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A Vehicle Bi-fuel Petrol Engine Condition Prognosis in Service Based on Combined Vibrational and Exhaust Emission Signals

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Abstract The operation of a particular component in deteriorating condition will cause a high machine stop time. This is due to the damage of component at unexpected time. This causes increase cost of maintenance and production lost. One of the solutions to this matter is to use Preventive Replacement (PR). PR is one of the maintenance optimization strategies that can balance the failure cost in unexpected time (maintenance and production lost) and maintenance benefits (minimize downtime) for a deteriorating component. However, the objective of this paper is to introduce the PR strategy for determining an optimal replacement time for component that deteriorates over time for vehicle bi-fuel engine. The combined exhaust emission and vibration acceleration signatures were used as predictors, while the level of engine lubricant oil was considered a fault. Smart phone sensors was used for the vibration acceleration signals record mounted upon the engine valve cover. The AGE-200 gas analyzer is used for measure the exhaust emission components values. This data processed to estimate the failure time and investigate the maintenance cost. The models are used for the cost per unit time based on the stochastic behavior of the assumed system. The model reflects the cost of storing a spare as well as the cost of system downtime. The minimum-cost (optimum) policy time was calculated with the consideration of availability. It is noted that all maintenance cost results converge to the optimal value of the age replacement policy which has the same configuration. Moreover, the combined exhaust emission and vibration acceleration signatures 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 Prognostic, deterioration preventive maintenance, availability limit, maintenance cost optimization, compressed natural gas and gasoline

Introduction

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 available literature that focuses on the machine prognostics was presented. Generally, prognostic models can be classified into four categories: physical model, knowledge-based model, data-driven model, and combination model. Various techniques and algorithms have been developed depending on what models they usually adopt [1, 2]. Based on the review of some typical approaches and new introduced methods, advantages and disadvantages of these methodologies are discussed. From the literature review, some increasing trends appeared in the research field of machine prognostics are summarized

An overview of two maintenance techniques widely discussed in the literature: time-based maintenance (TBM) and condition-based maintenance (CBM) have introduced. The paper discusses how the TBM and CBM techniques work toward maintenance decision making. Recent research articles covering the application of each technique are reviewed. The paper then compares the challenges of implementing each technique from a practical point of view, focusing on the issues of required data determination and collection, data analysis/modelling, and decision making [3-5]. The paper concludes with significant considerations for future research. Each of the techniques was found to have unique concepts/principles, procedures, and challenges for real industrial practice. It can be concluded that the application of the CBM technique is more realistic, and thus more worthwhile to apply, than the TBM one. However, further research on CBM must be carried out in order to make it more realistic for making maintenance decisions.

A novel condition-based maintenance system that uses reliability-centered maintenance mechanism to optimize maintenance cost, and employs data fusion strategy for improving condition monitoring, health assessment, and prognostics. has presents The proposed system is demonstrated by way of reasoning and case studies. Maintenance has gained in importance as a support function for ensuring equipment availability, quality products, on-time deliveries, and plant safety [6-8]. Cost-effectiveness and accuracy are two basic criteria for good maintenance. Reducing maintenance cost can increase enterprise profit, while accurate maintenance action can sustain continuous and reliable operation of equipment. As instrumentation and information systems become cheaper and more reliable, condition-based maintenance becomes an important tool for running a plant or a factory. The results show that optimized maintenance performance can be obtained with good generality.

A case study that demonstrates the proposed proportional covariate model (PCM) can be used to estimate hazard functions of mechanical components or systems in cases of sparse or even zero historical failure data provided the covariates of the components or systems are proportional to the hazard of the components or systems has presented. The hazard functions of a mechanical component or system can be estimated through a combination of PCM and accelerated life tests provided that the hazard of the component or system is proportional to its deterioration [9-11]. In principle, the reliability function of a mechanical system can be estimated by a single accelerated life test when PCM is used. Therefore, the number of accelerated life tests for estimating the reliability of a mechanical system can be significantly reduced by a combination of PCM and accelerated life tests. PCM research is still in its infancy and requires more case studies for its verification. Further work is continuing using PCM to make reliability predictions when the hazard of a component or system is not proportional to its deterioration. Yet another research direction could be the prediction of reliability using PCM based on both historical data (failure data and covariates data) and on-line condition monitoring data.

The results of vehicle exhaust measurements that were used to establish emission standards for an inspection/maintenance I/M program have presented. For this purpose, a total number of 100 private autos distributed across model years ranging between 1972 and 2002 were tested under idling conditions [12-15]. The monitored indicators included air to fuel ratio %, CO %, CO2 %, HC parts per million, ppm, NOx ppm, and O2 %. Private autos with model years greater than 1994 were found to be compliant with international standards and are relatively well maintained. Emissions from older models increased significantly with a lack of engine maintenance. They have concluded with criteria for proposing I/M emission standards based on exhaust measurements taking country specific socioeconomic characteristics into consideration.

A policy for optimal scheduling replacement intervals of technical systems only on the basis of maintenance cost parameter: a system is replaced by a new one as soon as the maintenance cost within a replacement cycle reaches or exceeds a given level has motivated and discussed. It is shown that with respect to the long-run total maintenance cost rate, this policy is superior to the well-known economic lifetime approach [16-17]. The simple structure of this policy, the fact that maintenance cost data is usually available and that no lifetime data are required, facilitate its practical application.

Maintenance policies for systems whose device failures are ‘non self-announcing’ have considered: They can be discovered only by inspection. Many types of protective equipment (e.g., circuit breakers or alarms), or equipment used in stand-by mode, experience such failures; consider maintenance policies for such systems. Incipient faults also fit this scenario [18]. To simplify the exposition, consider two possible maintenance actions: If at an inspection—

1) The device is found failed, then it is replaced with an identical device.
2) The device is found operational, then it is undisturbed.

A widely used inspection policy for systems with non-self-announcing failures is to inspect periodically, i.e., inspections are scheduled at constant inter-inspection time's regard less of the age of the device. While a periodic inspection policy is relatively simple to implement, since it does not use any information about the time since the last replacement (amount of time for which the current device has been in use), at the same time it might "over inspect" at less likely failure times and "under-inspect" at more likely failure time.

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 value that best corresponds to the given set of vehicle bi-fuel engine exhaust emission and engine valve cover vibration acceleration data. The vehicle bi-fuel engine faults considered are changing the level of lubricant oil to be 50%. The hazard value of the vehicle bi-fuel engine is determined under a deteriorating phase, which their failures engine exhaust emission and engine valve cover vibration acceleration follows the Weibull distribution. A model is used for the average cost per unit time based on the stochastic behavior of the assumed system. The model reflects the cost of storing a spare as well as the cost of system downtime. The minimum-cost policy (optimum) time is calculated with the consideration of availability.

2. Signal Processing and Prognostic System Scheme

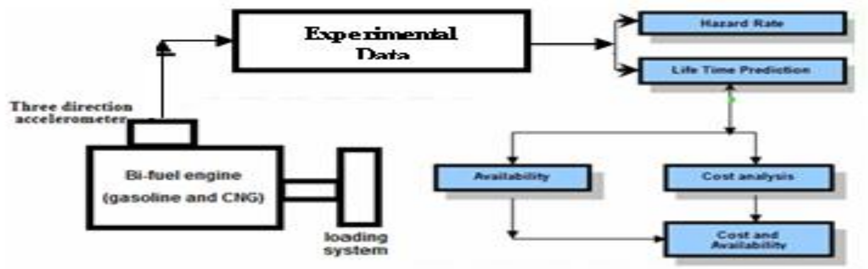

Figure 1: The prognostic system scheme

To achieve the goal of prognostics, three main steps are needed. At first, the failure or defect should be able to be detected at its early stage. Secondly, the component or system performance needs to be assessed robustly and tracked continuously. Finally, a prediction with confidence interval needs to be generated estimating the remaining useful life and possible failure mode of the engine or system. Furthermore, a generalized age repair policy based on a cumulative repair cost limit is used. Figure 1 shows the signal processing and system scheme.

3. Background Theoretical Knowledge's

3.1. 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 it's 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 (t0) to (t1), represents reducing the hazard rate due to surface roughness between the main bearing and shaft. The second interval of time, from (t1) to (t2) represents the operating normal conditions where the hazard rate is constant approximately. On the other hand, the portion of the curve beyond t2 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 t2 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.

3.2. Hazard Value Model Based on Data-Driven Technique

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.

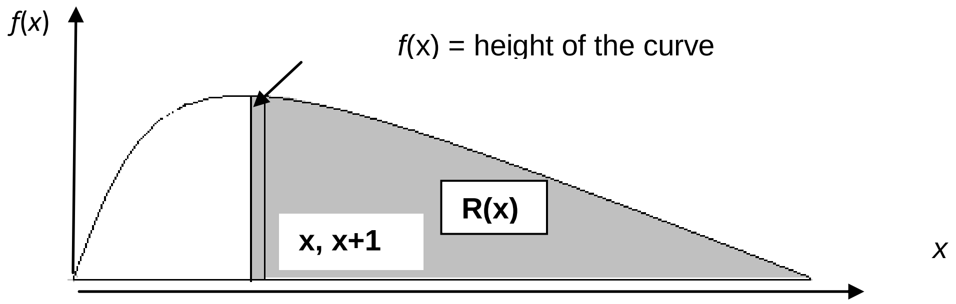

Figure 2: Derivation of Failure Rate [19]

The rate at which failures occur in a certain time interval [t, t+1] is called the failure rate during that interval (Figure 2). It is defined as the probability that a failure per unit time occurs in the interval, given that a failure has not occurred prior to t, the beginning of the interval. Thus the failure rate (hazard rate) is

$$h(x) = \frac{\int_{t}^{t+1} f(x)dx}{R(x)} = \frac{f(x)}{R(x)} \tag{1}$$

$$\int_{t}^{t+1} f(x)dt = f(x) \tag{2}$$

It will be seen that if dt is equal to 1 and the height of the curve is assumed to be height f(t) between t and t + 1. That means, when the decision maker obtains the probability distribution function from the actual data for any system, he can derive the hazard function or the measured degradation of it. On the other hand, after knowing the measured degradation of the system, the remaining useful lifetime of it can be predicted. A prognostic system in terms of remaining lifetime output that only reported a specific time-to-failure without having any confidence bound associated with the prediction would be unwise. This is true for simple prognostic approaches that only utilize historical reliability data (such as Weibull distributions) to the more advanced prognostic modeling approaches that take design parameter and operating condition uncertainties into account. The data-driven prognostic modeling approach implemented in this paper takes advantage of the directly sensed parameter together with the historical reliability data to provide critical inputs for producing accurate failure predictions. Information from rotational vibration acceleration data measurements to represent gear's fault with high certainty are used.

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 **[19]:**

$$f(x) = \frac{\beta (x)^{\beta-1}}{\eta^{\beta}} \exp[-(\tfrac{x}{\eta})^{\beta}] \tag{3}$$

From equation (1), then

$$F(x) = 1 - \exp[-(\tfrac{x}{\eta})^{\beta}] \tag{4}$$

From equations (3.3.2) and (3.3.3), the hazard rate given by

$$h(x) = \frac{\beta}{\eta}\left(\frac{x}{\eta}\right)^{\beta-1} \tag{5}$$

Where:

x: is the threshold value (testing time or vibration RMS)

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

β : is the shape factor.

3.3. Optimum maintenance policy for replacement

3.3.1. Age replacement cost model

The classical policy used in maintenance application is called age replacement principle (ARP). The principle of this maintenance strategy is to replace the component with a new one (i.e. maximal repair) when it fails or when it has been in operation for Tp time units, whichever comes first. The expected maintenance cost per unit time, C, can be written as **[20]**:

$$C(T_p) = \frac{C_p R(T_P) + C_c F(T_p)}{\int_0^{T_P} R(t)dt} \tag{6}$$

Where:

Cp : is preventive maintenance cost.

Cc : is corrective (failure) maintenance cost.

C (Tp) : is the maintenance cost function per unit time.

Tp : is preventive replacement age.

R(t) : is reliability function of the component.

F(Tp) : is probability) function of the component for preventive replacement.

R(Tp) : is reliability function of the component for preventive replacement.

3.3.2. Availability model

Availability deals with the duration of up-time for operations and is a measure of how often the wind turbine planetary component is alive and well. It is often expressed as (up-time)/(up-time + downtime) with many different variants. Up-time and downtime refer to dichotomized conditions. Up-time refers to a capability to perform the task and downtime refers to not being able to perform the task, i.e., uptime = not downtime. Availability issues also deal with at least three main factors [21] 1) increasing time to failure, 2) decreasing downtime due to repairs or scheduled maintenance, and 3) accomplishing items 1 and 2 in a cost effective manner. As availability grows, the capacity for making money increases because the component is in service a larger percent of time.

A maximum availability model is one of the three options for the selection of an optimal predictive maintenance strategy. The parameters of this strategy must to be considered. They are fixed values for the downtimes incurred by:

1. preventive renewal (maintenance), and
2. renewal as a result of failure.

The costs of materials and labor are not considered significant in this model, or they are believed to be proportional to downtime and, thus, can be ignored.

$$AV(T_p) = \frac{\int_0^{T_P} R(t)dt}{\int_0^{T_P} R(t)dt + t_p R(T_P) + t_c F(T_p)} \tag{7}$$

where:

AV (Tp): is availability

tp : is preventive replacement downtime

tc : is failure replacement downtime

In a symmetrical way, the maximum availability model focuses completely on downtime. In this report, high availability had bought by paying for it with more frequent intervention. It is assumed that the cost of repair was negligeable, or was proportional to the cost, and therefore could be ignored. The difference between failure and preventive repair times (rather than costs) dictated the exact nature of the compromise to achieve high component availability.

3.3.3. Maintenance cost and availability (CAV) model

The combined cost and availability optimization option is used to minimize expected maintenance cost per unit time taking into account costs and duration of preventive and failure downtimes, and cost of downtime. This cost model allows for flexibility in setting up realistic parameters upon which to build the optimal decision model. For example

- the fixed cost of failure replacement may be high (say due to the cost of a new part), but
- the downtime required may be short (just to replace the part).

Or, by comparison, the situation may be that:

- the cost of preventive work can be small, but
- the time to complete the work (downtime) can be long.

This model resolves the extremely difficult problem of deciding upon maintenance policies in the light of actual maintenance costs. The expected maintenance cost and availability per unit time, C + AV, can be written as **[22]**:

$$C(T_p) + AV(T_p) = \frac{(C_p + a_p t_p)R(T_P) + (C_c + a_c t_c)F(T_p)}{\int_0^{T_P} R(t)dt + t_p R(T_P) + t_c F(T_p)} \tag{8}$$

where:

C(Tp) + AV(Tp) : is maintenance cost function and availability combined

ap : is hourly preventive replacement cost per unit time

ac : is hourly corrective (failure) replacement cost per unit time

4. Experimental Methodology

4.1. Test Rig

The test setup consisted of a four-cylinder spark-ignited engine The measurements of vibration and emission used in this study are shown in Figures 3 and 4 respectively. It consists of bi-fuel engine with its two phases (gasoline and compressed natural gas). The engine has been tested in the healthy condition of full lubricant oil and for fault state prognosis. The fault is the reduction of lubricated oil level (50%). The engine rotational speed is being 2000 rpm and torque load is provided by a hydraulic brake connected to load the engine at 30.0 Nm. The gas is then filtered and dried before entering the analyzer. The speed is measured by a photo electric probe. Recordings were carried out at constant speed condition. Figure 4 shows Emission measurement system. Recordings were carried out at constant speed. After acquiring the measured vibration signals in the time domain as described above, it is processed to obtain feature vectors

4.2. Description of Instrumentations System

Smart phone sensors was used for the vibration acceleration signals record mounted upon the engine valve cover. The sampling frequency used was 6.0 kHz and signals of 22.0 sec duration were recorded. The ICM-20608-G is the latest 6-axis device offered by InvenSense for the mass market. Measures the acceleration force in m/s^2 that is applied to a device on all three physical axes (x, y, and z), including the force of gravity. The

ICM-20608-G is a 6-axis Motion Tracking device that combines a 3-axis gyroscope, and a 3-axis accelerometer in a small, 3 mm x 3 mm x 0.75 mm (16-pin LGA) package. The gyroscope has a programmable full-scale range of ±250, ±500, ±1000, and ±2000 degrees/sec. The accelerometer has a user-programmable accelerometer full-scale range of ±2*g*, ±4*g*, ±8*g*, and ±16*g*. Factory-calibrated initial sensitivity of both sensors reduces production line calibration requirements. Figure 2 shows vibration sensor position AGE-200 gas analyzer is infrared rays exhaust gas analysis module, to be connected to the serial port of any personal computer with the integrated software type OMNIBUS-800. The analyzer and software are belong Brain Bee. The small size and the 12V DC- power supply allows using it as portable tool wherever required used during the experimental work. The gas analyzer is equipped with gas sampling probe to collect the exhaust gas from the muffler.

4.3. Test Procedure

The measurements technique has been employed to test the vehicle bi-fuel engine during operation, namely vibration acceleration generation and exhaust emission components. One fault has been made artificially on the engine, namely reduce the lubricant oil by 50% to create a wear which eventually led to a propagating failure. For 50% oil level, a recordings every 30 min were acquired and a total of 7 recordings (0-3 hr of test duration) were resulted until the termination of the test. This type of test was preferred in order to have the opportunity to monitor path fault modes, i.e., the natural fault propagation. Failure is assured by increasing the test period to the point of where the remaining metal in the contact components have enough wear to be in the plastic deformation region. Since the engine is not new, the residual signals of vibration acceleration and the exhaust emission components measured between the signal at lubricant oil 100% and 50% is considered Figures 1 and 2 show vibration sensor position and Emission measurement system respectively**.** Data was measured and processed for healthy conditions (100% lubricant oil level) and for conditions with artificially induced **(50%** lubricant oil level**).**. 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. Moreover, periodic monitoring is, therefore, used due to it being more cost effective and providing more accurate diagnosis using filtered and or processed data. Of course, the risk of using periodic monitoring is the possibility of missing some failure events which occur between successive

Figure 3: Vibration sensor position overview

Figure 4: Emission measurement system overview

5. Results and Discussion

5.1. Time Domain Signal Analysis

Analysis in the time domain reveals the overall signal amplitude, periodic features, and emission components and vibration acceleration signals type. Figures 5 show the raw recorded signals residual (50%-full oil level) of total hydrocarbon (THC) for gasoline and CNG, as an examples. The figures show that the emission components level and vibration acceleration values was proportional to the reduction of the lubricant oil level.

5.2. Frequency Domain Signal Analysis

Analysis in the frequency domain reveals the overall signal amplitude, periodic features, and emission components and vibration acceleration signals type. Figures 6 show the raw recorded signals residual (50%-full oil level) vibration acceleration for gasoline and CNG in Z-direction as an examples. The figures show that the emission components level and vibration acceleration values was proportional to the reduction of the lubricant oil level.

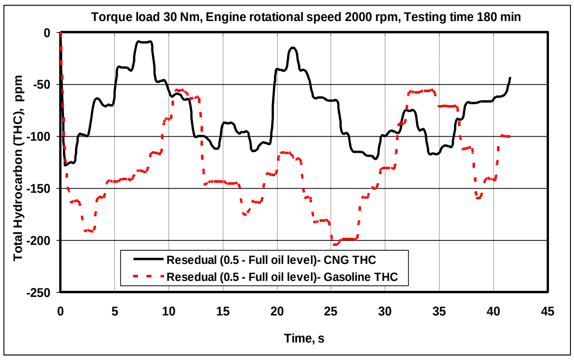

Figure 5: Residual values of total hydrocarbon (THC) for gasoline and CNG

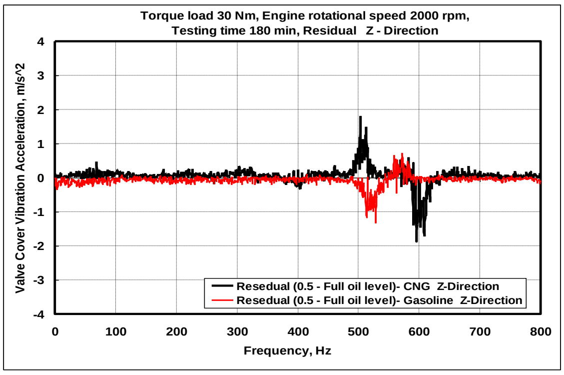

Figure 6: Residual vibration acceleration for gasoline and CNG in Z-direction

5.3. Decision Making Determination

5.3.1. Background

A further purpose of condition monitoring is health prognosis. Health prognosis is able to predict and prevent possible fault or system degradation before failure occurs. Prognosis is based on the component's historical data and current condition, its physical models of failure and the short term usage plan. Health prognosis allows maintenance personnel to optimize the maintenance policies to find the balance between the risk of running with damages and the lost revenue while waiting for maintenance. Prognosis has the largest potential return of all condition monitoring technologies.

5.3.2. Vehicle bi-duel engine emission components and vibration acceleration data

Individual operating vehicle bi-fuel engines do not replace reliability data that reflect population characteristics. CM data mainly provide information for short-term condition prediction only. Several data-driven prognostics models enabled the vehicle bi-engine prognosis using time series prediction. These models mainly performed single-step-a head predictions to estimate the vibration acceleration and emission components signal feature values. The details of experimental testing system and experimental procedure were presented in section 4, where tests were conducted on the bi-fuel vehicle engine. Two test cases (one full and 50% oil level faults) were considered.. For each test case, the corresponding hazard rate is determined. The test cases differed in terms of vibration acceleration response and emission components scales, while the time scale is ranged up to 45.0 s (Figure 5) and 800 Hz (Figure 6), from which, RMS value of vibration acceleration response and emission components levels, where RMS values are found to be a good indicator for diagnosis process. However, the RMS value will be used in prognostic process in terms of hazard values prediction Examples of the residual emission components prediction (emission shape factor (β) and scale parameters (η)) for the vehicle bi-fuel engine at (full-50%) lubricant oil level condition. from the residual emission component of (NO_x) for CNG fuel phase and component of (CO) for gasoline fuel phase are shown in Figure 7 and 8 respectively at testing time from 0.0 to 3.0 h with increment of 30 min for all the tests considered, while all the rest of RMS data as condition monitoring indicators are tabulated in Table 1. On the other hand, examples of residual vibration acceleration responses prediction (vibration shape factor (β) and scale parameters (η)) for the vehicle bi-fuel engine at (full-50%) lubricant oil level condition. from the residual vibration acceleration at (Y-direction) for CNG fuel phase and at (Z-direction)) for gasoline fuel phase are shown in Figure 9 and 10 respectively at testing time from 0.0 to 3.0 h (180 min) with increment of 30 min for all the tests considered, while all the rest of RMS data are tabulated in Table 2.

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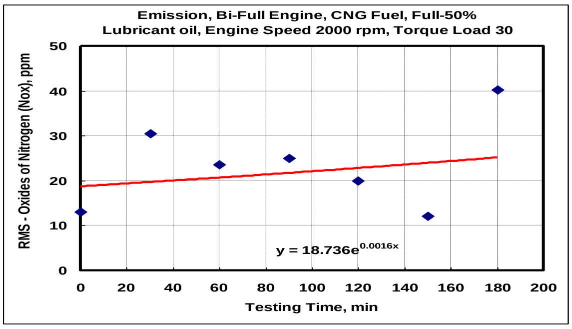


Figure 7: RMS- Emission scale values measured vs. testing time 50% oil CNG

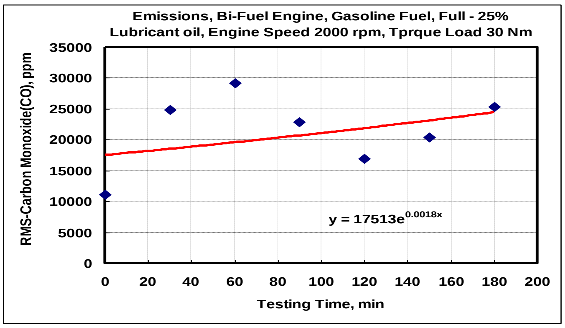


Figure 8: RMS- Emission scale values measured vs. testing time 50% oil Gasoline

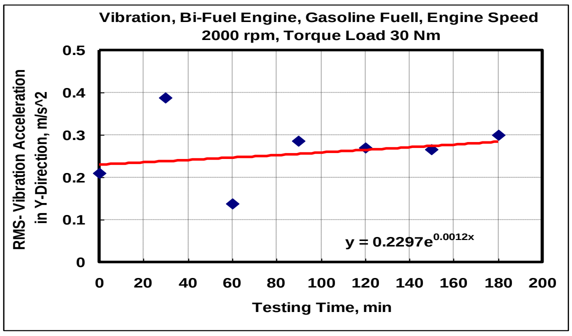


Figure 9: RMS- Vibration scale values measured vs. testing time 50% oil CNG

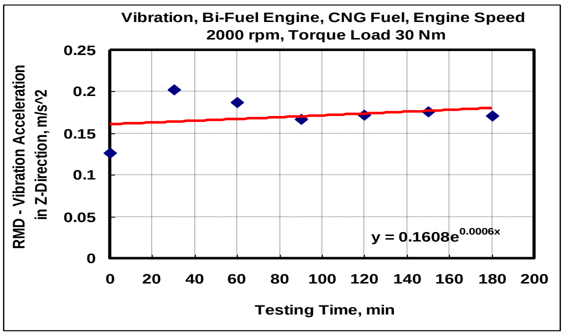


Figure 10: RMS-Vibration scale values measured vs. testing time 50% oil Gasoline

5.3.3: Vehicle bi-fuel engine hazard values and remaining life time

Individual operating vehicle bi-full engine does not replace reliability data that reflect population characteristics. CM data mainly provide information for short-term condition prediction only. Several data-driven prognostics models enabled gearbox prognosis using time series prediction. The shape factor (β) and scale parameters (η) data of Weibull distribution presented in Tables 1 and 2 are substituted in equation (5). Samples for the emission hazard value and the remaining life time are shown in Figures 11 and 12, while Table 3 tabulates the digit numbers of the data. On the other hand, Figures 13 and 14 show samples for vibration acceleration hazard value and the remaining life time (RLT), where the digit numbers of the data are presented in Table 4. The remaining life time data presented in Tables 3 and 4 for the vehicle bi-fuel engine in its CNG phase which are higher than that of gasoline phase. Furthermore, it can be seen that the remaining life time are used effectively. It captured the system behavior exactly and gives an alarm signal about possible irregularity before the vehicle bi-fuel engine actually broke. This is a very valuable indication for the vehicle bi-fuel engines health. On the other hand, averages have been carried out and are presented in Table 3 for the emission components RLT at full oil level (healthy) which is 15870 min (264.5 h), for gasoline residual (full=50%) is1095 min (18.25 h) and for CNG residual (full-50%) is 1590 min (26.5 h), while in Table 4, modulus have been calculated for the vibration RLT, where at gasoline full oil level (healthy) is 42744.35 min (712.1 h), at gasoline residual (full=50%) is 2286.31 min (38.11 h) and for CNG residual (full-50%) is 4237.12 min (70.62 h).

Failure lifetime factors (FLF) are computed from the data in Tables 3 and 4, where FLF for the emission 0.068998 in gasoline phase and 0.099127 in CNG phase Table 3. In vibration acceleration the FLF is 0.053488 in gasoline phase and is 0.100189 in CNG phase. Bearing in mind that the FLF is considered to be the vibration/emission (modulus / average) for either gasoline or CNG at full-50% oil level over the vibration/emission (modulus / average) for full oil level. These data indicate that for gasoline fuel phase is more serious (severity) that than for CNG.

Table 1: Condition monitoring indicators bi-fuel engine - exhaust emission components

Emission Component	**Testing Time, min**							**Shape factor (β)**	**Scale parameters (η)**	
	0.0	**30.0**	**60.0**	**90.0**	**120.0**	**150.0**	**180.0**		**ppm**	**Time, min**
RMS, ppm -gasoline- full oil level (healthy), engine speed 2000 rpm, torque load 30 Nm										
NOx	179.96	43.13	59.72	58.06	67.54	67.54	21.69	3.5	307.67	13080.8
CO	20225	5127 1	48029	48029 .	57334	57323	54515	3.5	388439	8478.1
CO 2	106170 0	9004 10	89210 0	87780 0	91980 0	91950 0	84800 03	3.5	238202	33166.7
THC	301.41	570.7	569.9	481.3	558.2	558.4	469.2	3.5	90858	16869.6
RMS, ppm-gasoline-residual (Full-50%) oil level, engine speed 2000 rpm, torque load 30 Nm										
NOx	12.944	21.94	20.10	38.72	30.21	36.45	25.41	3.5	307.6689	1476
CO	20958	30140	31740	29460	25050	27020	35490	3.5	388439.	808.7
CO 2	00283 9	83560	77600	00457	86600	00971	30100	3.5	238202	802.8
THC	259.43	300.1	260.3	351.7	324.0	394.0	323.6	3.5	90857.5	2377
RMS, ppm -CNG - residual (Full-50%) oil level, engine speed 2000 rpm, torque load 30 Nm										
NOx	13.00	30.44	23.647	24.980	19.95	12.12	8.183	3.5	307.76	853.5
CO	23.06	272.3	206.79	246.68	256.1	283.4	268.5	3.5	388439	1497
CO2	12050 0	00408	12429 0	20086 0	14030 0	19610 0	13090 0	3.5	238202	264.6
THC	37.78	55.63	89.074	107.44	94.30	73.74	84.35	3.5	90857.5	2205

Table 2: Condition monitoring indicators bi-fuel engine - vibration acceleration

Vibration Acceleration	**Testing Time, min**							**Shape factor (β)**	**Scale parameter (η)**	
	0.0	**30.0**	**60.0**	**90.0**	**120.0**	**150.0**	**180.0**		**Value m/s^2**	**Time, min**
RMS , m/s^2 - Gasoline – Full oil level (healthy), engine speed 2000 rpm, Torque load 30 Nm										
X-Direction	0.135	0.226	0.266	0.294	0.203	0.207	0.209	3.5	3.133	28930
Y-Direction	0.142	0.244	0.245	0.222	0.204	0.210	0.213	3.5	2.381	21797
Z-Direction	0.195	0.420	0.481	0.723	0.330	0.348	0.371	3.5	3.568	12050.7
RMS , m/s2 - Gasoline - Residual (Full-0. 50) oil level, engine speed 2000 rpm, Torque load 30 Nm										
7X-Direction	0.16	0.225	0.168	0.377	0.317	0.323	0.337	3.5	3.135	649.0981
Y-Direction	0.233	0.289	0.138	0.286	0.270	0.267	0.259	3.5	2.73	2022.499
Z-Direction	0.283	0.451	0.349	0.705	0.336	0.335	0.360	3.5	3.75	932.0851
RMS , m/s^2 CNG - Residual (Full-0. 50) oil level, engine speed 2000 rpm, Torque load 30 Nm										
X-Direction	0.201	0.253	0.255	0.267	0.250	0.322	0.318	3.5	3.135	1382.005
Y-Direction	0.107	0.252	0.226	0.227	0.219	0.272	0.262	3.5	2.73	2348.951
Z-Direction	0.127	0.202	0.187	0.167	0.172	0.176	0.171	3.5	3.75	3313.034

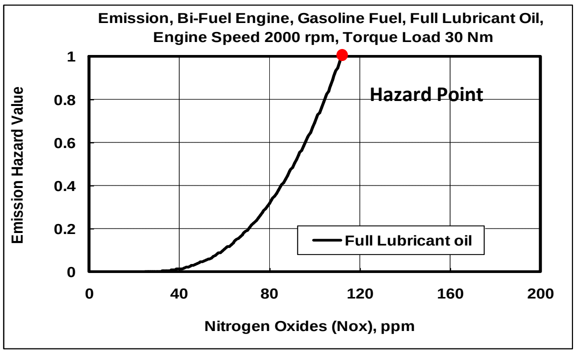


Figure 11: Nitrogen oxides (NOx), hazard value - gasoline full lubricant oil level

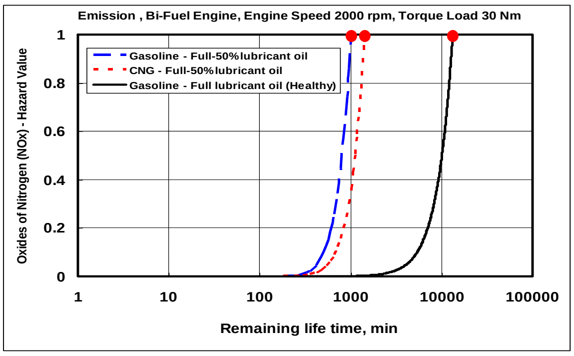
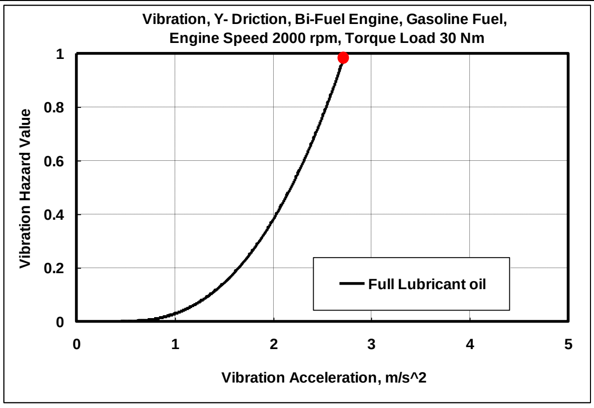


Figure 12: Nitrogen oxides (NOx)-remaining life time - (full-50%) lubricant oil level

Table 3: Single numbers of emission hazard value and corresponding remaining life time

No.	Exhaust gas Emission Component	Condition	Emission component hazard value, full oil, ppm	Faults	Remaining Life Time, min (h)
1	Nitrogen Oxides (NOx),	Gasoline Fuel	111	Full oil (healthy)	13200 (220)
2	Carbon Monoxide (CO),		10400		8520 (142)
3	Carbon Dioxide (CO2),		10000		24720 (412)
4	Total Hydrocarbon (THC)		1325		17040 (284)
				Average	**15870 (264.5)**
1	Nitrogen Oxides (NOx),	Gasoline Fuel	111	Full-50 % Lubricant. oil	1020 (17)
2	Carbon Monoxide (CO),		10400		1140 (19)
3	Carbon Dioxide (CO2),		10000		1020 (17)
4	Total Hydrocarbon (THC)		1325		1200 (20)
				Average	**1095 (18.25)**
5	Nitrogen Oxides (NOx),	CNG Fuel	111	Full-50 % Lubricant oil	1440 (24)
6	Carbon Monoxide (CO),		10400		2100 (35)
7	Carbon Dioxide (CO2),		10000		480 (8)
8	Total Hydrocarbon (THC)		1325		2340 (39)
				Average	**1590 (26.5)**



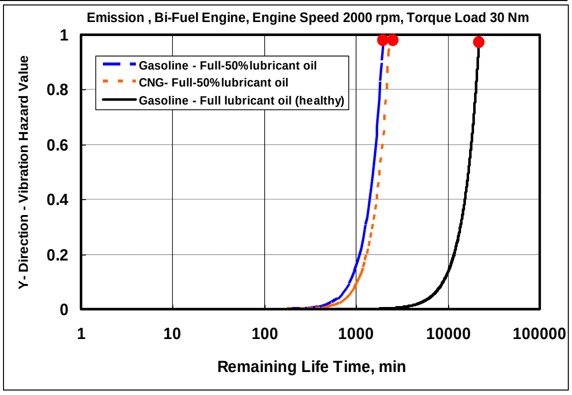


Figure 13: Vibration, Y-direction hazard value – gasoline - full lubricant oil level

Figure 14: Vibration, Y-direction - remaining life time - (full-50%) lubricant oil level

Table 4: Single numbers of vibration hazard value and corresponding remaining life time.

No.	Vibration Direction	Conditions	Vibration hazard value, full oil, m/s2	Faults	Remaining Life Time min (h)
1	X Direction	Gasoline Fuel	3.135	Full oil (healthy)	29280 (488)
2	Y-Direction		2.73		22020 (367)
3	Z-Direction		3.75		12120 (202)
				Modulus	**42744.35 (712.1)**
1	X Direction	Gasoline Fuel	3.135	Full-50 % Lubricant oil	600 (10)
2	Y-Direction		2.73		2040 (34)
3	Z-Direction		3.75		840 (14)
				Modulus	**2286.31 (38.11)**
4	X Direction	CN Fuel	3.135	Full-50 % Lubricant oil	1260 (21)
5	Y-Direction		2.73		2340 (39)
6	Z-Direction		3.75		3300 (55)
				Modulus	**4237.12 (70.62)**

5.3.4. Vehicle bi-engine maintenance cost rate - availability and preventive-corrective costs

The maintenance cost and availability of the vehicle bi-full engine (gasoline and CNG) were calculated with respect to its emission components and vibration acceleration in (X, Y, Z) signatures when the engine was in healthy condition (lubricant oil level is full) and in faulty conditions (lubricant oil level 50%). in the range of remaining life time (RLT) (which is discussed in the previous section) and based on equation (8). Samples from the emission cost rate-availability and preventive and corrective costs with availability results are shown in Figures 15 and 16 respectively and all the results where the digit numbers of the data are tabulated in Table 5. On the other hand, Figures 17 and 18 show samples for the vibration cost rate-availability and preventive and corrective costs with availability results where the digit numbers of the data are presented in Table 6. The average/modulus maintenance cost saving data shown in Tables 5 and 6 for the vehicle bi-fuel engine in its CNG phase which are lower than that of gasoline phase. On the other hand, averages have been carried out and are presented in Table 5 for the emission components percentage cost saving at full oil level (healthy) which is 22.72%, for gasoline residual (full=50%) is 32.84%) and for CNG residual (full-50%) is 29.29%, while in Table 6, modulus have been calculated for the vibration percent cost saving, where at gasoline full oil level (healthy) is 42.04% , at gasoline residual (full=50%) is 56.89% and for CNG residual (full-50%) is 65.60%

Cost savings factors (CSF) are computed from the data in Tables 5 and 6, where CSF for the emission 1.45 in gasoline phase and 1.29 in CNG phase Table 5. In vibration acceleration the CSF is 1.33 in gasoline phase and is 1.56 in CNG phase Table 6. Bearing in mind that the CSF is considered to be the vibration/emission (modulus / average) for either gasoline or CNG at full-50% oil level over the vibration/emission (modulus / average) for full oil level.

Based on Figures 16 and 18 as examples for preventive and corrective cost and availability data were determined based on the vehicle bi-full engine (gasoline and CNG) were calculated with respect to its emission components and vibration acceleration in (X, Y, Z) signatures when the engine was in healthy condition (lubricant oil level is full) both in gasoline fuel and in faulty conditions (lubricant oil level 50%).in gasoline and CNG fuels for the range of remaining life time (RLT) (which is discussed in the previous section).The preventive and corrective cost and availability data were determined based on equation (8) after was divided into two parts related to the preventive (optimum maintenance cost (Cp). and to the corrective (failure) maintenance cost (Cc) .. For engine healthy conditions full lubricant oil level), the percentage of preventive cost and availability from the total basic cost and availability at failure point is 0.0, while for the corrective is 100. Tables 5 and 6 depict the variation of preventive and corrective cost with respect to emission and vibration respectively, where the variation of preventive cost is nearly the same for either healthy or faulty bi-engine, while the variation of corrective cost is higher for faulty bi-engine (gasoline and CNG) with shorter operating time than that for healthy bi-engine. An important notice is that the preventive and corrective cost are equal at intersect point, where the emission average cost is 7294 L.E./hr at 102.5 h (healthy gasoline engine), is 454.6 L.E./hr at 9.713 h (faulty gasoline engine) and is 478.8 L.E./hr at 10.53 h (faulty CNG engine), Table 5 . On the other hand, the vibration modulus cost is 8073 L.E./hr at 117.7 h (healthy gasoline engine), is 505.7 L.E./hr at 9.9 h (faulty gasoline engine) and is1. 281.7 L.E./hr at 15.97 h (faulty CNG engine), Table 6 .

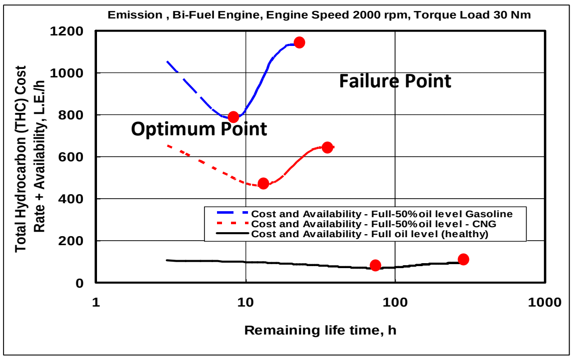


Figure 15: Total hydrocarbon, cost rate - availability (full-50%) lubricant oil level

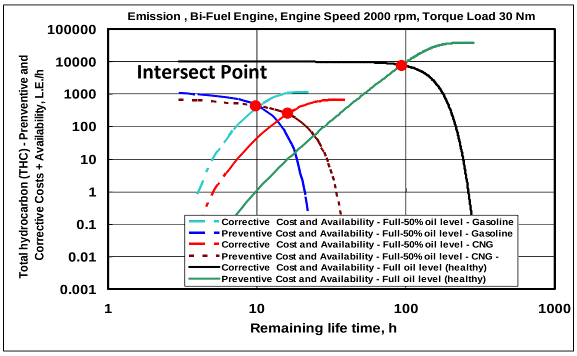


Figure 16: Total hydrocarbon (THC) - preventive - corrective with availability - (full-50%) lubricant oil level

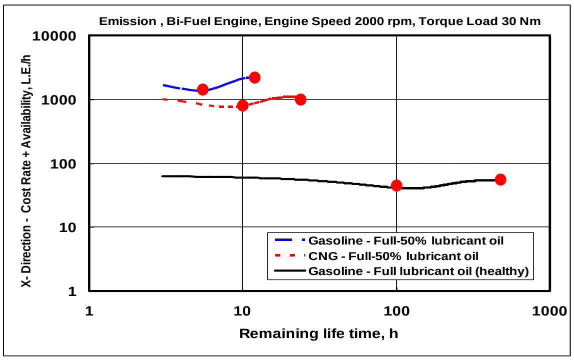


Figure 17: Vibration X-Direction, cost rate - availability (full-50%) lubricant oil level

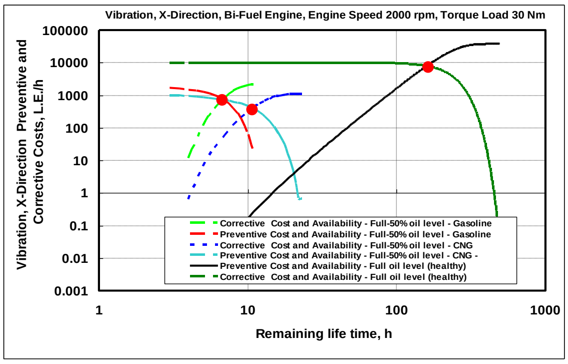


Figure 18: Vibration X- Direction, preventive-corrective with availability costs – (full-50%) lubricant oil level

Table 5: Single number of emission cost rate-availability and preventive-corrective costs estimated at engine speed 2000 rpm - torque load 30 Nm

No.	Emission Component	Replacement Policy	Conditions	Fault	Cost rate-availability		preventive-corrective costs	
					L.E/h	Time h	L.E/ h.	Time h
1	Nitrogen Oxides (NOx),	Failure	Gasoline Fuel	Full oil (healthy)	92.06	284	Intersect point	
		Optimum			60.99	76		
		Saving,%			33.75%	208	8652.	76
2	Carbon Monoxide (CO),	Failure			46.91	560	Intersect point	
		Optimum			35.21	142		
		Saving,%			24.94%	418	2959	49
3	Carbon Dioxide (CO2), %	Failure			182.8	143	Intersect point	
		Optimum			135.7	37		
		Saving,%			25.61%	106	8370	186
4	Total Hydrocarbon	Failure			118.6	221	Intersect point	

	(THC)	Optimum			80.75	53		
		Saving,%			31.91%	168	9193	99
					Average= 22.72%		**7294**	**102.5**
1	Full oil (healthy)	Failure	Gasoline Fuel	Full-50 % Lubricant oil	1291	19	Intersect point	
		Optimum			875	7		
		Saving,%			34.47%	12	486.6	9.5
2	Carbon Monoxide (CO),	Failure			2453	8	Intersect point	
		Optimum			1641	5		
		Saving,%			33.1%	3	432	10
3	Carbon Dioxide (CO2), %	Failure			724	35	Intersect point	
		Optimum			488	13		
		Saving,%			32.59%	22	480	9.2
4	Total Hydrocarbon (THC)	Failure			1132	22	Intersect point	
		Optimum			779	8		
		Saving,%			31.18%	14	420	10.15
					Average= 32.84%		**454.6**	**9.713**
5	Nitrogen Oxides (NOx),	Failure	CNG Fuel	Full-50 % Lubricant oil	1024	24	Intersect point	
		Optimum			709.7	9		
		Saving,%			31.89%	15	384	11
6	Carbon Monoxide (CO),	Failure			1808	13	Intersect point	
		Optimum			1177	6		
		Saving,%			34.9%	7	650	7.5
7	Carbon Dioxide (CO2), %	Failure			1781	13	Intersect point	
		Optimum			1162	6		
		Saving,%			34.76%	7	640	7.6
8	Total Hydrocarbon (THC)	Failure			545	39	Intersect point	
		Optimum			460	12		
		Saving,%			15.6%	27	241	16
					Average=29.29%		**478.8**	**10.53**

Table 6: Single number of vibration cost rate-availability and preventive-corrective costs estimated at engine speed 2000 rpm - torque load 30 Nm

No.	Vibration Direction	Replacement Policy	Conditions	Fault	Cost rate-availability		preventive-corrective costs	
					L.E/h	Time h	L.E/h	Time h
1	X Direction	Failure	Gasoline Fuel	Full oil (healthy)	53.73	488	Intersect point	
		Optimal			40.35	129		
		Saving,%			24.9%	359	7771	159
2	Y-Direction	Failure			53.60	367	Intersect point	
		Optimal			41.46	101		
		Saving,%			22.71%	662	8755	125
3	Z-Direction	Failure			129.2	202	Intersect point	
		Optimal			96.73	40		
		Saving,%			25.13%	162	7694.	69

					Modulus= 42.04%		**8073**	**117.7**
1	X Direction	Failure	Gasoline Fuel	Full-50 % Lubricant oil	2109.9	11	Intersect point	
		Optimal			1351.6	5		
		Saving,%			35.94%	6	697	7
2	Y-Direction	Failure			740	34	Intersect point	
		Optimal			524.5	11		
		Saving,%			29.12%	23	270	14.2
3	Z-Direction	Failure			1522	16	Intersect point	
		Optimal			1018	7		
		Saving,%			33.11%	9	550	8.5
					Modulus= 56.89%		**505.7**	**9.9**
4	X Direction	Failure	C NG Fuel	Full-50 % Lubricant oil	1077.7	23	Intersect point	
		Optimal			746.9	9		
		Saving,%			30.42%	14	440	11
5	Y-Direction	Failure			955.9	39	Intersect point	
		Optimal			467	12		
		Saving,%			51.15%	27	230	15.9
6	Z-Direction	Failure			468.9	55	Intersect point	
		Optimal			339.5	16		
		Saving,%			27.60%	39	175	21
					Modulus= 65.60%		**281.7**	**15.97**

5.4. Combined Engine Exhaust Emission and Vibration Signatures

The capabilities and limitations of two various techniques (signatures) including vibration analysis and exhaust emission.. Based on the health condition, maintenance personnel can make decisions on maintenance actions. Compared to other maintenance policies, CBM can avoid unexpected downtime, and prevent the failure from propagation from a component level to a subsystem level. Accordingly, the combination of engine exhaust emission and vibrational signatures when the engine was in healthy condition (lubricant oil level is full) and in faulty conditions (lubricant oil level 50%). in the range of remaining life time (RLT) (which is discussed in the previous section) at 2000 r/min and torque load of 30 Nm**.** The analysis started by collecting the failure lifetime factors (FLF) from section 5.3.2 and the emission components percentage cost saving and savings factors (CSF) from section 5.3.3 and presented in Table 7. The combined FLF indicates that the fault of full-50% for gasoline fuel is lower than that the fault of full-50% for CNG fuel, while the combined CSF indicates that the fault of full-50% for gasoline fuel is higher than that the fault of full-50% for CNG fuel.

Table 7: Single number of remaining life time and Cost and Availability Saving estimated at engine speed 2000 rpm - torque load 30 Nm

Condition	Fault	Remaining Life Time, h				Cost and Availability Saving, %			
		Emission	Vibration	Combined		Emission	Vibration	Combined	
		Average	Modulus	Value	FLF	Average	Modulus	Value	CSF
Gasoline Fuel	Full oil (healthy)	264.5	712.41	488.5	1	22.72	42.04	32.38	1
Gasoline Fuel	Full-50 % Lubricant oil	18.25	38.11	28.2	0.0577	32.84	56.89	61.29	1.89
CNG Fuel	Full-50 % Lubricant oil	26.5	70.62	48.6	0.0995	29	65.60	47.3	1.47

6. Conclusions

1. Decision making determination through a single signature may lead to misjudgment, so that additional maintenance cost is caused. The application of the methods combined several signatures is necessary. Two signatures were used and applied on a vehicle bi-fuel engine, where the fault considered is reduction of the level of lubricant oil level (50%). The capabilities and limitations of two various signatures including vibration analysis and exhaust emission signature-based were used. The results showed that the necessity of combining various techniques.

2. Results are presented for cost analysis of the vehicle bi-fuel engine conditions using cost analysis models. The prognostic performance was illustrated using five types of engine faults. Maintenance managers can use the methods described herein as a practical way to improve the return on investment in their existing CBM programs. The sample size of the data (number of histories, not number of inspections) analyzed in this sub-task is relatively low. Although larger sample size would provide greater confidence, the test rig data was found to be adequate for demonstrating the usefulness of PHM and decision policy methodology described in this analysis for predicting and preventing gearbox failures.

3- In general, the information of the vehicle bi-fuel engine failure risk assessment can help for prognostic procedure. The cost saving associated with early detection of incipient failures are quantified. This will require better tracking of costs associated with various types of repairs, including repairs completed in the nacelle versus repairs done in a repair facility. Therefore, the combined FLF indicates that the fault of full-50% for gasoline fuel is lower than that the fault of full-50% for CNG fuel, while the combined CSF indicates that the fault of full-50% for gasoline fuel is higher than that the fault of full-50% for CNG fuel.

4- 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 the vehicle bi-fuel engine condition are under consideration for further work.

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