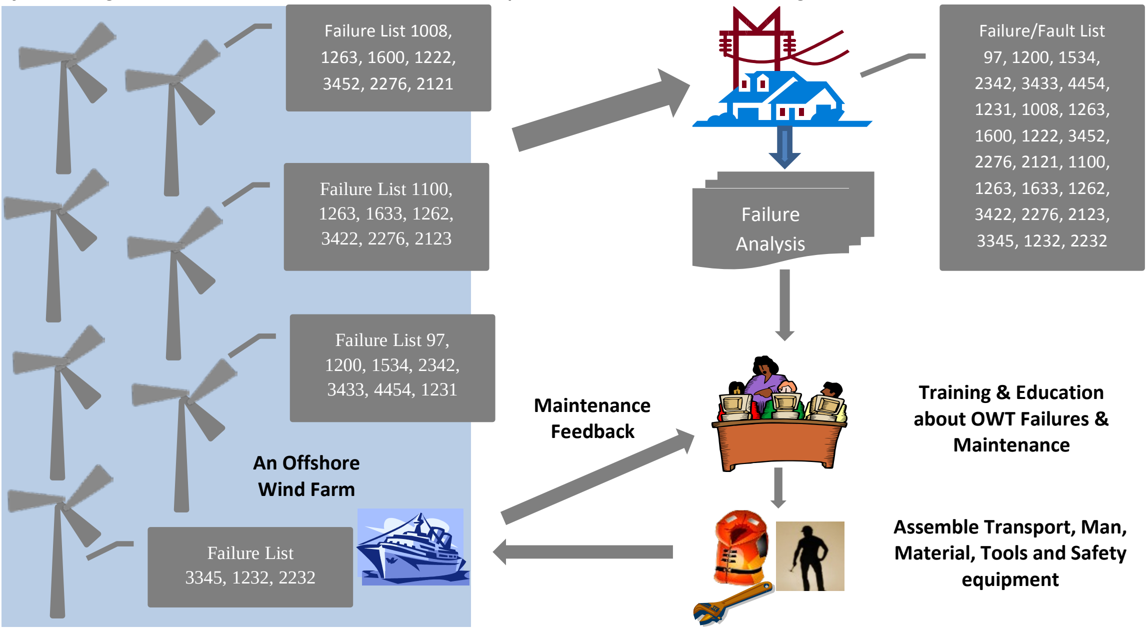


Figure 1 A setup for CBM based offshore wind farm maintenance program

Different wind turbine service operators may use different versions of CBM methodology, however this study recommends using a CBM based maintenance scheme that has been shown in Figure 2 to observe, anticipate and fine tune the anticipation level of failures in wind turbines. In line with the process shown in Figure 1, in Figure 2, the condition of wind turbine parts are monitored for failures on an active basis. The data obtained from online monitoring and any inspections performed on wind turbine components are processed and condition of OWT components are determined. Such analysis is fed into a custom made Bayesian network to anticipate any other additional failures and faults that might have been in incipient mode and was not detected. All such observed and anticipated failures are recorded in FFL. Since, information related to wind turbine failures are not readily available, a customised intelligent system, like Artificial Neural Network, is used to remember and update information related to circumstances surrounding failures, their impact level and other related information. In this way, it will be possible to find tune prediction of various failures with time and conditions surrounding failures. This is important since all wind turbines, especially offshore based wind turbines operate under varied conditions and hence their failures and failure patterns are different. By having knowledge of failures, suitable techniques can be designed to determine vulnerability of wind turbine failure, like by using Reliability Block Diagram. So, by using the concept of Artificial Neural Network and Bayesian Network, an up-to date reliability database can be developed that will only assist in improving the confidence level of anticipating failures in OWT and hence assist in planning better and economical maintenance. By saving time and cost, and by improving maintenance, such a model is of great assistance in optimising wind turbine maintenance.

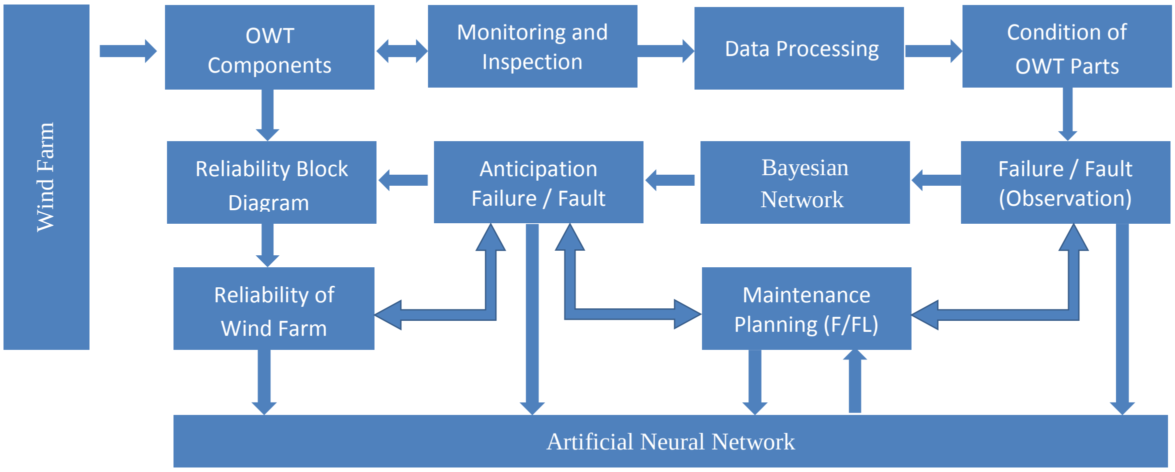


Figure 2 Diagram shows a CBM scheme to plan for wind turbine maintenance

A2. Components in wind turbines

The first step of Figure 2 identifies various components in wind turbines. EU FP7 ReliaWind Consortium[85] has proposed a list of wind turbine components in various subsystems, assemblies and subassemblies of wind turbines. An abridged list of this proposal is shown in Table 1. In this listing there are more than 150 different types of components varying from hose and pump to data and signal cables and switches. Although this listing can be further expanded into much smaller units like subcomponents and its parts, however as a first step towards designing CBM maintenance as shown in Figure 2, for this study the list proposed by EU FP7 ReliaWind Consortium has been taken. This decision has also been made as the cost of maintenance for failures below component level may actually be higher its benefits.

System	Subsystem	Assembly	Subassembly	Component
Wind Turbine	Drive Train Module, Electrical Module, Nacelle Module, Rotor Module, Support Structure, Collection System, Metrological System, Substation	Gearbox, Generator, Main Shaft Set, Auxiliary Electrical System, Control & Communication System, Frequency Converter, Power Electrical System, Hydraulic System, Nacelle Auxiliary, Yaw System, Blade, Pitch System, Foundation	Bearing, Cooling System, Lubrication System, Metrological / Nacelle/ other Sensors, Rotor, Structural & Mechanical, High / Low Speed Side, Mechanical Brake, Electrical Services, Lightening Protection System, Ancillary Equipment, Communication System, Condition Monitoring System	Hose, Pump, Radiator, Thermostat, Motor, Bushing, Case, Mounting, Torque Arm, Filter, Debris/Level/Pressure/Temp Sensor, Fan, Resistance Controller, Lamination, Slip Ring, Encoder, Wattmeter, Magnet, Coupling, Rotor Lock, Shaft, Transformer, High speed / position sensor, Fan, Fuse, Relay, Switch, Power, Point, Pushbutton, Space Heater, Surge, Arrester, UPS, Circuit Breaker, Cable, Analogue Digital I/O, Data logger, Protocol, Adapter Card, CPU, Watch Dog Unit, Control Software, Power / Vibration / Watch Dog Switches

Table 1 An abridged listing of EU FP7 ReliaWind Consortium proposed wind turbine parts

A3. Inspection Techniques for OWT

Several online and offline manual methods are used to inspect wind turbine components. Such inspection techniques are important for condition monitoring OWT components and in establishing and predicting failures. Some of these methods for various components and assemblies of wind turbines have been compiled in Table 1. It can be observed from Table 1 that for majority of components and assemblies, there are more than one inspection techniques. This is because any single inspection technique is limited in its scope and application due to limitations created by its operating principle. For example, Pressure Measurement technique is used apart from Oil analysis and temperature analysis inspection techniques for a Hydraulic system where characterisation of pressure, constituents in oil surrounding temperature are all useful in identifying failures in a Hydraulic system and any one inspection method is incapable of detecting failure characteristics for other methods. However by implementing more than one inspection technique, especially for OWT that contains > 10,000 components, both time and cost associated with monitoring, failure detection and analysis, and designing preventive methods, gets increased. Hence, there is a need for methods that can reduce the requirement for such large number of inspections techniques to detect failures and faults in wind turbine assemblies and components.

WT Units	Inspection Methods	WT Units	Inspection Methods
Blade	Fibre Optic Method	Grid	Controller Failsafe Technique
	Vibration Monitoring Technique	Hub	Variation in Performance Parameter Technique
	Visual Inspection Technique		Vibration Monitoring Technique for Blades
	Strain Measurement Method	Hydraulic System	Hydraulic Oil Analysis Technique
	Variation in Performance Parameter		Hydraulic Oil Temperature Measurement
	Variation in Process Parameter		Visual Inspection Technique
Cable	Cable Twist Sensors Status		Pressure Measurement Technique

	Visual Inspection Technique		Tribology Technique
	Electrical Effects Observation	Low Speed Shaft	Relation to Pitch Angle and Rotor Position
Controller	Visual Inspection Technique		Vibration Measurement Technique
	Process Parameter Variation Technique	Main Bearing	Lubrication oil Analysis
	Thermograph Technique		Temperature Measurement of Main Bearing
Foundation	Corrosion Monitoring Technique		Vibration Monitoring Technique for Main Bearing
	Visual Inspection Technique	Main Shaft	Vibration Monitoring Technique
	Vibration Monitoring of Tower		Accelerometer Technique
Coupler	Visual Inspection Technique		Vibration Monitoring Technique
	Variation in Process Parameter	Metrological	Variation in Wind Speed Method
Gearbox	Gearbox Oil Analysis	Nacelle	Variation in Process Parameter Method
	Component Replacement Technique	Pitching System	Acceleration Measurement Technique
	Online Oil Examination		Vibration Monitoring Technique
	Temperature Monitoring Technique	Tower	Corrosion Monitoring Technique
	Vibration Monitoring Technique		Visual Inspection Technique
	Visual Inspection Technique		Strain Measurement Method
Generator	Visual Inspection Technique		Vibration Monitoring Technique of Tower
	Oil Analysis Technique Generator Bearing	Wind Speed	Variation in Process Parameter Technique
	Temperature Monitoring Technique	Gear Wheel	Visual Inspection Technique
	Variation in Performance Parameter		

Table 1 Various Inspection techniques used for wind turbine components and assemblies[86,87,88,89,,90,91,92,93,94,.95,96,97]

A4. Methods to predict failures in wind turbine components

A4.1. Overall Failure Result Method

A process is proposed here that can assist service personal consolidate results from two or more different inspection techniques and derive information about incipient failures (if any). This process has been shown in Table 2. In this process failures are categorised into three categories, i.e. No Failure (0), Partial Failure (X) and Complete Failure (1) (Table 2 (a)). The process assumes that the results obtained from any inspection technique is correct and truly represents a failure without dispute. As a result if any inspection technique infers No Failure (0), Partial Failure (X) or Complete Failure (1), it is correct (Table 2 (a)). As a result, if one inspection technique does not detect Partial Failure (X) or Complete Failure (1) in a machine, it actually refers to the case of No Failure (0). Results of two or more inspection methods are joined by using a truth table as shown in Table 2(b). So if one inspection method shows complete failure ‘1’, while another inspection method shows no failure ‘0’, this would indicate a complete failure ‘1’ of the component. An application of this process is shown in Table 2(c). Assuming that a machine contains 7 different components, M_1 – M_7, where the numbers are assigned in ascending order from either the input or output side of the machine such that adjacent parts are assigned consecutive numbers. Let us assume that three different inspection techniques provided results as shown in Table 2 (c). So by using Table 2(b) one can evaluate the Overall Failure Result (OFR) for different components of the machine that would provide a comprehensive and consolidated report about components who have either failed or are expecting failure. OFR can also assist in predicting failure, like if component M_2 and M_4 show complete failure, it is unlikely that M_3 would not have experienced any failure, or at least incipient failure. Hence there is a need to maintain M_3 along with all other failed components. So, OFR not only confirms failure in components, it provides information about components where inception of failure may have started to occur, making this method very useful.

Category (C)	Type of Failure
0	No Failure
X	Partial Failure
1	Complete Failure

(a)

C 1	C 2	Result (C 1 + C 2)
0	0	0
X	0	X
1	0	1
0	X	X
X	X	X
1	X	1
0	1	1
X	1	1
1	1	1

(b)

	M_1	M_2	M_3	M_4	M_5	M_6	M_7
IR 1	0	1	0	X	0	0	1
IR 2	0	0	0	0	1	X	0
IR 3	X	0	0	1	0	0	0
Overall Failure Result	**X**	**1**	**0**	**1**	**1**	**X**	**1**

(c)

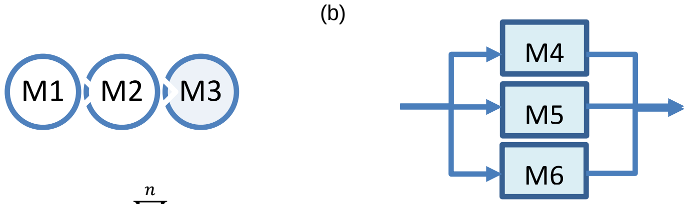
Table 2 A process to join two or more Inspection Results (IR) (a) categories of failures, (b) Truth Table (c) An example illustrating the process (M_1 – M_7 denotes parts of a machine)

A4.2. Reliability Block diagram

A machine is built of many components arranged in series and parallel combinations. Due to proximity of components to each other, failure or fault in in component will have an influence on other adjoining components and the machine as a whole. To illustrate this point, in Figure 3(a) and Figure 3(b), a series and parallel connection of components in a machine are shown. From Figure 3(a) it can be observed that failure in either M1 or M2 will result in the failure of the overall system and would directly influence the performance of M3. However in parallel arrangement shown in Figure 3(b), M4, M5 and M6 operate independent of each other and failure in any one of them does not influence other components. In this case, the machine will only fail when M4, M5 and

M6 were to fail simultaneously. If likelihood of failure of all such components were equally likely, the machine shown in Figure 3(b) would be less likely to fail than machine shown in Figure 3(a). This is the reason why compensatory provisions that introduces additional components in machines to bypass failure are connected in parallel to the working component.

(a) (b)



$$RoM_{Series} = \prod_{i=1}^{n} RoM_i$$

$$RoM_{Parallel} = \sum_{i=1}^{n} \mathrm{RoM}_i$$

$\mathrm{RoM}_{\mathrm{Series}} = \mathrm{RoM}_1 * \mathrm{RoM}_2 * \mathrm{RoM}_3$ $\mathrm{RoM}_{\mathrm{Parallel}} = \mathrm{RoM}_4 + \mathrm{RoM}_5 + \mathrm{RoM}_6$

Figure 3 Calculation of Reliability of Machine (RoM) for machine parts connected in (a) Series, and (b) Parallel

Reliability is defined as the likelihood of a machine or component to perform its intended function under a given condition[98]. We define a term Reliability of Machine (RoM) to be the expectation that the machine will perform its intended function under given condition. According to the concept of Reliability Block Diagrams, the RoM can be calculated by multiplying the Reliability of its components in series and parallel combinations, as shown in Figure 3. So, Unreliability of Machine (UoM) will equal to (1 - RoM) and will denote the probability of a machine to not perform its intended function under a given condition. This method can be used to determine the reliability of a wind turbine if reliability of its individual components is known or can be established statistically. This is useful to categorise wind turbines in urgent need of maintenance based on its higher likelihood of failure. This is part of the planning process for wind turbine maintenance as shown in Figure 2. However this method has some limitations, like:

- RoM value for feedback circuits has not been defined and hence cannot be calculated,
- This method only provides a quantitative value of reliability and does not provide any information about the type or nature of anticipated failure in components
- Effect of external conditions is not considered while calculating reliability value. This reduces confidence level in the value of reliability, especially for OWT components
- It requires that reliability value of all wind turbine components is known, data of which is difficult to obtain

However this method is useful in finding the reliability of the wind turbines, and expanding it to obtain the reliability of a wind farm, if reliability values of wind turbine components have been identified. Also, if reliability values of modules, in which components are connected in parallel, are found, this method has many advantages.

A4.3. Using Bayesian Network

A Failure Modes Effects and Criticality Analysis (FMECA) database has been made of generic failures in wind turbine gearbox, generator and the electrical systems (Sinha, 2015). Analysis of these failures shows that:

- a root cause of failure can result in one or many failures types and failure modes
- a failure can gives rise to other failures
- combined effect of two or more failures can create situation for another type of failure
- a failure can either have no, moderate or severe effect on power generation capability of OWT
- rectification of a failure does not guarantee a solution or reduced likelihood of occurrence of linked failures
- it is also uncertain that occurrence of a failure explicitly implies the occurrence of its linked failures
- there is a greater certainty in determining the occurrence of a failures when linked to its root failure cause
- the root causes for a failure can have intrinsic, operational, human negligence and environmental factors

In view of such observations, a failure dependency model has been proposed to anticipate likelihood of a failure based on intrinsic, operational, human negligence and environmental factors. Such a method has been used in medical science for treatment, in sports, wireless networks etc[99] where likelihood of occurrence of one event determines the next course of action. This model uses the fundamentals of Bayes' Theorem[100] and Bayesian Network as each step is linked to the other steps by using conditional probability that determines the likelihood of occurrence of the next step based on the likelihood of its previous steps. This has been shown in Figure 4.

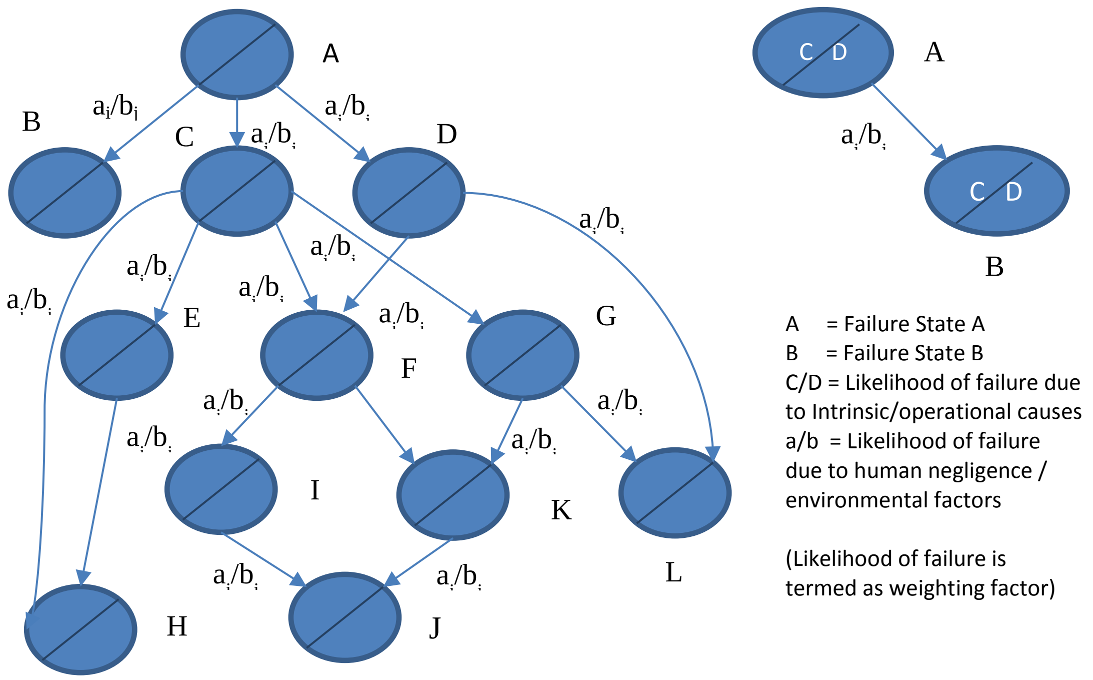


Figure 4 Schematic of a proposed network for determining failure in OWT components and assemblies

This process can be understood by an example of Bayes' Theorem according to which, probability of occurrence of failure type A, given that it's a root cause event B has occurred, can be calculated using:

$$P(A|B) = \frac{P(A).P(B|A)}{P(A).P(B|A)+P(A').P(B|A')}\ ;$$ *where A' represents the probability when failure type A does not occur*

As an example, suppose that a component fails due to two root causes of failure (R_1, R_2) whose probability of occurrence are 0.51 and 0.49 respectively. Now suppose that chance of occurrence of failure due to these root causes were 0.1 and 0.65 respectively. So, the probability of occurrence of failure (F) given root causes R_1 and R_2 can be calculated as under:

$$P(R_1|F) = \frac{P(R_1).P(F|R_1)}{P(R_1).P(F|R_1) + P(R_1').P(F|R_1')} = \frac{0.51 * 0.1}{0.51 * 0.1 + 0.49 * 0.65} = 0.138$$

$$P(R_2|F) = \frac{P(R_2).P(F|R_2)}{P(R_2).P(F|R_2) + P(R_2').P(F|R_2')} = \frac{0.49 * 0.65}{0.51 * 0.1 + 0.49 * 0.65} = 0.862$$

Hence, the conditional probability that failure would occur for root causes R_1 and R_2 are 0.138 and 0.862 respectively. One can see that in-spite of the higher value occurrence of R_1 , the likelihood of a failure occurring due to R1 is lower and coincides with the low value of the likelihood of the failure. Hence this method provides a more realistic figure for anticipating failure.

The model proposed in Figure 4 aims to use the above concept of Bayes' Theorem to interconnect various failure states using the likelihood of occurrence of the four root causes of failures, namely inherent faults 'C', operational causes 'D', human negligence 'a' and external factors 'b', i.e. environmental factors. So by having knowledge of C, D, a and b, transition from one failure state to the next failure state can be determined. Whereas C/D calculates the conditional probability of failure for a particular state, a_i/b_j calculates the conditional probability of failure due to human negligence and environmental factors. Some equations that are used in the process are shown below. These have been listed below.

$$P(A/B) = \frac{P(A \cap B)}{P(B)}\ ; P(A\ \cap B) = P(A).P(B)\ ;\ \ P(A_i/E) = \frac{P(A_i).P(\frac{E}{A_i})}{P(A_1)P\left(\frac{E}{A_1}\right) + P(A_2)P\left(\frac{E}{A_2}\right) + \cdots + P(A_n)P\left(\frac{E}{A_n}\right)}$$

Where P = probability, (A/B) = conditional probability of A given B.

A4.4. Using Artificial Neural Network

It was outlined in Section A4.3 that failures could be determined with greater certainty if knowledge about its root causes of failure was known. So, if a self-learning knowledgebase is built that over a period of time can store and fine tune the correspondence between root causes of failure and occurrence of the failure, this would improve the accuracy of failure prediction in future. A conceptual model has been proposed in this work that uses a concept similar to Artificial Neural Network as shown in Figure 5. In this method a recurring relationship is established between Root Causes of Failures (RC) and various Failure Types (FT) of a Failure Mode (FM). A mathematical relationship that combines these together has been shown below.

$FT_j = \sum w_{ji} RC_i$; $E_k = \sum z_{kj} FT_j$; $Y_i = \sum E_k$; *where w_{ji} and z_{kj} are scale factors from Bayesian Network Theory.*

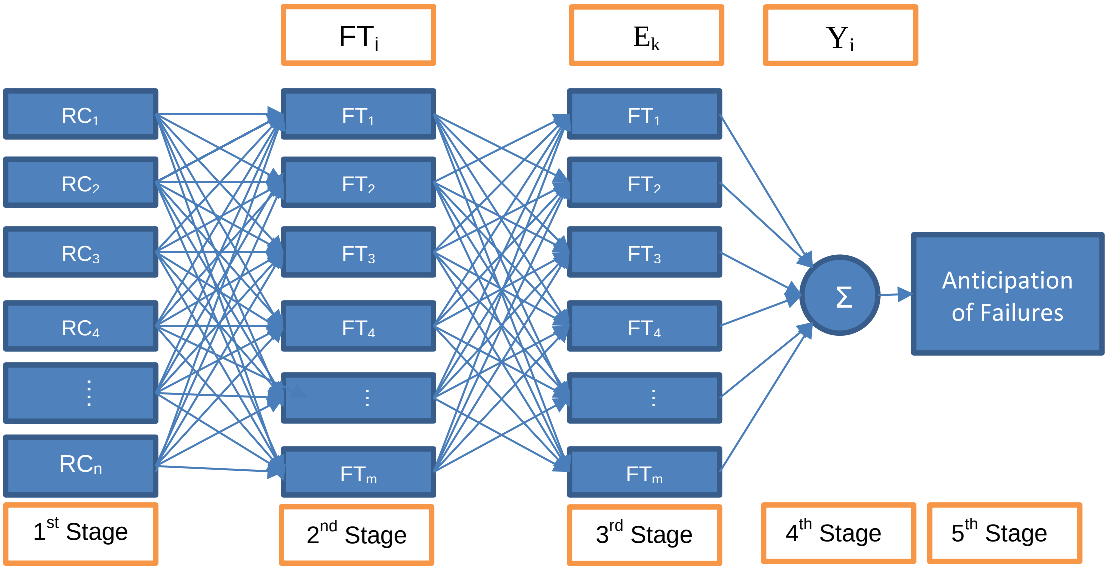


Figure 5 Schematic shows a failure anticipation method using Artificial Neural Network schema

A5. Understanding types of failures in wind turbine components

It was shown in Section 1 and Section A1 that there are numerous types of failures in wind turbines assemblies, subassemblies and components. In Table 3, some generic failures in components of wind turbine gearbox have been shown. For example, gear shafts can become seized, cracked, misfire, misaligned etc. However a gear shaft that has misaligned would also ultimately result is seizure and cracking as a next step. So, if the likelihood of these events can be established, using Section A4.3 and Section A4.4, a model can be developed to predict failure in gearboxes. Similarly, a leaking hose, if left unattended, can fracture and result in the cooling (/lubricating) system to be shunted out of gearbox operation. In the absence of a cooling (/lubrication) system, the gearbox would develop many other types of failures and result increase in frictional energy from shafts that can result in the abnormal expansion of shafts and its ultimate failure. Hence, by inter-relating such failures, with their root causes, and by determining the likelihood of their occurrence, it may be possible to predict failures and design better and economical maintenance. In view of the limitation encountered in getting access to real operational and failure data, there is a need for more work in this particular area.

Assembly	Subassembly	Component	Generic Failures – Failure Modes
Gearbox	Gearbox Bearing	Carrier/Planet/Shaft	Worn, Binding, Sticking, Seized, Jammed, Excessive Play, Dry/No Lubricant, Misaligned, Fitting Issue, Pitted, Aged, Scored, Corroded, Brinelling, Vibrations, Clogging, Fatigued, Induced
	Generator Bearing	Shaft/Rear	
Gearbox	Cooling/Lubrication	Hose	Broken, Worn Out, Cracked/Fractured, Leaking, Induced
Gearbox	Cooling/Lubrication	Pump	Leaking, No Operation, Shorted, Seal/Gasket Failure, Induced, Misalignment, Degraded Operation, Bearing Failure, Mechanical Failure, High Current, Drift, Cooling Failure, No Start Intermittent Operation, Lubrication problem, Burned, Fatigued, Corroded, Cavitation
Gearbox	Gears	Shaft	Seized, Cracked, Warped, Rusted, Induced, Alignment Issue
Gearbox	Gears	Bushing	Loose, Corroded, Misfire, Aged/Deteriorated, Fracture, Loose, Scarred, Induced
Gearbox	Housing	Case	Binding, Excessive Use, Broken, Cracked, Misaligned, Skipping, Induced, Leaking Lubricating Oil
Gearbox	Housing	Mounting	Broken, Excessive Play, Loose, Induced
Gearbox	Lubrication System	Filter	Leaking, Improper Output, Clogged, Degraded operation, Cracked, Broken, Out of Specification, Burst, Warped, media Migration, Channelling
Gearbox	Lubrication System	Seal	Leaking, Cut, Punctured, Aged, Worn, Loose, Induced, Gasket Failure, Cracked
Gearbox	Sensors	-	Degraded Output, Opened, Shorted, No Operation, Zero or Maximum Output, Drifting Output, Closed, Internal Failures, Induced, No Signal Output, Mechanical Failure

Table 3 Some common types of failures in wind turbine gearbox

A6. Advantage of failure prediction on the cost of maintenance: Offshore Wind Turbines

An offshore wind farm contains many OWT along with their steel or concrete foundations, power cables, offshore and onshore substations, onshore power stations for power conditioning and transmission, communication networks and other entities that contribute towards the overall cost of maintaining offshore wind farm. However, as this study is focused around maintenance of wind turbines, cost of other avenues are not considered in this work. If 'MC_{WF}' is the cost of maintaining an offshore wind farm containing 'N' OWT, this is given by $MC_{WF} = \sum_{n=1}^{N} MC_{OWT}$. However failure in OWT assemblies, subassemblies and components, can all be attributed to failure at the component level and so if functions Φ_{ijk}, S_{ijk} and W_{ijk} are defined such that Φ, S and W represent cost of repairing minor failure, fault and component replacement respectively, and 'i', 'j' and 'k', denote assembly, subassembly and component of OWT, the cost of maintenance of OWT. However there are additional costs, like cost of manpower, transport and training (if any), that adds to this overall cost. So the overall cost of offshore wind farm maintenance will be given by:

$$MC_{WF} = \sum_{n=1}^{N} \{\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} [\Phi_{ijk} + S_{ijk} + W_{ijk}]\}_n + C_{manpower} + C_{transport} + C_{training}$$

In order to demonstrate the benefit of failure prediction in lowering cost of offshore wind farm maintenance, as an example consider a wind farm with 50 wind turbines in which only the gearbox and generator are monitored for failures and faults. So for example, if condition monitoring of OWT components shows that 12 of 50 OWT have failures or faults, maintenance would be planned for these 12 OWT. For visual representation these failures are marked by symbol 'X' in Table 4. If cost of manpower is £30/hr and the trip requires 10 staff members to work 2 shifts in a day (8 hours each) for 5 days, transportation costs £10,000/day, the cost of training is £10,000 and the overall cost of repairing failures, including spares is £75,000, the overall cost of this maintenance will be £159,000. Now assuming that some failures were predicted (marked as 'Y' in Table 4) whose maintenance cost was of the value £12,000 and which left to itself for a later date would require an offshore visit of 5 staff members for 3 days and cost £45,000 to repair, the cost of this additional maintenance would be £71200(assuming use of smaller offshore vessel costing £5,000/day and training cost £4000). However if such failures were predicted, and included in the first maintenance, the savings made will be £59,200. If such failures were to result in downtime of OWT in a wind farm that leads to revenue losses amounting to £45,000, the overall savings made by failure prediction would equal to £104,200. This is a significant amount to be saved by just investing £12,000 additional amount in latest maintenance.

In real case scenario, there are many other avenues and conditions, and associated cost factors that need to be considered while deciding and designing a maintenance plan for wind turbines. As the number of factors involved in this work is numerous, the next section discusses about design of the database of a software tool that can assist in performing such tasks.

OWT ID	Failures in Gearbox																		
	Bearing			Cooling System			Gear		Housing			Lubricating System				Sensors			
	Planet	Carrier	Shaft	Coil	Hose	Pump	Shaft	Gear	Bushing	Case	Mounting	Hose	Filter	Seal	Pump	Temperature	Pressure	Debris	Oil Level
A3																			
A6		X			Y		Y										X		Y
A8					Z	Y		X					Z		Y				
A15	Y		Y									X			X				
A19																			
A22										X									
A23		Y											Z	Z					
A35			X																
A39					X		Y		Y		X								
A42									X										
A46													X	X		X			
A49		Y	Y							X			Y	X				X	

OWT ID	Failure in Generator																		
	Cooling System			Lubricating System				Rotor				Sensor			Structural & Mechanical				
	Cooling Fan	Filter	Hose	Pump	Seal	Hose	Filter	Commutator	Exciter	Controller	Slip Ring	Temperature	Wattmeter	Encoder	Front Bearing	Rear Bearing	Housing	Silent Block	Shaft Bearing
A3				X												Y			
A6														Z			X		
A8						X			X									X	
A15			X				Z												
A19										X				Y					
A22	X											Y			X				
A23							Z						X		Y				
A35								Y	X										
A39																			
A42					X		Z	Y	X			X			Y		X		Y
A46																			
A49						X									Y	Y			

Table 4 Depicts component level failures in an Offshore Wind Farm (X = observed failures, Y = anticipated failures, Z = requires component change)

SECTION B

B1. Introduction

It was discussed in Section 1 that there is need of a dedicated software tool to assist with the planning aspect of wind turbine maintenance. A key prerequisite of such a tool is a robust design of its database to store varied types of data and information, in various formats, of various sizes, for different purposes and for both online and offline data. Hence it is important that such a database be designed with care and meets all requirements of software part of the tool. A database is a combination of physical space and a database software that can assist in managing (insert, update, delete, format, etc.) the data stored in such locations. Such database software in association with a software program builds a software tool.

According to Cambridge dictionary "*Relational Database is a computer database that allows the user to find and organise data in many different ways*"[101]. A Relational Databases (RDB), a database software, divides the physical space into many tables with columns and rows to store data of various formats. These tables and their rows and columns are related to each other by a relationship and hence the term relational database.

Relational Database Management System (RDBMS) is a software tool that assists in handling database structure and its data using commands, like select, insert, delete, update, create table, drop table, where, join, etc. Information about RDB and RDBMS can be obtained from Microsoft SQL Server 2008 Database Development training kit or any book on similar topic. An example of a table containing columns and rows is shown in Figure 6. The table contains anonymised information about two wind farms, their location, turbine model, year of manufacture, installation date and Operator Company. If the name of table was "*WindFarm Details*", and it was required to obtain information about wind turbine models in the WindFarm of name "WF Sample 1", the following RDBMS command can be used to obtain the result.

<u>**COMMAND**</u>
SELECT Turbine_Model **FROM** WindFarm Details **WHERE** WindFarm = 'WF Sample 1'

<u>**OUTPUT**</u>
Model 19
Model 17
Model 19
Model 22

TABLE

COLUMN

ROW

ID	WindFarm	Location	Turbine_Model	Model_Year	Installation_Date	Operator_Company
1	WF Sample 1	Location 1	Model 19	2002	3/5/2003	Company A
2	WF Sample 1	Location 1	Model 17	2005	12/6/2008	Company A
3	WF Sample 1	Location 1	Model 19	2002	3/5/2003	Company B
4	WF Sample 1	Location 1	Model 22	2004	5/3/2007	Company C
5	WF Sample 2	Location 2	Model 21	1999	5/9/2001	Company X
6	WF Sample 2	Location 2	Model 46	2005	6/6/2010	Company X
7	WF Sample 2	Location 2	Model 39	2003	5/3/2005	Company X

Figure 6 Sample figure illustrating table, column and row architecture of a relational database.

RDB provides the facility of joining multiple tables using a unique column name. Such a linkage of two tables is shown in Figure 7. It is seen that when two tables are linked by unique column name, information between these tables can be shared. For example Fischer Sam, who is an Inspection Engineer and earns £34,600 (from first table) has a degree in Instrumentation Engineering and is HSE trained with Project Management experience (from second table). Although it is possible to combine tables, working with large tables are time consuming, takes more processing time of computer and can bottleneck the database. Hence tables with many columns are often divided into smaller tables containing fewer columns using a method called Normalisation without losing any information[102,103] and is normally performed for any large databases. This work has designed a 3rd Order Normalised database for use in SQL database software environment.

Linking of two Tables

Emp_Code	Emp_FName	Emp_LName	Salary	Position
025	John	Kerry	40,000	Wind Farm Manager
095	Fischer	Sam	34,600	Inspection Engineer
128	Preet	Singh	33,650	Monitoring Specialist
112	Samual	Jackson	58,000	Head Inspections

Emp_Code	Q1	Q2	Q3	Q4	Q5
025	Degree Power Engineering	Post Graduate Electrical Engineering	MBA (Services)	HSE Trained	Project Mgmt.
095	Degree Instrumentation Engineering	HSE Trained	Project Mgmt.		
128	Degree Electronics Engineering	Six Sigma Qualified			
112	PhD Electrical Engineering	MBA (Marketing)	HSE Trained	PMP	APMP

Figure 7 Figure shows linking of two Tables so that information between them can be shared

B2. Database architecture for software package

The database of the software tool planned for wind turbines, Enterprise Resource Planning Software for Offshore Wind Turbines Maintenance (ERP-OWTM) has been divided into 3 distinct parts on purpose. All the parts contain a 3rd order Normalised database for data storage. This is shown in Figure 8. In Database Section A, identification of all wind turbine components (uniquely identified by special codes), their monitored data and their conditions are identified and stored. The status of component health and failures are recorded as unique codes. In Database Section B, data about inventory, spares, service standards, HSE regulations, finance, etc. are stored for ready reference by software program. The software program modules use these data to plan maintenance. In Database Section C, processed data or information is stored. For example, a software program module that caters to a query of estimating the time till next maintenance would use data from Section A and Section B, and save its output result in Database Section C. The result of these queries can be referenced at a later date. Similarly, a program module that stores information for HSE compliance about number of accidents and deaths during maintenance execution, and any special hazards encountered during work etc. would reference Section A and Section B data to generate a result that it would store in Section C.

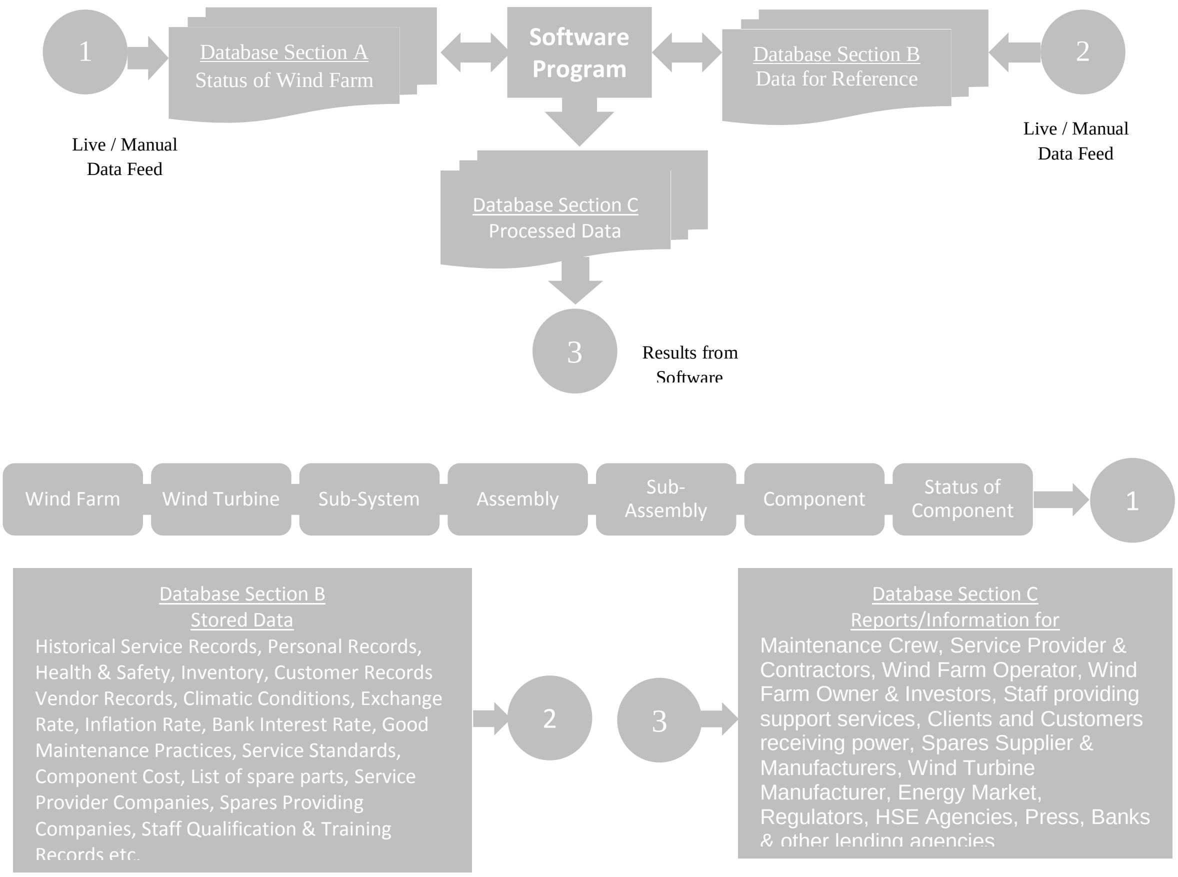


Figure 8 Shows division of database for an ERP-OWTM tool

B3. Prerequisites from physical database and its controlling software

The prerequisites for choosing a database and its controlling software for use in ERP-OWTM are many. These have been summarized in Table 5. Any database software that fulfils these requirements would be an ideal choice for fabricating Enterprise Resource Planning Software for OWT Maintenance (ERP-OWTM). In this work SQL 2008 has been used for developing a database for supporting ERP-OWTM software package as it satisfies majority of the prerequisites listed in Table 5.

Support for	Required Characteristics from Database Software
Large Volume of data	Condition Monitoring, SCADA systems very quickly generate gigabytes of data. Selected Database software should be able to support large volumes of data.
Relationship	Stored data would have relationship to each other hence the chosen database should be capable of simultaneously establishing and handling many relationships between data
Formats of Data	Incoming data are in various formats, hence database software should be able to support various formats of data, like integer, floating number, date, picture
User Interface	Software would be used by trained and unskilled personal, so its user interface need to be simple and easy to understand and navigate
Safety / Privacy	Since multiple users will logon to the database software simultaneously, hence viewing selected data need to be restricted by user authorisation
Reliability	Database should ensure that stored data does not become corrupt with time and hence facility should be there for both local and remote data backup
Commands	Common words enabled user interface would assist unskilled people easily interact with the database using the software tool.
Storage / Retrieval	The database software should have easy and short to remember commands that does not take appreciable time to execute to storage, manipulate or retrieve data
Expansion	With new modules, the size of database would increase. Hence the selected software should have a scalable architecture
Redundancy	Facility for identification, retrieval and archiving of long time unused, corrupt and unwanted data should be present. This is essential for housekeeping.
Protection of stored Data	Accidental deletion of related data should be avoided by the database software least it would form redundant sets of data
Access and Access Time	Database software should provide facility for efficient management of data so that data can be accessed in very short interval of time
Migration	Selected database should be compatible with other available databases so that in case of need, data can be transported between different types of databases

Table 5. Characteristics of a database to be used in the development of a software tool for OWT maintenance planning

B4. A nomenclature for Wind Turbine Parts, Failures, Maintenance, Spares

This section discusses about a hierarchical naming convention to uniquely identify all wind turbine subsystems, assemblies, subassemblies and components. The proposed convention assigns and concatenates codes of different levels in a wind turbine to determine an overall code. This is shown in Figure 4. As shown, the code for a carrier bearing has been evaluated to be WDGEBC based on the combination of codes of subsystem, assembly, subassembly and the carrier bearing it. In similar terms, code for a filter in the cooling system of the generator of drive train module would be WDGNCF. Similarly all other parts can be uniquely named and identifiable.

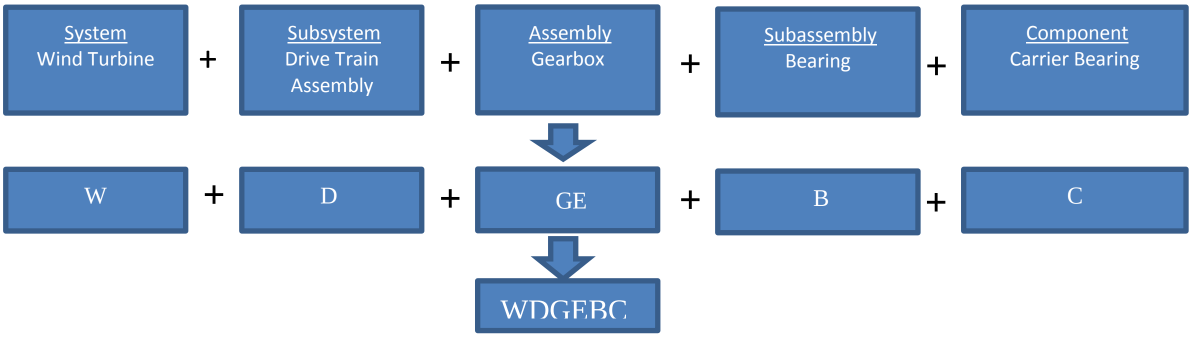


Figure 9. A hierarchical naming convention for wind turbine parts

In a wind farm where there are many wind turbines, to uniquely identify any particular wind turbine, a unique number is assigned prior to the letter 'W'. So for example in a wind farm containing 150 wind turbines, the wind turbines are identified by numbers such as 1W, 2W, …NW, where N is number of wind turbines in the wind farm. So 56WDGEBC would be the identification code of the carrier bearing in the Gearbox of wind turbine number 56. This convention can be used to reference failures and maintenance of OWT parts. Here failure associated with any component is suffixed with _FXX. For example, 56WDGEBC_F32 would denote a failure type denoted by F32 in the database for the carrier bearing in gearbox of 56 number wind turbines. Similarly, corresponding maintenance can be represented by suffixing the component code with _MXX, where it would refer to the maintenance strategy to failure type _FXX. Spares related to a particular component are denoted by suffixing _SPXX.

B5. Data types

Various types and formats of data would be made available to database of ERP-OWTM from live condition monitoring, offline inspection results, historical service records, troubleshooting manuals, etc. The database must be capable of identifying and storing such diversified formats of data. SQL 2008 offers the facility to handle different formats of data and type definition characteristic using which the data type of a column in a table can be restricted to accept only certain data format. This facility ensures that the database accepts and stores different formats and prevents unrecognised formats or unwanted data to populate the database. Thus by ensuring that only correct data format is entered in database, the database software maintains high level of integrity of the database. For example if a column in a table of the database is configured to accept date of birth of employees, that column will only accept data in the format of a date and not any arbitrary number. Similarly a column that is configured to accept only numbers to represent money, will not accept any characters as an entry. In Table 6 a list of different data types have been shown from the perspective of use in database of ERP-OWTM software package.

Data Type	Comment
varchar	Variable width character string, maximum 8,000 characters
nchar	Fixed width Unicode string, maximum 4,000 characters
bit	Allows 0,1 or null
image	Variable width binary string. Maximum 2GB
smallint	Allows whole numbers, -32,768 and 32,767
int	Allows whole number between $-2.14*10^9$ and $2.14*10^9$
float	Floating precision number, $-1.79*10^{308}$ to $1.79*10^{308}$
money	Monetary data from $-922*10^{12}$ to $922*10^{12}$
real	Floating precision number data from $-3.4*10^{38}$ to $3.4*10^{38}$
date	Stored date only
time	Store a time only
timestamp	Stored unique number that gets updated every time a row gets created or modified
varbinary	Variable width binary string. Maximum 2GB

Table 6. Data Types and Variables used in the database

B6. Tables, Columns and Rows of ERP-OWTM

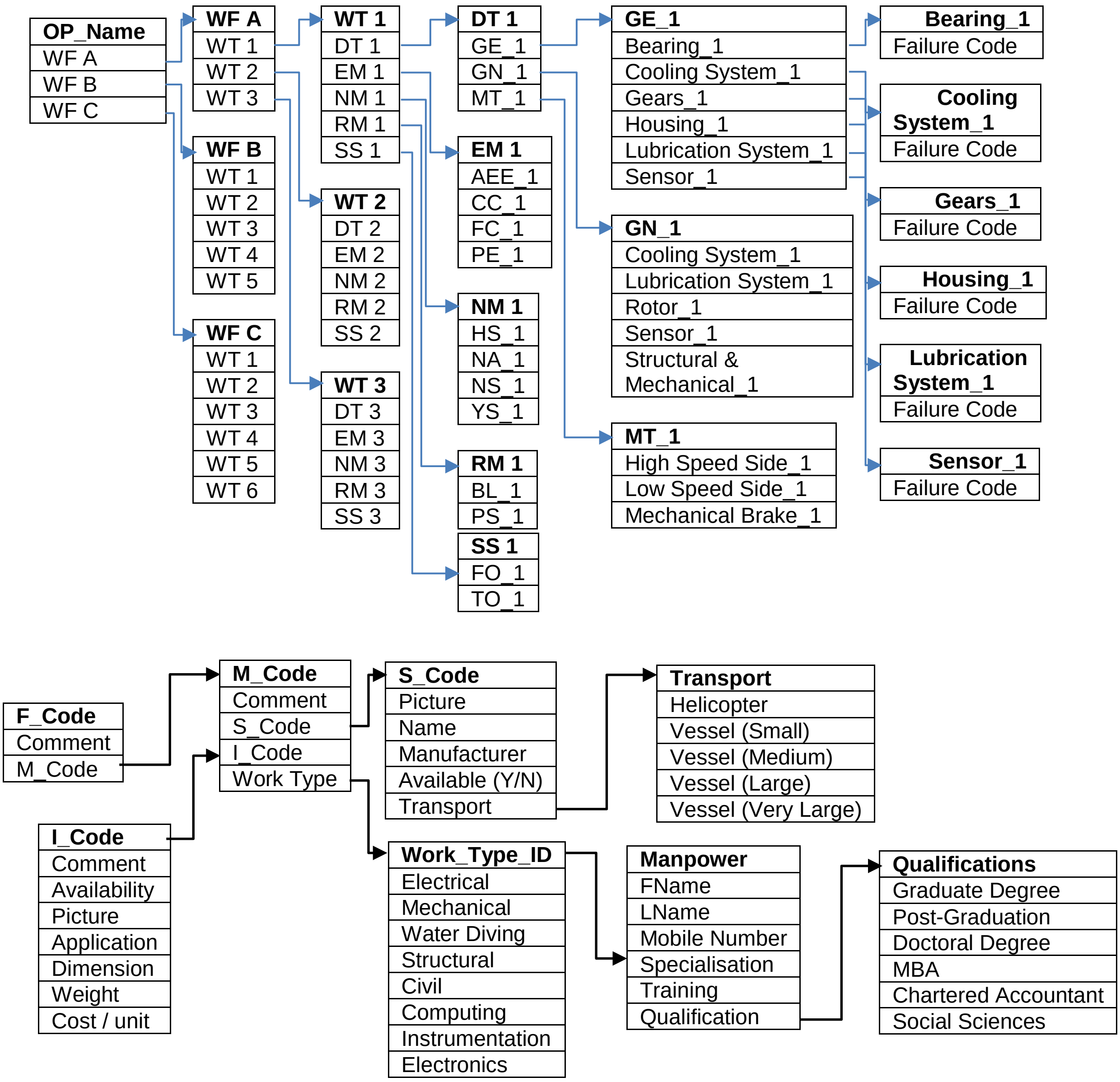
Various tables can be defined for the database of OWT maintenance software package to accommodate the diverse nature of information sources. This section shows some tables along with the names & data types of its columns. As is seen from Table 7, there are many tables containing variety of information about wind farm, wind turbine and its assemblies. For example the table by name of '*Wind Farm*' contains columns that aim to collect information about the location, distance, onshore/offshore, commissioning date etc. for a wind farm such that any wind farm can be uniquely identified. Similarly, table by name of '*Wind Turbine*' is designed to store information about all the wind turbines. In the table by name of '*Wind Turbine*', there is a column by the name of '*Wind Farm*' and is a pointer by the table by similar name so that any wind turbine can be uniquely identified to a wind farm. Similarly the table by the name of '*Wind Turbine Assembly*' contains pointers to other tables which contain more detailed information about assemblies of the wind turbine. These tables are linked to the parent table '*Wind Turbine Assembly*' using a pointer of '*WT ID*'. Such design of the database ensures that only limited number of information is contained within any table to avoid data duplication and reduces chances of database corruption.

Wind Farm	**Data**	**Wind Turbine Assembly**	**Data**	**Generator**	**Data**	**Frequency C**	**Data**
Wind Farm Name	char	WT ID	Int	WT ID	Int	WT ID	Int
Farm ID	Varchar	Main Shaft Set	Char	Generator SN	Int	Module FC SN	Int
Country	Char	Gearbox	char	Generator ID	Int	FC ID	Int
Location	Char	Generator	Char	Manufacturer	Char	Manufacturer	Char
Onshore/Offshore	Char	Auxiliary Electrical	Char	Model	Char	Model	Char
Distance (KM)	smallint	Control & Communication	Char	Type	Char	Type	Char
Power Rating (MW)	smallint	Frequency Converter	char	Rating	Int	Rating	Int
Farm Developer	Char	**Gearbox**	**Data**	Installation	Date	Installation	Date
Address/Phone	Char	WT ID	Int	Last Service	Date	Last Service	Date
Commission Date	Date	Gearbox SN	Int	Last Overhaul	Date	Last Overhaul	Date
Warranty (Years)	Smallint	Manufacturer	Char	**Main Shaft**	**Data**	**AE Comp Parts**	**Data**
Warranty Expiration	Date	Model	Char	WT ID	Int	Module ID	int
AMC Company	Char	Type	Char	Main Shaft SN	Int	Transformer	char
AMC Period (Years)	smallint	Rating	Char	Main Shaft ID	Int	Circuit Break.	char
AMC Start Date	Date	Installation Date	Date	Manufacturer	Char	Cabinet	char
AMC End Date	Date	Last Service	Date	Model	Char	Fan	char
Wind Turbine	**Data**	Last Overhaul	Date	Type	Char	Fuse	char
Wind Farm Name	Char	**Aux Electrical System**	**Data**	Rating	Int	Prot. Relay	char
Wind Turbine Name	Char	WT ID	int	Installation	Date	Light	char
WT ID	Int	Module SN	int	Last Service	Date	Mech Switch	char
Manufacturer	Char	Module ID	Int	Last Overhaul	Date	Pushbutton	char
Model	Char	Serial Number	Char	**Control Com.**	**Data**	Relay	char
Serial Number	Int	Manufacturer	Char	WT ID	Int	Space Heater	char
Installation Date	date	Model	Char	Module SN	Int	Surge Arrest.	char
Cut-in Speed	float	Type	Char	Module ID	Int	Thermal Prot.	char
Cut-out Speed	Float	Voltage Rating	Int	Manufacturer	Char	UPS	char
Swept Area	Float	Current Rating	Int	Model	Char	**Cont Comm Parts**	**Data**
Rated Power	float	Installation Date	Date	Type	Char	Module ID	Int
Gearbox Parts	**Data**	Last Service	Date	Rating	Int	Breaker	char
GB SN	int	Last Overhaul	date	Installation	Date	Temp Sensor	char
C Bearing	char	**Generator Parts**	**Data**	Last Service	Date	Cable	char
P Bearing	char	GN SN	int	Last Overhaul	Date	Contactor	char
S Bearing	char	Filter	char	**Freq Conv Parts**	**Data**	Digital I/O	char
Hose	char	Hose	char	FC ID	int	Bus Master	char
Pump	char	Pump	char	CC Filter	char	Frequency	char
Coil	char	Commutator	char	**Main Shaft Parts**	**Data**	Condition Cab	char
Hollow Shaft	char	Exciter	char	MS SN	int	Data Logger	char
Bushing	char	Resistance Controller	char	Coupling	char	Sensor	char
Case	char	Slip Ring	char	Rotor Lock	char	Power Supply	char
Mounting	char	Core Temperature	char	Trans Shaft	char	CPU	char
Hose	char	Encoder	char	Shaft	char	Comm Bus	char
Primary Filter	char	Wattmeter	char	Axial Bearing	char	Closed Loop	char
Pump	char	Front Bearing	char	Compr Coupler	char	Emerg Button	char
Seal	char	Housing	char	Connect Plate	char	Max Spe. itch	char
Secondary Filter	char	Rear Bearing	char	Bearing Seal	char	Power Switch	char
Debris Sensor	char	Shaft Bearing	char	Main Shaft	char	SC Switch	char
Pressure Sensor	char	Silent Block	char	Radial Bearing	char		
T Sensor	char	Cooling Fan	char	Rotor Lock	char		
				Slip Ring	char		
				HS Sensor	char		
				LS Sensor	char		
				Posit Sensor	char		

Table7. Wind Farm, Wind Turbine and its assembly description

B7. Defining a Wind Farm

This section shows how information about a wind farm is laid out in the database such that it characterises all of its wind turbines and their different assemblies, sub-assemblies and components in a unique fashion. This has been shown in Figure 10. As can be seen from Figure 10, wind farms, WF A, WF B and WF C, individually point to wind turbines that are present in their wind farm, while those wind turbines point to its individual assemblies which then point to subassemblies and components. Finally at the component level a failure code can be assigned corresponding to the failure that may have occurred. By default all components are assigned a No Failure code, which is updated in the event a failure is encountered. This information is then taken further to analyse and plan maintenance. If a spare would be required for this maintenance work, then the failure code would indicate this and hence a reference would be made to the maintenance database and spares inventory. When failure codes are determined, all necessary resources can be collected using references to their individual databases. This has also been shown in Figure 10 where manpower and transport are linked to unique failures.



Notations Used in the table

Wind Farm	WF	Tower	TO	Gearbox	GE	Support Structure	SS
Wind Turbine	WT	Foundation	FO	Main Shaft	MT	Operator	OP
Drive Train	DT	Pitch System	PS	Auxiliary Electrical System	AEE	Nacelle Assembly	NA
Electrical Module	EM	Blade	BL	Control & Communication	CC	Generator	GN
Nacelle Module	NM	Yaw System	YS	Hydraulic System	HS		
Rotor Module	RM	Nacelle Structure	NS	Power Electrical System	PE		

Figure 10. Shows the database tables and its relationships for a component level status (failures) in an OWT

B8. Overall Outlay of the Database

An overall design framework of the ERP-OWTM has been shown in Figure11 that provides guidelines for the design of database and interrelation between them. Any individual block in the figure is an outcome of a interrelated database modules. It also provides an indication to various performance indicators that are useful to measure the success or failure of a maintenance regime. In Figure 11 maintenance planning for only wind turbine gearbox has been shown but it can be extended to include other components as well.

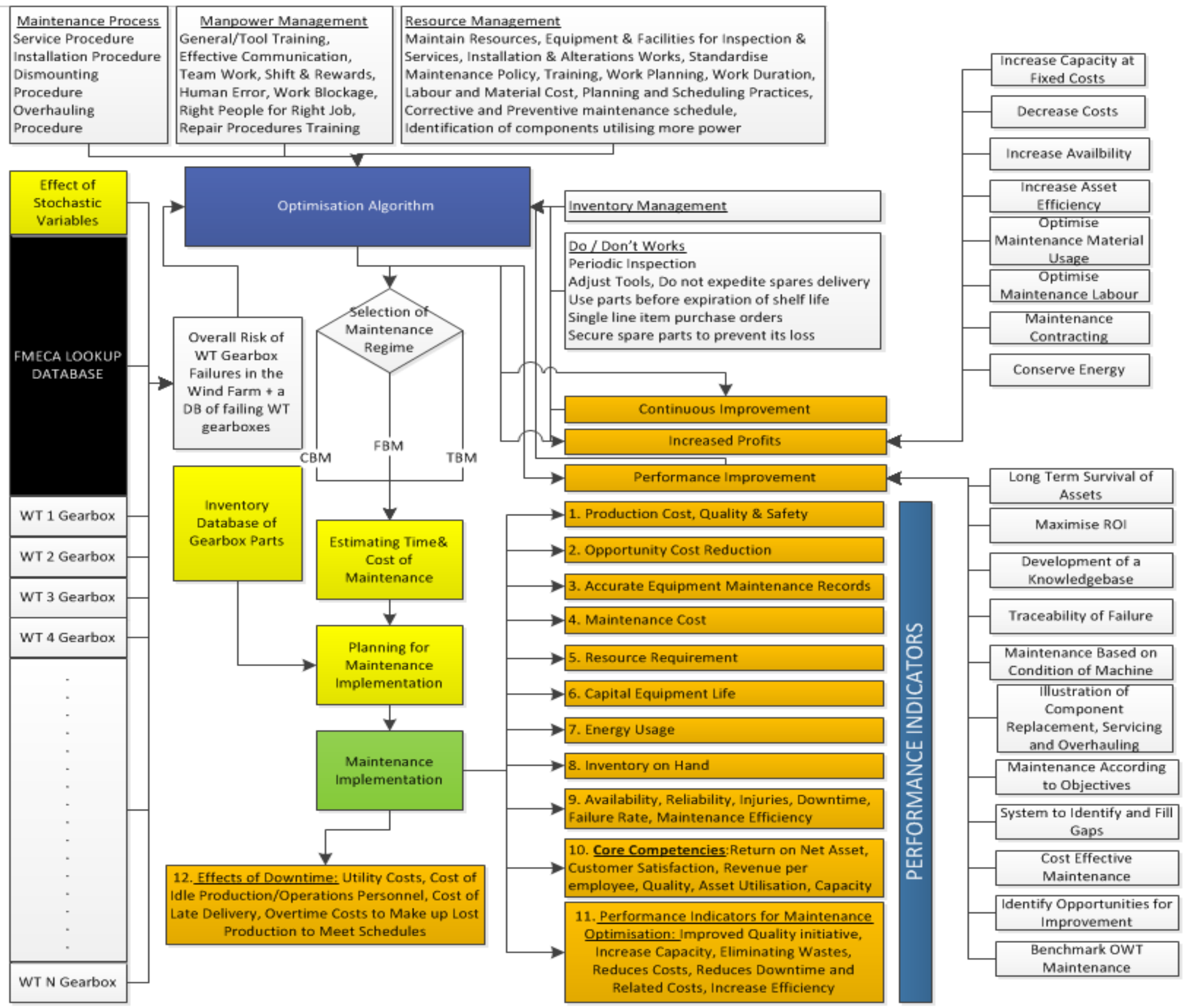


Figure 11 Schematic diagram of database layout and software framework for the design of ERP-OWTM

2. Conclusion

The ability to predict failure has a profound effect maintenance planning and its costs. Failures in machines, like wind turbines can be interrelated by their root causes, dependences on other failures and operating conditions. In this work such dependency between failures and root causes were studied and it is found that such information could be used to plan a Condition Based Maintenance and make savings on spares, transportation and manpower. In fact, use of condition monitoring information in itself bypasses many complexities which statistical methods have faced since long time, like incorporating effect of weather conditions on OWT failure. However this work is fundamental and there is a need for more information about failure to make this model more accurate. This work also looked into the design and development of a database that would support a software tool for management of wind turbine maintenance. Design of a database is fundamental and an important step in the development of any software tool especially for projects that are developed from inception and those which are built for large applications. It is intended that database designed in this work will reduce the amount of software code that would otherwise have been required. Whilst it is difficult to source data related to wind turbine, especially for OWT, this work makes use of some dummy data to test the outputs from the database. However it is expected that many additional modules would be incorporated with time in the database, which would then increase the size of the database. The 3 module structure developed for the database (Section B2) would be effective in incorporating all such modular expansions. Further with new information, many columns and rows would need to be modified but as all the tables have been normalised, any negative effect on database structure would be minimal.

Acknowledgement

The author wants to acknowledge the financial support provided for this project by Robert Gordon University (Aberdeen), Stork Technical Services (Aberdeen) and Energy Technology Partnership (Aberdeen).

References

[1]Wang Y, Study of Technology of Feature Extraction of Gearbox Fault, Taiyuan, North University of China, 2007
[2]Li S, Jiang D, Zhao M, Experimental Investigation and Analysis for Gearbox Fault, IEEE, 2010
[3]Caselitz P, Giebhardt J, Rotor Condition Monitoring for Improved Operational Safety of Offshore Wind Energy Converters, Institute of Solar Energy Suly Technology, Kassel
[4]Elforjani M, Mba D, Detecting Natural Crack Initiation and Growth in Slow Speed Shaft with the Acoustic Emission Technology, Engineering Failure Analysis, Vol 16, pp 2121-2129, 2009
[5]Dongxiang J, Liangyou H, Qian H, Yongshan D, Condition Monitoring and Fault Diagnosis Techniques for Wind Turbine, Power System and Clean Energy, Vol. 23, pp 40-44, 2008
[6]Amirat Y, Choqueuse V, Benbouzid M E H, Wind Turbine Condition Monitoring and Fault Diagnosis Using Generator Current Amplitude Demodulation, IEEE International Energy Conference, 2010
[7]Heywood R, Lapworth J, Hall L, Richardson Z, Transformer Lifetime Performance: Managing the Risks, "3rd IEEE International Conference on Reliability of Transmission and Distribution Networks, London, 2005
[8]Wilson A, Heywood R, Richardson Z, The Life time of Power Transformer, Insucon, 2006
[9]Heathcote, J&P Transformer Book, 13th Edition, Elsevier, 2007
[10]Dongxiang J, Liangyou H, Qian H, Yongshan D, Condition Monitoring and Fault Diagnosis Techniques for Wind Turbine, Power System and Clean Energy, Vol 23, pp 40-44, 2008
[11]Guo H, Wu B, Fault Diagnosis of Wind Turbine Power Electronic Equipment based on SOM Neural Network, Sixth International Conference on Natural Computation (ICNC), 2010
[12]Ye X, Veeramachaneni K, Yan Y, Osadiw L. A., Unsupervised Learning and Fusion for Failure Detection in Wind Turbines, 12th International Conference on Information Fusion, ISIF, 2009
[13]Becker E., Posta P, Keeping the Blade Turning: Condition Monitoring of Wind Turbine Gears, Vol 7(2), pp 48-51, 2006
[14]Editorial, Managing the Wind - Reducing kilowatt-hour Costs with Condition Monitoring, Refocus, Vol 6,(3), pp 253-261, 2005
[15]Andrawus J A, Maintenance Optimisation for Wind Turbines, PhD Thesis, Robert Gordon University, Aberdeen, UK, 2008
[16]Ding H, Heywood R, Lapworth J, Ryder S, Why Transformers Fail, Euro TechCon, 2009
[17]Yang S, Li W, Wang C, The Intelligent Fault Diagnosis of Wind Turbine Gearbox Based on Artificial Neural Network, International Conference on Condition Monitoring and Diagnosis, Beijing, China, 2008
[18]Leite A, Borges C, Falcao D, Probabilistic Wind farm Generation Model for Reliability Studies applied to Brazilians Sites, IEEE Transaction on Power Systems, Vol 21, 1493-15016, 2006
[19]Karki R, Billinton R, Cost Effective Wind Utilisation for Reliable Power Supply, IEEE - Energy Conversion, Vol 19 (2), pp 435-440, 2004
[20] Sinha Y, Steel J A, A Progressive study into offshore wind farm maintenance optimisation using risk based failure analysis, Renewable and Sustainable Energy Reviews, Vol 42, pp 735- 742, 2015
[21]Walford C, Wind Turbine Reliability, Understanding and Minimising Wind Turbine Operation and Maintenance Costs, Sandia National Laboratories, Report No. SAND2006-1100, 2006
[22]Renewables Global Status Report, 2011 (Available: http://www.ren21.net/Portals/97/document s/GSR/REN21_GSR2011.pdf) (Accessed: 13/08/2012)
[23]Tavner P, Offshore Wind Turbines – Reliability, Availability and Maintenance, IET Renewable Energy Series, 1st Ed, 2012
[24] www.amariner.net/cblog/index.php?/archives/17-unknown.html (Assessed: 8/7/2014)
[25] Koch H R, Connecting Large Offshore Wind Farms to the Transmission Network, T&D Conference New Orleans, IEEE, 2010
[26] Moskalenko N, Orths A, Study of Wake Effect for Offshore Wind Farm Planning, Motor Electric Power System, Poland, 2010
[27]Electricity Generation Costs, Department of Energy & Climate Change, October 2012, 2012
[28] Rodriguez I, Gracia M, Morant F, Correcher A, Quiles E, Application of Latent Nestling Methods using Coloured Petri Nets for the Diagnosis in the WT Subsets, IEEE Int. conference of Emerging Technologies and Factory Automation, pp 767-73, 2008
[29] Guo H, Wu B, Fault Diagnosis of WT Power Electronic Equipment based on SOM Neural Network, Sixth International Conference on Natural Computation (ICNC), 2010
[30] Benbouzid M A, Review of Induction Motors Signature Analysis as a Medium for Fault Detection, IEEE Transactions on Industrial Electronics, Vol 47 (5), pp 984-993, 2000
[31] Cusido J, Romeral L, Ortega J, Rosero J, Espinosa A, Fault Detection in Induction Machines using Power Spectral Density in Wavelet Decomposition, IEEE Transaction on Industrial Electronics, Vol 55 (2), pp 633-643, 2008
[32] Stack J R, Harley R G, Habetler T G, An Amplitude Modulation Detector for Fault Diagnosis in rolling Element Bearings, IEEE Transaction on Industrial Electronics, Vol 51 (5), 2004
[33] Amirat Y, Choqueuse V, Benbouzid M E H, Charoentier J F, Bearing Fault Detection in DFIG Based WT Using the First Intrinsic Mode Function, XIX International Conference on Electrical Machines – ICEM, Rome, 2010
[34] Elforjani M, Mba D, Detecting Natural Crack Initiation and Growth in Slow Speed Shaft with the Acoustic Emission Technology, Engineering Failure Analysis, Vol 16, pp 2121-2129, 2009
[35] Al-Ahmar E, Benbouzid M E H, Amirat Y, DFIG-Based Wind Turbine Fault Diagnosis Using A Specific Discrete Wavelet Transform, In Proceedings Of Icem'08, Vilamoura, Portugal, 2008
[36] Becker E, Posta P, Keeping the Blade Turning: Condition Monitoring of Wind Turbine Gears, vol 7(2), pp 48-51, 2006
[37] Editorial, Managing the Wind: Reducing kilowatt-hour Costs with Condition Monitoring, Refocus, Vol 6 (3), pp 253-261, 2005
[38]Amirat Y, Choqueuse V, Benbouzid M E H, Charoentier J F, Bearing Fault Detection in DFIG Based Wind Turbine Using the First Intrinsic Mode Function, XIX International Conference on Electrical Machines – ICEM, Rome, 2010
[39] Sinha Y, Steel J A, Andrawus J A, Gibson K, A SMART Software Package for Maintenance Optimisation of Offshore Wind Turbines, Wind Engineering, Vol 37 (6), pp 569-577, 2013
[40] Palma J, Hijes F C G, Martinez M C, Careles L G, Scheduling of Maintenance Work: A Constraint based Approach, Expert Systems with Applications, vol. 37, pp 2963-2973
[41] Zaher A S, McArthur S D J, A multi agent fault detection system for Wind Turbine defect recognition and diagnosis, IEEE, 2010
[42] Li P, He Q, Kong F, A New Method of Feature Extraction for Gearbox Vibration Signals, 3rd International Congress on Image and Signal Processing, IEEE, 2010
[43]Igarshi T, Hamada H, Studies on the Vibration and Sound of Defective Roller Bearings, First Report: Vibration of Ball Bearing with one Defect, Bull JSME, Vol. 25 (204), pp 1791-1798, 1982
[44]Ribrant J, Reliability Performance and Maintenance - A Survey of Failures in Wind Power Systems, Master Thesis, KTH, Stockholm, Sweden, 2005
[45]Ben-Daya M S, Duffuaa A R, Handbook of Maintenance Management and Engineering, Springer, London, 2009
[46]Neale M, Condition Monitoring Manual, HMSO, UK (Available: http://books.google.co.uk/books?id=j2mN2aIs2YIC&pg=PA467 &lpg=PA467&dq=Neale+M.,+Condition+Monitoring+Manual,+HMSO,+UK&source=bl&ots=Qqz9l0KTVA&sig=3mBJeF7tW10J6 uekghmzCzVXBjI&hl=en&sa=X&ei=t6MgUaOtI82Thge_pIHYAQ&ved=0CDIQ6AEwAA#v=onepage&q=Neale%20M.%2C%20Condition%20Monitoring%20Manual%2C%20HMSO%2C%20UK&f=false) (Assessed – 10/1/2013)

[47]Hameed Z, Hong Y S, Choa Y M, Ahn S H, Song C K, Condition Monitoring and Fault Detection of Wind Turbines and Related Algorithms: A Review, Renewable and Sustainable Energy Review, Vol 13, pp 1-39, 2009

[48]Tandon N, Makra B C, Vibration and Acoustic Monitoring Techniques for the Detection of Defects in Rolling Elements Bearings – A Review, Shock and Vibration Digest, Vol 24 (3), pp 3-11, 1992

[49]Yoshioka T, Takeda M, Classification of Rolling Contact Fatigue Initiation using Acoustic Emission Technique, Lubrication Engineering, Vol 51 (1), 1994

[50]Tan C C, Application of Acoustic Emission to the Detection of Bearing Failures, Proceedings Tribology Conference, Brisbane,110-114, 1990

[51] Morfiadakis E, Papadopouls K, Philippidis T P, Assessment of the Strain Gauge Technique for Measurement of Wind Turbine Blade Loads, Wind Energy, Vol 3 (1), pp 35-65, 2000

[52]Giebel G, Oilver G, Malcom M, Kaj B, Common Access to Wind Turbine Data for Condition Monitoring, RISO International Symposium on Material Science, Denmark, pp 157-164, 2006

[53]Morando I E, Measuring Shock Pulses is Ideal for Bearing Condition Monitoring, Pulp and Paper, Vol 62 (12), 96-98, 1988

[54]Tandon N, Nakra B C, Comparison of Vibration and Acoustic Measurement Techniques for the Condition Monitoring of Rolling Element Bearings, Tribology International, Vol 25 (3), 205-212, 1992

[55]Deshpande V S, Modak J P, Application of RCM for Safety Considerations in a Steel Plant, Reliability Engineering and System Safety, Vol 3 (78), pp 325-334, 2002

[56]Endrenyl J, McCauley J, Singh C, The Present Status of Maintenance Strategies and the Impact of Maintenance on Reliability, IEEE Transaction Power System, Vol 16 (4), 638-646, 2001

[57]Verbruggen T W, Wind Turbine Operation and Maintenance based on Condition Monitoring, WT-O, Final Report, ECN-C-03-047, 2003

[58]Leske S, Kitaljevich D, Managing Gearbox Failure, Dewek, Dewek Magazine, N 29, 2006

[59]Schoen R R, Lin B K, Habetler T G, Schlag J H, Farag S, An Unsupervised On-line System for Induction Motor Fault Detection using Stator Current Monitoring, IEEE Transaction on Industry Applications, Vol 31 (6), pp 1280-1286, 1995

[60]Sep D C, Lee J J, Damage Detection of CFRP Laminates using Electrical Resistance Measurement and Neural Network, Composite Structures, Vol 47, pp 525-530, 1999

[61]Zaher A S, McArthur S D J, A Multi-Agent Fault Detection System for Wind Turbines Defect Recognition and Diagnosis, International Proceedings IEEE Lausanne POWERTECH 2007, pp 22-27, 2007

[62]Sorensen B F, Lading L, Sendrup P, McGugan M, Debel C P, Kristensen O J D, Fundamentals for Remote Structural Health Monitoring of Wind Turbines Blades – A Pre-project, RISO-R-1336(EN), 2002

[63]Dale S L, Dolan, Lehn P W, Real Time Wind Turbine Emulator Suitable for Power Quality and Dynamic Control Studies, International Proceedings of International Conference on Power Systems Transients, Montreal, Canada, pp 1-6, 2005

[64]Fantidis J G, Potolias c, Bandekas D V, Wind Turbine Blade Non-destructive Testing with a Transportable Radiography System, Science and Technology of Nuclear Installations, ID 347320, 2011

[65]Dolinski L, Krawczuk M, Damage Detection in Wind Turbine Blades by Vibration based Methods, 7th International Conference on Modern Practice in Stress and Vibration Analysis, Journal of Physics, Conference Series 181 012086, 2009

[66]Al-Ahmar E, Benbouzid M E H, Amirat Y, DFIG-Based Wind Turbine Fault Diagnosis Using A Specific Discrete Wavelet Transform, In Proceedings Of ICEM'08, Vilamoura, Portugal, 2008

[67]Amirat Y, Choqueuse V, Benbouzid M E H, Wind Turbine Condition Monitoring And Fault Diagnosis Using Generator Current Amplitude Demodulation, IEEE International Energy Conference, 2010

[68]Amirat Y, Benbouzid M, Al-Ahmar E A, A Brief Status On Condition Monitoring And Fault Diagnosis In Wind Energy Conversion Systems, Renewable & Sustainable Energy Reviews, Vol 3 (9), pp 2629-2636, 2009

[69]Holland C, Modern Condition Monitoring Methods – Advantages On-board, Underhall, 2008 (Available: http://www.google .co.uk/url?sa=t&rct=j&q=condition+monitoring+techniques+pdf&source=web&cd=2&cad=rja&ved=0CEQQFjAB&url=http%3A%2F%2Fwww.uhfg.se%2Fhtml%2FMarinpresentationer%2FLR%2520Chris%2520Holland.pdf&ei=Q88wUO4Kpo7QBeL5gOgM&usg=AFQjCNFuX5QOf3ZlIKTHHiRSbXclR4BM9Q) (Last Accessed on 19/08/2012)

[70]Nilsson J, Bertling L, Maintenance Management of Wind Power Systems using Condition Monitoring Systems - Life Cycle Cost Analysis for Two Case Studies, IEEE Transaction on Energy Conversion, Vol 22 (1), 223-229, 2007

[71]Benbouzid M A, Review of Induction Motors Signature Analysis as a Medium for Fault Detection, IEEE Transactions on Industrial Electronics, Vol 47 (5), pp 984-993, 2000

[72]Cusido J, Romeral L., Ortega J, Rosero J, Espinosa A, Fault Detection in Induction Machines using Power Spectral Density in Wavelet Decomposition, IEEE Transaction on Industrial Electronics, Vol 55 (2), pp 633-643, 2008

[73]Stack J R, Harley R G, Habetler T G, An Amplitude Modulation Detector for Fault Diagnosis in Rolling Element Bearings, IEEE Transaction on Industrial Electronics, Vol 51 (5), 2004

[74]Rodriguez I, Gracia M, Morant F, Correcher A., Quiles E, Application of Latent Nestling Methods using Coloured Petri Nets for the Diagnosis in the Wind Turbine Subsets, IEEE International Conference of Emerging Technologies and Factory Automation, pp 767-73, 2008

[75]Echavarria E, Tomiyama T, Huberts H, Van Bussel G, Fault Diagnosis System for an Offshore Wind Turbine using Quantitative Physics, EWEC 2008, Brussels, Belgium, 2008

[76]Xingjia Y, Guangkun Shan, Donghai, Study on Variable Pitch System Characteristics of Big Wind Turbine, Energy Saving, Environment Protection and Sustainable Development in the Manufacturing Industry, International Technology and Innovation Conference, 2006

[77]Ranchin T, Furevik B, Stette M, et al, Obtaining Data for Wind Farm Development and Management: The EO-WINDFARM Project

[78]Amirat Y, Choqueuse V, Benbouzid M E H, Charoentier J F, Bearing Fault Detection in DFIG Based Wind Turbine Using the First Intrinsic Mode Function, XIX International Conference on Electrical Machines – ICEM, Rome, 2010

[79]Sainz E, Liombart A, Guerrero J J, Robust filtering for the characterization of wind turbines: Improving its operation and maintenance, Energy Conversion and Management, Vol 50, 2136-2147

[80]Tana C K, Irvinga P, A Comparative Experimental Study on the Diagnostic and Prognostic Capabilities of Acoustic Emission, Vibration and Spectrometric Oil Analysis for Spur Gears, Mechanical Systems and Signal Processing, Vol 21, pp 208-33, 2007

[81]Wei X, Liu L, Fault Detection of Large Scale Wind Turbine Systems, 5th International Conference on Computer Science and Education, Hefei, China, IEEE pp 1299-1304, 2010

[82]Lu B, Li Y, Wu X, Yang Z, A Review of Recent Advances in Wind Turbine Condition Monitoring and Fault Diagnosis, IEEE, 2009

[83]Johnson K E, Fleming P A, Development, Implementation and Testing of Fault Detection Strategies on the National Wind Technology Centre's Controls Advanced Research Turbines, Mechatronics, Vol 21, pp 728-736, 2011

[84]Application of Condition Monitoring Systems in Wind Energy Converters, EWEC 97, Dublin, Ireland, pp 597-582, 1997

[85] http://www.gl-garradhassan.com/assets/downloads/20100129-EWEC2010_full_paper_(SUBMITTED).pdf (Last Assessed: 26/01/2015)

[86]Al-Ahmar E, Benbouzid M E H, Amirat Y, DFIG-Based WT Fault Diagnosis Using A Specific Discrete Wavelet Transform, In Proceedings Of ICEM '08, Vilamoura, Portugal, 2008

[87]Amirat Y, Choqueuse V, Benbouzid M E H, Wind Turbine Condition Monitoring And Fault Diagnosis Using Generator Current Amplitude Demodulation, IEEE International Energy Conference, 2010

[88]Amirat Y, Benbouzid M, Al-Ahmar E A, A Brief Status On Condition Monitoring And Fault Diagnosis In Wind Energy Conversion Systems, Renewable & Sustainable Energy Reviews, Vol 3 (9), pp 2629-2636, 2009

[89]Rodriguez I, Gracia M, Morant F, Correcher A, Quiles E, Application of Latent Nestling Methods using Coloured Petri Nets for the Diagnosis in the WT Subsets, IEEE Int. conference of Emerging Technologies and Factory Automation, pp 767-73, 2008

[90]Guo H, Wu B, Fault Diagnosis of WT Power Electronic Equipment based on SOM Neural Network, Sixth International Conference on Natural Computation (ICNC), 2010

[91]Benbouzid M A, Review of Induction Motors Signature Analysis as a Medium for Fault Detection, IEEE Transactions on Industrial Electronics, Vol 47 (5), pp 984-993, 2000

[92]Cusido J, Romeral L, Ortega J, Rosero J, Espinosa A, Fault Detection in Induction Machines using Power Spectral Density in Wavelet Decomposition, IEEE Transaction on Industrial Electronics, Vol 55 (2), pp 633-643, 2008

[93]Stack J R, Harley R G, Habetler T G, An Amplitude Modulation Detector for Fault Diagnosis in rolling Element Bearings, IEEE Transaction on Industrial Electronics, Vol 51 (5), 2004

[94]Amirat Y, Choqueuse V, Benbouzid M E H, Charoentier J F, Bearing Fault Detection in DFIG Based WT Using the First Intrinsic Mode Function, XIX International Conference on Electrical Machines – ICEM, Rome, 2010

[95]Al-Ahmar E, Benbouzid M E H, Amirat Y, DFIG-Based Wind Turbine Fault Diagnosis Using A Specific Discrete Wavelet Transform, In Proceedings Of Icem'08, Vilamoura, Portugal, 2008

[96]Amirat Y, Choqueuse V, Benbouzid M E H, Wind Turbine Condition Monitoring And Fault Diagnosis Using Generator Current Amplitude Demodulation, IEEE International Energy Conference, 2010

[97]Amirat Y, Benbouzid M, Al-Ahmar E A, A Brief Status On Condition Monitoring And Fault Diagnosis In Wind Energy Conversion Systems, Renewable & Sustainable Energy Reviews, Vol 3 (9), pp 2629-2636, 2009

[98]British Standards, Glossary of terms used in terotechnology, British Standards BS 3811:1993, Published 15th December 1993

[99] http://www.quora.com/What-are-some-real-life-applications-of-Bayesian-Belief-Networks (Accessed: 24/01/2015)

[100] http://faculty.washington.edu/tamre/BayesTheorem.pdf (Accessed: 11/11/2014)

[101] http://dictionary.cambridge.org/dictionary/business-english/relational-database?q=relational+database (Accessed: 9/06/2014)

[102] http://www.cs.cityu.edu.hk/~helena/cs34622000B/Normalization.pdf (Accessed: 6/06/2014)

[103] http://www.cs.utexas.edu/~cannata/dbms/Class%20Notes/06%20Normalization.pdf (Accessed 9/6/2014)