A LUBRICANT CONDITION MONITORING APPROACH FOR MAINTENANCE DECISION SUPPORT - A DATA EXPLORATORY CASE STUDY

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Abstract: *Lubricant condition monitoring is a Condition Based Maintenance (CBM) technique which indicates the state or condition of the equipment, the lubricant and any contamination noted within the lubricant. Failure of the various lubricant parameters translates to loss of lubrication capability which consequently leads to wear of the equipment and catastrophic failure of critical rotating elements if intervention is not made. Trend analysis on used oil data has been in use for a long period of time, but the results from the analysis is seldom used for robust maintenance decision support. The aim of this study is to analysefailure patterns within the lubricant parameters , and embedded in data of used oil analysis, where a case study of a thermal power plant is evaluated. In this study, a methodology is adopted starting with correlation analysis performed on the parameters of the used oil with a view of evaluating the associtations or relationships where such relations are validated from both literature and expert assessment. Next,trend analysis is performed where the parameters of the used oil are compared against thresholds recommended in industry standards and in practice,to expose the performance of various parameters. Next, from the trend and correlation analysis, failure patterns embedded in the used oil data were mapped alongside failure events recorded in maintenance databases, from which useful decision support was derived regarding feasible associations between degradation of oil parameters and occurence of specific failure events. This methodology demonstrates that correlations between deterioration of common lubricant parameters vis a vis equipment failure events can be better monitored and predicted. This could enhance the maintenance decision making through averting impending equipment failures or assist in better maintenance planning. This will invariably reduce downtime and improve operational efficiency of technical systems.*

Keywords: *Correlation, Used Oil Analysis, Condition Based Maintenance*

INTRODUCTION

In modern power plants, a hybrid maintenance strategic approach is used to ensure synergies are harnessed from different strategies. Condition based maintenance (CBM) has been growing in use in sectors such as manufacturing, or power generation for both prognosis and diagnosis of maintenance related aspects. Among the main condition monitoring techniques used in the process plants underthe CBM strategy include the lubrication oil condition monitoring (also known as Used oil analysis), vibration analysis, thermography, ultrasound among other strategies. 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.Lubrication oil condition monitoring plays a critical part in maintaining the optimal operating condition of machineries and plants. In recent years, equipment health condition monitoring and prognostics of lubrication oil have become a significant topic of research interest among academia and practitioners(Zhu, He, & Bechhoefer, 2013). More and more efforts have been put into development of diagnostic and prognostic systems for used oil analysis. The purpose of most research is, by means of monitoring the oil degradation process, systems can be developed which will provide early warning on impending machine failure and moreover, extend the operation lifetime of the lubricant. By monitoring the used oil analysis, and developing diagnostic and prognostic systems, researchers and practitioners aim to increase the machine availability, prevent unnecessary cost of oil replacement, and further reduce waste

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which adversely affects the environment. Lubrication oil is an important source of information for detecting early machine failures, and performs a similar role of analyzing 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.

A lubrication oil analysis or commonly known as a used oil analysis program(UOA), is applied for analyzing the physical and chemical properties of the oil (lubricant), and highlights possible contamination within the oil, or component wear through metals ingression tothe oil. The UOA program also highlights deterioration of important additives in the oil which influences the lubrication properties of the oil.

LUBRICANT CONDITION MONITORING

Lubricant condition monitoring involves sampling the used oil, analyzing the lubricant parameters, and thereafter interpreting the results of the analysis, for instance, parameters exceeding acceptable thresholds. Among the objectives of monitoring the condition of the lubricant is to confirm or guarantee that the lubricant is of acceptable condition and able to fulfil its function, andto monitor the condition of the equipment, i.e. level of component wear indicated through particulate ingression in the used oil. Properly performed, the UOA allows the practitioners mitigate critical equipment failure and allow proactive maintenance planning, hence avoid expensive downtime and repairs, and also prolong the operating lifetime of the equipment(Almeida & Energia, 2003).

1. UsedOilAnalysis

In most used oil analysis laboratories, the main characteristics of the lubricant that are analyzed include physical and chemical properties of the oil, oil contamination, additive analysis and wear metals analysis as seen in figure 1:

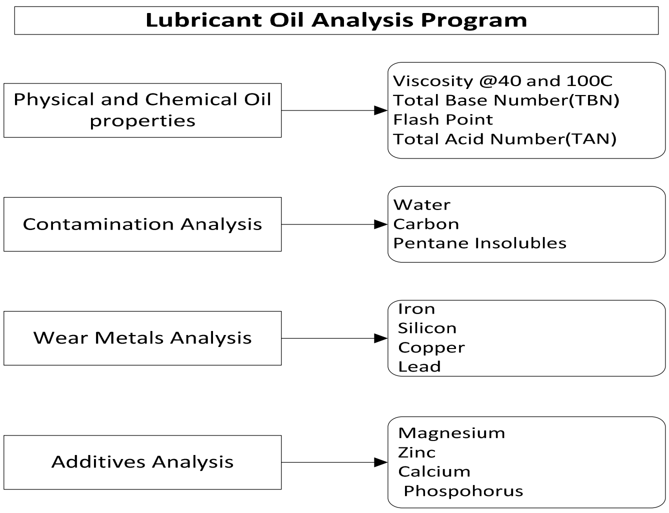

Figure 1.-Lubricant Oil analysis program

– ***Physical and Chemical properties***

Viscosity

This parameter indicates the lubricant's internal resistance to flow. The results of viscosity can indicate eitherphysical changes within the lubricant, orindicate contamination by other fluids. The test for viscosity is usually performed at between 40°C and 100°C for most engine oils. The viscosity of the lubricant for engines is defined at 100°C according to the SAE J300 classification system. The units of measure are in mm^2s^{-1} or cSt(centistokes)

Total Base Number (TBN)

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This is the quantity of hydrochloric acid required to neutralize one gram of oil (mg KOH/g) or the alkaline reserve in a lubricant. It identifies the acid neutralizing capacity or the alkaline reserve that the lubricant possesses. The TBN may indicate physical changes in the lubricant, hence the need for replacing the lubricant. Depletion of the total base number is mainly attributed to the Sulphur content of the fuel in use, the level of oil consumption as well as the operational conditions of the engine.

Flash Point

This is the lowest temperature at which a source of ignition can ignite the oil vapor. It has different test methods, for instance, the Open Cup, where test is done in the open and Closed Cup where it is done in a closed environment not allowing evaporation losses (CIMAC, 2011).Flash point can indicate the presence of dissolved solvents in a lubricant(Zhu et al., 2013).

Total Acid Number (TAN)

Measures or identifies acidic component or amount in a lubricant which is mainly influenced by the lubricant degradation hence making it corrosive. The by-products of oxidation and contamination would affect the Acid number of a lubricant.

– ***Contamination analysis***

Pentane Insolubles

This is the solid matter that can be isolated when a solvent is added to the lubricant and filtration or centrifuging performed on the lubricant.

Sootor Carbon

This identifies the by-products of unburned fuel, which alsoindicates contamination within the lubricant.

Water

The water content in the used oil is measured using the Karl-Fischer titration or infrared spectroscopy. The test identifies the presence of water, a common and potentially harmful fluid contaminant that can accelerate physical changes of the lubricant which could enhance rapiddegradation and corrosion of metal surfaces.

Particulates

These are particles that can be traced in the used oil and come from other contaminants. Examples of the particles include Silicon, Sodium, Nickel and Vanadium. Some of the elements can also originate from various parts of the equipment.

– ***Wear Metals analysis***

These are elements that come or represent the metallurgy of components found in the equipment for example iron, aluminium, lead, copper, chromium, silver and tin. During the operation of the equipment, different types of wearoccur, for example cavitation, adhesive, abrasive etc., which are influenced by the operational and environmental aspects of the equipment. Due to this wear, the wear metal will increase in the lubricant signifying occurrence of wear.

– ***Additives analysis***

Additive elements in the lubricants can also be analyzed in the UOA. The levels of key elements in the additives analysis may indicate the type of lubricant formulation used in the equipment. The formulation depends on the operating context of the equipment. Analyzing the additives may also indicate the level of depletion of the additive as well. Lubricant replacement or addition(top-up) with new oil is often used to replenish the additive levels. Some of the additive elements include zinc, calcium and magnesium.

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2. AnalysisInterpretation

Once the oil analysis is performed, perhaps the most important part of the lubricant condition monitoring program is interpreting the results of the Used Oil Analysis. Often, the analysts are qualified to correctly appraise the findings of their tests. They can only go as far as identifying degradation of lubricant parameters using the results derived from the analysis. The interpretation exposes the condition of the oil which indicates the environment in which the machine operates and the user can be able to establish or adjust the operating and or maintenance programs accordingly.

MOTIVATION OF THE STUDY

Utilizing the used oil analysis alone and following the interpretation of the results could assist the plant in maintenance decision making, but also has limitations.

Firstly, used oil analysis, is based on results of parametric analysis of various lubricant properties. Hence, aspects such as the operating environment of the equipment are seldomly considered. In a case study for Heavy Earth-moving machines, UOA was done and exposed wear in the engines with causes attributed to contamination(Kumar & Ghosh, 2016).The root cause analysis did not consider the operating environment of the machines which could have a huge effect on the causes.

Secondly, the interpretation of the results of the UOA relies on the main effects of single parameters where it is biased on the result of one parameter, whereas the interactions of the parameters are rarely considered. Two studies used Pearson correlation of wear metals and pollutants to estimate the useful lifetime of oil in diesel engines(Adnani, Hashemi, Shooshtari, & Attar, 2013; Da-Silva, Neto, Assis, Matamoros, & Medeiros, 2012). The studieshowever did not test the data to confirm if the sample data followed a normal distribution to use Pearson method. They also concentrated on only elemental analysis metals whereas more interactions would be expected in this instance from other parameters of the lubricant.

Thirdly, relating the results of the used oil analysis with the actual operating context of the equipment is challenging, and seldom considered in the literature. Fourthly, the analysts are limited to the lubricant parametric behavior and operational knowledge of the equipment, and may not be in a good position of identifying how the lubricant changes influences equipment failures. And lastly, the analysts involved in the interpretation are limited to the extent to which they can suggest changes to the maintenance regimes.

Owing to these limitations, this research seeks to derive decision support enhancement from analysis of UOA data. The proposed approach aims at evaluating the effects of interactions between the analyzed parameters of the used oil through adapting methods such as correlation analysis and trend analysis. Thereafter, important associations mapped from the trend and correlation analysis are linked to actual failure events of thermal power plant engines recorded in a separate maintenance data set.

METHODOLOGY

In this section, the methodology as depicted in figure 2 will address data collection, preparation, testing of the data, analysis and results interpretation.

Lubricant condition monitoring is best accomplished by analyzing numerical data associated with lubricant properties which if not within specified thresholds, would indicate deterioration of the lubricant, or component wear(Almeida & Energia, 2003). The numerical data can be analyzed by statistical methods to determine the relationships between various test parameters and their respective fluid and machinery failure modes.

In addition, the statistical analysis can be used to determine potential data interference sources, the various threshold or alarm limits for each parameter and other criteria to be used for evaluating the used oil, in the daily evaluation of used oil.

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1. *Data collectionand pre-processing*

The data used in this study was from a thermal power plant that uses heavy fuel oil to drive the engines which eventually drive the generators. The plant maintains data on used oil analysis which is done by an independent laboratory and failure event data for all the failures and respective repair actions undertaken. Data used dated from 2011 to 2015.

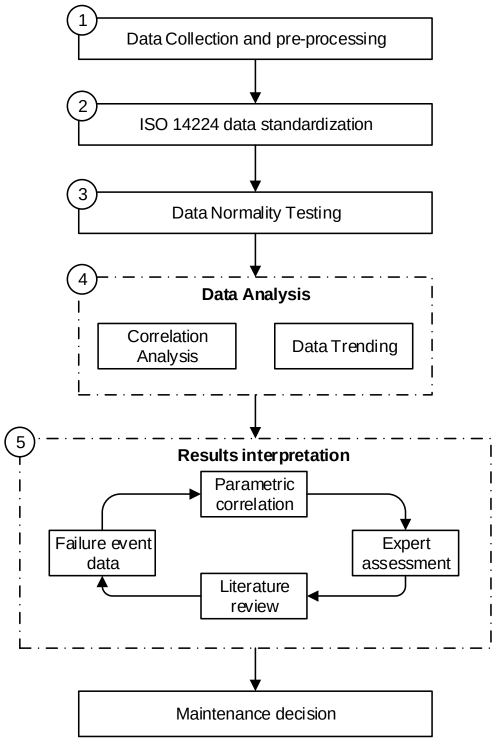

Figure 2: Schematic representation of the methodology

Since most of the times the data will likely be imperfect, and contain inconsistencies and redundancies, the data is often not directly applicable for starting any analysis. The preprocessing step adapts the data to the requirements of the data analysis hence enabling efficient analysis of the data which would be unfeasible otherwise.

In this study, the data preparation or preprocessing includes a wide range of steps or phases, for instance data transformation, integration and cleaning. The preprocessing stage also involves the maintenance team of the plant to verify the data and give some interpretation and linkages. After completion of the preprocessing stage, the preprocessed data is regarded as a reliable and suitable source for analysis.

2. *ISO 14224 data standardization*

The pre-processed failure data was standardized to meet the data structural requirements, while terms and vocabularies from the ISO 14224:2016 were also adopted. The importance of adopting the standard data structuring is seen in the data interpretation while comparing the used oil parameters correlation with the equipment failure events which require to be categorized and classified as per the ISO subsystem classification.

3. *Data Testing (Normalitytesting)*

This test compares the scores in the sample to a normally distributed set of scores with the same mean and standard deviation; the null hypothesis being that the "sample distribution is normal." If the test is significant, the distribution is non-normal. For small sample sizes, normality tests have little power to reject the null hypothesis and therefore small samples most often pass the normality tests (Unwin, 2013). For large sample sizes, significant results would be derived even in the case of a small deviation from normality, although this small deviation will not affect the results of a parametric test(Unwin, 2013). A number of

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research on different type of tests conclude that the Shapiro-Wilk test as powerful for all types of distribution and sample sizes although for small sample sizes, the power may be low(Farrel & Stewart, 2006;Razali & Wah, 2011;Keskin, 2006).These tests will confirm the data distribution which enables selection of the correlation method to use.

4. *Data Analysis:*

Data analysis employed two methods i.e. Correlation analysis and data trend analysis as briefly outlined. This step was used to expose the correlation or relationships between the various lubricant parameters analyzed in the UOA.

– ***Correlation analysis***

Correlation is a statistical method that determines the degree of relationship between two different variables. The relationship between any two variables can vary from strong to weak or none. When a relationship is strong, this means that knowing a person's or object’s score on one variable helps to predict their score on the second variable. Correlations are useful because they can signify a predictive association that can be applicable in practice. Data to be analyzed for correlation require first to be tested for normality. There are two main methods of carrying out correlation analysis as discussed in the following section.

Pearson correlation coefficient gives an indication if there is a linear relationship between two continuous variables X and Y and to express how strong this linear relationship is. It is used when both variables being studied are normally distributed hence parametric in nature(Hauke & Kossowski, 2011). This coefficient is affected by extreme values, which may exaggerate or dampen the strength of relationship, and is therefore inappropriate when either or both variables are not normally distributed.

Spearman rank correlation coefficient is a nonparametric (distribution-free) rank statistic to measure, a monotone association that is used when the distribution of data makes Pearson’s correlation coefficient undesirable or misleading(Hauke & Kossowski, 2011). Spearman’s rank correlation coefficient is not a measure of the linear relationship between two variables, as some may understand and allude. It assesses how well an arbitrary monotonic function can describe the relationship between two variables, without making any assumptions about the frequency distribution of the variables. Unlike Pearson’s product-moment correlation coefficient, it does not require the assumption that the relationship between the variables is linear, nor does it require the variables to be measured on interval scales; it can be used for variables measured at the ordinal level.

– ***Data trending***

Trending analysis of used oil analysis data is best performed through visual trend plots. The trends often reveal the rate of change of a parameter with time. The use of data trending against defined threshold limits reveals the performance of the lubricant parameters over time. Limits or alarm level for oil analysis results can be specified to monitor the machine’s condition. Typically, the absolute thresholds are usually recommended by the equipment manufacturer, lubricant suppliers’ and/or the industry bodies such as The International Council on Combustion Engines(CIMAC). However in practice, they are based on the average operational and performance situations that may not correspond to the actual application condition of the machine(Tsang, Yeung, Jardine, & Leung, 2006). Often, the original equipment manufacturers have their own threshold limits which are based on operational experience of usage of the lubricant which are recommended to be used first before any other(CIMAC, 2011). The limits assist in evaluating the lubricant parameters that have deviated from the expected values which indicates that either the lubricant or equipment condition are not as expected.

Though in use, evaluating trends alone may not confirm the nature and severity of a problem and cannot predict a future event(Fitch, 2007). Hence, trend analysis of the oil data alone is not a maintenance strategy since the trend may reveal normal trends, yet the oil and the equipment maybe in unhealthy condition. Lastly, the trend analysis may not yield decisions of the need for adopting alternative maintenance strategies that need to be performed. Moreover, the trend analysis alone may not reveal potential damage

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within the equipment prior to occurrence. Perhaps validation of the trending will be important by using the actual maintenance data to reveal the conditions of both the lubricant and the equipment. Early discovery of the trends and associations may deter failures of the lubricant and equipment.

5. Data interpretation

Despite the limitations of trend analysis, it still forms a major fundamental part of interpreting used oil analysis data. However, as will be seen in this study, the results of the trend analysis often confirm correlations between lubricant parameters depending on the correlation strength which could be positive or negative. Further, the correlations of the lubricant parameters are in this study validated through literature and expert assessment which exposes the logic and association of the correlations.

After analyzing the correlations between the used oil parameters, a comparison between the correlations and equipment failure events is performed. For this, a different data set of maintenance events which incorporates failures events and repair actions is used for the comparison from which, important inferences are derived, and moreover, the rationale behind the correlated parameters and the failure events.

RESULTS AND DISCUSSION

In this section, sample results are provided with discussion on the same made, where the trend analysis of the lubricant parameters, correlations, and comparison with failure events of equipment within the power plant are presented. Moreover, insights from the analysis are evaluated both in the perspective of literature, and considering expert input.

1. Casestudy data

The data used for this case study was from a thermal power plant running ten medium speed engines on heavy fuel oil. The data for each engine is recorded autonomously and maintained for the whole plant. For consistency, the data used in this study was for one engine. Two engines were selected for exploration and researcher found similar trends hence settled for one engine in this study we name it Engine E2. The plant maintains two sets of data sets as described in the following section.

– ***Used oil Analysis data***

This data incorporates the results for the test parameters for the used oil analysis done monthly. The data for engine E2 had 75 test samples results. The data was consolidated into one file, the missing data were retrieved from the actual physical reports and where values were not consistent with outliers, the maintenance team was consulted. Due to inconsistencies, some sample results were dropped.

– ***Failure events data***

The failure event data is maintained for all failures that occur and are repaired. The record contains the unique serial number, date and time of occurrence, failure mode description, repair action taken and any spares used. This is a descriptive data. The data was standardized using the ISO 14224 to capture all the subsystems maintained like the Cylinder(CYL), Turbocharger(TC), Fuel system(FS) etc. See a sample extract of the data in table 1. Extraction of failure data and equipment failed from the data also utilized the maintenance team for the non-explicitly mentioned failed equipment. For engine E2, the data set contained 86 failure events over the period under study.

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Table 1.- Sample extract Failure event data

S/N	ENGINE NO.	INCIDENCE DATE	CODE	DESCRIPTION	CORRECTION
F/2/95/11	E2	30/09/11	CYL	CYLINDER LEAKING COOLING WATER STOPPAGE	Warped cylinder head gasket replaced. Cause: water hammer Investigate water source if any is found during blow over. Replacement of multiducts in place.
F/2/10/12	E2	26/10/12	FS	ENGINE STOP ON HIGH EXHAUST GAS TEMPERATURE	The injector which was replaced had burnt lower o-ring and caked fuel deposits on the body, possibly caused by high temperatures in combustion chamber.
F/2/11/12	E2	05/11/12	FS	ENGINE STOP DUE LOW EXHAUST GAS TEMPERATURE	Injector pump replaced
F/2/110/12	E2	25/09/13	CYL	WATER LEAKAGE	Cylinder Liner ,O-ring replaced. Cylinder head multiducts broken bolts extracted. Solved,correction of other water sources underway

2. NormalityTesting

The preprocessed data for the used oil analysis as discussed in the methodology section 4, was tested for normality using the Shapiro Wilk test. See the results table 2.

Table 2.- Shapiro test for normality

Parameter	Shapiro-test p-value	Parameter	Shapiro-test p-value
VISCOSITY @ 40 (CSt)	0.0119	FINA WATER (%)	2.96E-11
VISCOSITY @ 100 (CSt)	0.3418	CARBON CONTENT (%)	0.146
FLASH POINT (Degrees C)	6.419E-09	IRON (ppm)	0.00077
TBN (mg KOH/g)	0.042	CHROMIUM (ppm)	0.00055
MAGNESIUM (ppm)	0.0004	LEAD (ppm)	3.76E-09
CALCIUM (ppm)	0.286	COPPER (ppm)	4.76E-05
ZINC (ppm)	0.0006	TIN (ppm)	2.43E-14
SILICON (ppm)	0.0116	ALUMINIUM (ppm)	0.556
SODIUM (ppm)	3.11E-09	NICKEL (ppm)	0.06295
PENTANE INSOLUBLES (%)	0.00145	VANADIUM (ppm)	0.2242

The null-hypothesis of this test is that the population is normallydistributed. Thus, if the p-value is lessthan the chosensignificance level, then the nullhypothesis is rejectedandthere is evidencethat the data testedarenotfrom a normallydistributedpopulation; in otherwords, the data arenotnormally distributed, whereas if the p-value is greaterthan the chosensignificancelevel, then the nullhypothesisthat the data camefrom a normallydistributedpopulationcannot be rejected. For example, the p-value for Viscosity @40^{o}C is 0.0119 which is lower than our significance level of 0.05(5%), hence we reject the null hypothesis that it came from a normal distribution. Using a significance level of 5%, we note that only 25% of the data show to have come from a normal distribution. This normality tests will be used in the next section to select the correlation analysis method to be used on the data.

3. Data Analysis

In this section, we analyze the data in two different methods. Correlation analysis and trending for the used oil data.

– ***Correlation Analysis***

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As discussed in the previous section, 25% of the data was considered to follow normal distribution, while the rest were non-parametric. We used Spearman's correlation coefficient due to the following reasons. Firstly, not all the variables were normally distributed and it is more robust to outliers than is Pearson's correlation coefficient.

Figure 3 shows the correlogramfor all the parameters correlation. The p-value for each correlation is computed and using a significance level of 0.05, the significant correlations are determined (p-value less than 0.05) using a null hypothesis that the correlation is insignificant and are marked in color blue or brown. Correlations with p-value greater than 0.05, are considered as insignificant hence are not marked in any color. For example, correlation between Flash point and Water had a p-value of 6.437232×10^{-20},which is lower than 0.05, is significant hence colored deep blue with a spearman's correlation coefficient of 0.9. Correlation of Lead and Viscosity @100°C had a p-value of 0.5635688033, which is higher than 0.05 hence considered insignificance with a correlation coefficient of -0.03. The values indicated on the correlogram are the Spearman's rank correlation coefficient which show a strong positive correlation of two parameters as the value approached 1 and negative correlation as the value approach -1. In the example highlighted, flash point and water have a very strong positive correlation (0.90), while from the correlogram, water and tin have a strong negative correlation (-0.96).

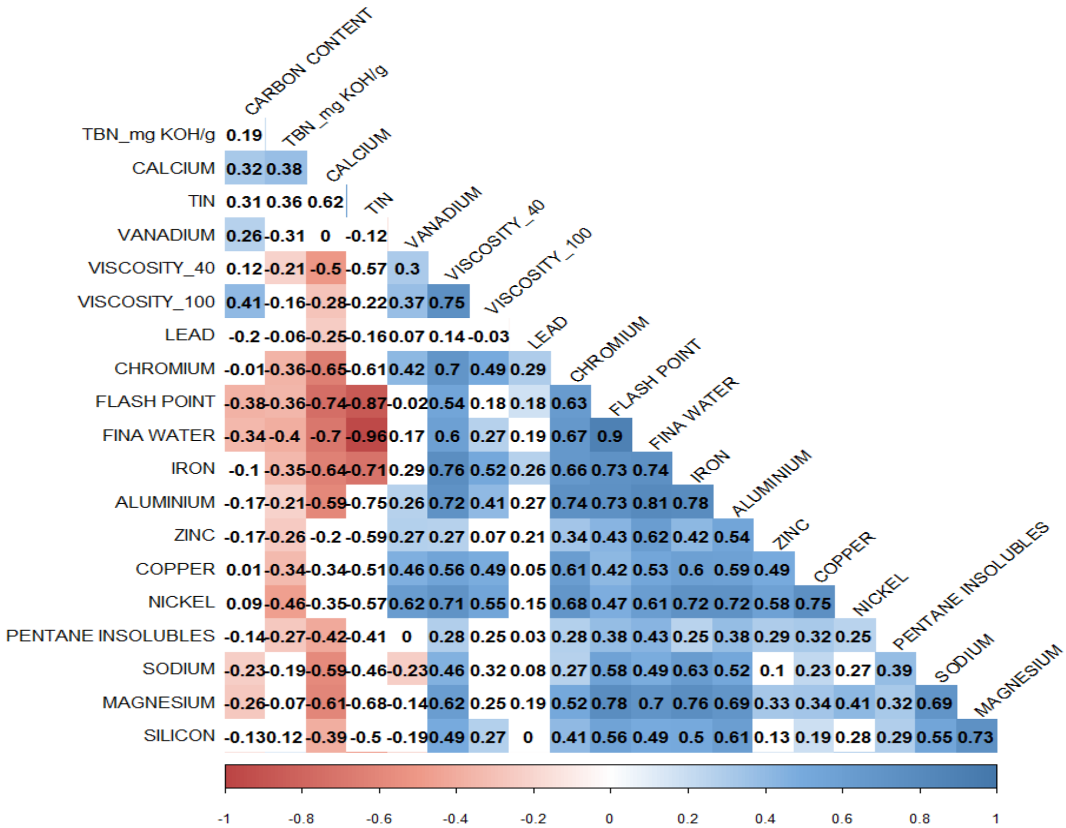

Figure 3.-Corellogram for the lubricant parameters

– ***Trend Graphs***

The trending was performed using trend plots of each of the used oil parameter against the calendar date (here we use the year) when the sampling of the oil was done. Below find some sample trend plots and their brief discussion.

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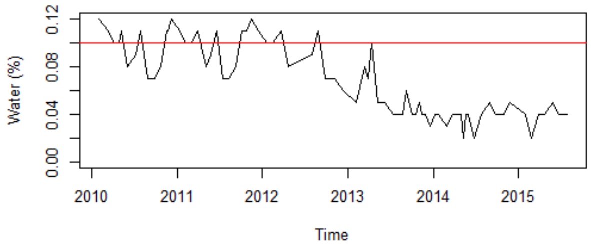

Figure 4.- Trend plot for Water

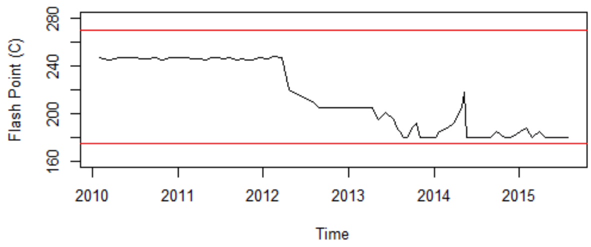

Figure 5.- Trend plot for flash point

From the trend plot figure 4, it shows that water content in the lubricant has generally been decreasing. There are instances that the level surpassed the limit (in this case 0.1% by volume). This might mean that there was a general problem of ingression of water or the off-line centrifuge was not working well as it is supposed to purify the oil in circulation by removing water and other contaminants. Towards end of the year 2012, the problem seems to have be solved with the water content remaining below the threshold limits. Figure 5 plots the trend of flash point with the thresholds usually ±20% of the new lubricant value in this case was 230^{o}C, hence the thresholds set at minimum 185^{o}C and maximum 275^{o}C. The flashpoint seems to have been stable until start of 2012 when it started to decrease and later stabilized. This might point to a solution to a persistent problem that was causing the flash point to be high though at no instance deviating above the maximum allowable threshold.

Figure 6 shows the trend of zinc with time. Zinc as an additive ingredient, remained well over the minimum threshold of 300ppm (parts per million). Zinc is an additive compound offering anti-wear properties to the lubricant by forming a surface film to reduce wear, hence depletion below the limit indicates more wear is likely to take place. The trend shows one instance that the depletion surpassed the limits in the mid-year of 2013. Figure 7 trends tin with time against the threshold of maximum 5ppm. Tin level in the lubricant was below the alarm limit till after start of 2013, where some marked increase is noted. Under two instances at the start and towards end of 2014, the level surpassed the limits. This indicates, some wear on equipment having tin their metallurgy.

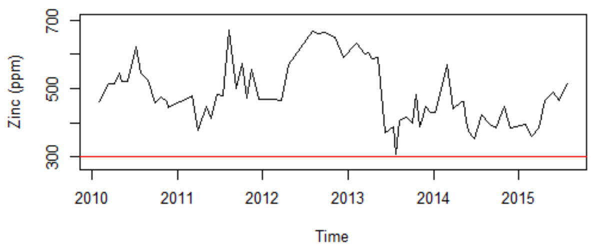

Figure 6.-Trend plot for Zinc

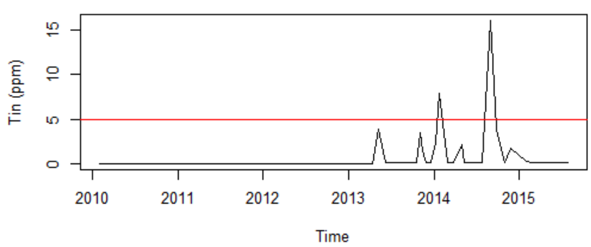

Figure 7.- Trend plot for Tin

Figure 8 trend viscosity at 40^{o}C against the minimum alarm limit of 102cSt (-25% of new oil value) and maximum of 195cSt (+45% of new oil value) where new lubricant value is 135cSt.It shows some stability in the parameter with instances in 2011and 2012 surpassing the maximum alarm limit. Increase in the viscosity may be due to various factors like admixture with another lubricant which is of a higher viscosity, use of wrong oil, high oxidation, contamination by heavy fuel oil, soot or carbon increase or water contamination. Increase in viscosity would increase the internal fluid friction, create a drag in operations of the engine and can lead to clogging of the oil filters which would lead to lubricant starvation in various parts of the engine that could end in catastrophic failure due to lack of a lubricant. Figure 9 trends iron indicating an inconsistent pattern of the levels, but generally on a decreasing trend. Instances over the alarm limitwere in the years 2010, 2011 and 2012. These indicate wear occurrence in equipment with iron like the engine liners, oil pumps, crankshaft and valves.

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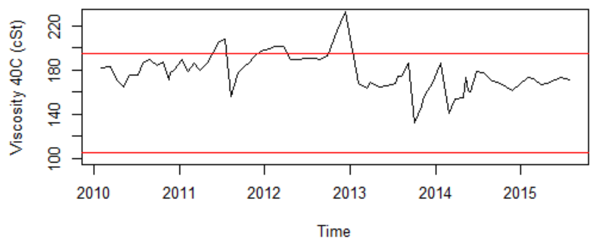


Figure 8.- Trend plot for viscosity @40^{o}C

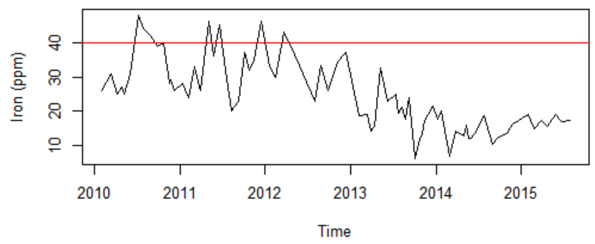
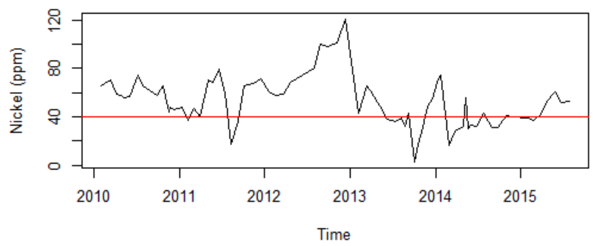


Figure 9.- Trend plot for iron

Figure 10 show the trend of nickel against the maximum limit of 40ppm. It depicts a rampant behavior with high levels beyond the allowable limits dominating most of the time. Nickel sources can be wear of valve alloys, crankshaft and contamination of marine heavy fuel oils, while figure 11 trends aluminiumversus a maximum limit of 20ppm. Aluminium has steadily remained below the maximum allowable limits but shows rampant changes of the levels in the lubricant marking wear on equipment with aluminium like pistons, thrust bearings, turbocharger bearing etc.



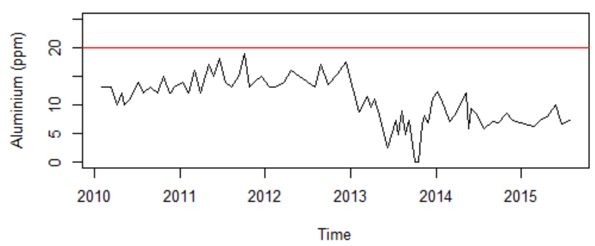


Figure 10.- Trend plot for NickelFigure 11.- Trend plot for Aluminium

4. ResultsInterpretation

In this section, we review the interactions and relationships of the used oil parameters and relate the association to the failure even data to pick inferences. We shall review some of the relationships exposed in section 5.3.1 and trends in section 5.3.2, link the relations exposed and map them with the actual failure event data.

– ***Flash point and Water***

From section 5.3.1 and figure 3, the correlation coefficient of flashpoint and water is 0.9 indicating a strong positive correlation between these two properties. A high positive correlation means that with high water content in the lubricant we expect a high value for the flashpoint. From figure 4, the trend graph for flash point and figure 5 for water, similar patterns are noted from mid-2011 to mid-2012 where both the parameters were exhibiting high values.Figures 12 and 13 expands the view to the durationmid-2011 to mid of 2013. Since the flashpoint is the lowest temperature at which the lubricant vapor will ignite upon introduction of a source of ignition, this follows that a high flash point means that the temperature needed for the lubricant vapor ignition is rather high, hence less unlikely to ignite. The situation of high flash point may result from contamination of the lubricant by water, hence the high flash point. High flash point implies that the fuel does not easily burn at expected engine temperatures. This would cause an increase in unburnt fuel, which may pass into the crankcase causing lubrication oil dilution, reducing the engine efficiency as well as can cause exhaust system clogging, high temperature in the exhaust system which could cause a trip of the engine.

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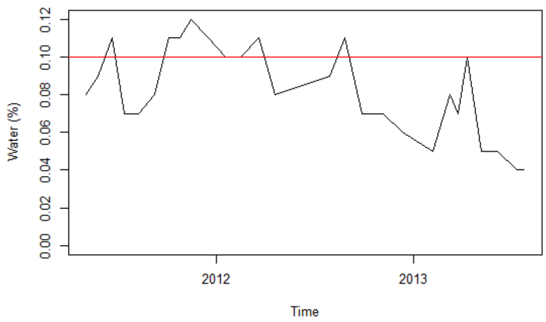


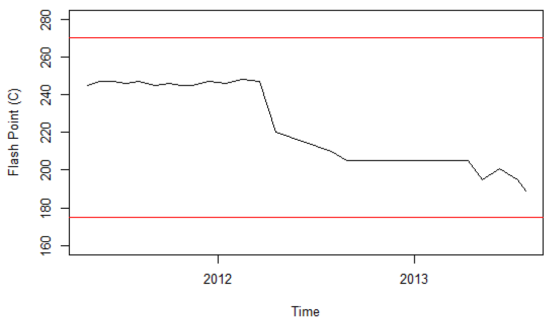


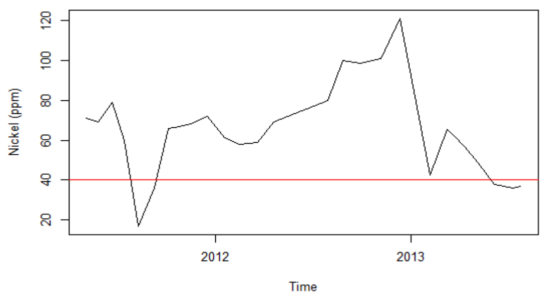
Figure 12.- Trend plot for Water

Figure 13.- Trend plot for flash point

Evaluating further the effect of possible detrimental effect of the high flash point owing to water contamination, the failure event data of the power plant engines were examined. From the examination, two instances the engine failures associated with water leakage during a similar period the used oil was analyzed were noted. More specifically,the failure was linked to a multi-functional duct used to circulate cooling water within the engine block for purposes of cooling the exhaust valves and the cylinder head flame deck (Woodyard, 2009). The same period the cylinder head gasket failed and was replaced due to the same problem. It was also noted that the failure of the multi-duct system occurred after the oil analysis, hence the correlation could have pointed to the anticipated failure in advance.

– ***Viscosity at 40^{o}C, Nickel and Iron***

From the correlogram figure 3, the correlation coefficient for viscosity at 40^{o}C and Nickel is 0.71 while for viscosity at 40^{o}C along with Iron is 0.76.Both correlations depict a moderately high positive correlation. Evaluating viscosity at 40^{o}C and Nickel using figures 8 and 10, shows similar pattern in the trends during the period starting 2012 to mid of 2013. From the expanded view of the trends figures 14 and 16, the correlation and similar trend is seen towards the end of 2013, where both Nickel and Viscosity at 40^{o}C surpassed their respective maximum threshold limits.



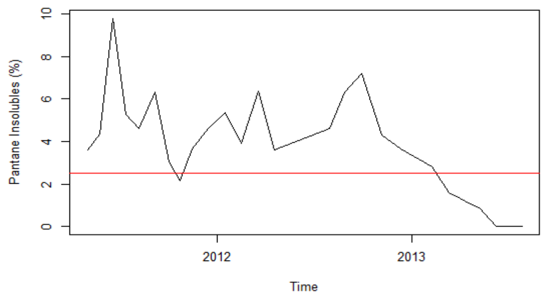
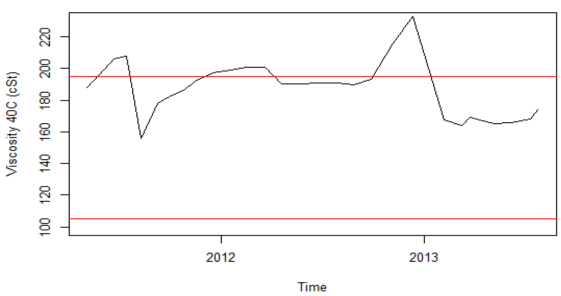


Figure 14.- Trend plot for Nickel

Figure 15.- Trend plot for Pentane Insolubles



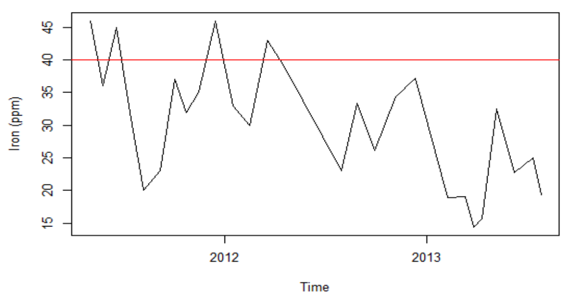


Figure 16.- Trend plot for viscosity @40^{o}C

Figure 17.- Trend plot for iron

Figure 9: Trend charts of Aluminium and Iron (2012 – 2014)

Viscosity which is the internal resistance to flow of the lubricant at a defined temperature is one of the most important properties of the lubricant. The increase of the viscosity parameter measured at 40^{o}C can

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be attributed to either contamination of the lubricant with more denser contaminants such as heavy fuel oil. Another potential cause of the increase in viscosity is high operating temperature of the equipment which may lead to oxidation of the lubricant(Jacazio, Libraro, Mornacchi, & Sorli, 2013;Rowland., 1919). Denser contaminants such as insolubles, soot, water and heavy fuel oil potentially will increase the value of viscosity(CIMAC, 2011). Since fuel contains Nickel and Vanadium as part of the ingredients as alluded by(CIMAC, 2011), these elements may lead to a potentially valid reason for the rise in the viscosity especially when there is fuel ingression in the lubricant.

Evaluating further the effect of possible detrimental effect of the high viscosity at 40^{o}C owing to heavy fuel oil contamination, the failure event data of the power plant engines were examined. It was noted that, at approximately the same period the oil was sampled and analyzed, failure of the fuel injector pump was reported. The injectors were also found not atomizing and caked fuel deposits found inside. Hence from the experts view, the high temperature was envisioned as a cause of high viscosity could have potentially caused the caked fuel deposits which ultimately blocked the injectors hence could not atomize the fuel. This has detrimental effect on the engine running as atomization facilitated the start of burning and ensures continualburning. The fuel ingression in to the lubricant could have occurred through leakages of the fuel injector pumps and fuel pumps which eventually failed. Though vanadium and nickel (which both link fuel ingression to the lubricant) can both be present in the drain oil as combustion products, asphaltenes like pentane insoluble would give a better indication of the fuel contamination(CIMAC, 2011), which in this case at the same time, showed a remarkable high value as seen in figure 15.

At the same period towards end of 2012, figure 17 shows that the level of iron particles in the lubricant increased. Similarly, the correlation coefficient of viscosity at 40^{o}C and Iron was moderately high at 0.76. As indicated in section 5.3.2, iron in the lubricant may be attributed to among otherswear of oil pumps or the injector pump shafts(Vähäoja, Välimäki, Roppola, Kuokkanen, & Lahdelma, 2008).On further examining the failure event data of the power plant engine, there is high possibility that the increase in iron particles in the used oil can be attributed to the wear of the injector pump which from the failure events data indicates failed slightly some weeks after this incident. The fuel leakage into the lubricant can be considered as the main reason for viscosity increase for engines operating on heavy fuel oil (HFO) as coagulation of asphaltenes from the HFO takes place in the lubricant when the HFO ingresses(CIMAC, 2011).

CONCLUSION

Monitoring the condition of the lubricant through used oil analysis will help an organization get the most value from their lubricant and equipment. The determination of the condition of the lubricant in service, enables the maintenance team to make decisions to enable correction of any mechanical, operational or environmental conditions that is affecting the lubricant which consequently the lubricant’s performance will affect the operations and integrity of the equipment. Relationships and interactions of the used oil analysis parameters can closely be monitored and predict some events that could possibly occur on the equipment in advance. This could enhance the maintenance decision making that can avert the impending failures or delay to the next maintenance schedule thereby reducing the downtime and improving in equipment efficiency and availability.

The proposed methodology has provided meaningful interpretations derived from the associations exposed by the various tools and methods used. The statistical correlation of the used oil parameters presented a good starting point for exploring the associations in the used oil data and acted as a dimensional reduction tool enabling the researcher to investigate on parameters that were correlated. The trend graphs offered useful visualization of the trends linked to each of the used oil parameters and enabled interpretation of the correlations. Expert assessmentalongside corroboration from literature validated the associations of the used oil parameter trends and the anticipated equipment operational condition. Lastly the use of a second data set for failure events enabled mapping the patterns from the used oil data to eventual failure events in the engine under study(Prabhakaran & Jagga, 1999).

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Future work would be to investigate how these relationships would enhance predictive maintenance decision support.

REFERENCES

/1/ Adnani, S. A., Hashemi, S. J., Shooshtari, A., & Attar, M. M. (2013). The initial estimate of the useful lifetime of the oil in diesel engines using oil analysis. *Tribology in Industry*, *35*(1), 61–68.

/2/ Almeida, A. ., & Energia, G. (2003). Lubricant condition monitoring. In *Gears and Transmissions Workshop* (pp. 231–244). Faculdade de Engenharia da Universidade do Porto, Portugal.

/3/ CIMAC. (2011). *USED ENGINE OIL ANALYSIS -USER INTERPRETATION GUIDE on Combustion Engines*.

/4/ Da-Silva, E. ., Neto, R. ., Assis, L. ., Matamoros, E. ., & Medeiros, J. . (2012). Study of chemical analysis of oil applying data mining techniques. In S. International (Ed.), *21st SAE BRASIL Internantional Congress* (Vol. 36–0412).

/5/ Farrel, P. J., & Stewart, K. R. (2006). Comprehensive study of tests for normality and symmetry: Extending the Spiegelhalter test. *Journal of Statistical Computation and Simulation*, *76*(9), 803–806. https://doi.org/10.1080/10629360500109023

/6/ Fitch, J. (2007). The Truths About Oil Analysis Data Trending. Noria Corporation.

/7/ Hauke, J., & Kossowski, T. (2011). Comparison of Values of Pearson's and Spearman's Correlation Coefficients on the Same Sets of Data. *Quaestiones Geographicae*, *30*(2), 87–93. https://doi.org/10.2478/v10117-011-0021-1

/8/ Jacazio, G., Libraro, M., Mornacchi, A., & Sorli, M. (2013). Lubricants Health Monitoring. *Phm*.

/9/ Keskin, S. (2006). Comparison of Several Univariate Normality Tests Regarding Type I Error Rate and Power of the Test in Simulation Based Small Samples. *Journal of Applied Science Research*, *2(5)*, 296–300.

/10/ Kumar, A., & Ghosh, S. K. (2016). Oil condition monitoring for HEMM – a case study, *68*(October 2015), 718–722. https://doi.org/10.1108/ILT-09-2015-0124

/12/ Prabhakaran, A., & Jagga, C. R. (1999). Condition monitoring of steam turbine-generator through contamination analysis of used lubricating oil. *Tribology International*, *32*(3), 145–152. https://doi.org/10.1016/S0301-679X(99)00028-6

/13/ Razali, N. M., & Wah, Y. B. (2011). Power comparisons of Shapiro-Wilk , Kolmogorov-Smirnov, Lilliefors and Anderson-Darling tests. *Journal of Statistical Modeling and Analytics*, *2*(1), 21–33. https://doi.org/doi:10.1515/bile-2015-0008

/14/ Rowland., G. R. (1919). Lubrication and Lubricants. *Journal of the American Society for Naval Engineers*, *31*(1), 97–138. https://doi.org/10.1111/j.1559-3584.1919.tb04845.x

/15/ Tsang, A. H. C., Yeung, W. K., Jardine, A. K. S., & Leung, B. P. K. (2006). Data management for CBM optimization. *Journal of Quality in Maintenance Engineering*, *12*(1), 37–51. https://doi.org/10.1108/13552510610654529

/16/ Unwin, A. (2013). *Discovering Statistics Using R by Andy Field, Jeremy Miles, Zoë Field*. *International Statistical Review* (Vol. 81). https://doi.org/10.1111/insr.12011_21

/17 Vähäoja, P., Välimäki, I., Roppola, K., Kuokkanen, T., & Lahdelma, S. (2008). *Wear Metal Analysis of Oils*. *Critical Reviews in Analytical Chemistry* (Vol. 38). https://doi.org/10.1080/10408340701804434

/18/ Woodyard, D. (2009). *Pounder's Marine Diesel Engines and Gas Turbines - Doug Woodyard - Google Books*. (Butterworth-Heinemann, Ed.) (9th ed.). Macmillan Publishing Solutions. Retrieved from https://books.google.be/books

/19/ Zhu, J., He, D., & Bechhoefer, E. (2013). Survey of Lubrication Oil Condition Monitoring, Diagnostics, and Prognostics Techniques and Systems. *Journal of Chemical Science and Technology*, *2*(3), 100–115.

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