RUL prediction of wind turbine gearbox

Abstract

This project aims to establish an integrated prognostics method for predicting the remaining useful life of a planetary wind turbine gearbox. The prediction of the time to failure for components within a wind turbine is becoming more important because of enlargement of the wind turbines. Gearbox is a very critical component in a wind turbine, and it is important to predict the aging of gearbox with accurate approximation so that downtime and excessive cost can be minimized. The physics-based models require fewer data compared to data-driven methods, providing the most accurate estimates of all modeling options if the physics of models remain consistent across the component. However, the physics-based models are complex to develop, and they require detailed and complete knowledge of system behavior, being defect specific. The data-driven methods are efficient and practical at modeling multi-dimensional, complex, and non-linear systems. But they require a large amount of data as representative of actual data range and it´s variability for training, computationally intensive. Therefore, an integrated approach has been chosen in this project considering the dynamic behavior of gearbox wear. The integrated prognostics method for failure time prediction of gears subjects to the surface wear failure mode, utilizing both physical models, i.e., Archard's wear model and condition monitoring data, i.e., inspection data on gear mass loss in this study. By noticing the importance of the wear coefficient in Archard's model, the proposed method can result in a more accurate value of the wear coefficient so that the wear evolution in the future is forecasted with more accuracy. To achieve this, a Bayesian update process is implemented to incorporate the mass loss observation at an inspection point to determine the posterior distribution of the wear coefficient. With more mass loss data available, this posterior distribution gets narrower, and its mean approaches the actual value of the coefficient. To use Archard' model, the gear mesh geometry and Hertz contact theory are applied to compute the sliding distance and the contact pressure for different points on the tooth flank.

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1. Introduction

Wind turbines (WTs) are subject to unexpected failures due to operational and environmental conditions, aging, and so on. An accurate estimation of time to failures assures reliable power production and lower maintenance costs. In recent years, a notable amount of research has been undertaken to propose prognosis techniques that can be employed to forecast the remaining useful life (RUL) of wind farm assets. Gearbox is an extremely critical object for the wind turbine and it´s very important to predict the RUL (Remaining Useful Life) of the gearbox. There are multiple methods of predicting gearbox aging. A literature review has been conducted to identify the existing works done in this process. Then an integrated prognostics method has been set up which can predict the remaining useful life of a planetary gearbox used in wind turbines (WT).

2. Literature Review

Predictive maintenance deals with timely replacement and of industrial components relatively to their failure. It allows to prevent shutdowns as in reactive maintenance and reduces the costs compared to preventive maintenance. Therefore, RUL prediction of industrial components has become a key challenge for condition-based monitoring [1]. WTs are complex machines, assembled combinations of numerous technologies, functioning in challenging environmental and operating conditions including unpredictable loads due to gust wind, humidity, dustiness, corrosion, fatigue, wear, a wide range of temperatures, and air pressures. These severe environmental and operating conditions may result in increasing component defects and machine malfunctions. As an integrated system, some of the components are more critical than others. Thus, it is essential to identify components with the highest failure rate and downtime [2]. Based on 350-WT operation over five years throughout Europe, Carroll *et al*. [3] revealed that the highest failure rates are related to generators, gearboxes, and blades. Operation and Maintenance (O&M) is considered an important part of the total cost associated with offshore wind farm operations, reaching 20%-30% of the Levelized Cost of Energy (LCOE) [4]. A risk assessment of Offshore Wind Turbines (OWT) has identified the gearbox as one of the most critical components regarding failure severity, occurrence and detection [4]. The gearbox is a large assembly; therefore, specialized jack-up vessels, trained personnel and long weather windows are required to repair or replace it. OWT operators need to ensure the availability warranty by applying different O&M strategies to avoid the cost of gearbox failures and consequential damage in the rest of the drive train [5].

2. 1. Gearbox Failures:

The health of gears is important for the safety of engineering systems. With the mission of transmitting heavy load, gears mainly suffer from four types of failure modes: surface wear, bending fatigue (fatigue cracking), contact fatigue, and scoring [6]. Bearing damage, gear damage, leaking oil, broken shaft, and insufficient oil cooling are the typical defects observed in WT gearboxes. The WT gearboxes' failures are due to a combination of several factors, such as crack initiation and propagation, surface fatigue, surface wear, structural fatigue, and loss of lubrication [7]. It is worth noting that bearing failures are detected as the majority of the gearbox failures due to white structure flaking, scuffing, and micro pitting [8] [9]. During the mesh process of gear pairs, the tooth flanks are loaded to contact with each other. The gear surface movement is a combination of rolling and sliding motions. When the surface velocities of the two contact teeth are different, the sliding component is introduced. The sliding contact will cause the material removal from the gear teeth, and hence, the gear mass is reduced. For the case of an involute profile in spur gears, all the points on the tooth flank experience sliding movement except for the pitch point. At the pitch point, a pure rolling condition occurs because the sliding velocity is zero. Material loss will alter the gear tooth profile geometry and, hence, the dynamic characteristics of the gearbox. Therefore, the level of vibration and noise will increase, and furthermore, other failure mechanisms may also be accelerated. The prediction of gear wear propagation is of great interest for an effective maintenance after the transmission systems are deployed in service. With the information about the wear depth on gear teeth predicted in advance, we can evaluate the dynamic performance of gearbox in the future and timely arrange the repair or the replacement schedule to avoid unexpected further damage and downtime. Given a threshold of the wear severity, the remaining useful life (RUL) of the gear will be estimated accordingly. The prediction of component RUL associated with the prediction confidence estimation is the objective of component prognostics and health management [10].

2. 2. Prognostics Methods

The main goal of prognosis is to evaluate how long a faulty component can work under reliable operating conditions, still achieving desired performance metrics [2]. The existing prognostics method can be grouped into three categories: physics-based methods, data-driven methods, and integrated methods. The three categories are adopted typically in different scenarios when considering the availability of physical models, failure histories, condition monitoring data, and computational complexity [10].

2.2.A Physics Based methods

Physics-based methods use damage propagation models based on the physic laws of failure mechanism. The well-known Paris' law [11] is the one that is widely used to describe the fatigue crack growth with time. Robust physics -based techniques also comprise Paris' law crack growth modeling with FEA [12], the Forman law crack growth modeling [13], fatigue spall initiation and progression model [14], contact analysis for bearing prognostics [15], and stiffness-based damage rule model [16]. The research work in [17] considered the effect of a moving load on the crack growth prediction. The authors divided the tooth engagement phase into multiple steps to obtain accurate values of stress intensity factor (SIF), which is the most important quantity in Paris' law.

Finite-element (FE) methods were implemented to handle the SIF calculation under complex loading. In addition to improving the accuracy of SIF, researchers also investigated ways of estimating crack sizes through condition monitoring to better estimate RUL. Gray and Watson [18], first, identified different failure modes, their causes, and the damaging operating conditions of WT gearboxes. Afterward, they proposed a prognostic approach based on a mathematical model, as shown in Algorithm 1, for WT gearbox damage calculation for a specific failure mode, bearing high cycle fatigue due to edge loading. The experimental study on six WTs experiencing severe gearbox failure among 160 WTs, recorded as heavy debris in lubricating oil, revealed the efficacy of the proposed method. Breteler et al. [19] proposed a generic physics-based diagnostics and prognostics for WT gearbox for a specific failure mode, helical gear tooth fault due to bending fatigue during misalignment. This study employs an FEA model to estimate bending stress based on the gear geometry and an averaged misalignment value, obtained through laser measurements of three-year WT operation. Next, the gear tooth damage is projected by employing the Palmgren–Miner rule and degradation trend analysis. Although the proposed method was not able to detect misalignment continuously, its robustness was shown, predicting a 20-year lead time to gear fault due to bending stresses. By defining a threshold value of crack size, the failure time of the component bearing this crack can be predicted. In [20] Lewicki and Ballarini studied factors that could have influences on the crack propagation path in the gear tooth, including backup ratio, initial crack location, fillet geometry, rim/web compliance, gear size, and pressure angle. Kacprzynksi et al. [21] proposed a prognostic method that can predict the gear failure probability by fusing physics-of-failure models and diagnostics information. However, due to complicated damage initiation and propagation processes, physics-based methods are restricted to very limited areas of simple and specific applications. It also costs extra efforts in the form of a large number of experiments conducted to determine the parameters used in the physical laws [10].

2.2.B Data-driven methods

Data-driven methods apply when sufficient failure histories or condition monitoring data are available, based on which we can compute the failure distribution or form the relationship between ages and condition monitoring (CM) data. AI-based prognostic methods, such as ANNs, DL, and ANFIS, have been widely investigated in WTs. Hussain and Gabbar [22] compared a Nonlinear Autoregressive model with Exogenous inputs (NARX) to ANFIS for prognostics of WT gearbox health conditions. For this aim, sun-spot activity data of the RWC Belgium World Data Center for years 1749–2012 and vibration data of the National Renewable Energy Laboratory from a planetary gearbox inside a WT were practiced. Test results indicated that NARX outperforms ANFIS in anticipation of the WT gearbox prognostics. Chen et al. [23] introduced a priori knowledge (APK)-based ANFIS approach to predict WT pitch faults RUL based on the SCADA data. The automated APK-ANFIS was able to accurately determine the WT pitch RUL within a prognostic horizon of up 21 days with an optimal threshold and a window size of 0.3 and 6, respectively. In another study, Matthews et al. [24] indicated that ANFIS outperforms other AI techniques, such as K-means clustering, fuzzy inference system (FIS), ANN, and SOM in WT pitch RUL forecast. Pan et al. [25] proposed an ELM optimized by an FOA for WT gearbox RUL forecast. FOA-ELM predicted model was trained on extracted HIs from vibration signals. Then, the trained FOA-ELM predicted model was validated using an accelerated life test. Experimental results indicated that FOAELM is less time-consuming with higher accuracy compared with PSO-ELM, BA-ELM, GA-ELM, and BFO-ELM. Banjevic et al. [26] proposed a proportional-hazards model with time dependent stochastic covariates as a lifetime model to predict the component failure rate and to optimize the replacement policy. Gebraeel et al. [27] selected the degradation model as an exponential in which the parameters were updated using a Bayesian approach. In addition to the degradation models with predefined mathematical form, the data-driven models that are established through machine learning are also playing an important role for large datasets. Gebraeel and Lawley [28] developed neural networks to predict the bearing failure time, which aimed to train a relationship between the bearing service time and the corresponding vibration spectrum. Tian et al. [29] developed a neural network to predict the RUL using both failure and suspension condition monitoring histories. Wang et al. [30] investigated a neuro-fuzzy approach and a recurrent neural network for gear prognostics with various failure modes. An extended recurrent neural network was proposed to predict the health condition of gears in [31], in which the Elman context layer was incorporated to enhance its ability to model nonlinear time series. Xi et al. developed a copula-based sampling method for data-driven prognostics, where a copula-based statistical model was proposed for degradation modeling, and a simulation-based method was employed for the remaining life prediction [32]. These processes require data to be sufficient so as to gain the statistical property; otherwise, the prediction could be unsatisfactory. The scarcity of failure histories, time-varying operating conditions, and thresholding setting are examples of challenges for data-driven methods to be effective.

2.2.C Hybrid methods

By noticing the merits and shortcomings of these two abovementioned methods, integrated methods are proposed to combine physics of failure and condition monitoring data to benefit from both. In integrated methods, the physical model parameters are treated as random variables, and they are updated using condition monitoring data so as to approach their real values. Cheng *et al.* [33] proposed a combination of ANFIS and PF to anticipate RUL of WT gearboxes utilizing current signals. The proposed approach employed an ANFIS to learn the state transition function of the extracted fault feature and a PF to predict the gearbox RUL based on the trained state transition function. Results illustrated that the ANFIS outperforms the RNN in learning the state transition function of the fault feature in the PF algorithm. Ding *et al.* [34] expected WT gearbox fatigue crack propagation and remaining life by explicitly examining varying external load. The proposed approach integrated the physical gear model utilizing FESA in modeling and accessible health state data. Finally, RUL prediction was enhanced by updating the distribution of the uncertain material parameter modeled in the crack degradation process via the Bayesian inference. The case studies demonstrated the efficacy of the introduced varying load approach, and its benefits compared with the constant load approximation method. A Bayesian framework fits well to achieve the goal of integrated prognostics because of its natural environment for sequential learning and uncertainty quantification. Therefore, it is widely used in integrated prognostics. Coppe et al. [35] studied the problem of crack propagation in an aircraft fuselage panel, where a Bayesian inference was used to estimate parameters in Paris' law and error term with assumption of independence of model parameters. Later on, An et al. [36] extended the methods to consider the correlation between model parameters. In [37], integrated prognostics methods were proposed for gear health prediction and uncertainty quantification. The authors then proposed to use polynomial chaos expansion to improve the efficiency of the Bayesian update process in prognostics [38]. To handle the time-varying operating conditions, an approach was devised in [39] to make the integrated prognostics applicable in various loading environments. The Bayesian inference also applied to study the spall propagation in bearings [40]. In recent years, there is an increasing volume of publications that used dynamic systems as degradation models because of its natural interface with real-time condition monitoring data. In [41], the Kalman filter was implemented to update the RUL prediction of bearings using a vibration signature as observations. Prognostic models presented in [42], [43] and [44] are established in a particle filtering framework, in which the problem of nonlinear state transition and non-Gaussian noise can be tackled.

Archard's wear model proposed in [45] is a simple but classic model based on the theory of asperity contact. It expressed the worn volume as a function of sliding distance, applied load, and hardness of materials. The coefficient in Archard's model was related to the probability that the two asperities would produce a wear particle. A summary of understanding in wear modeling for metals was presented in [46]. The paper also proposed future research areas for metal wear prediction. Williams [47] examined two mechanical wear processes, severe abrasive wear, and mild sliding wear, to show that due to variety and complexity of the mating surface conditions, tests are actually needed to determine the parameters in wear propagation laws. In [48], Zhao *et al.* did an analysis on steel surface using scanning electron microscopy and auger electron microscopy and proposed mathematical expressions for the wear rate. The author in [49] discussed the wear resistance, wear model, and wear rate using experimental results, and explained the wear phenomenon from the viewpoints of plastic deformation and fracture. The sliding model proposed in [50] considered two wear mechanisms: thermal desorption at low contact temperature and oxidative mechanism.

at elevated contact temperature. The microelastohydrodynamic lubrication (micro-EHL) effects were included by simulating two rough surfaces using digitized surface roughness profiles. Yan *et al.* [51] investigated sliding wear from micromechanics level. Periodic unit cell-type continuum mechanics models were used to obtain the wear rate. A wear model was proposed in which the authors researched the influence on the wear rate of the principal material, loading, and surface roughness. In [52], analytical time-domain models were used to predict wear status in transient- and steady-state operating conditions. A sliding polymer-based contact was adopted in the wear model. Abdo [53] developed a mathematical model to correlate the material volumetric loss due to wear with the dissipation energy in sliding contacts. Two mechanisms of energy loss were considered: plastic deformation and elastic energy of the particulate. This model can be used to predict the service life of components and structures. The FE model developed in [54] generalized Archard's law by allowing hardness of the soft material to be a function of temperature. The model presented in [55] used a free mesh to investigate the sliding wear in a composite alloy. Buentello-Hernandez and Palazotto [56] considered mechanical wear between two materials at high velocity. Apart from the above-mentioned physics-based models, data-driven methods are also presented to investigate the relationship between wear loss and potential effective conditions. For example, empirical models of wear rate were obtained by a response surface method [57], [58] and artificial neural networks were used in [59] and [60]. Among the preceding research work, Archard' wear model is now generally accepted as a suitable framework within which a quantitative analysis on wear progression can be discussed [61]. Archard's model was further generalized to regard the wear process as an initial value problem in [62] and was described by a differential equation as

$$\frac{dh}{ds} = kp \tag{1}$$

where h is the wear depth, s is the sliding distance, k is a dimensional wear coefficient, and p is the contact pressure. The wear coefficient k is considered as a random variable to account for its variation in different units.

3. Proposed Integrated method

In this project, an integrated method has been implemented as shown in [10]. Compared to data-driven prognostics methods, predictive models that are based on physics of failure bear better accuracy, but requires efforts to build physical models, which could be very complex, and determine the model parameters. Therefore, an integrated model is used to combine the physical model and data available in [10] to predict the damage progression and remaining useful life. Bayesian inference approach has been used to combine the physical model and data. The framework of the integrated approach has been shown in the below figure.

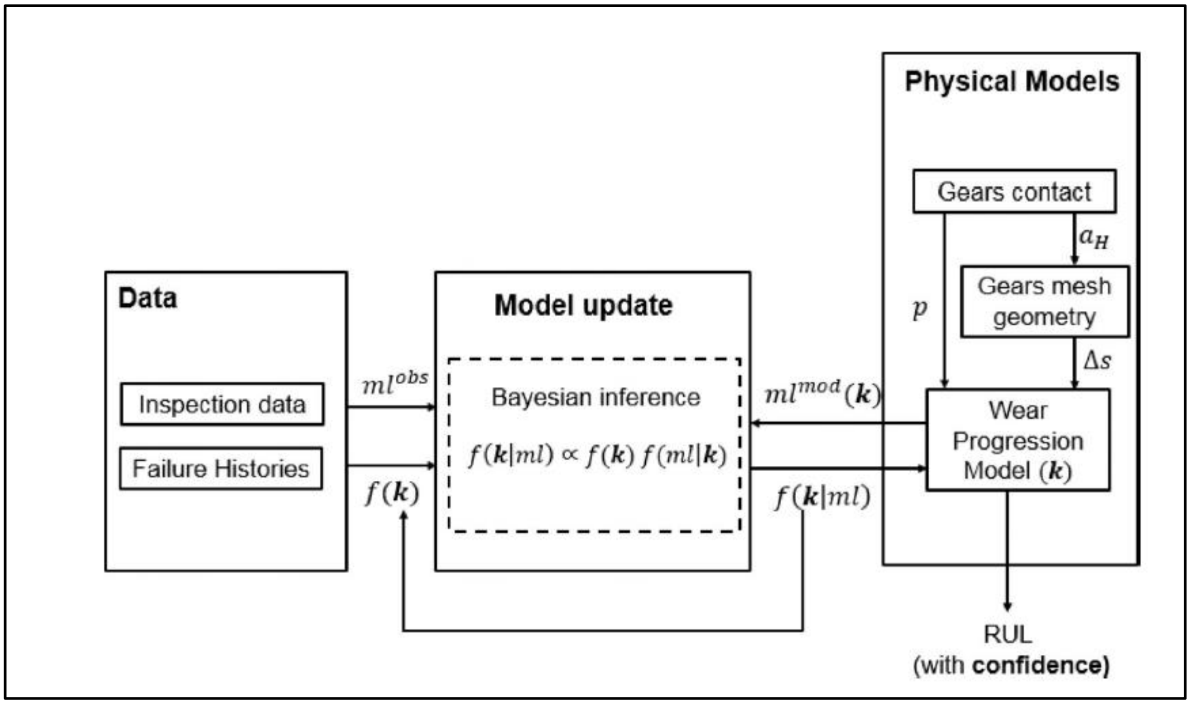


Fig. 1. Framework of an integrated prognostic method for gear wear prediction [10]

There are three parts in this framework: physical models, data, and update process. In the part of physical models, the wear progression model, that is Archard's wear model, is used to predict the wear depth evolution. The wear coefficient k is treated as a random variable. The sliding distance and contact pressure used in Archard's model are calculated based on the gears mesh geometry and contact process. In the part of data, two types of data are listed. The data of failure history could give us prior information of the wear coefficient value as a statistical property of gear population. In contrast, the inspection data are collected from the specific individual gear that is currently in use. In this paper, the mass loss of spur gear at inspection times serves as the inspection data. The purpose of the model update part is to use Bayesian inference to update the distribution of the wear coefficient by taking in the inspection data as observations in the inference.

3.1. Physical model in gear wear prediction

In this section, physical quantities that are needed to implement Archard' model and Bayesian inference are computed, which include contact pressure p, sliding distance s, and the mass loss ml.

3.1.A. Contact Pressure and Sliding Distance

During the mesh process of gears, there is a relative movement between the two meshing teeth because of the difference in tangential velocity, except for the pitch point in spur gears. The sliding movement causes wear of gear surface. The material particles will be removed due to the surface wear and the tooth profile will be altered. As discussed before, the Archard wear model describes the wear rate. We can discretize the model into the following form:

$$h(i) = h(i-1) + kp(\Delta s) \tag{2}$$

In order to use Archard's wear model to predict the gear surface wear, two important quantities are needed: the contact pressure and the sliding distance of all the points on the tooth flank during the mesh process.

From [10], the mean contact pressure is derived as

$$P_N = \frac{4F}{3\pi a_H} \tag{3}$$

Where a_H is the half contact width.

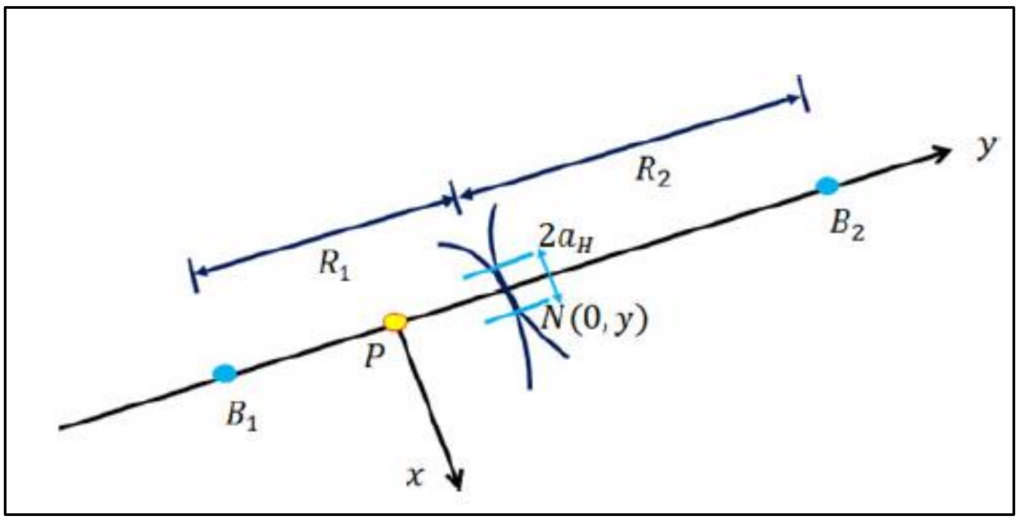


Fig. 2. Contact of a pair of teeth. [10]

The sliding distance s is given as:

$$s = a_H - \sqrt{(R_2)^2 - \left(R_{p2}sin\alpha_0 - y_{1d}\right)} + R_{p2}cos\alpha_0 \tag{4}$$

$$R_2 = \sqrt{\left(R_{p2}cos\alpha_0 - a_H\right)^2 + \left(R_{p2}sin\alpha_0 - y_{1e}\right)^2} \tag{5}$$

$$y_{1e} = \sqrt{R_1 - \left(R_{p2}cos\alpha_0 + a_H\right)^2} - R_{p1}sin\alpha_0 \tag{6}$$

$$y_{1d} = \sqrt{R_1 - \left(R_{p2}cos\alpha_0 - a_H\right)^2} - R_{p1}sin\alpha_0 \tag{7}$$

$$R_1 = \sqrt{\left(R_{p1}cos\alpha_0\right)^2 + \left(R_{p2}sin\alpha_0 - y\right)^2} \tag{8}$$

With the contact pressure and the sliding distance available, the determination of wear coefficient is required before using Archard's model to predict wear depth evolution.

3.1.B. Mass Loss of Wear

The gear type we consider in this paper is spur gear, which has a symmetric geometry. Therefore, the volume of metal loss is equal to the area removed according to the wear depth in two dimensional (2-D) multiplied by the thickness of the tooth. As wear accumulates, the tooth profile will change due to material loss. Fig. 3 depicts the 2-D shape of the spur gear tooth, in which a dashed line is used to represent the tooth profile after some wear accumulation.

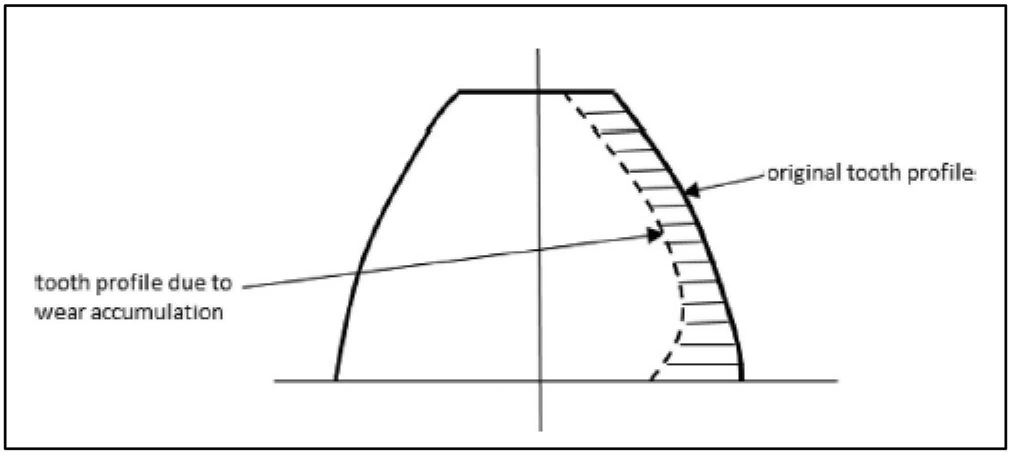


Fig. 3. Area of material loss due to wear accumulation [10]

The shaded area between the original tooth profile and the new one is the area of material loss. This area can be approximated in the following way. First, divide the tooth height vertically at the points where the wear depth is computed. Then, calculate the area of each small element using the wear depth and sum them up. The mass loss will be calculated by multiplying this area by the thickness of the tooth, and then by the density of the material.

3.2 Model update through Bayesian interface

Archard's wear model is used to predict the wear depth evolution at each point on the tooth surface. More accurate wear coefficient in the model leads to more accurate wear prediction. However, different gears most likely have different wear evolution processes due to variations in material property, manufacturing process, and working conditions. Therefore, the wear coefficient is considered as a random variable to account for the uncertainty in the wear evolution process from the population point of view. Meanwhile, the health condition of a specific individual is of our interest. The uncertainty in failure time for an individual unit is much less than that for the population. Hence, a mechanism of uncertainty reduction is needed in the wear prediction process. By noticing the material removal as a direct consequence of gear wear process, the gear mass loss would be a good indicator of wear status. The Bayesian inference will take the data on gear mass loss as observations to update the distribution of the wear coefficient. The formula for determining the posterior distribution of the uncertain parameter, wear coefficient k, is given as follows:

$$f_{post}(k|m) = \frac{l(m|k)f_{prior}(k)}{\int l(m|k)f_{prior}(k)dk} \tag{9}$$

Where m represents the mass loss. The update on the wear coefficient distribution is conducted at each inspection time when a new measurement of gear weight is available. The posterior distribution will serve as the prior distribution for the next update at the next inspection time.

At each inspection time T_j, the measured mass loss is m_j^{obs}. With the wear coefficient k^{j-1} obtained at the previous inspection time T^{j-1}, the predicted mass loss at inspection times T_1 up to T_j are thus denoted by $m_{1:j}^{mod}$. The measurement error is defined as $e = m^{obs} - m^{mod}$ and assumption is made that it follows zero-mean Gaussian distribution with standard deviation σ. It is further assumed that the measurement errors at inspection times are identical and independently distributed. Thus, the likelihood to observe the mass loss at inspection times up to T_j is:

$$l\left(m_{1:j}^{obs}|k^{j-1}\right) = \prod_{i=1}^{j} \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{\left(m_{i,obs}-m_{i,mod}\right)^2}{2\sigma^2}\right) \tag{10}$$

The prior can be obtained using the following way in practice. For example, we suppose that N degradation paths from N test units are available. For each path, we use least square to obtain an estimate for the coefficient. Then, we use Gaussian distribution to fit these N coefficients. Then, this Gaussian distribution will be used as a prior distribution in the Bayesian equation. When no or little prior information on the failure history is known, it is more reasonable to use a noninformative prior.

The physical parameters of the planetary gearbox are given below in Table 1:

Parameters	**Sun Gear**	**Planet Gear**	**Ring Gear**
Number of teeth	19	31	81
Module (mm)	3.2	3.2	3.2
Pressure angle	20°	20°	20°
Mass (kg)	0.7	0.7	0.7
Face width (m)	0.0381	0.0381	0.0381
Young's modulus (Pa)	2.068×10^{11}	2.068×10^{11}	2.068×10^{11}
Poisson's ratio	0.3	0.3	0.3
Base circle radius (mm)	28.3	46.2	120.8

A simple flow chart of the RUL calculation process has been shown below in Fig. 4. As given in [10], the threshold value of mass loss has been given as 28.71 g. In order to account for the contribution of rolling contact to the mass loss, it has been proposed by the authors in [10] to remove the material using the maximum wear depth.

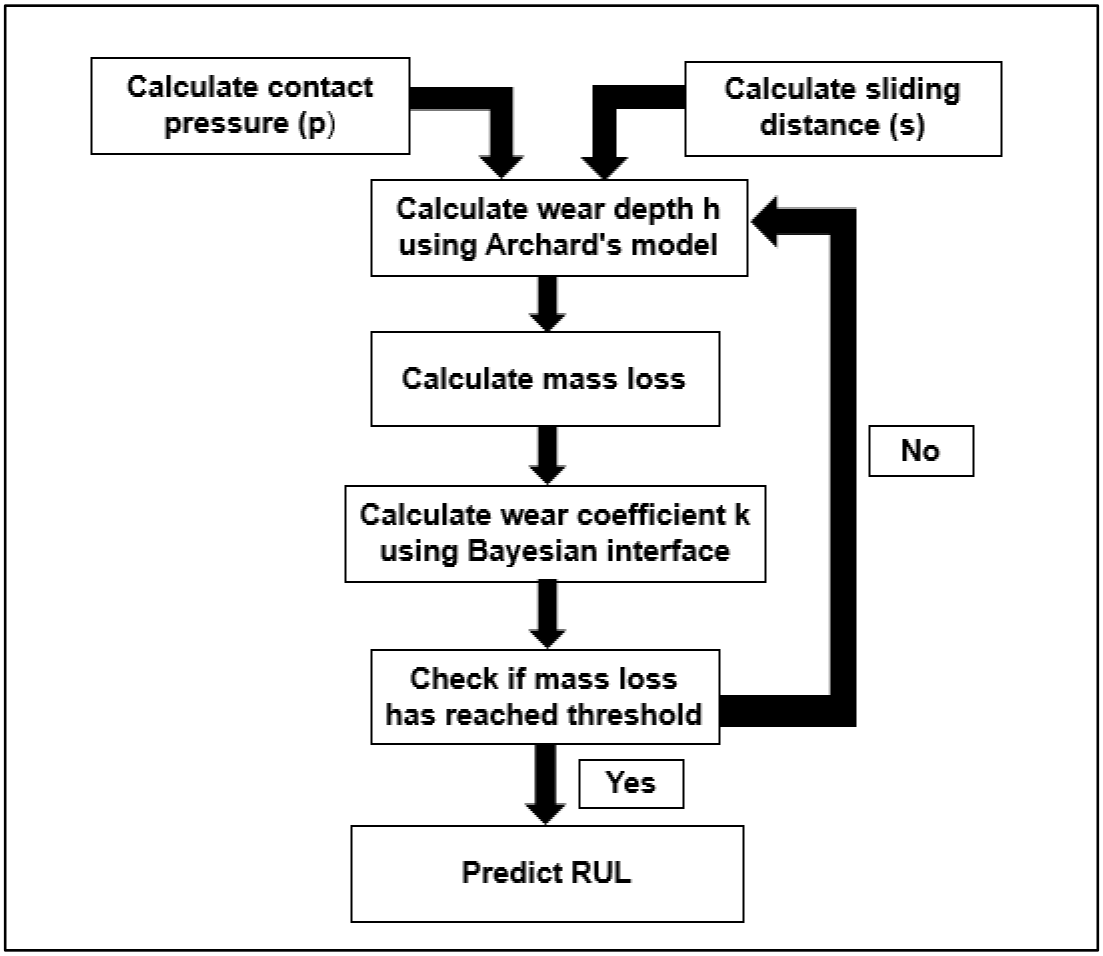


Fig. 4. The flowchart of RUL calculation

4. Result

The predicted and actual mass loss has been plotted in the below waveform. The actual mass loss data has been taken from the experiment data mentioned in [10]. The waveform of RUL has also been plotted in the same manner.

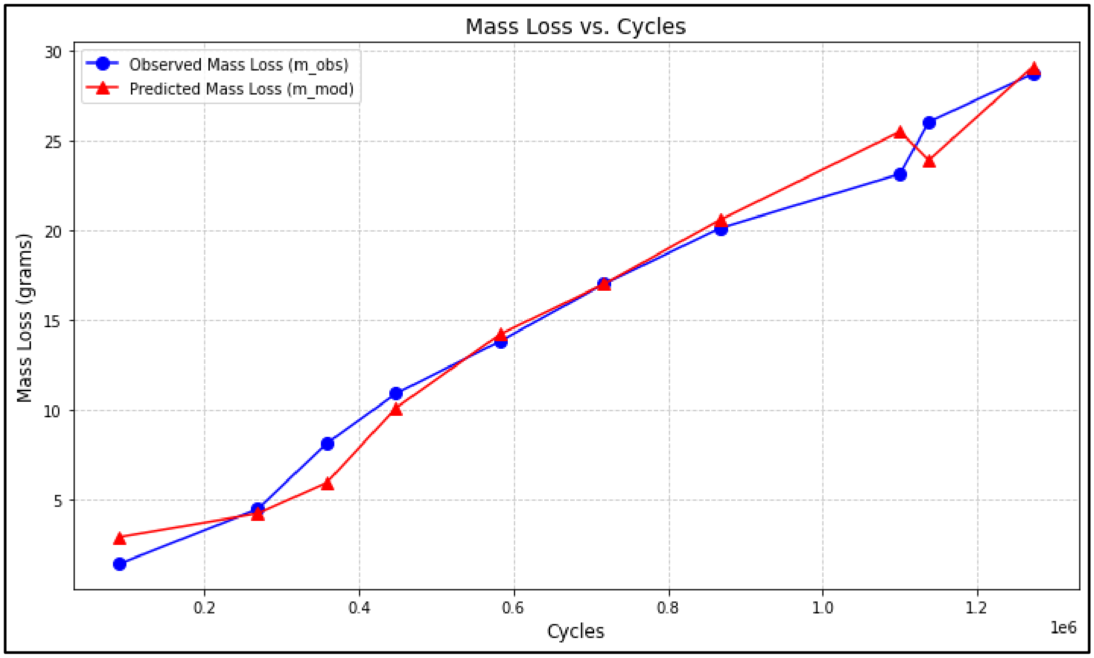
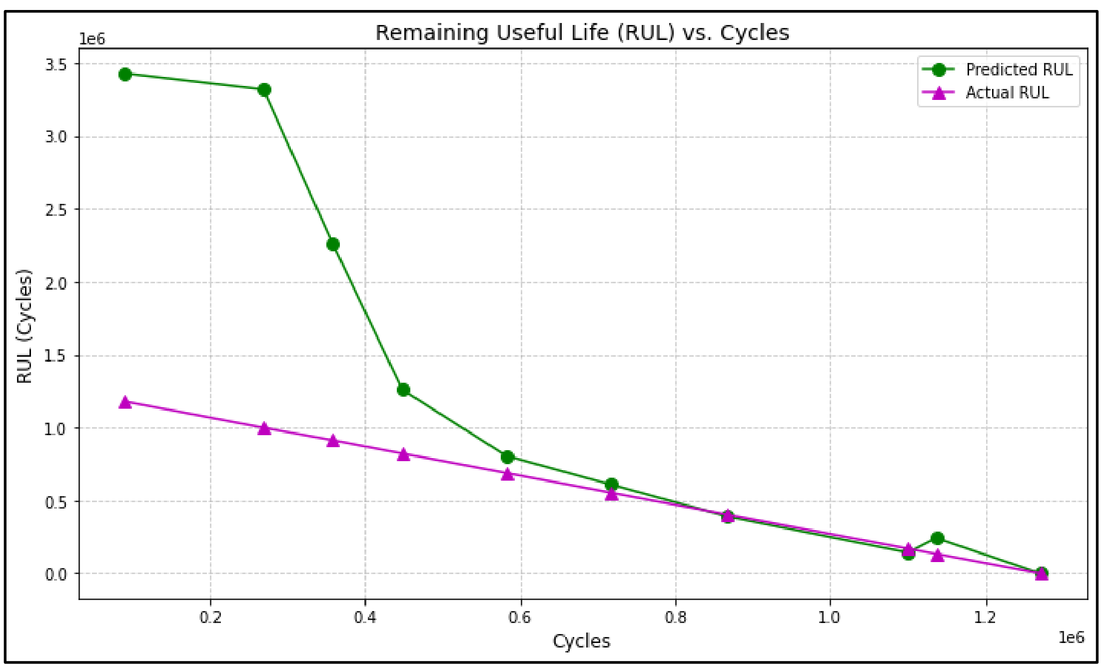


Fig 5. The waveform of observed vs predicted mass loss of the gear



5. Conclusion

In this project, the failure time prediction has been performed considering the surface wear failure mode of planetary gear. A hybrid integrated prognostics method has been implemented in this project by combining the physics-based model of Archard's equation and Bayesian inference for considering the dynamic behavior of wear coefficient. The physics-based models are complex and require mathematical analysis, but they are accurate to predict the RUL. There are some discrepancies observed in the obtained waveforms which can be improved by modifying the algorithm of Bayesian inference. Furthermore, the assumption of constant contact pressure and sliding distance does not seem to be suitable for the late stage of the wear process with severe profile change. This can be investigated and implemented to accommodate the dynamic behavior to further improve the failure prediction.

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