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A Short Review on Direct Detection Method of Wear Particles In Used Lubricant

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Abstract

Analysis of wear particle is considered to be one of the most nondestructive techniques in industry. In this method used lubricant of different hours of operations has to be collected for the testing purpose. The wear particles that has been generated due to friction of two or more mating surfaces are carried away by the lubricant are detected, tested and analyzed. The prime advantage of this method is the information regarding engine, gears or any machine part where lubricant is used can be obtained without opening the assembly. Many researchers have also related this technique with the blood test of the human body. The oil condition monitoring can be performed in both in-situ and ex-situ condition. Mostly three different methods i.e. Direct Detection method collection and Inspection method and Sampling and analysis method are there which have been used to identify the problems into the assembly. In this article a discussion related direct detection method will be done.

Introduction

Wear debris analysis of used lubricant are now being used in different research organization as well as in many industries due to their accuracy of failure prediction. The most advantageous fact about this technology is this testing can be performed in both is situ and ex situ method, and both of them are very less time consuming.

It is a very common fact that the mostly machine failure occurs due to wear and tear of the components [1]. In nondestructive testing method there are mainly two types of testing are involve. One is vibration monitoring and another is oil condition monitoring [2, 3]. It has been reported by many researchers that the cost and time requirement in the report preparation is higher in oil condition monitoring as compared to vibration monitoring. But oil condition monitoring gives us a overall idea of the system. In actual practice the wear particles are generated in the machine are due to the friction of the two or more mating part [4]. These particles carry information about the machine part from where it is generated. Testing of this particle can give the information about the type of wear, and the reason behind the wear mechanism. This data are actually derived from wear particle shape, composition of the particles, size distribution and the curves of the particles. The current wear mechanism inside the machine due to improper loading or force distribution can be analyzed with this testing method. The

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expert examination of the particle morphology and composition are also required to examine the wear mechanism [5]. The oil condition monitoring has been classified in Fig. 1.

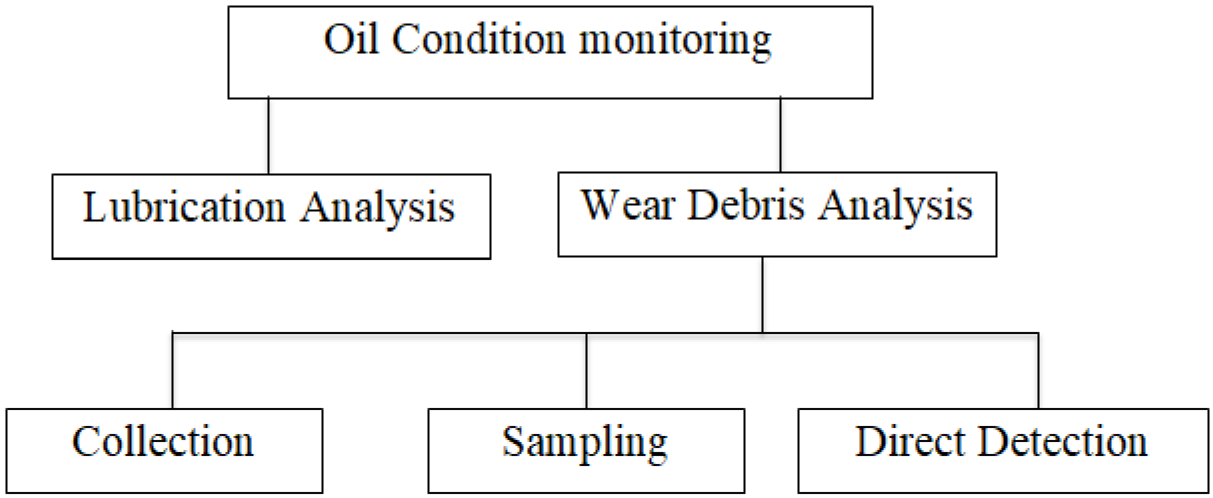

Fig.1. Classification of oil condition monitoring

Methodology

From the open literature it has been observed that there are many different types of wear particle analysis have been performed. Direct Detection method collection and Inspection method and Sampling and analysis method are the most common among all and have been performed by many researchers. Although in this article the discussion about the direct detection method will be done. The online direct detection methods are mainly consist of two sensor i.e. Single oil property sensors and integrated oil properties sensors.Single oil property sensors are responsible for the identification of the size distribution and integrated oil property sensors are mainly responsible for analyzing oil degradation information. Integrated oil properties sensors used to collect data related to wear debris, water content, viscosity, soot content, TAN, etc. These sensors can further be classified into Inductive, Capacitive, Ultrasonic, Optical, XRF sensors. The detail analysis with the help of these sensors and technique will be discussed in the next section.

Direct debris detection

Direct debris monitoring provides real-time information about machine health that could be used for avoiding the catastrophic component failure during operation and gives a prognosis of pending machine fault[6], failures, and long-term trends to facilitate engine overhaul and maintenance planning. Close to 60% of the occurrences of failure in bearings due to either corrosion, solids contamination in the oil [7].

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Direct detection of wear debris is classified in tot two major categories based on their outputs: wear degree and wear mechanism. Wear degree is always reflected by wear debris producing rate and is obtained easily by most on-line technologies. Wear mechanism, generally reflected by features of wear debris such as morphology, color and composition [8, 9]. The online wear degree sensors are simple and gives near results as offline and wear mechanism extractors are much complicated and results varies widely. All these reasons maintenance engineers won't blindly depends on the online analysis results but in recent developments in online sensors gains the trust of reliable information about the condition of machine.

Online sensors are two types: [10, 11]

1. **Single oil property sensors**: Single-purpose sensors like size, viscosity, quantity is most available. Those are Inductance, Capacitance, Ultrasonic, Optical and X-Ray sensors listed table below [12].
2. **Integrated oil properties sensors***:* Integration of multiple sensors to collect more information regarding oil degradation (e.g. wear debris, water content, viscosity, soot content, TAN, etc) rather than to a specific property.

A multi-parameter rather than one-parameter description is necessary and effective for better understanding the condition of the machine[13]. These are suffering from the multiple factors affecting the accuracy (cross-sensitivity) and miss-accuracy occur by variation in flow and temperature of the oil, it can be corrected by closed-loop analysis [14]. The weighted combination method gives the sophisticated results one such method used in diesel engines [15]. Although the increase in sensors generates big data, artificial neural network (ANN), principal component analysis (PCA) are more helpful due to their complex problem-solving capabilities.

Separation and Characterization

It remains a bottleneck of getting the geometrical dimensions of on-line particles because of the low-resolution determination, contamination and particles chain example of an online image analysis. Because of the low quality of online molecule pictures, it is essential that suitable clever calculations are created by the geometrical properties for multivariate flotsam and jetsam order [16]. The recent improvement in on-line wear checking with wear flotsam and jetsam image recognizes each single particles [17], automatic and intensive sampling make direct condition monitoring highly reliable to real-time wear conditions [18].

Separation and characterization of particles in liquids by direct debris difficult due to the blurred edges, complex morphology (colour, shape, and surface texture) of debris [19]. Particle morphology gained from current two-dimensional (2D) images does not contain thickness information which can be basic in wear component elucidation. A new 3D technique which by video film provides the thickness data as well as particle volume which can be used to estimate both material loss and wear rate [20]. The thickness information, are very useful for identifying wear particles which have similar features on their dominant surfaces but different heights [16].

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Online image analysis transforms images into binary form, computer-aided analysis are neural network [21] and ant-colony [22] has been applied to singular wear debris, yet separating the debris from their current patterns remains a teddies task [23] with regard to aggregated particle disassociation in the image [24].

For debris quantitative analysis distance-based methods are popular [25] but these have errors of over-segmentation that increase debris counting [24]. In addition that ultimate corrosion by extreme corrosion and conditional expansion (UCCE)) transformation results in an flawed ID of dividing lines of separated wear debris but it leads to miss- ID of the boundaries of wear debris due to consider a undeviating or uniform scale. The enhanced multi scale technique by incorporating the ultimate corrosion and condition growth (Considering different scales) developed for on-line purposes give the higher separation accuracy and efficiency by applying a adaptive corrosion strategy [26].

The approach makes utilization of images captured from both transmitted and reflected illuminations on the oil passage. To ensure particles are either individually single or not, initially the step followed started with binarizing the diffused image followed by extraction of edges, and further reflecting image was processed with help of enhanced watershed algorithm at its grey levels [27]. Watershed algorithm is delicate to noise and local excesses, over-segmentation is predictable when it is applied to the segmentation, especially to large size wear particles. Wang [19] tried to eliminated by relating the grey clustering algorithm and marker-controlled watershed for separating wear particles rapidly and accurately.

WU [18] built up an arrangement of debris using their statistical RBGcolours formats into hue, saturation, intensity (HSI). These online images were first binarized to detect all wear debris and the exact wear debris was extracted by their pixels from the corresponding reflected image. Hove ever these images are not proper for evaluating each and every particle. This can avoid image pre-processing method by separate the particles from the background prior to the colours of the wear debris were extracted to enhance the image quality through a motion-blurred restoration process [28] even though some problems with the size and sensing range are facing by these sensors, but this size difference can be eliminated malty size filters technique.

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Table 1: Types of online wear debris sensors [8]

Type of sensor	Measuring Range (µm)	Material Detected	Reference
Inductive	10-3360	Ferrous & Non-Ferrous Debris	[18]
Capacitive	10-1000	Metallic Debris	[5]

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Ultrasonic	50-1000	Metallic Debris & Air Bubbles	[32]
Optical	5-160	Solid Debris	[30]
XRF	0-50	Metals & Non-metals	[14]

Conclusion

In this paper a detailed discussion about direct detection method of wear particle from available open literature has been done. It has been seen that the researchers are basically single oil property sensors and integrated oil properties sensors for online condition monitoring. Size distribution of the wear particle is mostly performed by the single oil property sensors and the oil degradation parameters are mainly performed by the integrated oil properties sensors. It has also been reported that wear flotsam and jetsam image technique have been increased the accuracy of the wear particle analysis. The 3D analysis of wear particle is increasing the accuracy because traditional 2D particle imaging system is unable to generate the particle thickness data. Particle thickness can only be available in 3D technique. With the help of particle thickness the exact volume losses can also be calculated. Although it has also been discussed that only these techniques are not sufficient enough to conclude the exact oil and machine part condition. Many more supporting information of used lubricant from analytical ferrogram , FTIR and atomic emission spectroscopy is also required.

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