World Journal Control Science and Engineering, 2013, Vol. 1, No. 1, 1-8
Available online at http://pubs.sciepub.com/wjcse/1/1/1

DOI:10.12691/wjcse-1-1-1

Optimal Wind Turbine Planetary Gearbox Replacement Decision Using Vibration Monitoring and Hazard Model

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Received June 29, 2013; Revised July 22, 2013; Accepted July 25, 2013

Abstract A reliable machine fault prognostic system can be used to forecast damage propagation trend in rotary machinery and to provide an alarm before a fault reaches critical levels. Wind turbine planetary gearbox components have no exception, where hazard rate model was used. The objective of this paper is focused specifically on the use of a generalized statistical method for characterizing and predicting system Weibull density function hazard rate that best corresponds to the given set of filtered vibration data. The prognostic performance was illustrated using five types of gearbox faults. Faults have been artificial made in the wind turbine gearbox components, where the details and dimensions of these faults are presented. The failure hazard rate in terms of RMS value of rotational vibration acceleration prediction was considered. The information incurred in this paper can help for prognostic procedure. The results show that the predicted RMS of vibration acceleration response at failure based on the Weibull distribution with assured reliability was quite close to the healthy value for planet gear tooth spalling followed by planet gear tooth breakage, planet gears carrier crack and main bearing inner race crack with the less close of planet gear tooth crack. The results show that the predictive failure hazard rates are effective in estimating the progress of the prognostic process well in advance of the impending catastrophic failure. Moreover, the results also show the effectiveness of using the hazard rate model in estimating the variations of the failure hazard rate.

Keywords: *optimization, reliability, hazard rate, prognostic, failure, Weibull distribution, deterioration*

Cite This Article: Abouel-seoud, Shawki A., and Mohamed I. Khalil, "Optimal Wind Turbine Planetary Gearbox Replacement Decision Using Vibration Monitoring and Hazard Model." *World Journal Control Science and Engineering* 1, no. 1 (2013): 1-8. doi: 10.12691/wjcse-1-1-1.

1. Introduction

Machinery prognosis is the forecast of the remaining operational life, future condition, or probability of reliable operation of an equipment based on the acquired condition monitoring data. This approach to modern maintenance practice promises to reduce downtime, spares inventory, maintenance costs, and safety hazards. Given the significance of prognostics capabilities and the maturity of condition monitoring technology, there have been an increasing number of publications on rotating machinery prognostics in the past few years. These publications covered a wide spectrum of prognostics techniques. These individual pieces of information in context, while identifying their merits and weaknesses are first synthesized and placed. It then discusses the identified challenges, and in doing so, alerts researchers to opportunities for conducting advanced research in the field. Current methods for predicting rotating machinery failures are summarized and classified as conventional reliability models, condition-based prognostics models and models integrating reliability and prognostics. Areas in need of development or improvement include the integration of condition monitoring and reliability, utilization of incomplete trending data, consideration of effects from maintenance actions and variable operating conditions, derivation of the nonlinear relationship between measured data and actual asset health, consideration of failure interactions, practicability of requirements and assumptions, as well as development of performance evaluation frameworks [1].

A condition based maintenance (CBM) policy is a procedure used by maintenance personnel to interpret a set of measured machine condition indicators and decide whether or not to renew physical asset at the current moment. Traditionally CBM data interpretive policies have been obvious. For example, for process machinery, if a temperature, pressure, sound, or vibration reading exceeds a pre-defined limit, maintenance should be carried out before functional failure. However, the ability to collect large amounts of condition data has continually outpaced the ability to define policies for the interpretation. The condition indicators may sometimes contradict one another. Upward or downward trends are frequently obscured by randomness in the data. In many instances no clear set of limits or rules have been developed to indicate whether or not a failure process is underway and how much time is available before the physical asset is no longer able to perform one of its functions**.** By utilizing condition monitoring information collected from wind turbine components, condition based maintenance (CBM) strategy can be used to reduce the operation and maintenance costs of wind power generation systems. The existing CBM methods for wind power generation systems deal with wind turbine components separately, that is, maintenance decisions are made on individual components, rather than the whole system. However, a wind farm generally consists of multiple wind turbines, and each wind turbine has multiple components including main bearing, gearbox, generator, etc. There are economic dependencies among wind turbines and their components. That is, once a maintenance team is sent to the wind farm, it may be more economical to take the opportunity to maintain multiple turbines, and when a turbine is stopped for maintenance, it may be more cost-effective to simultaneously replace multiple components which show relatively high risks [2].

Many industrial systems exhibit increasing wear and tear of equipment during operation. For example, an automobile has many pieces of equipment, such as the engine, gearbox and valves that exhibit various types of performance degradation due to erosion, friction, internal damage and cracks. Prognostics were viewed as an add on capabilities to diagnosis; they assessed the current health of a system and predicted its remaining life based on features that capture the gradual degradation in the operational capabilities of a system. Prognostics are critical to improve safety, plan successful missions, schedule maintenance, reduce maintenance cost and down time. Unlike fault diagnosis, prognosis is a relatively new area and became an important part of Condition-Based Maintenance (CBM) of systems. Currently, there are many techniques; their usage must be tuned for each application. The prognostic methods can be classified as being associated with one or more of the following two approaches: data-driven and model-based. Each of these approaches has its own advantages and disadvantages, and, consequently they are often used in combination in many applications. This section will provide an overview of the prognostic techniques and their applications [3,4,5,6].

2. Literature Review

A study was carried out where, an optimal CBM solution to the previous-mentioned issues were developed. The proposed maintenance policy was defined by two failure probability threshold values at the wind turbine level. Based on the condition monitoring and prognostics information, the failure probability values at the component and the turbine levels were calculated, and the optimal CBM decisions were made accordingly. In addition a simulation method was developed to evaluate the cost of the CBM policy where a numerical example was provided to illustrate the proposed CBM approach. A comparative study based on commonly used constant-interval maintenance policy was included and was demonstrated the advantage of the proposed CBM approach in reducing the maintenance cost [7].

The condition vibration data from eleven gearboxes run to failure on the mechanical diagnostic test-bed (MDTB) was obtained. The data was processed calculating the fault growth parameter (FGP) from the residual error signal. FGP, it was revised version FGP1 and some other variables calculated from the residual error signal were analyzed using the proportional hazards modeling (PHM) technique. Several statistical and replacement decision models were built based upon the observed condition data and failure events. The results of the data processing and the analysis were presented and eleven gearbox test runs were designated. Vibration acceleration readings were taken at 8-h intervals during the 96-h run-in period and at 30-min intervals during the high load ‘‘operational’’ phase. The MDTB makes a large number of condition indicators available for the analysis, for example, the conventional vibration features such as acceleration amplitudes at various gear and bearing frequencies. In particular the FGP was calculated from the residual error signal obtained by a signal processing algorithm. In this algorithm, a family of wavelets was constructed to decompose the gear motion error signal and to extract the residual error signal for gear fault detection. Besides FGP and FGP1, other useful indicators were extracted from the residual error signal. It was found that the revised version of FGP, FGP1, was superior to the FGP and other condition indicators for building the PHM and making the replacement decision. The failure mode examined was ‘‘Gear tooth fracture’’ [8].

New sequential imperfect preventive maintenance (PM) models incorporating adjustment/ improvement factors in hazard rate and effective age were presented. The models were hybrid in the sense that they were combinations of the age reduction PM model and the hazard rate adjustment PM model. It was assumed that PM is imperfect: It not only reduces the effective age but also changes the hazard rate, while the hazard rate increases with the number of PMs. PM was performed in a sequence of intervals. A preventive maintenance (PM) policy specifies how PM activities should be scheduled. One of the commonly used PM policies is called Periodic PM, which specifies that a system is maintained at integer multiples of some fixed period. Another PM policy is called Sequential PM, in which the system is maintained at a sequence of intervals that may have unequal lengths. Periodic PM is more convenient to schedule, whereas sequential PM is more realistic when the system requires more frequent maintenance as it ages. A common assumption used in both these PM policies is that minimal repair is conducted on the system if it fails between successive PM activities. A minimal repair only restores the system to the functioning state once it fails, but does not improve the overall health condition of the system. In other words, minimal repairs do not change the hazard rate or the effective age of the system [9].

Prognostic is a rapidly developing field and seeks to build on current diagnostic equipment capabilities for predicting the system state in advance. In machine condition prognostics, the current and past observations are used to predict the upcoming states of the machine. Signal-de-noising and extraction of the weak acoustic signature are crucial to gearbox prognostics since the inherent deficiency of the measuring mechanism often introduces a great amount of noise to the signal. In addition, the signature of a defective gearbox is spread across a wide frequency band and hence can easily become masked by noise and low frequency effects. As a result, robust concepts are needed to provide more evident information for gearbox performance assessment and prognostics. In [10,11], studies have been introduced the enhanced and robust prognostic concepts for gear tooth including a wavelet filter based method for weak acoustic signature measurements for fault identification and statistical analysis technique based method for performance degradation assessment. The experimental results demonstrate that the gearbox defect can be detected at an early stage of development when both optimal wavelet filter and statistical analysis technique are used.

The objective of this paper is to use an analytical method combined with experimental data to make the prognosis. It is focused specifically on the use of a generalized statistical method for characterizing and predicting system Weibull density function hazard rate that best corresponds to the given set of filtered vibration data. The wind turbine gearbox components faults considered are planet gear tooth crack, planet gear tooth spalling, planet gear tooth breakage, planet gear carrier crack, and main bearing inner race crack. The hazard rate of the gearbox components is determined under a deteriorating phase, which their failures rotational vibration acceleration follows the Weibull distribution.

3. Test Rig Set-Up

The experimental set-up used in this study is schematically shown in Figure 1. while Figure 2. shows the position of the accelerometers. A simulation of the wind turbine gearbox is made and comprises two stages one planetary gearbox and the other helical both have a total of speed ratio of about 26. The simulated system connected by 15 horsepower (hp), 1440 rev/min AC drive motor and inverter (speed controller) represent the system output, while a hydraulic brake represents the input from the wind. The motor, hydraulic disc brake, flywheel and gearbox are hard-mounted and aligned on a bedplate. The bedplate is mounted using isolation feet to prevent vibration transmission to the floor.

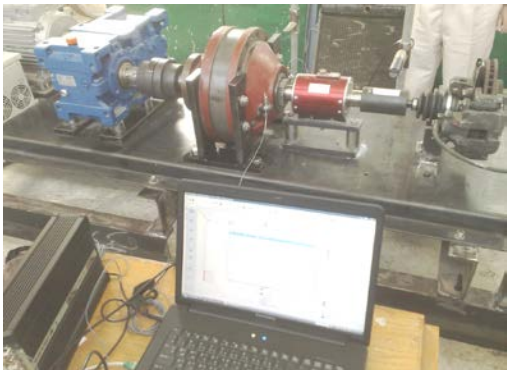

Figure 1. The experimental set-up

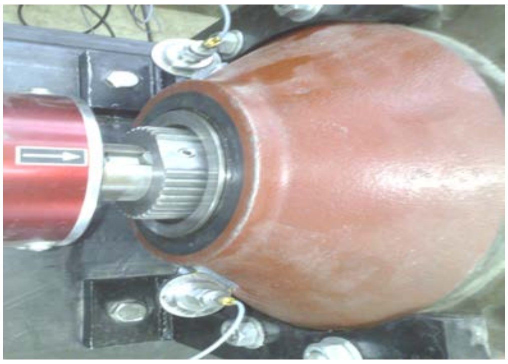

Figure 2. Position of the accelerometers

The planetary gearbox components which are shown in Figure 3. are tested for failure state prognosis. The gearbox faults dimensions are tabulated in Table 1, where Figure 4 and Figure 5 show an example of healthy and such fault for gears carrier respectively. The motor speed controller allows tested gear operation in the range of 20–40 rpm. The load is provided by a hydraulic brake connected to the load motor. The speed of the drive motor and the load can be adjusted continuously to accommodate the range of speed/torque operating conditions.

Figure 3. Planetary gearbox assembly

Figure 4. Planet gears carrier

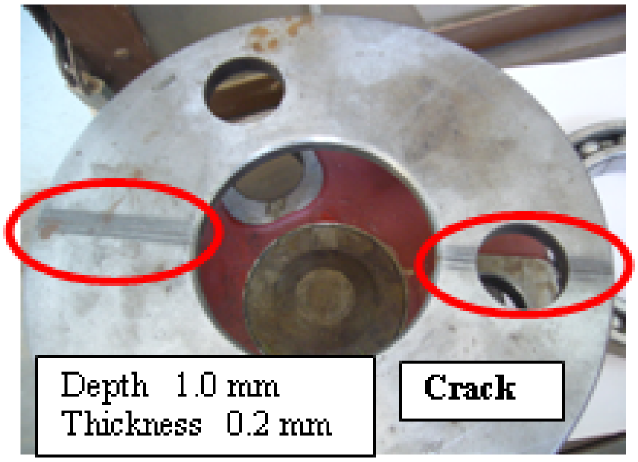

Figure 5. Planet gears carrier crack

Table 1. Wind turbine planetary gearbox faults dimensions

S/No.	Defect Type	Defect Dimensions
0	Healthy gearboxes	Free from defects
1	Planet gear tooth crack	Depth 1.0 mm Thickness 0.2 mm
2	Planet gear tooth Spalling	Spalling length = 0.9 mm Spalling height = 1 mm Spalling width = 4.6 mm
3	Planet gear tooth breakage	Breakage thick = 0.6 mm, Breakage width = 4.6 mm Breakage height = 1.35 mm
4	Low speed shaft (LSS) Main bearing crack	Depth 1.0 mm Thickness 0.2 mm
5	Planet gears carrier crack	Depth 1.0 mm Thickness 0.2 mm

The prognostic performance was illustrated using five types of gearbox faults. Faults have been artificial made in the wind turbine gearbox components, Fault types are as follows: (1) planet gear tooth crack, (2) planet gear tooth spalling, (3) planet gear tooth breakage, (4) planet gears carrier crack, (5) main bearing inner race crack as tabulated in Table 1. Faults have been artificial made in the wind turbine planetary gearbox components, where the details and dimensions of these faults were also presented in Table 1.

The vibration is measured with two Bruel & Jeer accelerometers mounted on the gearbox housing in the rotational direction of fault action, one in each side-axis as shown in Figure 2. The signals from both accelerometers are properly amplified, filtered. The sampling frequency used was 6.0 kHz and signals of 1.0 sec duration were recorded. B&K portable and multi-channel PULSE analyzer type 3560-B-X05 is used with the B&K PULSE lab shop which is the measurement software type 7700. The results then fed into the computer for further processing. The speed is measured by a photo electric probe. Recordings were carried out at constant speed. More details information can be found in [12].

4. The Continuous Wavelet Transform

Definition

In non-stationary vibration waveform, the Continuous Wavelet Transform (CWT) concept is used. Wavelet transforms are inner products between signals and the wavelet family, which are derived from the mother wavelet by dilation (scale) and translation [13].

$$W_g(a;b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) g^*_{a,b}(t) dt \quad (1)$$

where:

$W_g(a;b)$ is the function after transformed, and $g^*(t)$ stands for complex conjugation of g (t)

If a daughter wavelet is viewed as a filter, wavelet transform is simply a filtering operation. Usually, reconstructing the wavelet coefficients at selected scales through certain methods attempted to be discovered. To do this, prior information had to be known on the signal needs to be identified.

4.1. Morlet Wavelet Filter

Morlet wavelet is one of the most popular non-orthogonal wavelets. The definition of Morlet is:

$$\psi(t) = \exp(-\frac{\beta^2 t^2}{2}) \cos(\pi t) \quad (2)$$

4.2. Adaptive Morlet Wavelet Filter

A daughter Morlet wavelet is obtained by time translation and scale dilation from the mother wavelet, as shown in the following formula [14]:

$$\psi_{a,b}(t) = \psi(\frac{t-b}{a}) = \exp[-\frac{\beta^2 (t-b)^2}{2a^2}] \cos[\frac{\pi(t-b)}{a}] \quad (3)$$

Where: a is the scale parameter for dilation and b is the time translation.

It can also be looked at as a filter. To identify the immersed impulses by filtering, the location and the shape of the frequency band corresponding to the impulses must be determined first. Scale (a) and parameter β control the location and the shape of the daughter Morlet wavelet respectively. As a result, an adaptive wavelet filter could be built by optimizing the two parameters for a daughter wavelet.

5. Hazard Rate Model

Hazard (also called hazard rate or failure rate) is the probability of an item failing at any given instance. Hazard may change in time as result of many factors. If the probability distribution function is described mathematically by $f(x)$, then the cumulative distribution function $F(x)$ can drive by continuous integration as the following [15]:

$$F(x) = \int_0^t f(x) dx. \quad (4)$$

Whereas the sum of the reliability and the cumulative distribution function equal one then the equation can be written as

$$R(x) + F(x) = 1 \quad (5)$$

$$h(x) = \frac{f(x)}{R(x)} \quad (6)$$

where:

$f(x)$: is the probability distribution function (time, RMS,…etc)

$F(x)$: is the cumulative probability distribution function (time, RMS,…etc)

$R(x)$: is the reliability function (time, RMS,…etc)

Based on Weibull distribution and the rotational vibration acceleration data measured for a faulty component at different operation conditions, the failure Weibull probability density function is written as following [15,16]:

$$f(x) = \frac{\beta (x)^{\beta-1}}{\eta^\beta} \exp[-(\tfrac{x}{\eta})^\beta] \quad (7)$$

From equation (4), then

$$F(x) = 1 - \exp[-(\tfrac{x}{\eta})^\beta] \quad (8)$$

From equations (5) and (6), the hazard rate given by

$$h(x) = \frac{\beta}{\eta}(\frac{x}{\eta})^{\beta-1} \quad (9)$$

where

x : is the measured rotational vibration acceleration in RMS value, rad/s^{-2}

η : is the characteristic life or is the scale parameter.

β : is the shape parameter.

6. Results and Discussion

6.1. RMS Values of Rotational Vibration Response at Failure

Individual operating wind turbine planetary gearbox components do not replace reliability data that reflect population characteristics. PM data mainly provide information for short-term condition prediction only. Several data-driven prognostics models enabled gearbox prognosis using time series prediction. These models mainly performed single-step-a head predictions to estimate the vibration signal feature value. The details of experimental testing system and experimental procedure were presented in the project second progress report, where many tests were conducted on the wind turbine planetary gearbox components. Six test cases (one healthy and five faults), covering different wind turbine planetary gearbox component faults, are considered to illustrate their hazard rates. Figure 6 and Figure 7 show the time-domain of vibration acceleration responses in the form of measured signal and filtered signal at 20 rpm, 20 Nm and 40 rpm, 40 Nm for healthy gearbox respectively, while for planet gears carrier crack fault signals at testing time of 0.0 hr as an example are shown in Figure 8 and Figure 9. Table 2 collects the RMS values of rotational vibration response in filtered signal form at testing time from 0.0 to 6.0 with increment of 1 hr for all the tests considered, while Figure 10 and Figure 11 show the values of RMS at failure for healthy gearbox and planet gears carrier. Table 3 tabulates the values of the scale parameter and shape factor obtained from the interpretation of the results in Table 2 along with the filtered signal RMS at failure values when the hazard rate = 1 based on equation (9). It is indicated from Table 3 that the value of the RMS at failure based on the weibull distribution with assured reliability changed and the change in both speed and torque load, which decreased as the speed and torque load increased. The shape factor and scale parameter values for the healthy gearbox are taken from Ref. [4] The same discussion can be applied on the rest of the wind turbine planetary gearbox components faults considered.

6.2. Wind Turbine Planetary Gearbox Components Failure Risk Assessment

From the previous discussion, the RMS value in filtered signal form was used in prognostic process based on hazard rate prediction (equation 9). However, these RMS values are used to evaluate the wind turbine gearbox components failure risk assessment, where Figure 12 depicts the wind turbine planetary gearbox failure risk assessment which has been achieved by predicted the failure RMS value at failure for speed 20 rpm and 20 Nm and for speed 40 rpm and 40 Nm. It is observed that the predictive RMS at failure for speed-torque load of 40 rpm, 40 Nm for all the gearbox components faults are lower than that of 20 rpm, 20 Nm. It is recommended that the prediction of RMS at failure for any component should be done at maximum speed-torque load (power) conditions in either measured or filtered signal.

Figure 13 shows the percentage of the change of RMS at failure of filtered rotational vibration acceleration signal from that change from healthy gearbox (CFHL) at speed 20 rpm and 20 Nm; and speed 40 rpm and 40 Nm. In terms of filtered signal, the values are 67.1% to 71.3% (planet gear breakage), 90.5% to 87.4% (planet gears carrier crack), 71.9% to 76.6% (planet gear spalling), 87.3% to 95.2% (main bearing inner race crack) and 82% to 89.9% (gear crack). In general, this information can help for prognostic procedure. It has been shown that the predicted of RMS value at failure was quite close to the healthy value for planet gear tooth spalling followed by planet gear tooth breakage, planet gears carrier crack and main bearing inner race crack with the less close of planet gear tooth crack. The results show that the predictive failure hazard rates are effective in estimating the progress of the prognostic process well in advance of the impending catastrophic failure.

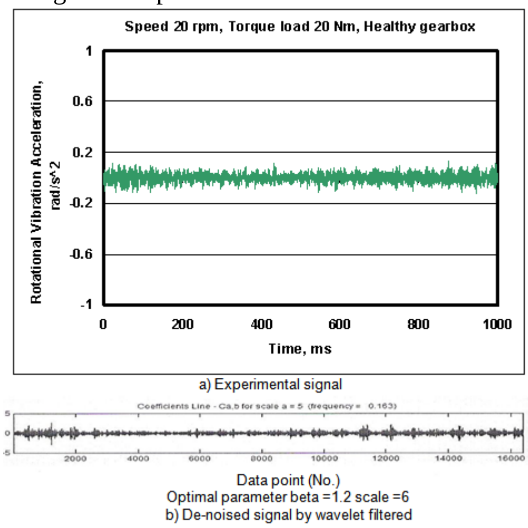

Figure 6. Vibration signal of healthy gearbox (20 rpm, 20 Nm)

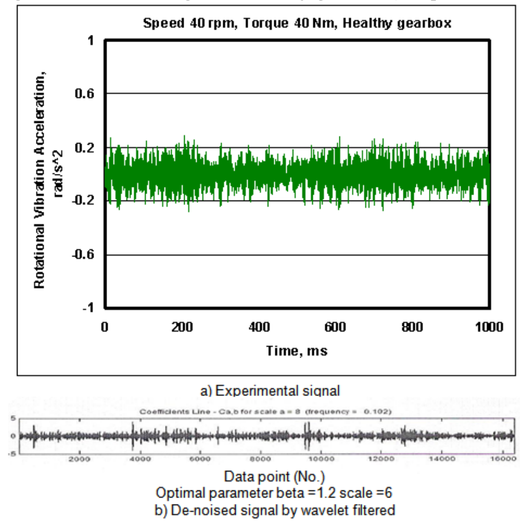

Figure 7. Vibration signal of healthy gearbox (40 rpm, 40 Nm)

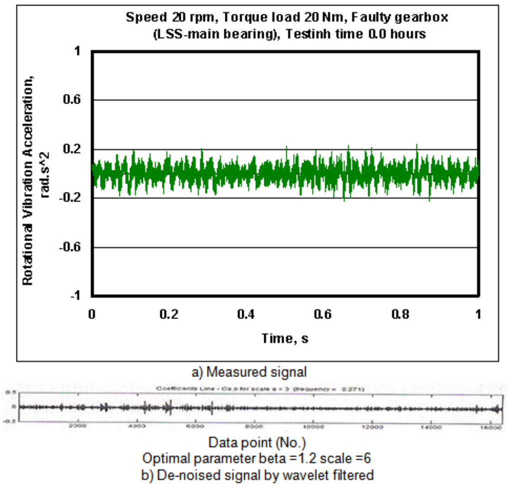

Figure 8. Vibration signal of planet gears carrier crack at 0.0 hr (20 rpm, 20 Nm)

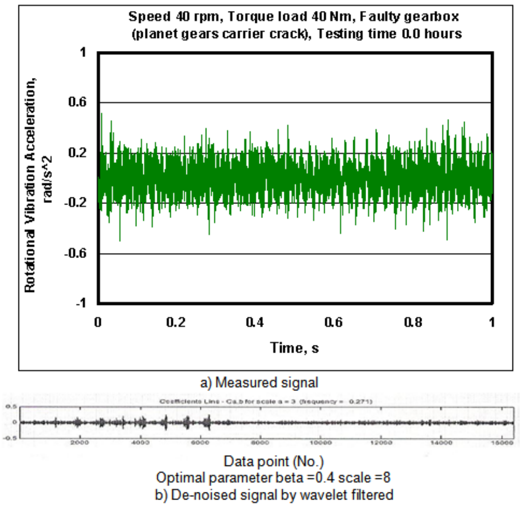

Figure 9. Vibration signal of planet gears carrier crack at 0.0 hr (40 rpm, 40 Nm)

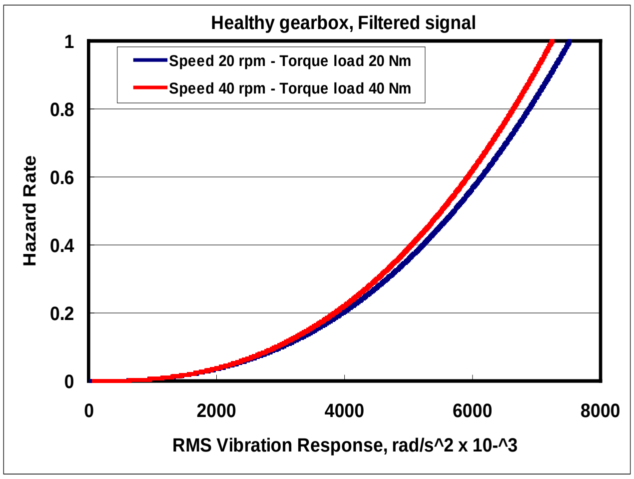

Figure 10. RMS of vibration response at failure, healthy gearbox

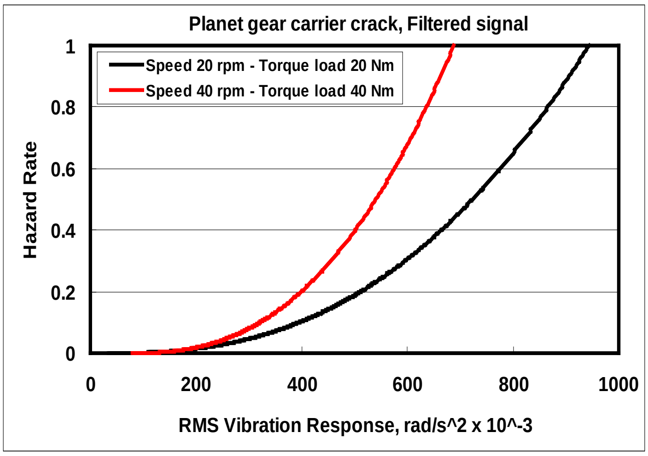

Figure 11. RMS of vibration response at failure, planet gears carrier crack

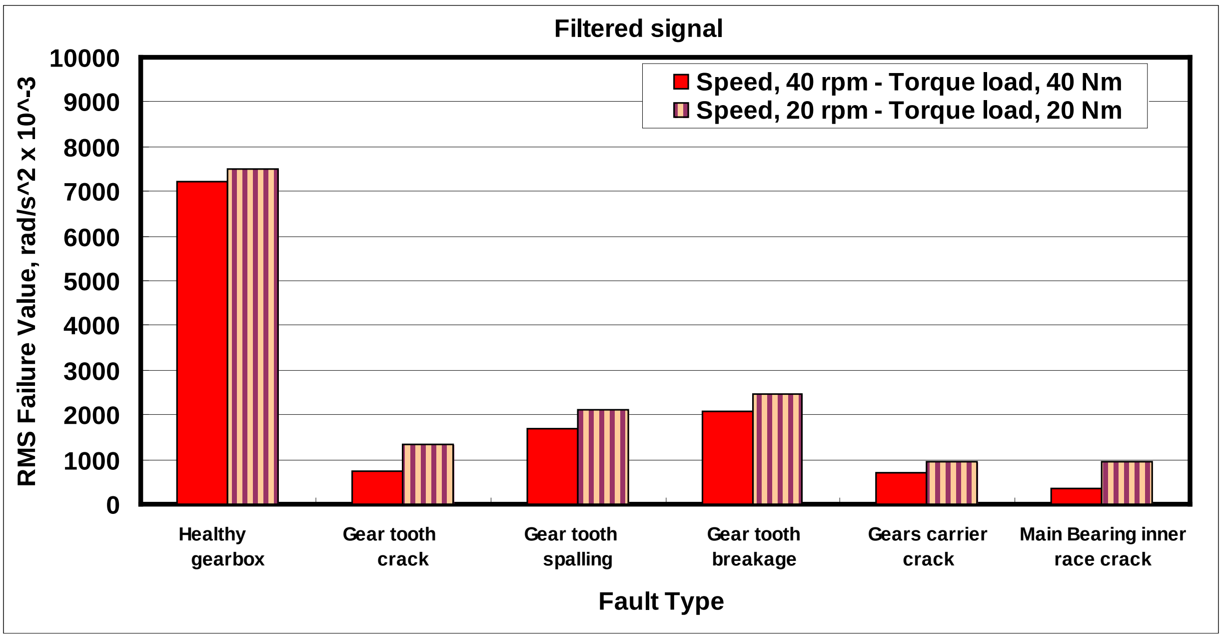

Figure 12. RMS value at failure for filtered rotational vibration acceleration signal

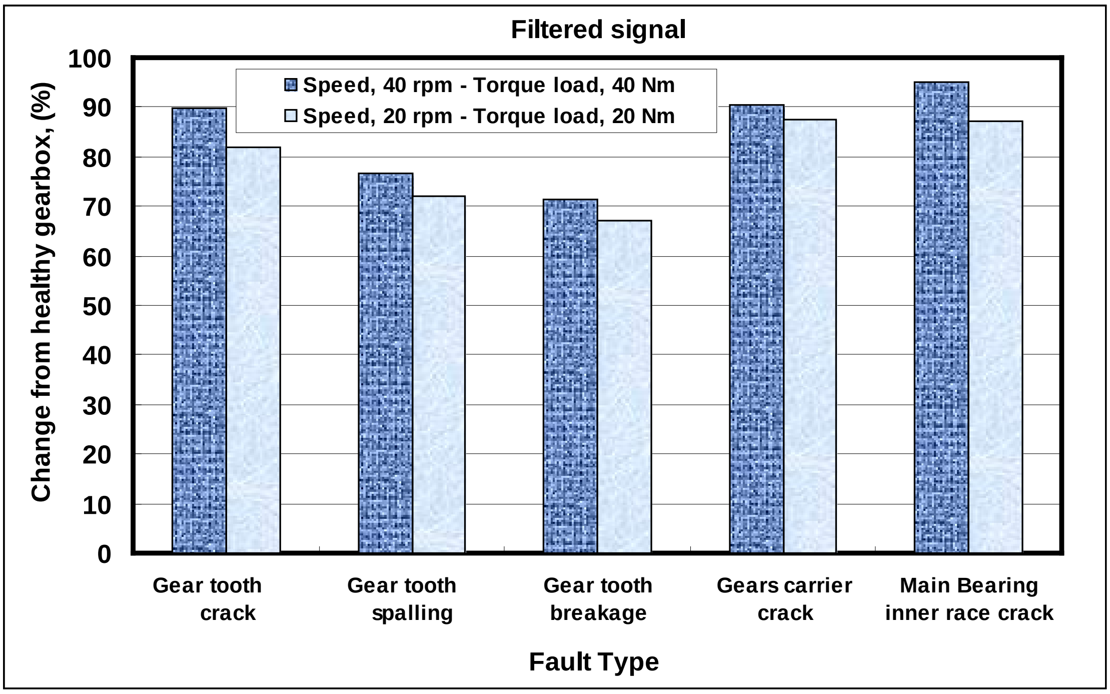

Figure 13. Change from healthy gearbox, (%)

Table 2. Collects the RMS values of rotational vibration response in filtered signal form

No.	Speed – Torque load, (rpm- Nm)	Testing Time, hr							
		Healthy	0.0	1.0	2.0	3.0	4.0	5.0	6.0
	20 rpm – 20 Nm	Planet gear crack - Filtered RMS value, rad/s^2 x10^{-3}							
1		30.30	45.3	51.7	57.4	59.2	61.9	62.3	68.5
		Planet gear spalling- Filtered RMS value, rad/s^2 x10^{-3}							
2		30.30	1208	1220	1228	1291			
		Planet gear breakage- Filtered RMS value, rad/s^2 x10^{-3}							
3		30.30	1335	2663	2663	2973			
		Planet gears carrier crack- Filtered RMS value, rad/s^2 x10^{-3}							
4		30.30	34	38.9	40.1	44.9	48.3	65.9	67.6
		Main bearing inner race crack-Filtered RMS value, rad/s^2 x10^{-3}							
5		30.30	39.2	43.4	62.2	63.2	65	67.2	69.1
	40 rpm – 40 Nm	Planet gear crack - Filtered RMS value, rad/s^2 x10^{-3}							
6		70.300	80.1	82.3	102.4	106	109.2	110.8	127.8
		Planet gear spalling- Filtered RMS value, rad/s^2 x10^{-3}							
7		70.300	2936.1	3281	3386	3386			
		Planet gear breakage- Filtered RMS value, rad/s^2 x10^{-3}							
8		70.300	4176	4255	4255	4360			
		Planet gears carrier crack- Filtered RMS value, rad/s^2 x10^{-3}							
9		70.300	80	83	92	93	95	96	102
		Main bearing inner race crack-Filtered RMS value, rad/s^2 x10^{-3}							
10		70.300	81.7	94.3	127.9	133.9	136.7	148	152.5

Table 3. Single number of the scale parameter, shape factor and filtered signal RMS at failure

No.	Speed – Torque load, (rpm- Nm)	Planetary Gearbox Component Faults	Shape Factor β	Scale Parameter	RMS $_{Failure}$ Value
				rad/s2 x10^{-3}	
1	20 rpm – 20 Nm	Healthy gearbox	3.5	7500	7507
2		Planet gear crack	3.5	735	727
3		Planet gear spalling	3.5	6854.7	2498
4		Planet gear breakage	3.5	8794.65	2665
5		Planet gears carrier crack	3.5	943.33	944
6		Main bearing inner race crack	3.5	1250	1245
7	40 rpm – 40 Nm	Healthy gearbox	3.5	7500	7225
8		Planet gear crack	3.5	688	726
9		Planet gear spalling	3.5	4500	1694
10		Planet gear breakage	3.5	5115	2076
11		Planet gears carrier crack	3.5	688	688
12		Main bearing inner race crack	3.5	346	346

7. Conclusions

1. Results are presented for prognostics of wind turbine planetary gearbox components conditions using Weibull distribution and the rotational vibration acceleration data measured and filtered for a faulty component at different

operation conditions, based on the failure Weibull probability density. The prognostic performance of the hazard rate was illustrated using five types of gearbox faults with different monitoring indices and time scales.

2. In general, the information of the wind turbine planetary gearbox failure risk assessment can help for prognostic procedure. It has been shown that the predicted of RMS value at failure was quite close to the healthy value for planet gear tooth spalling followed by planet gear tooth breakage, planet gears carrier crack and main bearing inner race crack with the less close of planet gear tooth crack. The results show that the predictive failure hazard rates are effective in estimating the progress of the prognostic process well in advance of the impending catastrophic failure.

3. The effectiveness of the hazard rate in estimating the variations of the monitoring RMS values are presented. In this work, one-step-ahead prediction was considered; the extension to multi-time-step a head prediction and the potential application of these techniques for the development of on-line prognostic systems for wind turbine planetary gearbox condition are under consideration for further work.

Acknowledgement

The authors acknowledge the support of Science and Technology Development Fund (STDF), Egypt, through the awarded grant No. ID 1484, on monitoring of wind turbine gearbox. The authors would like to thank University of Helwan, which made this study possible.

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