

Remaining Useful Life Prediction on Wind Turbine Gearbox

R Srinivasan, T Paul Robert



Abstract—This research proposes a methodology to estimate the reliability of gearbox using life data analysis and predict the Lifetime Use Estimation (LUE). Life data analysis involves collection of historical field replacements of gearbox and perform statistical analysis such as Weibull analysis to estimate the reliability. Remaining useful life is estimated by using Cumulative damage model and data-driven methods. The first approach is based on the physics of failure models of degradation and the second approach is based on the operational, environmental & loads data provided by the design team which is translated into a mathematical model that represent the behavior of the degradation. Data-driven method is used in this research, where the different performance data from components are exploited to model the degradation's behavior. LUE is used to make key business decisions such as planning of spares, service cost and increase availability of wind turbine. Gearbox is the heart of the wind turbine and it is made up of several stages of helical/planetary gears. Performance data is acquired separately for each of these stages and LUE is calculated individually. The individual LUE is then rolled up to estimate the overall Lifetime Use Estimation of gearbox. This will identify the weak link which is going to fail first and the failure mode which is driving the primary failure can be identified. Finally, corrective measures can be planned accordingly. The cumulated damage and LUE are estimated by using Inverse power law damage model along with Miner's rule.

Keywords—Reliability, Gearbox, Remaining Useful Life(RUL), Inverse power law, Lifetime Use Estimation (LUE)

I. INTRODUCTION

Wind energy continues to raise in popularity as it is a source of sustainable energy. However, maintaining the wind turbines is a very challenging one. Maintaining the Wind turbine components needs a monitoring technology & statistical simulation to predict the failures, here Lifetime Use Estimation (LUE) is derived. The Lifetime Use Estimation of a component or element is defined as the period for which asset is probable to stay operational. The intention of LUE prediction of an element or an equipment is to forecast the time left before the asset losses its performance due to operating conditions, maintenance and impact of fatigue aging over a time. LUE is typically random and unknown, and as such it is crucial to estimate from available sources of information such as field failures, regular maintenance, loads from operational data, operational condition and health monitoring.

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This study reviews the recent model developed for estimating the LUE using the physics-based failure model and a data driven method. Data driven model depends on the relationship that are derived by training the past data obtained from the system. The data driven approaches are applied to estimate the LUE of rotating machineries in [1] and [2].

The unique feature about this research is that it is a damage-based calculation model, wherein the cumulative damage is estimated [9] first and then it is compared with a baseline damage level to estimate the potential remaining damage. Then, the regression model is used to predict the LUE which forecast the potential remaining damage which can occur or survive before it fails.

II. SIGNIFICANCE OF STUDY

The main focus of this study is to investigate the literature which exists on the modeling methods for LUE assessment given the operational and historical maintenance data with condition and health monitoring information. The LUE of an asset is clearly a random variable and it depends on the current age of the asset, the operation environment and the observed condition monitoring (CM) with external environmental variables such as wind speed, fatigue stress or loading on the component. The gearbox is one of the most important components in the wind turbine and it is more concerned about turbine downtime and failures. The failure of gearbox causes unplanned shutdowns, reducing turbine availability and increasing the cost of energy. In addition to that, gearbox is the most expensive component in a wind turbine and therefore it is essential to continuously monitor the state and lifetime use estimation of gearbox components to make key business decisions. To measure the present reliability, historical failure data and load conditions like speed, torque data is collected for the population or for a representative sample of units and a statistical distribution (model) is fitted based on the collected data on failures and the one running in field. Based on the statistical distribution, the failure pattern is identified, and it is used to predict the life characteristics of the product (Reliability, Failure rate, Mean Life etc.). The statistical distribution for the data set can then be used to estimate important life characteristics of the product such as reliability or probability of failure at a specific time, the mean life and the failure rate. The reliability assessment will give us an idea on what is the current reliability or age of gearbox component and predicts the LUE which helps to make key decision.

III. PREDICTION METHODOLOGY IN LUE

Lifetime use estimation method and prognostics using online monitoring data for a component in operation is a relatively complex task.



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The assessment is problematic as LUE method to measure, inferentially, the ageing in service of a key mechanical or electrical component; especially for the purpose of comparison with the design-lifetime or target-lifetime of the component, and use in real-time on-line Lifetime-Use Control (LUC).

LUE is conditional to the component working under different environmental and operational conditions. LUE assessment is based on the system monotonic degradation and the degradation dynamics are from a nonlinear, time-variant and non-Gaussian system. There have been excellent papers over the last few decades on asset maintenance issues, predictive maintenance related issues, optimization of maintenance and predictive modeling and statistical techniques and diagnostics of faults referring [1], [2] and [10]. The challenge now is how to model the influence of external environmental variables such as speed or loading on LUE prediction. Also the development of a model which can deal with multiple failure modes for a single component is again a common scenario observed in conditioning monitoring practice. This may render the need of physics-based models with the help of subjective expert knowledge from design and manufacturing referring [2]. These review papers are extensive and cover many aspects of maintenance and reliability problems. However, there is one common thing, which tells little about LUE and the associated modeling techniques though some of the reviewed modeling techniques can be adopted for LUE. The recent advancements in sensing technologies, prognostics and health management (PHM) based upon condition monitoring (CM) has attracted much attention over the past years [16] and [17]. PHM is consist of prognostics, and health management. The main purpose of prognostics is to predict future performance of a component by assessing the extent of deviation or degradation of a system from its expected normal operating conditions according to the CM information. There are many research and development activities carried out on a variety of technologies and algorithms that can be used as the steps towards prognostic maintenance in [16] which discuss only on managerial problems in health monitoring and prognostics without discussing the modeling issues.. The machinery diagnostics and prognostics papers of [18] and [19] are comprehensive to extent and well structured, however they focus on rotating machinery prognostics with limited discussions on statistical based prognostic methods. Physics-based failure models rely on the physics of the underlying degradation process which predicts the onset of failures. Data-driven approaches attempt to derive models directly from collected CM and event data. In this type, there are machine learning and statistics-based approaches. From the above review of papers in relation to LUE prediction found that, though there is some research focusing on nonlinear degradation trajectories or degradation models adaptive to historical degradation data for LUE prediction, separately, few works concentrate on both of them simultaneously. To conclude that there is no such comprehensive review on statistical based failure mode specific and online data driven approaches for LUE. This paper plugs the gap and only focuses on statistical based data driven approaches using online fatigue for LUE. It basically includes four process steps: raw data collection, historical failure data, operational data and LUE prediction modeling with the help of health state assessment. It

proposes a hybrid approach consisting of both unsupervised learning and supervised learning to estimate the health state of a gearbox and it adopts vibration values from accelerometers.

IV. WIND TURBINE GEARBOX

Gearbox is the heart of a wind turbine and it is used to increase rotational speed from a low-speed rotor to a higher speed electrical generator. A common ratio is about 90:1, with a rate 16.7 rpm input from the rotor to 1,500 rpm output for the generator. The gearbox constructed between the rotor and generator convert low rpm, high torque power to high rpm, low torque power, which is used for the generator to produce electricity.

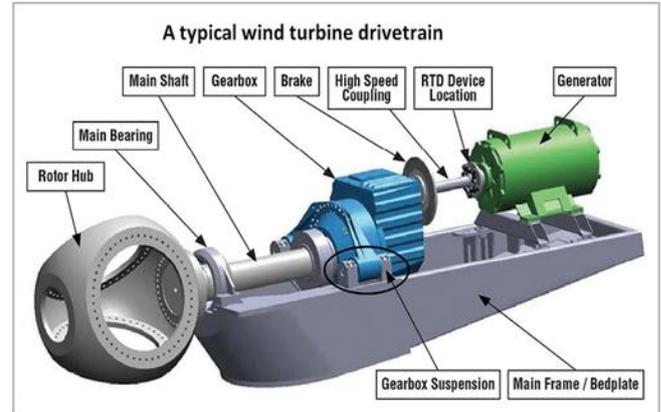


Figure 1: Gearbox arrangement in Wind Turbine

Conventional utility-scale wind turbines often use three-stage gearboxes as shown in Figure 1a. The 3 stages are: (1) Low speed stage- LSS (2) Intermediate speed stage-IMS (3) High speed stage-HSS. The low speed stage of the gearbox is a planetary configuration with either spur or helical gears. The sun pinion drives a parallel intermediate shaft that in turn drives a high-speed stage. Both the intermediate and high-speed stages use helical gears.

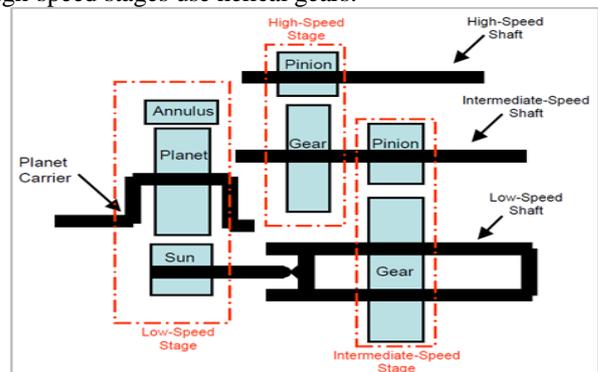


Figure 1a: Gearbox

Critical components include bearing that have exhibited a high percentage of application failures in spite of the use of best current design practices. In the generic configuration, there are three critical bearing locations, 1. Planet bearings 2. Intermediate shaft-locating bearings 3. High-speed locating bearings (see Figure 1a). Each location has exhibited a relatively high degree of bearing failures with a relatively low dependence on machine size, machine make or model. Typical design life of a wind turbine gearbox is 20 years and most of the gearboxes fail before the 20 years.



Gearboxes can fail drastically in different ways and most of the failures are caused due to bearings and gears/pinions. Both bearing and gear failures are concentrated in the parallel section. Predominant failure modes for bearing is axial crack and micro/macro pitting due to fatigue in case of gears. In this study, the focus is on the fatigue failure mode.

V. RELIABILITY ASSESSMENT ON LIFE DATA ANALYSIS

When performing life data analysis, the practitioner attempts to estimate reliability of the population by fitting a statistical distribution (model) to life data from a representative sample of units. "Life data" refers to the measurements of product life. Product life can be measured in hours, miles, cycles or any other metric that applies to the period of successful operation of a product. Since time is a common measure of life, life data points are often called "times-to-failure". The parameterized distribution for the data set can then be used to estimate important life characteristics of the product such as reliability or probability of failure at a specific time, the mean life and the failure rate.

Life data analysis is very essential for a company to know the reliability of their product and can control it in order to manufacture products at an optimum reliability level. This yields the minimum life-cycle cost for the user and minimizes the manufacturer's costs of such a product without compromising the product's reliability and quality. Life data analysis requires the practitioner to:

1. Historical failure data of product.
2. Select a lifetime distribution that will fit the data and model the life of the product.
3. Estimate the parameters that will fit the distribution.
4. Generate plots and results that estimate the life characteristics of the product, such as the reliability or mean life.

Statistical distributions have been formulated by statisticians, mathematicians and engineers to mathematically model or represent certain behaviour. There are many types of statistical distributions depending on the type of data (continuous or discrete) being analysed. The Weibull distribution is one of the many distributions and is widely used in reliability and life data analysis due to its versatility. Depending on the values of the parameters, the Weibull distribution can be used to model a variety of life behaviours. Mean and standard deviation are the parameters which is derived out of a normal distribution. Similarly, Weibull distribution has 3 parameters; they are shape (β), scale(η) and location parameter (γ). If $\gamma=0$, then the Weibull is called as 2-parameter Weibull.

To estimate reliability using Weibull analysis, we need time to failure data and operational time data of non-failed units. The unreliability or probability of failure is calculated using the following function. This function is called as cumulative distribution function (cdf) and it is a mathematical function that describes the distribution. The 2-parameter Weibull CDF is given by:

$$F(t) = 1 - \exp^{-(t/\eta)^\beta} \quad (1)$$

where

$F(t)$ - Cumulative distribution function or probability of failure

t - time at which unreliability needs to be estimated

β - shape parameter of Weibull distribution

η - scale parameter of Weibull distribution

An unreliability is derived from equation (1) for different points in time. The Weibull plot is on a log-log set of scales. The horizontal axis is time (could be cycles, operating or calendar time, etc.). The vertical axis is the probability of failure, from near zero to 1, often we use 0.01 to 0.99 indicating a 1% to 99% chance of failure. To plot the Weibull curve, we need to know the age of each component (in this case gearbox) for both failed and surviving components. Weibull analysis is performed by using Weibull++ software.

VI. LIFE DATA ANALYSIS

Ten identical units were considered in this study. The objective of this analysis is to use the complete data (failed) and right censored data (surviving) from the field to determine the unreliability for a mission duration of 226 hours, and the warranty time for a reliability of 85%. Five of the units fail after operating for the following numbers of hours: 16, 34, 53, 75 and 93. Remaining Five units were still operating (i.e., right censored or suspended) after 120 hours. Enter the data in the Weibull++ software as shown in Figure 2 below. The data sheet contains a "State F or S" column to indicate whether each data point represents a failure (F) or suspension (S).

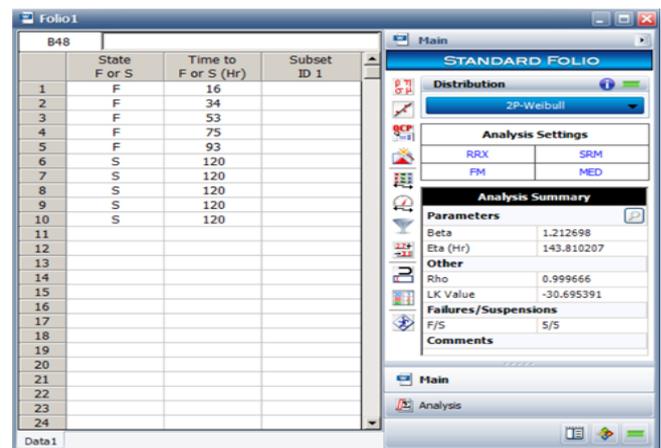


Figure 2: Data failure and suspension time

The data set is then analyzed using the 2-parameter Weibull distribution and rank regression on X (RRX). The results and plot are displayed below in Figure 2a; reliability is 82.2% at the end of 226 hours and a warranty time of 32.1437 hours for a reliability of 85%.

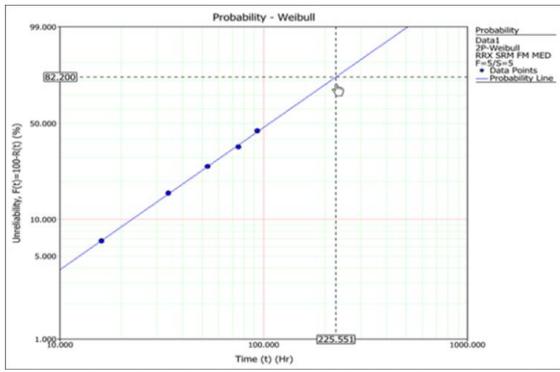


Figure 2a: Weibull Plot and Reliability Calculation

Field failure data is acquired separately for each of these stages and also Weibull analysis was carried out separately to calculate the reliability for 20 years. This reliability estimation can be taken as a primary source to perform a RUL prediction. Different organization follows different approach for estimating RUL. In some cases, they might directly do a RUL prediction without performing a Weibull analysis. The reason is service always wants RUL prediction to be done to aid in service strategic decisions. In this research, Weibull analysis is carried out first and based on the results from Weibull analysis, a decision will be taken to perform RUL prediction.

VII. REMAINING USEFUL LIFE

The Remaining Useful Life (RUL) is a subjective estimate of the number of remaining years that an asset or system is estimated to be able to function in accordance with its intended purpose before warranting replacement.

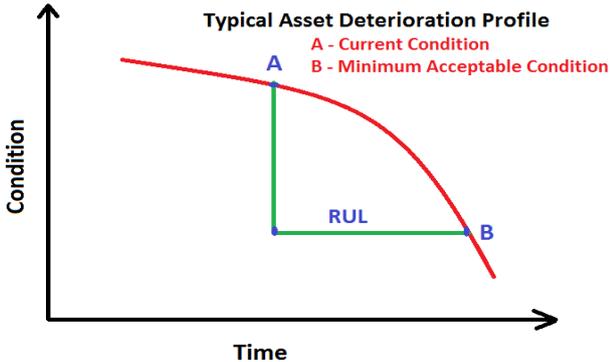


Figure 3: Asset Deterioration Profile

Determining an accurate remaining useful life for an asset is an important step in determining when the asset should be renewed/replaced. There are number of factors such as operational condition, operating environment and service level maintenance that will affect the RUL of an asset. The remaining useful life (RUL) of an asset or system is defined as the length from the current time to the end of the useful life. It is important to assess the RUL of an asset while in use since it impacts the owner's planning of maintenance activities, spare parts provision, operational performance, and the profitability of an asset. The RUL of an asset is clearly a random variable and it depends on the current age of the asset, the operation environment and the observed condition monitoring (CM) or health information. RUL prediction involves 3 main steps namely:

1. Miner's Rule
2. Cumulative damage calculation
3. RUL estimation using regression model

VIII. MINER'S RULE

Miner's rule is one of the most widely used cumulative damage models for failures caused by fatigue. This rule is not restricted only to the estimation of crack initiation but also used to predict a total fatigue life to fracture. The fractional damage consumed by one cycle of varying loading is defined as $D=1/N$, where N is the number of cycles to failure for the same stress level as in constant amplitude loading. Here, we consider a varying loading condition which is composed of different stresses $\sigma_1, \sigma_2, \dots, \sigma_i$. We define the fatigue life (cycles to failure) for each amplitude loading of stresses $\sigma_1, \sigma_2, \dots, \sigma_i$ as N_1, N_2, \dots, N_i cycles respectively, using the constant amplitude S-N curve. When each stress is loaded for n_1, n_2, \dots, n_i cycles, the damaging effect of each stress is assumed to as shown in below equation. Failure is assumed to occur when the sum of these ratios reaches 1.

$$\frac{n_1}{N_1} + \frac{n_2}{N_2} + \frac{n_3}{N_3} + \dots + \frac{n_i}{N_i} = 1$$

n_i - Number of applied load cycles of type i

N_i - Number of cycles to failure of type i

$$\frac{n_i}{N_i} = \text{Damage ratio at } i^{\text{th}} \text{ load value}$$

If the fraction of cycles at each loading value is taken as percentage rather than actual cycle number, the number of cycles can be expressed as:

$$n_i = \alpha_i N - (2)$$

α_i - Cycle Ratio (fraction of cycles) at the i th load value

N - Resultant fatigue life (total cycles).

Fatigue damage is accumulated in materials by the cyclic application of loads on assets or system.

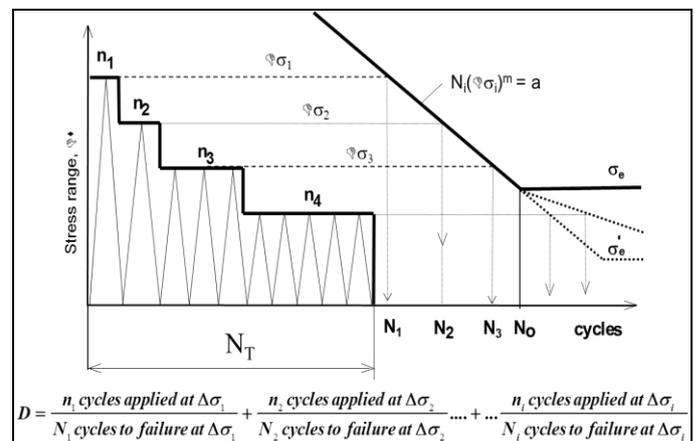


Figure 4: Linear damage accumulation

$$\sum_i \frac{n_i}{N_i} = 1 \quad (3)$$

n_i - Number of occurrences at the i^{th} load value

$\sum N_i$ - Total number of occurrences at all loading values.

A. Methods Where Stress Below the Fatigue Limit is Taken into Account

Modifications of linear damage accumulation laws have been proposed to reduce the shortcomings of Miner's rule. The major modification focused on accounting the damage effect caused by stress level below the fatigue limit. As shown in Figure 5, the modified methods use their own S-N curves. They also use the linear accumulation law expressed in Equation (1) for damage calculation.

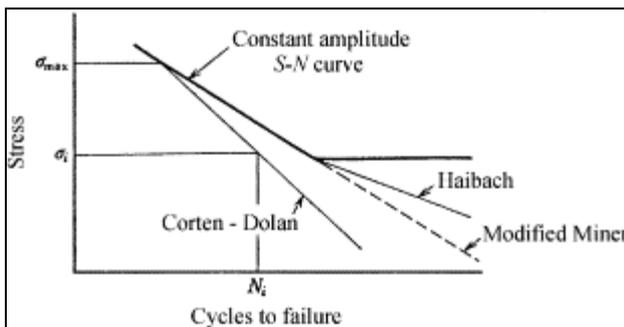


Figure 5: Modification of S-N curve for various damage accumulation laws

B. Modified Miner's rule

Miner's rule is obtained by linearly extrapolating the S-N curve into the region below the fatigue limit, as shown in Figure 5.

The modified Miner's rule is often used for fatigue evaluation of industrial machines. However, experimental results shows that the cumulative damage(D) failure is not always exactly equal to 1. It is somewhat different from 1.0 depending on stress profile materials, and so on. Therefore, some amount of deviation from cumulative damage(D) is not equal to 1 is introduced to the failure criterion as a usage factor. Since the appropriate amount of deduction depends on many conditions, it cannot be determined individually. It should be determined based on fatigue testing or on the past field experiences.

IX. DAMAGE ESTIMATION

The fatigue damage caused by a constant amplitude stress cycle is easily quantified by comparing the number of cycles applied to the fatigue life of the structure as determined experimentally. In variable amplitude fatigue analysis, the variable stress profile is defined as a group of constant amplitude stress accumulated each cycle. Thus, the fatigue damage caused by the variable amplitude stress history is the summation of the fatigue damage of the constant amplitude stress cycles. The accumulated damage over the lifetime shall be divided by the lifetime design damage of the turbine to provide a cumulative estimate of total lifetime used. In order to remain within the fatigue design loads, damage will be compared to the equivalent design damage

$$D=N*(S)^m \quad (4)$$

where,

- D - Total Damage
- N - Number of stress applications
- S - Actual stress level
- m - Exponent of element

Most systems and components do not see constant stress profile throughout their life. In most cases, there are low – high – low periods of loading. Similarly, in testing, it may not be practical to always run at fixed levels of input. At lower levels, closer to field conditions, the time required to run until failure may be prohibitive. Also, It is a time consuming process and involves huge money and resource investment. In these cases, it may be advantageous to "step-up" or increase the stress over time. Based on the different accelerated stress conditions data, life at use level can be extrapolated. One way of dealing with these kind of situations is to use Miner's rule damage model. This is based on the principle that damage from different portions of a duty cycle can be calculated and then added to estimate the total damage., See equation below.

$$D_{Total} = \sum_{1^{st} \text{ Step}}^{\text{Last Step}} \left(\frac{N_i}{L_i} \right) \quad (5)$$

When applying Miner's rule, each constant step stress accumulates damage and it is based on the ratio of the duration of the step stress cycles (N_i) to the life of the component at that level (L_i). The failure point is predicted when the total damage (D_{Total} – summed from each step) equals to one. An example is provided in table 1.

Table 1: Damage Calculation

Step	Stress (kN)	Duration (hrs)	Life at Level (hrs)	Step Damage
1	15	20	200	0.10
2	17	15	120	0.13
3	19	12	75	0.16
4	22	10	30	0.33
Total Damage				0.72

The total damage score level is 0.72 which represents that the component is not expected to fail by this point of time. Another way of looking at the same data is that 57 hours of testing time (4 steps) would accumulate a similar amount of damage as if the unit runs for 200 hours at the lowest level of 15 kN from step-1.

A. Example of a Cumulative Damage Calculation

To calculate the cumulative damage of a gearbox, it is necessary to define the loads acting on the gearbox as precise as possible. For instance, if one needs to calculate the damage due to fatigue, then the Load Duration Distribution (LDD) of the torque at the input shaft needs to be estimated. The LDD is created using SCADA(Supervisory Control and Data Acquisition) system which acquires data from different sensors in the turbine for every time interval. Data from SCADA is binned (see Fig 6 below) and LDD is constructed out of the binned data.



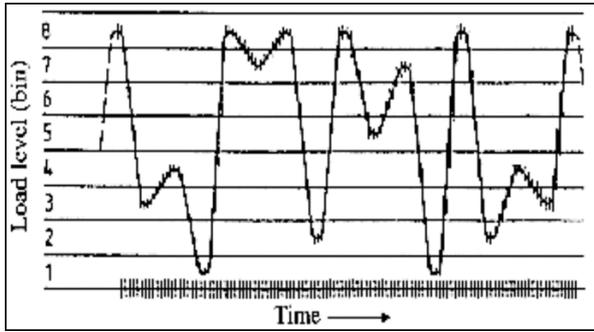


Figure 6: Binning of SCADA data

In this example, all the fluctuations are discarded between each time interval is recorded by using SCADA. The instantaneous torque is calculated as torque is the load coming on the shaft. Torque is not measured directly and it is calculated using speed and power which is measured and acquired using SCADA system as mentioned previously. This method is widely used in industry for reliability analysis and it can be seen implemented in the work of referenced [21], [22] and [23].

The relationship between torque and speed & power is given below

$$T = \frac{P \cdot 60}{2\pi N} \quad (6)$$

where,

T- Torque on the output shaft of gearbox

P - Power (kW/mW)

N- Speed on the input/output shaft of gearbox (RPM)

B. An example data set is provided below

Data collected for speed & power for the respective time interval for a specific wind turbine is provided below on the table 2.

Table 2: SCADA data and Torque

Time Stamp	Speed (rpm)	Power (kW)	Torque (kNm)
01-05-2016 01:10	1541	2200	13.63
01-05-2016 01:20	1638	2400	13.99
01-05-2016 01:30	1679	2600	14.79
01-05-2016 01:40	1505	2360	14.97
01-05-2016 01:50	1412	2100	14.20
01-05-2016 02:00	1567	2140	13.04
01-05-2016 02:10	1534	2200	13.70
01-05-2016 02:20	1702	2400	13.47
01-05-2016 02:30	1750	2600	14.19
01-05-2016 02:40	1639	2360	13.75
01-05-2016 02:50	1786	2100	11.23
01-05-2016 03:00	1634	2140	12.51
01-05-2016 03:10	1447	2200	14.52
01-05-2016 03:20	1775	2400	12.91
01-05-2016 03:30	1762	2600	14.09
01-05-2016 03:40	1483	2360	15.20
01-05-2016 03:50	1762	2100	11.38
01-05-2016 04:00	1596	2140	12.80
01-05-2016 04:10	1600	2200	13.13
01-05-2016 04:20	1546	2400	14.82
01-05-2016 04:30	1634	2600	15.19
01-05-2016 04:40	1798	2360	12.53
01-05-2016 04:50	1593	2100	12.59
01-05-2016 05:00	1544	2140	13.24
01-05-2016 05:10	1733	2200	12.12
01-05-2016 05:20	1693	2400	13.54
01-05-2016 05:30	1575	2600	15.76
01-05-2016 05:40	1582	2360	14.25
01-05-2016 05:50	1623	2100	12.36
01-05-2016 06:00	1695	2140	12.06

Once the torque is calculated, the next step is to bin the calculated torque and calculate the total duration for each bin interval which gives us the LDD. Damage is then calculated for each torque level using the damage equation (4), material exponent (m) is assumed as 5 for this example.

Table 3: Accumulated Damage

Torque (S)		Cycles (N)		Damage		
Designed Cycles	Actual Cycles	Designed	Actual Field	Designed $D=N^*(S^m)$	Field $D=N^*(S^m)$	Accumulated (%)
26	11	65	50	772289440	8052550	1.0%
24	12	84	70	668860416	17418240	2.6%
29	13	79	60	1620380771	22277580	1.4%
27	14	178	150	2554105446	80673600	3.2%
25	15	151	120	1474609375	91125000	6.2%
21	16	168	130	686128968	136314880	19.9%
29	17	63	40	1292202387	56794280	4.4%
Total Damage						38.6%

From table 3, it can be concluded that the total damage accumulated until the time of this analysis is around 38.6% compared to the baseline. Once the cumulative damage is determined, the next step is to predict the RUL using direct or indirect condition monitoring (CM) data by statistical methods to predict the life, which represents the remaining useful life is around 61.40% .

X. EXPERIMENTAL SETUP

This Lifetime Use Estimator will use a torque signal measured from the generator power and generator speed (rpm) considering mechanical and electrical power losses. The torque and rotor angular velocity will then be used to produce outputs of rate of life use (RLU) and total lifetime used. The rotor angular velocity will be derived from a filtered and down sampled generator rpm in a signal-conditioning of the gearbox LUEs. The rate calculation will be performed at a frequency of 10Hz, to ensure that accuracy is not lost when the Palmgren-Miner's calculation is performed because it is important that cycles with large torque are recorded correctly as they will make the highest contribution to the damage. Note that for this calculation the term 'rate' refers to a change in life used over a short time interval.

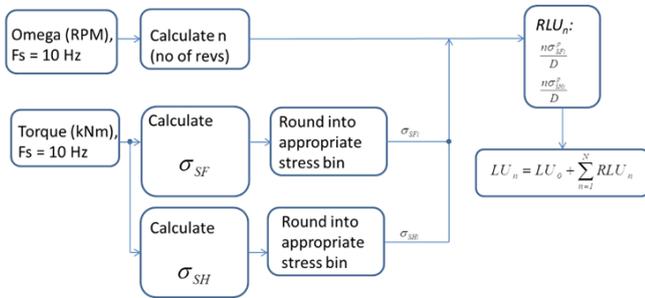
Inputs:	ω	RPM
	T	Torque
Outputs:	LU	Lifetime Used
	RLU	Rate of Lifetime Used

The LUEs will be calculated as follows:



Expansion of the LUE block:





Where:

n	Number of cycles completed in each time step
σ_{SF}	Scaled Bending Stress
σ_{SH}	Scaled Contact Stress
σ_{SF_i}	Scaled Bending Stress rounded according to the LRD-bins used for certification
σ_{SH_i}	Scaled Contact Stress rounded according to the LRD bins used for certification.
LU_0	Initial life used
D	Damage calculated in reference calculation (D will be different for the bending and the contact stress calculation)

Note that life-used and rate-of-life-use are calculated relative to the design case. The current signals are acquired from the instrument which is introduced into the controller software to measure by inference (inferential measurement) and it represents the rate at which the life of the gearbox components is being consumed (rate of ageing) during turbine service life, i.e. Rate of Life Use (RLU). Measurements of Rate of Life Use (RLU) shall be numerically integrated (summed) with respect to time to provide cumulative measurements of total Life Used (LU).

The facility to set an initial Life Used (LU_0) for each LUE as a percentage to a precision of 0.1% in the range 0.1-100%.

where,

The Life Used at time-step ‘N’

LU_N , is accumulated as increments added to LU_0 at successive time-steps ‘n’, thus:

$$LU_N = LU_0 + \sum_{n=1}^N \Delta LU_n \quad (7)$$

The value of LU_0 introduced after time-step ‘N’ will overwrite the memorised value LU_N . The initial condition in the software default settings shall be that $LU_0 = 0$. The default value of initial Life Used (LU_0) is calculated as the ratio of time-in-service to-date to target-life for the turbine:

$$LU_0 = \frac{(L_S)_N}{(L_T)_N} \quad (8)$$

Where:

$(L_S)_N$: Time-in-service to-date; i.e. at time-step ‘N’.

$(L_T)_N$: Target Lifetime in the software at time-step ‘N’.

a. Estimation of Revolutions

The number of revolutions calculated from the rotational speed of the main shaft, which will be derived from the generator speed signal (rpm), divided by the gear ratio. The rotational speed of the main shaft will then be used to determine the number of cycles in a calculation time-step for each gearbox LUE.

The conversion of main shaft revolutions per minute into rotational stress cycles will be:

$$n = \frac{\omega T_s}{60} \quad (8)$$

where:

n - Number of rotation stress cycles completed in each time step n

ω - Shaft rotational speed (rpm)

T_s - Calculation time step (s)

b. Gearbox Fatigue LUE

The LRD spectrum from the turbine design, can be summed using the Palmgren-Miner Rule (using a material-dependent Wöhler coefficient) in an offline calculation, and this can be compared in real time to the damage-equivalent calculated from an on line real-time LRD calculation, populating the same discrete scaled-stress spectrum with rotation cycles at each corresponding load level. The design damage used in the LUE calculations will be based upon the actual torque levels used in determining from design torque spectrum for the gearbox design. The relevant LRD discretization for the gearbox LUEs is taken from the design load cases.

Table 4 LRD for gearbox design

S.No	Torque Level (kNm)	Revs
1	1.79E+03	1.67E+03
2	1.73E+03	4.02E+03
3	1.67E+03	1.17E+04
4	1.50E+03	1.56E+05
5	1.44E+03	5.04E+05
6	1.38E+03	1.20E+06
7	1.33E+03	2.88E+06
8	9.22E+02	4.20E+06
9	8.65E+02	4.04E+06
10	8.07E+02	3.99E+06
11	7.50E+02	4.30E+06
12	4.61E+02	3.79E+06
13	4.04E+02	4.13E+06
14	3.46E+02	5.15E+06
15	2.88E+02	6.58E+06
16	1.15E+02	8.33E+06
17	5.77E+01	1.03E+07
18	0.00E+00	1.39E+07
19	-5.77E+01	8.28E+05
20	-1.15E+02	3.62E+04
21	-5.19E+02	4.28E+01
22	-5.77E+02	1.99E+01
23	-6.34E+02	2.21E+01

The prototype turbine operational data is acquired from the controller through SCADA system from the experimental setup on table 5.

Table 5: Turbine Operational Data

S. No	Time Stamp	Wind Speed (m/s)	Average Power (kW)
1	30-07-2020 08:47	13.4	1701.7
2	30-07-2020 08:47	14.3	1817.3
3	30-07-2020 08:47	15.1	1939
4	30-07-2020 08:47	14	1851
5	30-07-2020 08:47	13.8	1872.3
6	30-07-2020 08:47	13.8	1884.3
7	30-07-2020 08:48	13.4	1876.7
8	30-07-2020 08:48	12.1	1804
9	30-07-2020 08:48	12.6	1837.3
10	30-07-2020 08:48	12.6	1829.6
11	30-07-2020 08:48	12.8	1869.7
12	30-07-2020 08:48	14	1912.4
13	30-07-2020 08:49	14	1907.3
14	30-07-2020 08:49	14.5	1928.8
15	30-07-2020 08:49	15	1943.3

The rate of life use (RLU) is not reached the design damage of component, hence remaining component lifetime use estimation is 42%.

S. No	Design Damage (DD)	Rate of Life-Use (RLU)	Lifetime Use Estimation (LUE)
1	3.76E+34	2.182E+34	42%

XI. CONCLUSION

Weibull analysis is carried out for a gearbox (full gearbox) using the field failure data to calculate the probability of failure over a period of 20 years. This reliability estimation is used as a lead to perform a RUL prediction. In RUL prediction of gearbox, the methods using a unique regression model may be hard to represent the entire history and easily over fit the inconsistent patterns in some features. Therefore, instead of looking for an overall regression model, this research proposes a RUL prediction method based on multiple health state assessment. It basically includes four process steps: raw data collection, feature calculation, health state assessment, and RUL prediction method. With the help of health state assessment, the proposed method divides the entire gearbox life into different health states where a local regression model can be built individually. As no knowledge is available about health states at the very beginning of the proposed data-driven method and proposed a hybrid approach consisting of both unsupervised learning and supervised learning to estimate the health state of a gearbox. With the provided label knowledge, the supervised learning is employed to build a health state assessment model. In the experimental verification. The results showed that the proposed method provided a more accurate prediction, which demonstrated the effectiveness and superiority of this method in predicting the RUL of gearbox. Moreover, the proposed method is suitable for practical application and industrial field.

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