

Consequence Analysis in Predictive Health Monitoring of Automotive Diesel Engine Defects

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ABSTRACT

Reliability has always been an important aspect in the assessment of industrial products and/or equipments. Good product design is of course essential for products with high reliability. However, no matter how good the product design is, products deteriorate over time since they are operating under certain stress or load in the real environment, often involving randomness. Maintenance has, thus, been introduced as an efficient way to assure a satisfactory level of reliability during the useful life of a physical asset. The earliest maintenance technique is basically breakdown maintenance (also called unplanned maintenance, or run-to-failure maintenance), which takes place only at breakdowns. A later maintenance technique is time-based preventive maintenance (also called planned maintenance), which sets a periodic interval to perform preventive maintenance regardless of the health status of a physical asset. The vehicle component is judged to be safe depending on its reliability. Consequently, there is a general attention to establish approach by which the failure risk has to be known. To achieve this objective, the present work introduces an approach to establish the vehicle engine risk assessment using the excess air escaped inside the engine crankcase. The results indicate that the excess scalped air mass flow rate corresponding to the failure rate values computed based on the Weibull distribution with assured reliability can be considered to be guide for maintenance regime.

KEYWORDS: Diagnostic, reliability, hazard rate, prognostic, failure, Weibull distribution, deterioration

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INTRODUCTION

Data acquisition is a process of collecting and storing useful data (information) from targeted physical assets for the purpose of Conditions Based Maintenance (CBM) where CBM is a maintenance program that recommends maintenance decisions based on the information collected through condition monitoring. This process is an essential step in implementing a CBM program for machinery fault (or failure, which is usually caused by one or more machinery faults) diagnostics and prognostics. Data collected in a CBM program can be categorized into two main types: the so-called event data and condition monitoring data. Event data include the information on what happened (e.g., installation, breakdown, overhaul, etc., and what the causes were) and/or what was done (e.g., minor repair, preventive maintenance, oil change, etc.) to the targeted physical asset [1].

Maintenance information systems, such as Computerized Maintenance Management Systems (CMMS), enterprise

resource planning systems, etc., have been developed for data storage and handling. Collection of event data usually requires manual data entry to the information systems. With the rapid development of computer and advanced sensor technologies, data acquisition facilities and technologies have become more powerful and less expensive, making data acquisition for CBM implementation more affordable and feasible. One point the authors would like to make is that event data and condition monitoring data are equally important in CBM [2].

For condition monitoring data, data errors may be caused by sensor faults. In this case, sensor fault isolation is the right way to go. In general, however, there is no simple way to clean data. Sometimes it requires manual examination of data. Graphical tools would be very helpful to finding and removing data errors. A variety of models, algorithms and tools are available in the literature to analyze data for better understanding and interpretation of data. The models,

algorithms and tools used for data analysis depend mainly on the types of data collected [3]

The most common multidimensional data are image data such as infrared thermographs, X-ray images, visual images, etc. Data processing for waveform and multidimensional data is also called signal processing. Various signal processing techniques have been developed to analyze and interpret waveform and multidimensional data to extract useful information for further diagnostic and prognostic purpose [4].

The consequence analysis techniques discussed in [5-6] is a general risk evaluation tool for CBM optimization based on various kinds of criteria. The most obvious and widely used prognostics is to predict how much time is left before a failure occurs (or, one or more faults) given the current machine condition and past operation profile. The time left before observing a failure is usually called Remaining Useful Life (RUL). Most of the papers in the literature of machine prognostics discuss only the type of prognostics, namely RUL estimation [7].

A logistic regression model has been used to calculate the probability of failure for given condition variables and an Auto Regressive Moving-Average (ARMA) time series model to trend the condition variables for failure prediction. Then a predetermined level of failure probability was used to estimate the RUL. Moreover, to track sensor-level test-failure probability vectors instead of the physical system or sensor parameters for prognostics. A Kalman filter with an associated interacting multiple models was used to perform the tracking. Two statistical models in survival analysis, Prognostics and Health Management (PHM) and the Proportional Intensity Model (PIM), which adopts a stochastic process setting and assumes a similar form to the intensity function of the stochastic process, are useful tools for RUL estimation in combination with a trending model for the fault propagation process. In addition, PIM with covariate extrapolation has to be applied to estimate bearing residual life. The Hidden Markov Model (HMM), is a statistical model that can be used to analyze data gathered from, among other things, mechanical components, is also a powerful tool for RUL estimation [8, 9, 10].

All automotive fleets' ownerships want to increase their fleets' availability; therefore, they resort to consider the conventional maintenance policy. Despite of, this policy increases fleets availability but the cost will be high. This is due to replace the parts before the end of their lifetime. On the other hand, this policy is based on time where it is not cost-effective. Consequently, this conventional maintenance policy is not adequate to fulfill the needs of high availability for automotive fleets. The concept is based on predicting the system degradation and calculating the reliability function for the component. An application carried out on internal combustion engine crankshaft main bearing to illustrate the effectiveness of this technique [11].

Real-time, integrated health monitoring of gearboxes that can detect, classify, and predict developing gearbox faults is critical to reducing operating and maintenance costs while

optimizing the life of critical gearbox components. Statistical-based anomaly detection algorithms, noise measurement related faults and degradation can now be developed for real-time monitoring environments. Integration and implementation of these technologies presents a great opportunity to significantly enhance current gearbox health monitoring capabilities and risk management practices. However, methods for analyzing system status and health and for predicting system life expectancy need to be made more powerful, insightful, reliable, and robust for data collection onboard systems in real time. A developed robust analytical method for predicting remaining lifetime of transmission gears is presented in [12]. An investigation has been introduced with the aim of machine prognosis which is to provide decision support for maintenance actions. The main idea of prognostics incorporating maintenance policies is to optimize the maintenance policies according to certain criteria such as risk, cost, reliability and availability. Risk is defined as the combination of probability and consequence. Usually, consequence can be measured by cost. Since cost criterion applies to most situations, it is not surprising that the literature in CBM optimization is dominated by cost-based CBM optimization [13].

The aforementioned review has shown that almost all the efforts which have been done in predictive health monitoring was directed towards the studying prognostics and diagnostic theoretical or experimental using vibration, acoustic and oil analysis. However, the objective of the present work is to use the vehicle engine cylinder's excess air escaped (i.e. blow-by gas) for predictive health monitoring which hitherto has been given little consideration.

PREDICTIVE HEALTH MONITORING

Diagnostic and Prognostic Methods

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, gear box and valves that exhibit various types of performance degradation due to erosion, friction, internal damage and cracks. Prognostics are viewed as an add on capabilities to diagnosis; they assess the current health of a system and predict 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.

Hazard Rate Model Based Data-Driven Technique

Before modeling the hazard rate process of an engine cylinder kit where the engine cylinder kit is the piston, piston



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rings and the liner, it is crucial to design a suitable signal indicator that captures the evolution of the cylinder kit's degradation. The degradation signal that we considered is focused on the pressure inside the crankcase of the engine. The reason for choosing this signal is the relation between the pressure inside the crankcase during the operating condition and the clearance between the cylinder kit parts. There is a proportional relationship between the pressure inside the crankcase and cylinder kit parts clearance. The degradation measured of the engine cylinder kit can be calculated by using the hazard function. The probability of failure for a system in a given time interval $[x_1, x_2]$ can be expressed in terms of either the unreliability function as [14, 15, 16]

$$\int_{x_1}^{x_2} f(x) dx = \int_{-\infty}^{x_2} f(x) dx - \int_{-\infty}^{x_1} f(x) dx = F(x_2) - F(x_1) \quad (1)$$

or in terms of the reliability function

$$\int_{x_1}^{x_2} f(x) dx = \int_{-\infty}^{x_2} f(x) dx - \int_{-\infty}^{x_1} f(x) dx = R(x_1) - R(x_2) \quad (2)$$

where

$f(x)$: is the probability density function

$F(x)$: is the cumulative distribution function

$R(x)$: is the reliability function

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. The maintenance cost depends on the probability distribution function (pdf), 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:

$$F(x) = \int_0^x f(x) dx. \quad (3)$$

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

$$R(x) + F(x) = 1 \quad (4)$$

where

$f(x)$: is the probability distribution function (time, Root Mean Square (RMS),...etc)

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

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

$$h(x) = \frac{f(x)}{R(x)} \quad (5)$$

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

$$f(x) = \frac{\beta(x)^{\beta-1}}{\eta^\beta} \exp[-(\frac{x}{\eta})^\beta] \quad (6)$$

From equation (1), then

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

From equations (3.3) and (3.4), the hazard given by

$$h(x) = \frac{\beta}{\eta} (\frac{x}{\eta})^{\beta-1} \quad (8)$$

where

x : is the air mass flow rate (g/s) or distance (km) to failure

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

β : is the shape factor.

Individual hazard rate as a mean of fault diagnosis

To obtain the remaining traveling distance (RTD) of the operated faulty engine, the decision maker has to use equation (8) with respect to a specific traveling distance though calculated hazard rate.

For air mass flow rate, equation (8) become

$x = q$

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

where:

q : is the air mass flow rate at any condition, g/s

Failure rate as a mean of prognostic based on air mass flow rate

To obtain the failure rate of the operated faulty engine, the decision maker has to use equation (8) with respect to the air mass flow rate though calculated hazard rate. The failure air mass flow rate will be the air mass flow rate corresponding to the hazard rate of 1.0 (100% the reliability function).

For air mass flow rate, equation (8) become

Put $x = Q$

$$h(D) = \frac{\beta}{\eta} \left(\frac{D}{\eta} \right)^{\beta-1} \quad (10)$$

where:

Q : is the air mass flow rate to failure, g/s

Failure rate as a mean of prognostic based on vehicle driving distance

To obtain the vehicle driving distance (VDD) of the operated faulty engine, the decision maker has to use equation (8) with respect to the driving distance though calculated hazard rate. The failure driving distance will be the driving distance corresponding to the hazard rate of 1.0 (100% the reliability function).

For vehicle driving distance, equation (8) become

Put $x = D$

$$h(D) = \frac{\beta}{\eta} \left(\frac{D}{\eta} \right)^{\beta-1} \quad (11)$$

where

D : is the vehicle driving distance, km

BACKGROUND KNOWLEDGES

General

Reliability is the probability that an item will perform satisfactorily for a specified period of time or kilometer under specified operating conditions. In the field of reliability, there are many types for life time distributions. Some of these types are normal and Weibull distribution. The reliability function of any mechanical component is obtained through statistical life testing procedures that are usually conducted under ideal laboratory condition. On the other hand, the life time's data can also be collected during the components operation to estimate its distribution parameters and decisions. There has been growing interest in the recent years in reliability and maintenance models where the main emphasis is placed on the so called intrinsic age rather than its real age. The hazard rate is changed over the life time for any mechanical components as shown in Fig. 1. The figure explains the engine main bearing life time, as an example [11], the first interval of time from (t_0) to (t_1) , represents reducing the hazard rate due to surface roughness between the main bearing and shaft. The second interval of time, from (t_1) to (t_2) represents the operating normal conditions where the hazard rate is constant approximately. On the other hand, the portion of the curve beyond t_2 represents the wear-out failure or increasing the hazard rate due to increase the clearance between the engine cylinder kit components (piston, cylinder liner, and piston rings), if time t_2 could be

predicted with certainty, then the engine cylinder kit components will be replaced before this wear-out phase begins. The hazard function is taken to be a one parameter from the life time distribution that is obtained it through statistical life that is usually conducted under ideal laboratory condition. The life time's data of any mechanical component may also be collected during the operating to estimate the lifetime distribution. Therefore statistical procedures in estimating the lifetime distribution parameters and decisions related with replacement and distributions.

Survey of the Vehicle Fleet Faulty Engines

A total of 30 vehicles were considered in the survey, where 2 operate up to 100000 km, 6 operate up to 200000 km, 16 operate up to 300000 km, 4 operate up to 400000 km and 2 operate up to 500000 km as shown in Fig. 2. All installed engines in these vehicles have the same technical specifications. The engine technical specifications is presented in the **Table 1**

EXPERIMENTAL WORK AND INSTRUMENTATION SYSTEM

Description of Experimental Method

Figure 3 illustrates the layout of diagnostic and prognostic processes which indicates the path of the blow-by gases for an engine equipped with Positive Crankcase Ventilation (PCV) system. The PCV system operates by the engine vacuum at the intake manifold to create air circulation. Consequently, this circulation will help to remove the unwanted vapor mixtures, which contains burned and partially burned combustion gases. It is well known that the PCV system creates vacuum inside the crankcase and this vacuum is directly proportional to the engine speed. If any component from the PCV system has defect such as a hidden crack in a hose connection between the crankcase ventilation and intake manifold, or the PCV valve has slightly defect then the taken measurement will not be accurate. Therefore, the effect of any defective parts of PCV system should be avoided in the measurements by removing the whole PCV system during the tests and reinstalled it later. On the other hand, during the combustion process inside the vehicle engine cylinders, there is some gas flow inside the engine crankcase. The quantities of these gases are proportional to the vehicle engine cylinder condition or the clearance between the cylinder kit components.

Description of Instrumentations Tools

Sensors and sensing strategies constitute the foundational basis for fault diagnosis and prognosis. Strategic issues arising with sensor suites employed to collect data that eventually will lead to online realization of diagnostic and prognostic algorithms which are associated with the type, number, and location of sensors; their size, weight, cost, dynamic range, and other characteristic properties; whether