*International Journal of Engineering Inventions*
*e-ISSN: 2278-7461, p-ISSN: 2319-6491*
*Volume 2, Issue 8 (May 2013) PP: 01-08*

# Statistical Hypothesis Testing Of the Increase in Wear Debris Size Parameters and the Deterioration of Oil

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***Abstract:*** *The effectiveness of lubricant diminishes with use. It also affects the condition of the surface which it is lubricating. Hence characteristics of the wear particles from the surface it is lubricating may change with the condition of the lubricant. This work attempts to investigate the morphological changes of wear particles with the oil degradation and can be helpful in finding the correlation between the two, the age of the oil and the morphology of wear debris.*
*Wear particles from the two gear oil samples at substantial operating time interval were filtered and their images were captured using SEM (Scanning Electron Microscope). These images were binarized and size parameters of these binary images were extracted using blob analysis, using an image analysis software. Increase in these size parameters with oil ageing were investigated by statistical hypothesis testing at 5% significance level.*
*Significant increase in a few parameters of size of wear debris was observed with ageing of oil.*
***Keywords:*** *electron microscopy, ferrography, gear oil, mining, significance level*

## I. Introduction

Early and reliable diagnostics, prior to machinery failure, is one of the key requirements for any maintenance system. Methodologies like vibration and acoustic monitoring, thermal and visual inspection, and wear debris analysis are currently used by maintenance personnel for this requirement [1]. Wear debris analysis is a component of oil analysis in which the wear debris being carried by the lube oil are trapped and analyzed for their chemical composition, colour, concentration, size distribution and morphology. The deterioration in machine components and their unexpected failure can be monitored and avoided by morphological analysis of wear particles as their morphological features are directly related to the mode and mechanism of wear existing in the component [2]. Visual examination of wear debris has been used as a cost effective machinery diagnostic method [3]. Fig.1 shows optical debris monitoring in the hierarchy of machinery failure prevention technology.

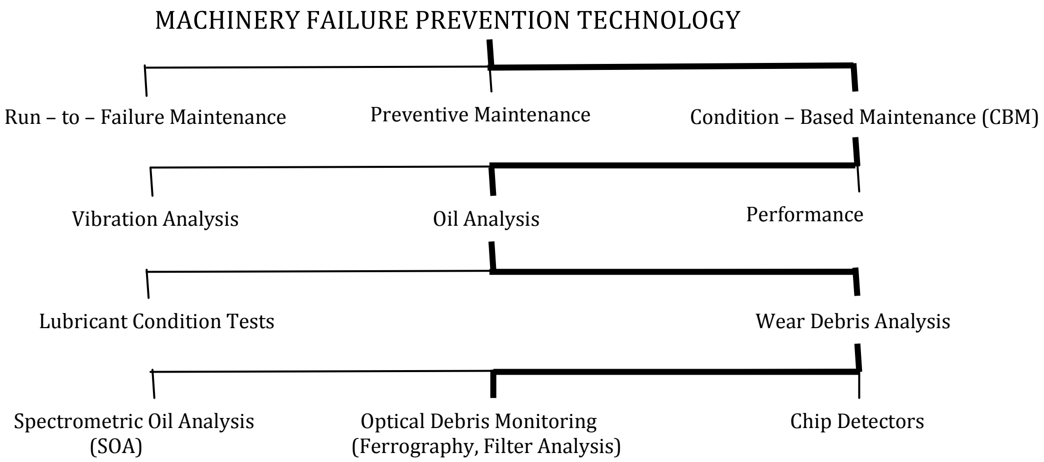



**Figure1: Optical debris monitoring in machinery failure prevention technology** [5]

The dependency on human expertise for the analysis and interpretation is the biggest hurdle for wear debris analysis to be exploited by the industry to its full potential and becoming one of the most powerful machine condition monitoring strategy. It makes the interpretation and result subjective in nature, costly and time consuming. Its remedy is developing an automatic and reliable wear particle classification standard [4]. In this conjunction, imaging techniques has been used to quantify the morphology of wear debris with numerical parameters. Two dimensional binary images of wear particles can indicate the specific wear condition under which they were generated [5]. This study uses binary images of wear debris separated from gear oil to extract some of the size parameters and performs statistical hypothesis testing to investigate their variation with the ageing of oil.

### 1.1. Previous Work

Since the advent of ferrography in 1970s, attempts are being made to use computer image analysis to extract the morphological features of the wear debris to develop a reliable and automatic wear debris classification system and also to study the distribution of these morphological parameters. Roylance and Pocock [6] have applied Weibull distribution function to the size distribution of wear particles for the study of wear condition. Kirk et al [7] have discussed different numerical parameters to describe the morphology of individual wear particles. The computer images of the particle were analyzed using software developed for this study. Ahn et al [8] have discussed statistical analysis based on the Weibull distribution function of skewness and mean particle size distribution of wear debris. Skewness give trend in wear debris generation and mean size represents severity of wear rating. Peng and Kirk [9, 10] and Peng [11] have used computer image analysis to extract different morphological parameters of wear debris and then applied some artificial intelligence tools to get an objective, reliable and automatic wear debris classification system. Cho and Tichy [12] have performed more comprehensive quantitative analysis of wear debris. Wear debris morphology is quantified with numerical parameters and further quantitative correlation is performed using multivariate statistical techniques to demonstrate how specific statistical data analysis can be used to find out morphological groups of wear debris. Cho and Tichy [5] have studied feasibility of observation of two-dimensional binary images of wear debris for detecting the change of wear conditions. Analysis of variance is applied to determine which morphological parameters are significantly affected by the difference in wear conditions. Laghari et al [13] describes a knowledge based system to classify wear particles according to their morphological attributes of size, shape, edge details, thickness ratio, colour and texture. Khan et al [14] describes an online debris shape analysis technique. It uses imaging technology and rule based algorithms to perform near real time debris analysis diagnostics.

### 1.2. Problem Definition

Cho and Tichy [5] using Analysis of variance had statistically investigated the influence of different wear conditions on two-dimensional debris morphology. Wear conditions were varied by changing loading conditions, material combinations, contact geometry, surface roughness and the oils used. They found that among the size, shape and curvature parameters, size parameters were significantly affected, shape parameters were moderately affected and curvature parameters were least affected by difference in wear conditions.

During its use lubricants degrade and many of its physical and chemical properties change. These changes must affect the wear conditions and hence a variation in the wear debris morphology is expected. The available literature on wear debris analysis focuses on determining the phase, mode and mechanism of wear to predict the condition of machines. No work has been found to study the change in morphological parameters of wear particles with the ageing of lubricating oil. Since among various two-dimensional morphological parameters, the size parameters are most affected by changing wear conditions, this paper tries to investigate the effect of oil ageing on some of the size parameters of wear particles.

## II. Methodology

Wear particles were filtered from the sample oil using a vacuum arrangement and their images were captured using electron microscopy. Image analysis software was used to process and analyze the image. Different size parameters were extracted from the images using blob analysis. When working with bright objects, a blob is a group of touching nonzero pixels. Any pixel with zero value is considered to be part of background. The size parameters used in this study were –

Area was calculated by counting number of pixels in the given blob in $\mu m^2$.

Perimeter was the total length of edges of the required blob in µm, with an allowance made for staircase effect.

Major length and minor length as described later in section 5.3, were determined using Feret's diameter.

Convex Perimeter is an approximation of the perimeter of the convex hull of the blob. It was derived from several Feret's diameters.

Hypothesis testing was used to verify our assumption about population parameter. Hypothesis testing is about making inferences about a population from only a small sample. In hypothesis testing we first make an assumption about the population parameter, called *null hypothesis*, $H_0$. Then this hypothesis is tested with the help of difference between the sample statistic and the hypothesized population parameter. How large the difference will be acceptable or not is totally the decision maker's choice and he decides it on the risk he assumes of rejecting a null hypothesis when it is true. This is quantified by a term called *Significance Level*, which sets a limit, when the difference between the sample statistic and hypothesized population parameter becomes significant enough to reject the hypothesized value [15]. For our studies, 5% significance level was chosen based on the available literature on wear debris analysis [5].

## III. Experimental Procedure

### 3.1. Sample Collection And Debris Separation

Gear oil samples were collected from the differential assembly of a dumper used for open cast coal mining. The first sample was at 200 hours of running after the drain off and recharge (called Sample1) and second sample was of drain off oil at 2000 hours of running (called Sample2). The dumper selected was of 100 ton capacity, Caterpillar make and the oil being used in it was of HTF C4 SAE60 type and MAK make. To ensure the sample drawing from mid layer of reservoir, vacuum pump with disposable plastic tube was used and samples were kept in plastic bottles with proper labels to identify them. The vacuum pump and storage bottles were rinsed with solvent and flushed with fresh oil to avoid contamination. Oil was filtered following a method described by Hunt [16]. 15 ml of sample was filtered without dilution with Axiva nylon filter of 0.2 μm pore size on a vacuum arrangement. The solvent was gently allowed to pass through the filter after switching off the vacuum pump. Then vacuum pump was run for around 20 minutes for air to pass through the filter paper to dry it, followed by drying in an oven at $120^0$C for approximately 24 hours.

### 3.2. Image Acquisition

A portion of around 12mmX12mm was cut from this filter and placed on a stub with both side adhesive carbon tape. The sample was gold sputtered at 5-10 Pa pressure and 10-15 mAmp current in Hitachi E1010 Ion Sputter. This sample was placed in SEM (Hitachi 3400N) with chamber pressure less than 1Pa to capture the images of wear debris. An Image at lower magnification of X40-X60 (Fig. 2) gives an overall idea of particle distribution in the oil. Our aim was to get random images of individual particles and ensuring also that the particles were not repeated. For this we started taking image of particle in one corner, say top left. After many trials, the magnification was fixed at X600 for image acquisition, as at this magnification image of most of the individual particles of significant size could be obtained. After capturing initial image at X600, we moved frame by frame with the direction keys, only in horizontal direction keeping the vertical coordinate fixed till we got a new particle in the frame. Image of this particle was captured and then we moved further right repeating the process till the other end of the sample was reached. Now we moved vertically downwards with direction keys, till all the area of previous frame disappeared from the new frame. We started moving left horizontally capturing the images appearing in the frame. The process was repeated till images of around thirty particles were captured. Thirty was kept to ensure that sample size was sufficient to apply central limit theorem and use normal distribution as an approximation to sampling distribution without having any idea about the actual distribution of population [15]. The process was repeated for Sample2. Fig.3 and Fig.4 are two such images from Sample1 and Sample2 respectively.

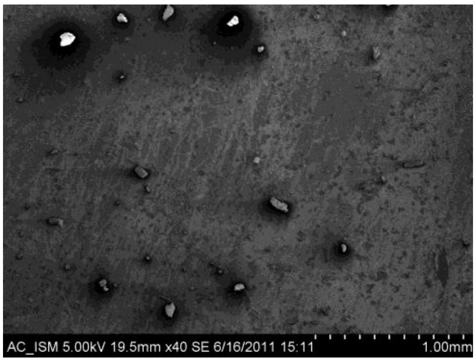



Figure2: SEM image at X40 magnification of debris filtered from gear oil Sample2

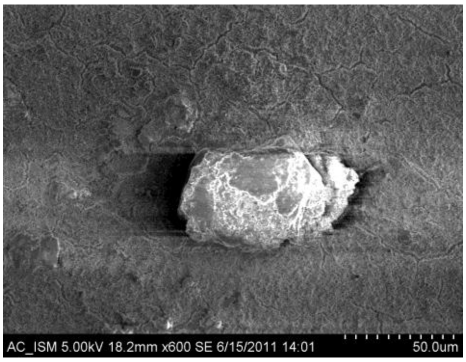



Figure3: SEM image of individual particle at X600 magnification filtered from Sample1

**3.3. Image analysis**

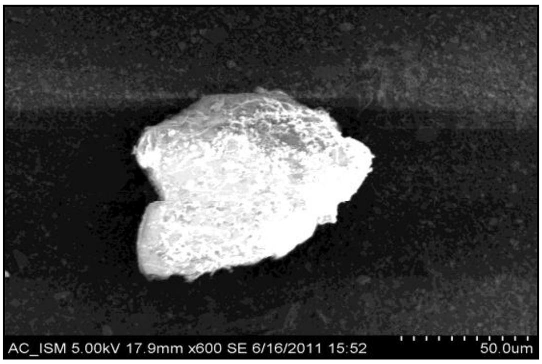



Figure4: SEM image of individual particle at X600 magnification filtered from Sample2

The image analysis was carried out using Matrox Inspector, Version 8.0. The main process steps performed on the image to extract different size parameters are shown in Fig. 5.

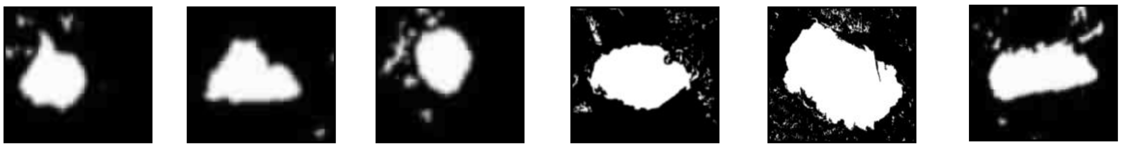
Loading the Image
↓
Preprocessing
↓
Image Calibration
↓
Cropping Image
↓
Recalibrating the Cropped Image
↓
Thresholding the image to
↓
First Blob Analysis
↓
Rotating the Image
↓
Second Bob Analysis
↓
Transfer of Data to Excel Sheet

Figure5: image processing steps performed

After loading an image it was preprocessed with brightness control, contrast control, flattening background and sharpening edges tools to improve the quality. Image was then calibrated to change the units from pixel world to real world. Image was cropped by selecting a rectangular region of interest around particle and removing the unnecessary portion of image. As cropped image may change its size, so it was again recalibrated. The image was binaries by thresholding to get white object and dark background. There might be some dark spots left inside the image of object and might be many bright noise in the background. They were rectified by Blob Reconstruct operations. Major length and minor length were determined using Feret's diameter, which is the maximum distance between two parallel lines which just touch the shape in the position it takes [16]. The angle of maximum axis of debris was found out in firs blob analysis step and the image was rotated by the same angle so that the maximum axis became horizontal. The major and the minor length are the width and the height of the rectangle box which just touch the debris [5]. Figure6 shows some of the rotated binary images of particles from Sample1 and Sample2. Size parameters: area, perimeter, convex perimeter, major length and minor length were derived in tabular form in second blob analysis step. By setting the minimum and maximum area options the calculations of other bright noise blobs present were discarded. The data was then transferred to Excel sheet for further calculations and analysis.

## IV. Result And Discussion

Table1 lists the range of values, mean value and standard deviation of different size parameters of images of particles in Sample1 and Sample2. Images of 33 particles were captured from Sample1 and 34 particles from sample2. The mean value of all the size parameters from Sample2 was found to be greater than Sample1. As the results of one set (Sample) might not be extended to the complete population, having uncountable particles, hence the hypothesis testing was used to draw inferences about the population.



**Sample**

**Sample**

Figure6: binary and rotated images of some of the particles from Sample1 and Sample2

Table1: Size parameters of images of particles in Sample1 and Sample2

| **Sample1 (for 33 particles)** | | | | | |
|---|---|---|---|---|---|
| **Range of Parameters** | **Area in μm$^2$** | **Parameter in μm** | **Convex Perimeter in μm** | **Major length in μm** | **Minor length in μm** |
| **Mean** | 29.083 – 4717.519 | 20.997 – 507.957 | 19.987 – 282.290 | 6.500 – 99.995 | 6.000 – 81.496 |
| **Standard. Deviation** | 672.862 | 123.639 | 84.480 | 30.778 | 22.803 |
| | 1129.791 | 115.237 | 65.932 | 23.684 | 19.051 |
| **Sample2 (for 34 particles)** | | | | | |
| **Range of Parameters** | **Area in μm$^2$** | **Parameter in μm** | **Convex Perimeter in μm** | **Major length in μm** | **Minor length in μm** |
| **Mean** | 33.111 – 5764.222 | 26.280 – 491.886 | 23.675 – 331.523 | 8.333 – 137.167 | 7.167 – 79.000 |
| **Standard. Deviation** | 1240.647 | 155.821 | 122.579 | 46.216 | 30.353 |
| | 1585.635 | 116.815 | 82.158 | 31.687 | 20.924 |

**4.1 Hypothesis testing**

The symbols used in the testing are –

$\mu_1$ - Mean value for population 1 (All wear particles in gear oil after 200 hrs. of running)

$\mu_2$ - Mean value for population 2 (All wear particles in gear oil after 2000 hrs. of running)

$\bar{x}_1$ - Mean value for Sample 1

$\bar{x}_2$– Mean value for Sample 2

α – Significance level

$\hat{\sigma}_1$- Estimated standard deviation of population 1 and $\hat{\sigma}_1 = s_1$

$\hat{\sigma}_2$- Estimated standard deviation of population 2 and $\hat{\sigma}_2 = s_2$

As standard deviation of populations are not known to us

$s_1$ – Standard deviation of Sample1

$s_2$ – Standard deviation of Sample2

$n_1$ – Number of observations in sample 1

$n_2$ – Number of observations in sample 2

**4.1.1. Hypothesis Testing** for area

$H_0 : \mu_2 = \mu_1$; Null hypothesis : There is no difference in the mean area of particles in population 1 and population 2.

$H_1 : \mu_2 > \mu_1$; Alternative hypothesis: Population 2 has particles with mean area greater than that of population 1.

α = 0.05; 5% significance level

| | |
|---|---|
| $\bar{x}_1 = 672.862\mu m^2$ | $\bar{x}_2 = 1240.647\mu m^2$ |
| $s_1 = 1129.791\ \mu m^2$ | $s_2 = 1585.635\ \mu m^2$ |
| $n_1 = 33$ | $n_2 = 34$ |

Standard deviation of populations was not known, hence the estimated standard error of the difference between two means

$$\hat{\sigma}_{\bar{x}_2-\bar{x}_1} = [\frac{\hat{\sigma}_1^2}{n_1} + \frac{\hat{\sigma}_2^2}{n_2}]^{\frac{1}{2}}$$

As $\hat{\sigma}_1 = s_1$ and $\hat{\sigma}_2 = s_2$

$$\hat{\sigma}_{\bar{x}_2-\bar{x}_1} = [\frac{1129.791^2}{33} + \frac{1585.635^2}{34}]^{\frac{1}{2}} = 335.601$$

When the difference of sample means, $\bar{x}_2$ - $\bar{x}_1$ , was standardized

$$Z = \frac{(\bar{x}_2 - \bar{x}_1) - (\mu_2 - \mu_1)_{H_0}}{\hat{\sigma}_{\bar{x}_2-\bar{x}_1}} = \frac{(1240.647 - 672.862) - 0}{335.601} = 1.692$$

Both samples were large enough to allow us to use Normal distribution. From Normal distribution table the nearest critical value of Z corresponding to 5% significance level was 1.65.

Statistical analysis gave results: Z=1.692 which was greater than $Z_{critical}$ =1.65. Hence, Null hypothesis was not accepted. The alternative hypothesis was accepted- that the particles in the oil after 2000 hours of running have mean area greater than that of oil after 200 hours of running. Graphical representation of the result is shown in Fig.7.

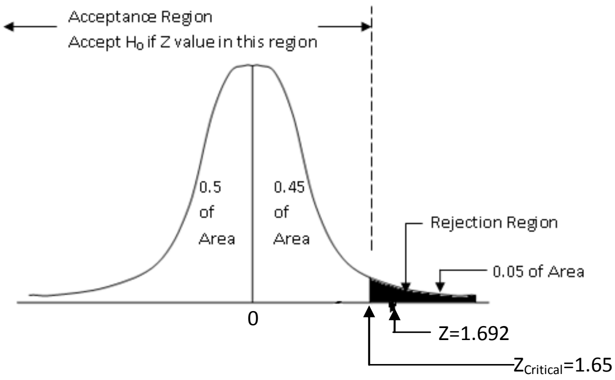



Figure7: Hypothesis test for increase of Area at o.o5 level of significance

During the study it was found that differential of the dumper was running without any trouble. It continued to perform well for a pretty long time. Hence, it may be concluded that the increase in mean area was due to oil deterioration.

**4.1.2. Hypothesis Testing For Other Size Parameters**

Similar analysis was done for other size parameters. Results are shown graphically, Fig.8 to Fig.11. For perimeter Z=1.135 < $Z_{critical}$ =1.65, null hypothesis was accepted. It can be inferred that particles in the oil after 2000 hours of running do not show significant increase in mean perimeter than that of oil after 200 hours of running (Fig.8).

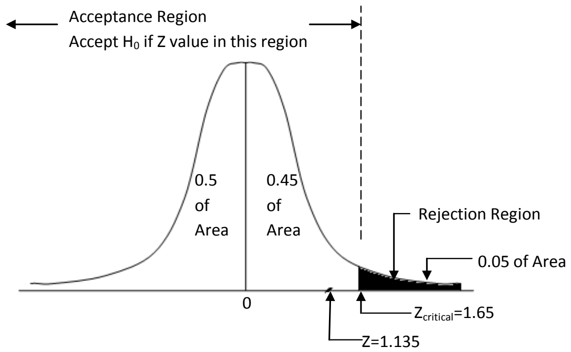



Figure8: hypothesis test for increase of Perimeter at o.o5 level of significance

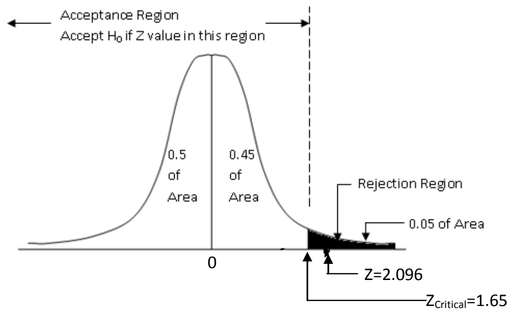



Figure9: hypothesis test for increase of Convex Perimeter at o.o5 level of significance

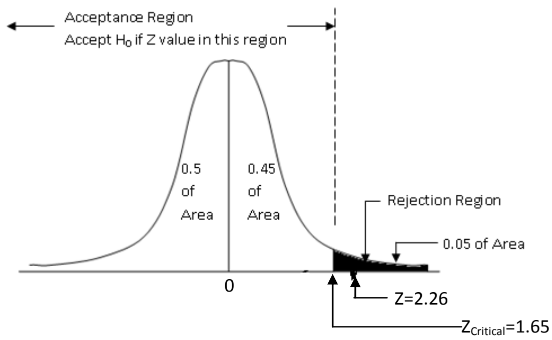



Figure10: hypothesis test for increase of Major Length at o.o5 level of significance

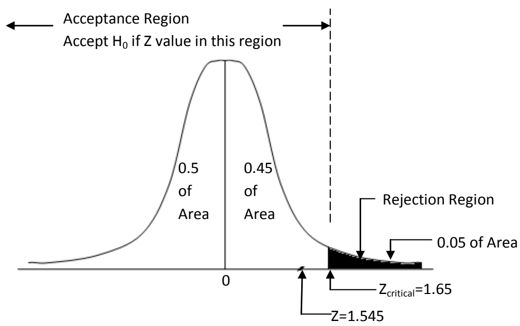



Figure11: hypothesis test for increase of Minor Length at o.o5 level of significance

The results for Convex Perimeter, Major Length and Minor Length are shown in Figure9, Figure10 and Figure11, respectively. For Convex Perimeter, $Z=2.096 > Z_{critical} = 1.65$, the alternative hypothesis was accepted. It can be said that Convex Perimeter of particles in oil after 2000 hours of running is greater than that of particles in the oil after 200 hours of running. Similarly, for Major Length being $Z=2.26 > Z_{critical} = 1.65$, significant increase with ageing of oil was concluded. Minor Length had $Z=1.545 < Z_{critical} = 1.65$, so the null hypothesis of equality was accepted: Minor lengths do not show significant increase.

## V. Conclusion

This paper investigated increase in size parameters, from the two dimensional binary images of wear particles, with ageing of gear oil. Five parameters – area, perimeter, convex perimeter, major length and minor length were measured. Among these, area, convex perimeter and major length showed a significant increase, whereas perimeter and minor length did not increase significantly. It indicates that some of the size parameters are significantly correlated with the oil condition, and this correlation needs to be investigated further.

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