Condition Monitoring of Engine Lubrication Oil of Military Vehicles: A Machine Learning Approach

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Abstract

Lubrication oil plays an important role in maintaining the health and performance of a land vehicle engine. Accurate condition monitoring of lubrication oil enables an effective predictive maintenance regime to be established. This can extend engine life as well as reduce over or under-servicing and other unnecessary maintenance costs. Machine learning models are useful for mining meaningful patterns from data samples. In this research, through the application of such models, we classify the condition of engine lubrication oil based on data from the Vehicle Health and Usage Monitoring System and laboratory test results of lubrication oil from a cohort of military land vehicles. The oil condition is classified into three categories: normal, degraded, and unsuitable. Feature selection methods are used to identify the best feature set for representing the lubrication oil condition. Importantly, the machine learning models employed provide the predicted output with justification in the form of explanatory rules pertaining to the lubrication oil condition. The findings indicate that (i) a good feature selection method is necessary to reduce the dimensionality of the feature set used for classification; (ii) machine learning provides a viable method for classifying oil condition with understandable justifications.

Keywords: Lubrication oil classification, machine learning, health and usage monitoring system, VHUMS, military vehicle.

Introduction

Land vehicle diesel engine components degrade during their operating life due to such factors as fuel quality, temperature, humidity, engine loading and engine lubrication quality [1-4]. The quality of engine lubrication is highly dependent on the condition of the oil, which minimises corrosion, dissipates heat, and reduces stress and wear on moving engine components [5-7].

The degradation of oil quality and operating condition variability affects the engine's dynamic performance, which is reflected in measured data acquired from the on-board sensors of the Vehicle Health and Usage Monitoring System (VHUMS) [8]. This study has focussed on designing an intelligent condition monitoring system for predictive maintenance of military land vehicles using machine learning models. Specifically, we perform classification of the lubrication oil condition by fusing on-board VHUMS data with lab based oil analysis data. VHUMS provides on-board sensory information relating to the vehicle's operating dynamics, whilst laboratory oil testing and analysis provides detail on the lubricant's precise condition. As such, a useful correlation between VHUMS data and oil analysis outcomes can be established by using machine learning models. Capitalising on the learning capabilities from a set of training data, the machine learning models allow us to predict and classify the oil condition into three categories: *normal*, *degraded* and *unsuitable*. This gives Defence the ability to develop a more precise and cost effective engine oil maintenance regime to be applied to the military vehicles, whereby over- and under-servicing of vehicles may be avoided.

The next section provides a review of condition monitoring methods for engine lubrication oil. Statistical and machine learning models for feature selection and classification using prototype software that was developed are described, with examples of classification results and rules subsequently presented. Finally, concluding remarks and suggestions for further work are provided.

Background

With the passage of time, diesel engine lubrication oil degrades due to oxidation, water and fuel ingress as well as the entrainment of soot and wear particles. The oil loses its effectiveness as its chemical and physical properties change, with viscosity being key for lubrication performance [9]. Higher viscosity creates a thicker fluid film between moving components, whilst a lower viscosity reduces resistance and may allow lubricated components to come into contact, thus increasing component wear. In practice, lubrication oil is selected based on the optimal level of viscosity for the anticipated operating temperature range, in order to reduce resistance and component wear. A number of studies have shown that monitoring the condition of lubrication oil is better able to predict some types of machine malfunction and failure than vibration-based condition monitoring methods [9, 10].

Vehicle trip time is an important factor that influences the life of lubrication oil. Short trips degrade lubrication oil and accelerate corrosion and increased wear and tear of engine components [4]. Another factor that contributes to degradation of lubrication oil is engine idling. Engine idling can lead to an increase in wear particles being deposited in the lubrication oil, reducing the life of both engine and oil [11].

To maintain engine performance and prolong engine component life, a short oil change interval regime can be employed. This helps to maintain the engine in excellent condition and reduces the likelihood of a catastrophic engine failure. However, a short oil change interval increases the cost of maintenance. As such, determining an optimal oil change interval would reduce maintenance cost while ensuring engine reliability. Car manufacturers provide specifications for when engine oil requires topping-up, draining, refilling, and changing. Most manufacturers recommend a change of lubrication oil based on either a time or usage trigger, for example, changing the oil every year or every 15,000 kilometres, whichever comes first. As explained earlier, the life of lubrication oil is dependent on driving style and duty cycle conditions [4, 12, 13]. In some situations, vehicles primarily driven on highways can have an extended lubrication oil life [1, 14], while vehicles driven under more severe situations (short trips, stop-and-go traffic in urban areas, idling, hot or cold climates, prolonged high engine speed or trailer towing) can significantly reduce the lubrication oil change interval [12].

The literature reveals a wide variety of approaches for monitoring the condition of lubrication oil. Some researchers determine oil condition from oil change intervals and from observing driving styles as well as loading conditions [4, 12, 13, 15]. Other approaches include spectrometric and ferrographic analysis of oil contaminants [16-19] and other oil properties such as Total Base Number (TBN) [20]. Some infer oil condition from calculating or deriving oil soot levels [21] while others further combine this with viscosity and TBN [22]. Still others infer oil condition from monitoring oil temperature with respect to ambient [23], using a proxy measure such as rate of engine coolant temperature rise [24], or by combining sump temperature with engine output power measurements [25]. Neural networks and fuzzy classification algorithms are proposed in [26] to create an oil degradation trend in order to predict the remaining useful life (although how the degradation is computed is unclear).

The above approaches are based on the notion of monitoring oil degradation, either directly or by inference. As an alternative, the approach taken in [1] is based on inferring the consumption of the oil's 'useful life', not its state of degradation. Given a baseline rate of life consumption, a number of 'correction factors' are applied to accelerate or decelerate this rate of life consumption. Such factors are based on engine rpm and load, operating environment (e.g. dusty/sandy, humid), and other factors that relate to oil ageing. However, the key challenge of the proposed model relates to the availability of the required information to compute the correction factors. For example, driving conditions are needed to compute the operating environment correction factor. Furthermore, this model has been verified using a relatively small time span data set and has not been validated.

Machine learning offers a reliable approach to detecting similarity and trends in data samples [27, 28]. All of the aforementioned methods either require laboratory tests, new sensors, or specific mathematical models to be developed. The benefit of machine learning over these existing methods is that once a data association model between the input and output variables is learned, the model can provide useful prediction for new data samples under dynamic conditions. As a result, we adopt machine learning to learn and predict lubrication oil condition based on sensory information from VHUMS and laboratory test reports. The model developed is flexible as it learns from data samples to establish an accurate relationship between VHUMS information and the lab based oil test analysis results, and further enables us to explore the relationship between the VHUMS sensor variables and the condition of the oil.

This research examines VHUMS data and laboratory test reports for Australian Army G-Wagon vehicles used in training [29]. These vehicles have a turbocharged 3.0 litre v6 cylinder diesel engine, generating 135kW of power and 400Nm of torque. Mercedes-Benz indicates that the engine lubrication oil should be serviced every 10,000 miles ($\approx$16,000 km) or 1 year, whichever comes first for G-Class vehicles [30]. The G-Wagon engine utilises a fully synthetic oil, TITAN GT1 Pro Flex SAE 5W-30, manufactured by Fuchs Lubrication Pty Ltd.

G-Wagon VHUMS Data and Laboratory Test Reports of Lubrication Oil

VHUMS sensor data are acquired from the G-Wagon through a MoTeC data logger. Up to 48 sensor fields are recorded, measuring different vehicle dynamics and conditions, such as engine RPM, engine temperature, throttle position, oil temperature, odometer, vehicle speed, fuel usage and ambient air temperature. The laboratory reports provide information on the physical properties and elemental concentrations in the lubrication oil taken at specific intervals, as well as a characterisation of its condition as either *normal*, *degraded*, or *unsuitable*. A *degraded* condition indicates that preparations should be made to change the oil, while an *unsuitable* condition indicates an immediate oil change is required. The available data set has been acquired in three timeframes over a 4-month period. Out of 20 G-Wagon vehicles with VHUMS data, 16 of them have 30 matching oil analysis reports. As a pre-processing step prior to classification (described in the next section), the VHUMS data set is first filtered to remove missing and abnormal samples, and the range of data features are limited to ensure an effective classification learning process. After this, VHUMS and laboratory test report data are combined and correlated, to allow the confirmed lubrication oil condition for each vehicle (either *normal*, *degraded,* or *unsuitable*) to be used as the target for training the machine learning model under supervised learning.

Machine Learning Approach

Machine learning models have been successfully applied to solve classification problems in many areas, which include speech recognition, computer vision, intelligent vehicle systems and medical health prediction [28, 31]. Classification is the process of organising data into specific targeted categories or labels according to their observed similarities. In this research, the lubrication oil condition is classified into three categories, namely *normal, degraded, and unsuitable*. In addition to the machine learning algorithm developed by the Institute for Intelligent Systems Research and Innovation (IISRI) Deakin University [28], we have employed the Weka [32] application programing interface (API) in the prototype software. The plugin interface to Weka allows us to evaluate a variety of machine learning models for classification and feature selection.

Feature Selection

Feature selection or variable selection is a process to determine the best subset of features with respect to the data samples. There are many feature selection algorithms and, in this research, Principal Component Analysis (PCA) [33], a well-established method for feature selection and extraction, is used to identify a set of important features/variables from VHUMS data and laboratory test reports that influence the classification outcome. PCA is a statistical method that performs an orthogonal transformation to convert correlated features into linearly uncorrelated features known as the principal components [33]. The number of principal components is fewer than or equal to the number of original features. As such, PCA helps tackle issues related to high data dimensionality. In this research, the initial feature set is selected based on variables described in the literature as well as from subject matter experts and engineering knowledge. The selected features are fed into PCA with the ranker search method [32]. The eigenvectors with lower eigenvalues (against a threshold) are removed, and an inverse transform to select the original features contributing to the key principal components is performed. The corresponding features identified from VHUMS data and laboratory test reports are shown in Table 1.

Engine RPM (ENGRPM), Accelerator Pedal Position (APP), Ambient Temperature Inlet (ATI), Engine Temperature (ET), Engine Oil Temperature (EOT), Dialog engine Hour (DLEH), Odometer (ODO), Gear, Ambient Air Temperature (ATT), Engine Torque (ENT2), Fuel Usage (FUG), FE, PQ Index, Viscosity

Table 1: Feature selection using the principal component analysis

Rule Extraction

Rule extraction is a method to extract knowledge from data samples. Based on the given input-output relationships, useful rules can be extracted using machine learning models. The rule set offers an explanation pertaining to some key input (independent) features that affect the outcome (dependent feature). As such, the outcome (oil condition) can be associated with the input features, in order to provide justification with respect to the predicted output class. As an example, Figure 1 shows excerpts of two rules extracted using a neural network model developed by IISRI (Figure 1a) and a decision tree from WEKA (Figure 1b). In Figure 1a, the lubrication oil condition is predicted as *normal* when the input features reside within the stipulated ranges, with a confidence level (CL) of 61% (an indication of certainty of the rule learned by the model). In Figure 1b, the tree indicates reasoning through the input features (primarily DLEH and ODO in this case) to reach the respective lubrication oil condition. The number of data samples predicted as belonging to each class are shown in parentheses.

ENGRPM	(700.0,1070.0)	CL 0.61	Normal
APP	(9.2,54.0)	CL 0.61	Normal
ATI	(33.0,35.0)	CL 0.61	Normal
ET	(29.2,36.0)	CL 0.61	Normal
EOT	(35.0,40.0)	CL 0.61	Normal
GEAR	(1.0,11.0)	CL 0.61	Normal
AAT	(34.0,35.0)	CL 0.61	Normal

(a) neural network model

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DLEH <= 471.9
|  ODO <= 13378.6
|  |  DLEH <= 277.2: Normal (12)
|  |  DLEH > 277.2: Degraded (13)
|  ODO > 13378.6: Normal (1806)
DLEH > 471.9: Unsuitable (76)
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(b) decision tree model

Figure 1: Rule extraction for condition monitoring of engine lubrication oil

Classification Results

An example of the classification outcome from the decision tree in the prototype software is shown in Figure 2. The stratified cross-validation outcome indicates a high prediction accuracy rate of 99.74%. The confusion matrix (Figure 2a) shows that the majority of the data samples belong to the *normal* category, with only a few samples in the *degraded* and *unsuitable* categories. The detailed results (Figure 2b) ascertain that the decision tree is able to accurately classify the oil condition with high true positive (TP), low false positive (FP), high precision and high F-measure scores.

a	b	c	← classified as
361	0	0	a = Normal
0	11	0	b = Degraded
0	1	15	c = Unsuitable

a) Confusion matrix

TP Rate	FP Rate	Precision	Recall	F-Measure	Class
1.000	0.000	1.000	1.000	1.000	Normal
1.000	0.003	0.917	1.000	0.957	Unsuitable
0.938	0.000	1.000	0.938	0.968	Degraded

b) Detailed classification results

Figure 2: An example of the classification outcome using the prototype software

Conclusions

This research presents the use of machine learning models for the classification of military vehicle lubrication oil condition. A software prototype has been designed and developed for demonstrating and evaluating how this can be done based on VHUMS data as well as laboratory test reports from a cohort of G-Wagon vehicles. The software prototype containing feature selection enables features to be identified for classification, in an attempt to tackle issues related to data dimensionality. Machine learning models, which include neural networks and decision trees, can then be used for performing classification. The empirical results in Figure 2 indicate the utility of the machine learning models to classify lubrication oil condition with a high level of accuracy. More importantly, the predictions from these machine learning models can be supplemented by useful knowledge elicited from data samples using the rule extraction capabilities, as shown in Figure 1.

It is beneficial for the Australian Defence Force to reduce its maintenance cost through effective use of VHUMS for condition-based maintenance actions, and with the intention to avoid the time and cost burden of laboratory based oil testing for its land vehicle fleets. The present study reveals the potentially useful correlations between VHUMS data and laboratory test results for inferring engine oil condition using machine learning models.

For future work, a sufficiently large data set is necessary to further ascertain the effectiveness of the proposed machine learning approach to condition monitoring of engine lubrication oil. The software prototype may be further developed and implemented on mobile devices for use in real operational environments.

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