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Analysis of lubrication oil towards maintenance grouping for multiple equipment using fuzzy cluster analysis

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Abstract. Maintenance of similar multiple equipment is challenged by the complexities brought by respective maintenance needs and intervals for each equipment. Therefore, maintenance scheduling and planning becomes expensive and time intense, affecting productivity and profitability of the plant. Organizations are embracing the need to enhance maintenance planning by evaluating equipment characteristics which potentially offer benefits from reduction in maintenance costs and downtime to avoiding of unplanned shutdowns and efficiency maximization. To address this need, this study proposes a methodology that groups equipment with similar characteristics picked from lubricant analysis using fuzzy cluster analysis. Grouped equipment tend to require similar corrective and preventive maintenance (PM) actions enhancing maintenance planning and equipment availability. To validate this framework, lubricant analysis data for seventeen medium speed engines (MSE) of a thermal power plant is utilized where the derived clusters are subsequently used to group the engines. The framework offers benefits towards reduction of maintenance cost, improved planning and overall availability of the plant and equipment.

1. Introduction

The basic steps involved in developing a preventive maintenance program embody determination of the critical equipment units and systems, identification of the components, determination of the PM procedure for each type of components, development of detailed procedures and plans and finally determination of the schedule. In an installation with similar multiple equipment, the challenge mainly faced by the maintenance manager, is the developing of detailed procedures and job plans for the divergent equipment. The term “multi-equipment” in an industrial setting refers to a facility or installation containing more than one equipment, where each of the equipment consisting of more than one component[1]. The primary maintenance related problems in such facilities involve situations where maintenance for a plant which consists of multiple equipment cannot be done wholesomely at once. While understanding the multi-equipment, one can perceive the concept of one equipment in many cases while evaluating on the system level. Wang and Chen [1] allude that traditionally, this scenario is depicted as a single equipment with an extension of the problem to several equipment. However, considering the complexity of an industrial plant such as a power plant realistically, it is no longer feasible to address the equipment in an independent way, moreover, if the equipment’s are many and similar in model and design. Evaluation of maintenance data for a plant composed of similar or heterogeneous equipment can be synthesized to expose patterns in the data which carry hidden information that can be used for developing a detailed procedure and job plan. The maintenance team can determine the replicability utilizing various techniques that expose information and patterns depicting similarities in some characteristics of the equipment or operations or its performances. This analysis not only shows the similarities, but also assists the practitioner to understand the equipment's health and status. A plant considered to incorporate several complex, expensive and sensitive equipment, can be considered a recipe where the random conditions observed can be analysed over time picking patterns thereby enhancing planning.

Equipment utilizing high volume charges of lubricant like the MSEs, display complex characteristics when considering maintenance and operations strategies. The power plant has limited storage capacity for the lubricants hence the need to simultaneously replenish the engines could portend longer downtime and loss of production. Competitiveness in the business environment, prohibits such plants to maintain high spares inventory as it negatively impacts the profitability and may also lead to high pilferages. Personnel planning when unexpectedly multiple equipment require maintenance interventions, is constrained which may lead to poor maintenance or outsourcing personnel which inherently could lead to increased maintenance cost. Furthermore, preventive maintenance scheduling is challenged by this complexity.

2. Motivation of study

Due to the aforementioned challenges, this study seeks to group the multiple engines exhibiting similar lubricant performance characteristics using cluster analysis. MSEs in one group will potentially exhibit similar challenges that will assist the maintenance team evolve a consolidated strategy and execution plan. This will not only enable the maintenance team to explicitly execute maintenance plans in a structured manner, but also offer insights to the respective MSE health and status. The results could offer probable insights on the PM scheduling which may reduce the tied working capital by enhancing timely spares replenishment. Despite the importance of cluster analysis in grouping for maintenance, there remains a paucity of evidence on utilization of the same on lubricant related field. This offers motivation to this study.

3. Related literature

Maintenance of multiple equipment in an installation can be tedious, time consuming and rampant. To overcome these challenges, organizations seek means to group the equipment with similar attributes to enable planning for preventive maintenance in a more consolidative manner. Here, grouping technology (GT), which can be comprehended as a philosophy that distinguishes and utilizes the similarity of different attributes exhibited by multiple equipment in manufacturing regime, can be advanced in the maintenance regime. Several authors concur that one of the main method to aid in forming the groups is clustering algorithms [2–4]. Abdelhadi [5] advanced a cluster framework for planning preventive maintenance actions using the GT concept. The types and severity of failures the equipment encounter was utilized to demonstrate the similarity of the equipment/machines. Hameed and Wang [6] utilized clustering to group wind turbines by exploring the wind speed and power output data offering behavioural similarities of different wind turbines. Alomani et al. [4], similarly utilized clustering to create preventive maintenance virtual cells based on the group technology concept that are utilized while conducting planning for PM actions.

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 from those derived from other clusters with respect to some characteristics [7].Clustering is a data mining technique that generates groups or clusters of the parameters in the data set to attain high similarity of objects in the cluster but high dissimilarity of objects in other clusters [8]. Cluster analysis has two methods variants namely hierarchical and non- hierarchical. Hierarchical methods do not have the number of clusters expected from the onset, operating in agglomerative or divisive way, while in nonhierarchical clustering, the desired number of clusters is specified in advance. Clustering algorithms include single linkage where the distance between two clusters matches the shortest distance between two variables, while complete linkage, the distance between the clusters is established on the longest distance between any two members of the clusters. In average linkage, distance is computed as the average between all pairs of any members of the two clusters while centroid is where the distance between centroids of the two clusters indicated cluster distance. To calculate the optimal number of clusters while using hierarchical techniques include among others using the silhouette width. Partitioning around medoids (PAM) which is robust with outliers, tests the silhouette width for multiple number of clusters and enables determination of the optimum number of clusters. In some cases, some objects are likely to be similarly expressed with different groups causing an overlap of the clusters they are in. This causes some uncertainty and ambiguity which require to be resolved. Fuzzy clustering facilitates the determination of such overlapping clusters or groups by allowing one object to simultaneously belong to multiple clusters [9]. To handle the identified ambiguity and uncertainty, fuzzy sets present a fabric to resolve this among the clusters.

Cluster analysis has been used in divergent studies in the lubricant analysis field. Hierarchical clustering was used to classify the variables in lubricant base oil into groups [10], while Yong et. al [11] used cluster analysis to establish the qualitative analysis models based on the two-channel and differential dielectric spectroscopy (TD-DES) data and Fourier transform infrared spectroscopy (FT-IR) data of the in-service lubricants. In their study, they proposed intervention for oil change at cluster five when there is strong indication of oxidation while six could cause damage. Valis et al. [12] used hierarchical cluster analysis to find the variable dependencies and further alleges to employ various CA techniques in their study to confirm lead and iron as critical wear metals for investigation [13]. Da-Silva et al [14], utilized most of CA techniques while clustering the chemical analysis of lubricant. CA was employed to differentiate two lubricants brands in criminal investigation [15]. In a recent study, CA was utilized to confirm fuel dilution in an engine oil [16]. A fuzzy clustering approach was proposed as lubricant system fault diagnosis framework using fuzzy sets theory on the system characteristics [17], while fuzzy clustering method was used to establish fault patterns of failed transformers using gas-in-oil data from the transformers [18].

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 Figure 1.

4.1. Data sample and collection

This study utilizes used oil analysis also known as in-service oil analysis results collected in a span of five years from an anonymous power plant with over 1,000 samples. The results consider twenty variables tested from the sampled oil in an internationally accredited laboratory. The variables include viscosity at 40ºC, viscosity at 100ºC, flash point, total base number (TBN), magnesium (Mg), calcium (Ca), zinc (Zn), silicon (Si), sodium (Na), pentane insoluble, water, carbon (C), iron (Fe), chromium (Cr), lead (Pb), copper (Cu), tin (Sn), aluminium (Al), nickel (Ni) and vanadium (V).

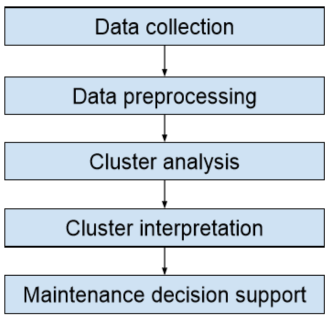

Figure 1. Schematic representation of methodology.

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4.2. Data preparation
The data collected required cleaning to verify missing data, expert assessment on some of the outliers found in the data, consolidation of separate results to one dataset warranting it ready for analysis. Due to various maintenance interventions expected to boost the state and condition of the lubricant such as top up and forced charges, the data was filtered for all equipment. The filtered data incorporated similar time frames as well as ensured it referred to one life cycle of the lubricant in a specific engine from the time replenishment occurred to the time the oil was discharged. The data was standardized since the variables were measured in different scales.

4.3. Cluster Analysis
The pre-processed data is subjected to cluster analysis to reveal the similarities. We use PAM which is similar to K-means but is more robust with outliers to establish the optimum number of clusters. This enables to figure the optimum number of clusters to use as input. Fuzzy clustering is utilized by applying the determined optimum number of clusters to generate the cluster formations from our dataset.

4.4. Cluster interpretations
The clusters generated in the cluster analysis were picked, and the respective members of the cluster explored to further illustrate cluster formation characteristics and the possible associations embedded in the clusters. The interpretation involved looking at the cluster characteristics and invoking literature and expert discussions to ascertain the same.

4.5. Maintenance decision support
From the cluster descriptions and interpretations, the authors draw maintenance related insights from the formed clusters that will assist the maintenance team in decision making concerning the clustered equipment.

5. Results and discussion
This section illustrates the results and further offers a brief discussion on each of the results obtained following the methodological steps as highlighted in Figure 1 under Section 4.

5.1. Equipment data pre-processing
The plant under study has medium speed engines that are driven using marine heavy fuel oil (HFO) to drive generators that generate power. The engines have similar speeds and cylinder bore of 750 rpm and 320mm respectively. The plant carries out periodic scheduled in-service oil analysis of the engine lubricant using an independent laboratory. The lubricating oil data was consolidated and processed with the following characteristics:

- The test analysis for each equipment incorporated a single life cycle of lubricant usage in the respective equipment meaning from charging to changing the oil. This will reduce the validity problems of the model as the lubricant properties for all the engines will not have different external influences like full change and renewal of properties to “as good as new” condition.
- The data was normalized to have a mean centred on zero with a standard deviation of one. This was due to the different scales of measurement of the various lubricant parameters such as calcium, water and pentane insoluble.

5.2. Optimum number of clusters
To determine the optimum number of clusters, PAM technique was applied. The number of clusters to be compared by the average silhouette width criterion ranged from a minimum of two and maximum of five clusters on normalized data. Three clusters were picked as the optimum number of clusters. The optimum three clusters had an average silhouette width of 0.4 whose range is usually from -1 to the ideal +1 as shown in Figure 2. This indicates that there are some clusters formed, though not

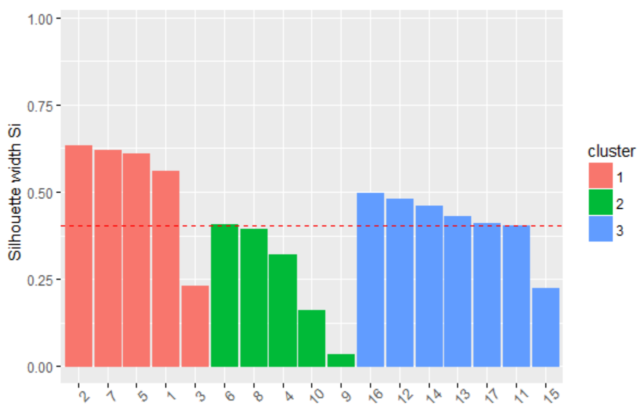

Figure 2. Clusters silhouette plot illustrating the Silhouette width of formed clusters.

explicitly substantial. A reasonable clustering is characterized by a silhouette width of greater than 0.5, and an average width below 0.2 should be interpreted as indicating a lack of any substantial cluster structure [19].

5.3. Cluster results

Fuzzy clustering was carried out with the optimum number of clusters as generated in Section 5.2. Fuzzy clustering was utilized since the K-means clustering generated overlapping clusters which either showed some uncertainty and ambiguity. Table 1 illustrates the respective cluster sizes depicting the number of objects/equipment in our case engines that are grouped in the cluster, where the first cluster had five members, second cluster had five while the third retained seven members depicted as cluster size in Table 1.

Table 1. Cluster size and constituents.

Cluster #	Cluster size	Cluster constituents	Average silhouette width
1	5	1,2,3,5,7	0.53
2	5	4,6,8,9,10	0.26
3	7	11,12,13,14,15,16,17	0.41

Table 2. Illustration of fuzzy cluster characteristics.

Engine	Cluster	Neighbor	Silhouette width	Membership coefficient		
				Cluster 1	Cluster 2	Cluster 3
1	1	2	0.559	64%	19%	16%
2	1	2	0.633	71%	15%	14%
3	1	2	0.230	41%	36%	23%
5	1	2	0.611	74%	14%	12%
7	1	3	0.618	71%	15%	14%
4	2	1	0.319	23%	56%	20%
6	2	1	0.408	21%	57%	22%
8	2	3	0.394	21%	55%	24%
9	2	3	0.033	25%	42%	34%
10	2	3	0.161	20%	48%	32%
11	3	2	0.403	16%	23%	61%
12	3	2	0.478	17%	23%	60%
13	3	2	0.431	20%	27%	53%
14	3	2	0.459	17%	23%	60%
15	3	2	0.225	25%	34%	41%
16	3	2	0.496	17%	21%	62%
17	3	2	0.408	19%	23%	58%

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Table 2 shows the different cluster characteristics where engine 3 has a low silhouette width depicting it might belong to cluster 1 to a high extent with 41% strength and cluster 2 (neighbour) to some extent with 36% membership coefficient. Similarly, other engines with some degree of uncertainty to some extent include engines 9 (42% in cluster 2 and 34% in cluster 3),10 (48% in cluster 2 and 32% in cluster 3) and 15 (41% in cluster 3 and 34% in cluster 2). For this four equipment's, it would be prudent for the maintenance team to consider their respective maintenance interventions along with the equipment of the neighbouring clusters as indicated.

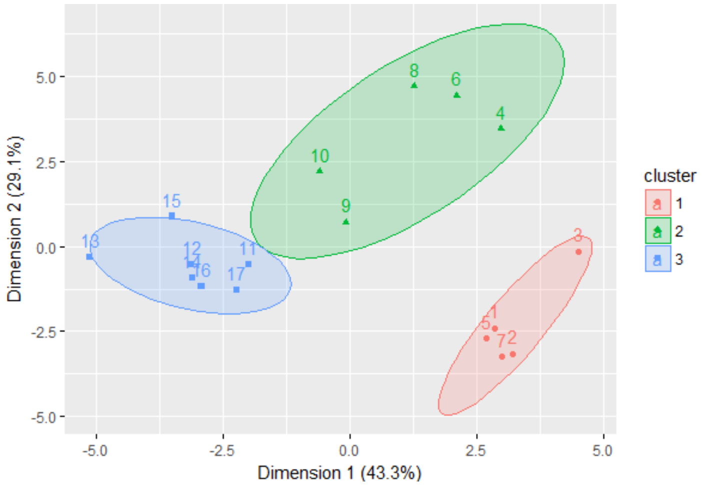

Figure 3. Cluster plot illustrating the different clusters generated.

Figure 3 is a cluster plot that schematically illustrates the clusters formed amongst the seventeen equipment. From Figure 3, it can be seen the clear demarcation of clusters 1, 2 and 3. While engines 4, 6 and 8 are in cluster two to a higher degree than engines 9 and 10, also depicted by the membership coefficient in Table 2. The normalized Dunn's partition coefficient which varies from 0 (completely fuzzy) to 1 (hard cluster) was found to be 0.4355 which indicates a moderate fuzzy clustering was found.

Table 3a. Illustration of cluster centres.

Cluster#	Viscosity @40ºC	Viscosity @100ºC	Flash point	TBN	Mg	Ca	Zn	Si	Na	Pentane insoluble
1	149.90	15.06	192.01	28.20	32.44	10340.48	370.39	18.86	17.03	0.93
2	154.78	15.56	200.84	38.56	61.14	14301.22	472.22	30.28	35.69	1.00
3	166.20	16.31	193.33	36.80	53.11	16267.06	473.13	19.97	43.52	2.41

Table 3b. Illustration of cluster centres.

Cluster#	Water	C	Fe	Cr	Pb	Cu	Sn	Al	Ni	V
1	0.04	0.32	17.43	1.37	2.17	7.39	0.67	4.53	18.93	41.93
2	0.06	0.73	23.71	2.10	1.26	9.78	0.77	9.45	35.09	80.73
3	0.07	0.87	17.12	1.27	0.97	5.73	0.83	8.15	50.24	93.90

Table 3 indicates the matrix of cluster centres or means for each lubricant parameter in the respective three clusters obtained using PAM technique. From the cluster centres in Table 3 (a) and (b), cluster one indicates a cluster characterized with low TBN, low calcium (Ca) and relatively moderate to high zinc (Zn). Cluster two is characterized with high TBN, high calcium (Ca), high zinc (Zn), high silicon (Si), high nickel (Ni), high vanadium (V). Cluster three considers properties depicting high viscosity at 40ºC, high zinc (Zn), high sodium (Na), high nickel (Ni) and high vanadium (V).

5.4. Cluster interpretations

The following section attempts to interpret the three clusters generated from cluster analysis. The constituent cluster centres as depicted in Table 2(a) and (b) are reviewed along with literature and expert assessment to further show the hidden characteristics of the respective group and further implications to maintenance decision support.

Cluster #1 – The TBN is a measure of an oil's ability to neutralise concentrated acids, caused by combustion products condensing on the cylinder walls and elsewhere within the engine. Calcium and magnesium exist as metallic elements associated with the detergent additives in the lubricant, and further could be associated with contamination by water or lime dust [20]. Low values of TBN and Ca indicate the depletion rate of alkalinity in the lubricant is high hence the potential of corrosive wear of the cylinder liners, piston rings and anti-friction bearings. This wear is attributed to the lubricant lacking the potential to neutralise the acidity produced during fuel combustion. Despite the aspect that calcium can also come from grease and some bearings [21], the decrease in TBN level potentially indicate the depletion of Ca from the metallic detergent also used to enhance TBN. A conventional source of zinc (Zn) is the commonly zinc phosphorous compound used as anti-wear and anti-oxidation inhibitor (ZDDP). Another viable source of Zn is the alloy in brass and galvanised steel found in filter canisters [20]. This could probably be a result of the onset of corrosive wear due to the lubricant inability to neutralise the highly corrosive sulphuric acid.

Cluster # 2 – Cluster two is characterized firstly with high level of TBN and Ca which indicates a high alkaline reserve of the lubricant as corroborated earlier that Ca source is related to the detergent used to enhance TBN. Secondly, Zn viable sources as seen include anti-wear additives or alloy in brass or galvanised steel. Silicon can come from dirt (Silica), silicon based synthetic, silicone sealants and silicates from anti-freeze in coolants. Nickel sources can be alloy in valves, crankshaft, gears, guides or cam shaft. It can also come from heavy fuel oil (HFO) especially if vanadium is present alongside nickel. Nickel sources include alloy metal or contaminant in marine HFO fuels (with nickel).

Cluster # 3 – This cluster depicts a high viscosity value. The viscosity of a lubricating oil in use may change in service, mainly by contamination of the oil with combustion soot and lubricating oil originated compounds (e.g. calcium sulphate), but also due to oil oxidation, thermal degradation, contamination with fuels, water, etc. Sodium can originate from salty water, spray wash, anti-freeze inhibitor (coolant leak). While Zn credible sources as seen earlier include anti-wear additives or alloy in brass or galvanised steel. Ni and V as highlighted can come from alloy in valves, crankshaft, camshaft or contaminant in marine HFO fuels when both are notable.

5.5. Maintenance implications

In this section, the revealed sources of the cluster characteristics are further discussed with the objective of revealing the implication of the group characteristics to the maintenance decisions support. The engines classified under cluster 1 which include numbers 1, 2, 3, 5 and 7, depict TBN depletion which potentially could lead to corrosive wear of the engine parts. There are several solutions a maintenance manager could conduct: reduction of the PM schedule where the lubricant is replenished earlier, to ensure the TBN level does not fall to a level that high corrosion wear can be triggered. Another viable solution if carrying out forced charge of the lubricant especially if the PM schedule is distant. In this case, a certain volume of in-service lubricant is drawn out and replaced with new lubricant of equal volume to re-energize or rejuvenate the lubricant properties. Inescapably, persistent depletion of TBN could be solved by changing the lubricant to one with higher treat rate of TBN though this action could require more investigations before being settled for.

Engines classified under cluster 2, are characterized with wear metals notably Zn, Si, Ni and V. The probable principal source could be ingression of dirt from the atmosphere to the engine. The dirt containing silica part of Si, which is fine and abrasive, has potential to cause abrasive wear especially in the main engine components where high contact pressure is expected like the crankshaft and valves. Abrasive wear of these components may lead to increase of Ni, V and Zn which are wear debris from the various components. The ingression of dirt can be due to worn seals, poor air filtration system and generally, the operating environment characteristics. In these clustered engines, the air filtration, seals and external environment is crucial to be investigated.

While reviewing the engines depicted in cluster three, there is a high possibility of HFO contamination in the lubricant as validated by increase in viscosity, Ni and V. In marine applications Vanadium and nickel are also valid indicators of cross-contamination with HFO products. Accordingly, changes in viscosity should be considered always in relation to other analytical data, like total acid number, pentane insoluble and water content for contamination, while a flash point drop for dilution by fuel [22]. Within this case, pentane insoluble increased compared to the other clusters while flash point decreased marginally, and water content remained within acceptable thresholds which could be interpreted as probable HFO contamination. Hence, for the maintenance aspects of the engines falling under this cluster, more investigations on fuel contamination under dilution require to be undertaken. Some of the causes and potential mitigations are discussed by Wakiru et al [16]. It is important to note as discussed in Section 5.3, engines 3, 9, 10 and 15 should be treated with consideration of the characteristics of their neighboring clusters.

6. Limitations

The applicability of the proposed methodology is limited to lubricant related maintenance actions and interventions, where the exposed cluster characteristics offer initial in-group similarities of the equipment in the lubricant condition monitoring context. Further investigations could be installed to deeper validate the revealed patterns potential link integrating failure events following a framework such as discussed by [23].

7. Conclusion

This study set out to generate clusters of multi-equipment with similar operational characteristics here using in-service lubricant analysis results. Cluster analysis using fuzzy sets method revealed three clusters or groups of the engines under study where respective equipment in the groups have similarities. The findings of this investigation complement those of more initial studies that employ the concept of GT, with the study utilizing lubricant condition monitoring, a maintenance field seldom investigated in the concept. The findings of this research provide insights for maintenance practitioners while undertaking maintenance analysis, planning and scheduling where grouped maintenance interventions could be used for several different equipment. The developed framework further enhances the practitioner’s ability to directly investigate probable causes of the cluster characteristics (constituent lubricant parameter deviated properties) which will enhance timely and appropriate interventions. Therefore, this study makes a major contribution to research on grouping technology (GT) by demonstrating the employment of lubricant condition monitoring, a concept that the authors have not found being utilized in research as well as in practice.

Further analysis based on reliability towards exploring the meant time to failure (MTTF) for each of the engine is viewed as a plausible future research work to check convergence and enhance the grouping maintenance techniques for preventive maintenance scheduling using lubricant in-service analysis framework.

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