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Analysis of lubrication oil contamination by fuel dilution with application of cluster analysis

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Abstract
Contamination via fuel dilution can result in degradation of the engine oil which could lead to increased engine wear and/or engine failure. Exposing lubricant contamination by fuel dilution can involve a multi-parametric evaluation while undertaking lubricant condition monitoring also known as used oil analysis (UOA). We utilize hierarchical cluster analysis to extricate the contamination related parameters caused by fuel dilution in the medium speed engine lubricant. Cluster analysis classifies several objects into some cluster according to the similarities between them but the results are uncertain due to sampling error of the data. We address this by evaluating the probability values (p-values) for each cluster, while Cluster validity is ensured by using a module to offer the best clustering scheme among different results. The result of the cluster analysis is analysed using expert assessment and literature to pick out the effects of fuel dilution contamination in a lubricant used in a medium speed engine. This methodology is applied to thermal power plant UOA case study. The novelty of the study is firstly, exposing the used oil parameters associated with fuel dilution using hierarchical clustering, secondly, assessment of the uncertainty of the hierarchical cluster developed, thirdly, use of expert assessment to confirm the cluster relationship developed as well as the effects of this contamination to the performance and integrity of the engine, and lastly provide insights for maintenance decision making and moreover, highlighting critical used oil analysis parameters that are correlated which are indicative of degradation via fuel contamination. By addressing such related parameters in UOA, organizations can better enhance the reliability of critical operable equipment like engines.

Key words: *Used oil analysis, Lubricant condition monitoring, Dilution, Cluster analysis*

1. INTRODUCTION

A lubricant is a vital component in ensuring the proper operability of an equipment through reduction or elimination of wear between rotating members of a machine, and further, facilitate reduction of heat and friction. Lubrication oil condition monitoring plays a critical part in maintaining the optimal operating condition of machineries and plants[1]. This monitoring enables the maintenance fraternity to draw knowledge on the equipment and lubricant's condition and state. Lubrication condition monitoring (LCM) is one of the important condition monitoring techniques utilized on a planned or scheduled maintenance period.

Knowledge of the equipment's or component's critical failure modes is essential for effective and comprehensive oil and equipment condition monitoring [2]. Through monitoring by used oil analysis, and developing diagnostic and prognostic systems, researchers and practitioners aim to increase the machine availability, reduce random failures, prevent unnecessary cost of oil replacement, and further reduce waste which adversely affects the environment. Lubrication oil is an important source of information for detecting early machine failures, and performs a similar role of analysing blood in human beings with a view of detecting ailments and diseases. The condition of the lubrication oil and its circulation within the equipment reflects the health status of the equipment and its components, and moreover, provides insights on the condition of the lubricant itself.

Upon introduction of a lubricant into an engine, the functionality of the lubricant starts to be impacted by the operation of the engine and its operating environment [3]. During the running period of the engine, lubricant samples are drawn and tested in the used oil analysis program or LCM. The main categories of the LCM program as alluded by [4] are physical and chemical properties, wear metals, additive analysis and contamination analysis. Physical and chemical properties include viscosity, flash point, total base number, while wear metals include metal particles mainly generated from wear within the parts of the equipment such as iron, aluminium, tin etc. The additive analysis entails the evaluation of some key ingredients used in the production of additives such as magnesium, calcium, zinc and others. Contamination analysis involves evaluation of the lubricant to extract various contaminants. Contamination could occur by water, fuel, glycol, dirt, wrong oil, metal particulate, soot, oil degradation and additive depletion [2].

2. MOTIVATION OF STUDY

While carrying out routine UOA in the LCM program, maintenance strategies are invoked on the failures and/or potential failures of the lubricant and the equipment. The use of one lubricant parameter to diagnose the lubricant condition or state is not comprehensive. Moreover, fuel dilution can only be detected comprehensively in the UOA results using more than one test results which means some association or correlation exist between the parameters[1]. Some contaminants such as fuel can act as catalysts to increase the rate of oil degradation which in effect establishes contamination (fuel dilution) in many occasions as the primary cause of degradation. This is not always discovered, because analysis usually show the changes in the physical and chemical properties where fuel dilution can cannot be directly delineated. Monitoring changes on individual lubricant parameters can be time consuming and in many cases may not show a deviation which would be picked by the normal thresholds used[1]. Due to the afore-mentioned challenges, this study seeks to confirm a statistical technique or methodology applying cluster analysis that will enable unmasking of fuel contamination in the lubricant from the onset of analysis of the UOA results.

3. RELATED LITERATURE

Fuel dilution in engine lubricants has not been researched much in the recent times. A number of studies have been done related to the testing methods to confirm fuel dilution, not necessarily direct methods but methods inclusive of the linchpins which cannot be independently identified [3][2]. The adverse effects of fuel dilution on the properties and performance of the lubricant has been studied by Ljubas[5]. Other researches that discuss fuel dilution include[6][7][8][9]. Due to the viscosity of the fuel in use in particular engine types, the interpretation of viscosity changes due to fuel dilution will be differ. For high speed engines (over 1200 rpms), automotive gasoline which has a lower viscosity compared to the engine lubricant is used, whilst for medium (300-1200 rpms) and slow speed engines (below 300 rpms), heavy fuel oil whose viscosity is higher compared to the engine lubricant's is used. For engines using fuel of lower viscosity compared to the engine oil, fuel dilution causes a reduction of viscosity [10], while for the heavy fuel oil, lubricant viscosity increases due to fuel dilution[11].

Cluster analysis has been used in several lubricants related studies in the recent past. Hierarchical clustering was used by Gong et.al[12] to obtain the dielectric sub-microscopic phase and heterogenous characteristics of the lubricating oil system with Fourier transform infrared spectroscopy (FT-IR) data. Despite using technical expert judgement, Valis et.al[13],used regression correlation assessment amongst variables and also several traditional clustering methods (hierarchical, non-hierarchical, centroid and nearest neighbour) for verification of the decision to use iron(Fe) and lead(Pb) particles observation. Hierarchical clustering was also used by Da-Silva[14], to determine the correlated groups of the oil parameters in the exploratory study and Palus[15] to differentiate two brands of used engine oil on the basis of infrared spectroscopy. Cluster analysis was also used to detect the possible relationships between various wear particles in the study of chemical oil analysis applying data mining techniques [14], while traditional clustering methods were applied to verify a decision towards concentration of iron and lead particles [16], CA was used to check values of UOA parameters similarities[13].Non-hierarchical clustering method based on average linkage was used to observe the clusters before picking iron and lead for the research on system condition estimation[13]. CA has some limitations that affects the consecutive results such as sampling errors and biasness towards setting the optimal number of clusters due its heuristic nature as well.

4. METHODOLOGY

This section will address the methods and techniques used in the data collection, data description and the statistical technique used in the analysis of the data as illustrated in figure1.

4.1 Data sample and collection

This study utilizes used oil analysis results collected in a span of five years from an anonymous power plant with over 1,000 samples. The results cover 20 variables tested from the sampled oil in an internationally accredited laboratory.

4.2 Data preparation

The data collected required data cleaning to confirm missing data, expert assessment on some of the outliers found in the data, consolidation of separate results to one dataset which is ready for analysis. The data was standardized due to the fact that the variables were measured in different scales.

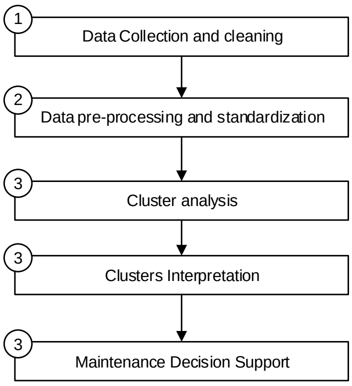

Figure 1. Schematic representation of methodology

4.3 Cluster Analysis – statistical analysis

Cluster analysis is a statistical method which aims to classify several objects or observations into some groups (clusters) according to similarities between them, such that each cluster is as homogeneous as possible with respect to the clustering variables which may be different those derived from other clusters with respect to some characteristics[17].There are two main types of cluster analysis:

a) Hierarchical methods

These methods do not have the number of clusters expected from the onset. There are two methods in this type of clustering which are, the agglomerative and divisive methods. In agglomerative methods, the variables are first grouped in their own separate clusters. The two 'closest' (most similar) clusters are then combined and this is done repeatedly until all variables are grouped in one cluster. At the end, the optimum number of clusters is then chosen out of all cluster solutions. In the divisive methods, all variables are grouped in the same cluster and the clustering approach is applied in reverse until every subject is in a separate cluster. Agglomerative methods are used more often than divisive methods due to ease of use.

b) Non-hierarchical methods (often known as k-means clustering methods)

In these methods, the desired number of clusters is specified in advance and the 'best' solution is chosen.

Cluster analysis has some shortcomings for instance, it is a heuristic technique hence clusters can be developed even where there may be no grouping of variables in the data[18]. Clustering can sometimes create groups from some noise in the data yet the noise may have been a sampling error or even sample procedure error, hence establishing reliability of the grouped variables is important where approaches such as external cross validation are performed.

The uncertainty of results caused by sampling error of data has not generally been evaluated in the context of cluster analysis of lubricant data in practice. In this study we seek to evaluate the uncertainty in order to generate clusters with a degree of certainity. For each cluster in hierarchical clustering, probability values (*p*-values) are calculated via a multiscale bootstrap resampling. *P*-value of a cluster is a value between 0 and 1, which indicates how strong the cluster is supported by data. Pvclust, an R software function developed[19], calculates probability values (**p**-values) for each cluster using bootstrap resampling techniques. Two types of **p**-values are available: approximately unbiased (AU) **p**-value and bootstrap probability (BP) value. Multiscale bootstrap resampling is used for the calculation of AU **p**-value, which has superiority in bias over BP value calculated by the ordinary bootstrap resampling. In addition, the computation time can be enormously decreased with parallel computing option. Pvclust is an implementation of bootstrap analysis on a statistical software R to assess the uncertainty in hierarchical cluster analysis[20]. The importance of uncertainty assessment has been well recognized in phylogenetic analysis, which is a special form of hierarchical clustering for inferring the history of evolution as a dendrogram[20]. Clusters with AU p-value>=95% are considered or judged to be strongly supported by the data. This method allows one to use Spearman's correlation coefficient which is appropriate when one or more variable do not follow a normal distribution, which was the case in the data under this study.

4.4 Cluster interpretations

The clusters generated in the cluster analysis with the AU p-values greater than 0.95 were picked and the respective members of the cluster explored to further illustrate cluster formation characteristics and the possible associations embedded in the clusters.

4.5 Maintenance decision support

From the cluster descriptions and interpretations, the author discuss draw maintenance related insights outlining the effects of fuel dilution and possible causes which if scrutinized, would lessen the occurence and impact of the problem.

5. RESULTS AND DISCUSSION

In this section, we review the results of cluster analysis performed, interprete the clusters formed and discuss deeper the clusters representing fuel dilution in the lubricant. Further, the effects and possible sources of the fuel dilution are looked into.

5.1 Cluster analysis

The cluster analysis was carried out on all the twenty variables representing the used oil parameters as indicated in section 4.1. Hierachichal clustering with Nbclust as highighted by Charard[21] was performed using the average method.The uniqueness of this method lies in the automatic determination of the optimal number of clusters using indices to propose the best number. The method provides 30 indices and

proposes the best clustering scheme from different results obtained by varying all combinations of number of clusters, distance measures and clustering methods [21]. The Hubert index in figure 2 is a graphical method of determining the number of clusters. In the plot of the Hubert index, one seeks to find a significant knee that corresponds to a significant increase of the value of the measure i.e the significant peak in Hubert index second differences plot.
Using Kmeans method as alluded by [19], which is a reallocation method, among the 30 indices, the number of clusters are proposed and the optimum number is taken as the one with highest number of indices. Seven indices which were the highest indeices compared to the rest, proposed three as best number of clusters as seen in table 1. Two clusters were proposed by 5 indices and 10 clusters by 4 indices.

Table 1. Proposed number of clusters by indices

No. of indices	Proposed No.of Clusters
5	2
7	3
3	5
1	6
2	7
1	8
4	10

Hence the study used the optimal number of clusters as three(3).

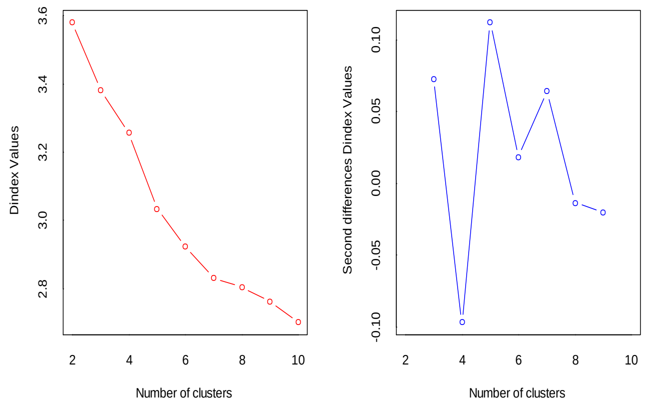

Figure 2. Hubert index plots

5.2 Cluster interpretation

Figure 3 shows the dendrogram from the hierarchical clustering using the average method with three clusters which are clearly marked. The first cluster with AU p-value of 1 and BP p-value of 1, contains total base number (TBN) and calcium, the second cluster with AU p-value of 0.99 and BP p-value of 1, contains zinc, water, iron, aluminum, sodium, flash point, magnesium, silicon, chromium, lead and copper, while the third cluster with AU p-value of 0.97 and BP p-value of 0.64, consists of viscosity at 40ºC, vanadium, nickel and carbon content.
Analyzing the clusters, we discover that, the first cluster can be interpreted to depict the alkalinity of the lubricant. This is further corroborated using literature that calcium is an ingredient of detergents and dispersants which are additives used in enhancing TBN in the lubricant [22]. The second cluster is composed of variables depicting both the wear metals and the lubricant properties.

The third cluster can be depicted as the cluster related to fuel contamination. The increase of the viscosity parameter measured at 40ºC can be attributed to either contamination of the lubricant with more denser contaminants such as heavy fuel oil, or high operating temperature of the equipment which may lead to oxidation of the lubricant[23][24]. Denser contaminants such as insoluble, soot, water and heavy fuel oil potentially will increase the value of viscosity[11]. Since fuel contains Nickel and Vanadium as part of the ingredients as alluded by[11][25], these elements may lead to a potentially valid reason for the rise in the viscosity especially when there is fuel ingression in the lubricant. The investigation of Schmitigal [26] on diesel engines demonstrated that the kinematic viscosity is capable of detecting lubricant soot particle, water contamination and oxidation deterioration, also corroborated by others[27][28][29].

5.3 Fuel dilution effects

Fuel dilution in an engine lubricant has adverse effects to the engine as well as the lubricant's condition and state. Some critical effects of this dilution are discussed in the following section.

a) Reduction of lubricant flash point
Fuel from the engine has a lower flash point compared to a lubricant [3]. The flash point of a lubricant is the lowest temperature of oil at which the application of defined test flame causes the vapors above the surface to ignite and the release of vapors at this temperature is not sufficiently rapid to sustain combustion[5]. Dilution of the lubricant with the fuel will reduce the flash point of the lubricant to some extent. Flash point is significant to many users of lubricants under circumstances of safety as it leaves the lubricant vulnerable to igniting at a lower temperature which is hazardous to the equipment and the plant in general [30] as it can cause a fire destruction.

b) Effect on additives
Ingression of fuel into the lubricant dilutes the concentrations of additive. Some of the lubricant additives include the anti-wear, anti-oxidants, corrosion inhibitors, detergent, dispersants, etc. Dilution of the concentration of the additives infer that the functions of the respective additives are severely compromised hence exposing the engine to the counter effects which adversely affect the performance of the engines, e.g. wear, acidity, oxidation etc.

c) Reaction with lubricant additives
The fuel inside the lubricant in some cases can react with the additives. When a reaction occurs, the additives could separate and coagulate out of the lubricant. This would render the lubricant to have less or no additives which will affect negatively the functions of the lubricant especially its wear reduction property.

d) Effect on lubricant viscosity

Depending on the viscosity of the fuel in use and the type of engine, the fuel will either lead to an increase or decrease of the viscosity. In high speed engines mostly used for automotive applications, the fuel used has a lower viscosity compared with the lubricant, hence in this instance, the fuel ingression will decrease the lubricants viscosity, while in medium speed and slow speed used in marine and power plants, the fuel in use has a higher viscosity and hence will increase the lubricants viscosity. Increase in viscosity will cause increase in internal fluid friction and can lead to higher temperature generation in the lubricant and high drag in the moving engine elements, which consequently would increase fuel consumption of the engine.

e) Increase rate of oxidation

Oxidation is a chemical breakdown of the lubricant molecules with oxygen as reagent. Some of the

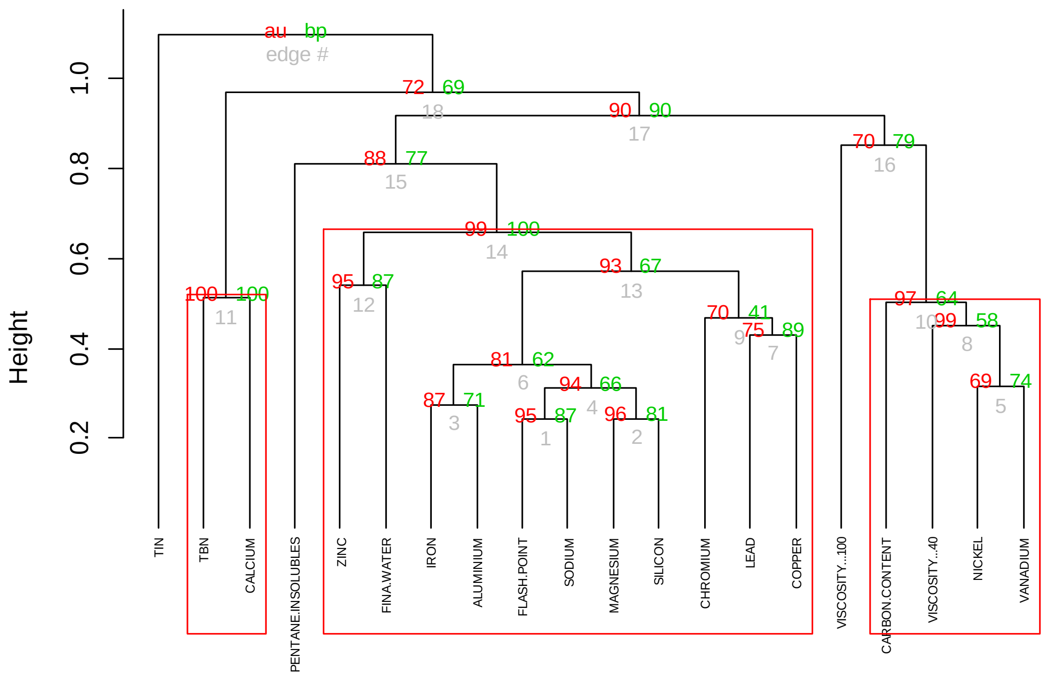

Figure 3. AU/BP Dendrogram using correlation and average method

catalysts towards oxidation include fuel contaminants[31] and depletion of oxidation inhibitors. Due to high temperature and resultant oxidation, considerable carbon deposits may be observed on the piston lands as well as on the oil ring of the piston [32]. This may lead to formation of sludges and high viscosity that has a potential of clogging the oil filters. Clogged oil filters deprive the equipment's off the lubricants required leading to oil starvation that lead to catastrophic failure or seize.

5.4 Fuel dilution sources

Fuel dilution is a common contaminant which seriously reduces oil viscosity and accelerates the wear process due to lack of lubricity[33]. Fuel contamination is usually the result of over fuelling, broken or defective fuel injectors, leaking high-pressure fuel lines, leaking oil/fuel heat exchangers, etc. Severe fuel leaks in medium speed diesel engines cause large decreases in the oil's viscosity, which in turn causes catastrophic damage to load-bearing components. Other sources of fuel contamination can be due to fuel condensation during the engine warm up period when the engine is cold. This is particularly so, for high speed engines using gasoline with the Gasoline Direct injection engines[10].The low viscosity due to the oil dilution has bad influence on keeping the strength of oil film and the metal parts separated, and therefore it increases the wear of the piston ring pack and bearings[34]. Engine wear appears to be associated with the accumulation of contaminants in the lubricant measured as pentane insoluble and total acid number[35].

7. CONCLUSION

A methodology using cluster analysis has been formulated that revealed the UOA parameters associated with fuel dilution in the same cluster which is able to act as the frontline diagnostic tool to capture the possibility of fuel dilution in an engine oil. An organization routinely carrying out LCM can use the methodology to pinpoint existence of fuel dilution. The effects of fuel dilution in an engine oil as well as the possible sources of the fuel diluent have been discussed in detail. This forms a very vital information for the maintenance decision making in terms of actions to avoid or reduce the effect of lubricant contamination due to fuel dilution. Most of the cluster algorithms depend on input variables like the number of clusters which if assigned inaccurate values, clustering may result to wrong decisions. This has been addressed using Nbclust and probability values of the clusters formed, to ensure certainty of the formed clusters. The methodology is generalizable to other types of engines or lubricants susceptible to fuel dilution. The limitation of the developed methodology, it can be accurately utilized in medium speed and slow speed engines such as used in marine and power plant applications, but could offer insights in the high-speed engines.

Future work will involve the study of the interactive effects of the parameters related with fuel dilution with the others in the LCM program.

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