

Predictive Health Monitoring of Gear Surface Fatigue Failure Using Model-Based Parametric Method Algorithms; An Experimental Validation

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ABSTRACT

Gears are one of the most important parts of any mechanical transmission system, and in order to achieve reliable operation effective monitoring techniques must be employed. Predictive health monitoring (PHM) systems are currently gaining in popularity due to their effectiveness in providing robust information about the system condition and reducing maintenance costs. However, PHM systems require reliable monitoring techniques, such as vibration, acoustic emission, and oil debris analysis. These techniques have been studied in recent years to discover which can best support the operation of PHM systems in tracing the condition of the operating transmission. These studies have shown the need to apply intelligent algorithms in order to benefit from the advantage of each technique in classifying faults and predicting the onset of failure. This paper presents a new online PHM system for monitoring different gear faults using vibration analysis and autoregressive (AR) algorithms. The intelligent health monitoring system (IHMS) has been implemented on a back-to-back gearbox and can be adapted to monitor the behaviour of transmission systems in automotive, aircraft, wind turbine, and industrial machinery. The study describes the operation of the online IHMS under variable conditions and its capability in detecting transmission gear defects and thus preventing sudden unexpected failure. The results of the experimental test prove the system's capability and support the recent trend of using IHMSs in PHM strategies.

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INTRODUCTION

Most gears fail as a result of a fatigue process, of which there are two types: surface contact fatigue and bending fatigue. Pitting is one of the most important forms of surface failure because it can lead to further destructive failure mechanisms in gears. Bending failure can occur in one of two ways: from advanced contact fatigue or as a result of high bending stress levels beyond the permissible limit that gear teeth can safely withstand [1]. Three monitoring techniques are commonly used to monitor these types of failures, namely: acoustic emission (AE), vibration and on-line debris analysis (ODA). However, recent studies have highlighted the advantages of using artificial intelligence (AI) algorithms with these techniques in HMSs to detect gear failures, although many such studies have been based largely on vibration information only. These studies have focused mainly on either surface or bending failures, do not provide

predictions, and in some situations do not overcome the issue of false alarms. These problems are overcome in the present research programme, which has already demonstrated the ability to monitor the two types of fatigue failures using the three techniques of AE, vibration and ODA [2,3,4], and also to predict the two types of fatigue failures via an IHMS using sensor fusion algorithms [5,6]. This paper builds on these achievements by introducing a model-based parametric method using AR algorithms with the recently developed IHMS that utilizes the three techniques simultaneously to provide robust predictive information that can be usefully applied to CBM strategies.

Conventional monitoring systems are currently used in gear transmission systems in order to improve maintenance scheduling and reduce failures by incorporating vibration, AE, and ODA. Vibration monitoring is used to acquire information about inaccessible transmission components under normal operating conditions. Several studies have



presented the application of time domain analysis (TDA) methods in order to recognise gear defects [7,8,9,10,11,12]. Samuel and Pines [10] have reviewed different TDA diagnostic methods applied to vibration. The effectiveness of AE, vibration, and oil debris sampling analysis monitoring was experimentally investigated by Tan et al [11, 12]. In both studies the authors concluded that the vibration analysis and oil sampling analysis results did not offer earlier indication of gear damage in comparison to the AE technique.

Intelligent health monitoring systems incorporate AI algorithms, where AI can be defined as “the science of making machines do things that would require intelligence if done by humans” [26]. To develop an IHMS, the running system condition must be recognized and classified. Researchers have devoted considerable effort to the application of various different soft computing methods to develop IHMSs, and have shown that this can be achieved using methods such as neural networks, fuzzy logic and mathematical modelling based on parametric approaches. All of these methods can provide important tools in the field of intelligent systems which can learn, adapt, and make decisions concerning the system they are in charge of [26].

Artificial neural networks (ANNs) have been used with different HMS techniques such as vibration and acoustic monitoring. An ANN requires input data of the healthy and faulty conditions to be pre-processed, and then these features are used to model the system's behaviour. Fenton et al [27] mentioned that there are two main basic network architectures: feed-forward and recurrent ANNs. Feed-forward ANNs do not have feedback between layers, and previous inputs are not remembered, whereas recurrent ANNs involve feedback between layers and previous inputs are remembered and can be used to reconstruct correlative memory. The two standard neural network architectures used in transmission diagnostics are the feed-forward back propagation network, and the Kohonen feature map which is also known as the self organizing map (SOM) [10]. Several research studies have been devoted to applying ANNs so as to provide a classification of the different transmission failures indicated in acoustic and vibration signals [28,29,30,31].

Fuzzy logic was developed by Zadeh in the 1960s to characterize types of knowledge that cannot be represented by classical Boolean algebra to cover approximate knowledge in describing the behaviour of systems which are difficult to describe mathematically [26]. The application of the different fuzzy models in sensory fusion algorithms has been studied to provide information about the condition of systems being monitored [5,6,41,42], and both surface and bending fatigue failures in gears have been successfully predicted [5,6]. Meanwhile, sensor fusion approaches have been used to monitor cutting tool failures and bearing fault identification in aircraft engine monitoring [41, 42].

The purpose of parametric methods based on mathematical modelling is to fit measured time series waveform data to a parametric time series model, and then

extract features based on this model [34]. Two models are currently in use: the auto regressive (AR) and auto-regressive moving average (ARMA) models. The reduced set of vector parameters of these models are used to describe the system data required. The method is based on matching the model to a specific data type, such as data from a healthy transmission, and any change in the signal characteristics due to failure will change the statistical properties of the output [20]. Samuel and Pines [10] discussed the differences between various types of parametric method, explaining the AR and ARMA models as follows.

The AR model for a time series X can be represented by a linear regression of X on itself plus an error series which is assumed to be noise having a Gaussian distribution. The AR model is given in Equation (1).

$$x_i = -\sum_{k=1}^p a_k x_{i-k} + e_i \quad (1)$$

where p is the model order and provides the number of past inputs required to model the signal, which is determined experimentally, a_k are the AR coefficients, i is the sample index, and e_i is the Gaussian error series [10].

The ARMA model is a generalized form of the AR model that can represent a time series X . The ARMA model is given by Equation (2).

$$x_i = -\sum_{k=1}^p a_k x_{i-k} + \sum_{k=0}^q b_k e_{i-k} \quad (2)$$

where p and q are the ARMA model order, a_k are the AR coefficients, b_k are the MA coefficients, i is the sample index, and e_{i-k} is the model error series. The MA coefficients b_k have to be computed after the AR coefficients are determined, hence the AR approach has a computational advantage over the ARMA approach [10].

The advantage of mathematical modelling based on parametric methods over the neural networks model-based method is its ability to deal with time series data directly without the need for a signal pre-processing step to extract useful features that can be modelled to represent the system [5]. However, they can only be used to model a time series signal such as a vibration signal, and cannot be applied to combined information from several techniques (vibration, AE and ODA) such as in the case of fuzzy logic.

EXPERIMENTAL TEST RIG

The tests were conducted at Newcastle University on a back-to-back gear test rig. The rig comprises a 75mm centre distance back-to-back test gearbox connected to a slave gearbox; Figure 1 shows the rig layout. A pair of helical test gears was tested under closely controlled conditions. The system is driven by a 5.5kW variable speed electric motor controlled by an inverter to provide a speed variation of

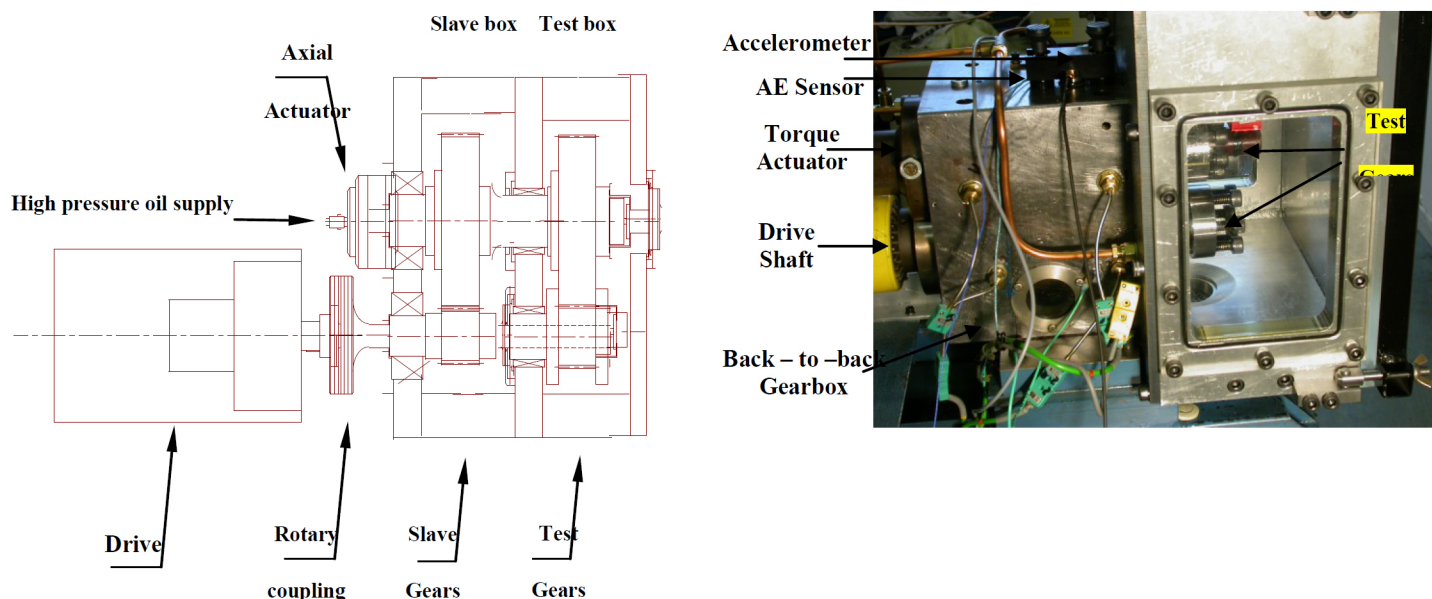


Figure 1. Newcastle University 75 mm back-to-back test rig layout.

0-6000 rpm. The slave gearbox is used to apply load via a hydraulic axial actuator. The rig can generate a load torque on the test gears in the range of 0-600 Nm. Torque is measured using calibrated strain gauges installed on the wheel shaft, and the measured torque values are transmitted to the control program by telemetry in order to provide closed loop torque control of the actual load on the gear itself. The rig is controlled using a National Instruments (NI) LabVIEW application which consists of a PCI-MIO-16E-4 E series data acquisition card (NI) with a multi-channel sampling rate of 250ksps (16 channel). Temperature was monitored using a USB-9211A temperature data acquisition card (NI). Three oil heaters and a water cooler were used to ensure that the running oil temperature was kept constant during the tests. Four temperatures were measured: rig oil temperature, test gear bearing temperatures and slave gear bearing temperature. Oil pressure and flow rate were also measured. A gear tooth trigger sensor was installed adjacent to the pinion test gear to ensure that tooth failure could be recorded. The input shaft speed and motor current were also monitored as a precaution. The test rig software provided the flexibility to change the control algorithm according to the test conditions required using LabVIEW's virtual instrument scalable architecture features. The test rig sensor actuation system layout is shown in Figure 2. The IHMS incorporated a DSA PCI-4472 24-bit data acquisition card (NI) to acquire the vibration signal. The vibration signals were acquired using two DJB Piezotronic constant current source accelerometers (model no. A/120/V) mounted adjacent to the test gear bearings transversely to the gearbox casing, and a shaft speed sensor was used to acquire the shaft rotation reference.

DESIGN AND IMPLEMENTATION OF AN ONLINE HEALTH MONITORING SYSTEM USING MODEL-BASED PARAMETRIC METHOD ALGORITHMS

An IHMS for power transmissions has been developed and validated by the authors [5, 6] to predict both gear bending and surface failures. In this paper new model-based parametric AR algorithms were introduced to the IHMS to provide independent information about the gear condition and confirm the previous validation results of the IHMS published in [5, 6]. The AR method is chosen because of its computational advantage over the other model-based parametric methods. The gear fatigue surface failure is monitored using two independent AR algorithms of the second order, since estimating too many coefficients requires more processing time and the second order model has been tested for online operation. Each AR algorithm is based on an independent vibration accelerometer.

The operation of the algorithms was based on acquiring the vibration data continuously then feeding it to the AR models to compute the AR coefficients by minimizing the least-square errors of the forward and backward predictions, which were then plotted and logged. The online change in the AR model coefficients were used to assess the development of micro-pitting failure.

EXPERIMENTAL VALIDATION

The system validation comprise a series tests were designed to achieve the proposed aim of developing and validating the behaviour of the IHMS and the AR algorithms, and investigating its capability to provide information to