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OPTIMIZATION OF WEAR PARTICLE AND DEBRIS CLASSIFICATION

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Abstract: *The paper presents the possibilities of automatic classification of wear particles and fragments, which carry significant information about the wear regime of complex mechanical closed systems using a lubricating medium, e.g. internal combustion engines, transmission, hydraulic and turbine systems. The paper presents the possibilities of optimizing the classification of particles obtained by ferrography using information obtained by a laser counter and a particle classifier. The author, in addition to the possible morphological classification of particle parameters, prefers machine learning using a feedforward neural network with backpropagation of the error. A relatively detailed expert classification of particles resulting from common wear mechanisms, which are used as a classifier, is presented here.*

Keywords: *wear particles and debris, image analysis, classification, machine learning, neural network*

1. INTRODUCTION

A significant phenomenon of tribotechnical diagnostics in the field of wear of mechanical systems is the classification of wear particles. Wear of mechanical systems does not depend only on the nature of friction, but is a relatively complex physicochemical process occurring on the surfaces of the tribological unit. An external, undesirable product of friction of mechanical systems is a wide range of wear particles and fragments [1]. From the point of view of technical condition diagnostics, however, it is important that particles and fragments carry basic information about the wear process, the conditions of particle formation and the wear regime of a given complex mechanical system usually using a lubricating medium (internal combustion engines, transmission mechanisms, hydraulic systems, turbines, etc.). A complex engineering product of this type is characterized by the simultaneous contact of many friction pairs and the simultaneous production of wear particles [2]. Tribotechnical diagnostics describes the processes that occur or predominate in the system based on the number, distribution, size, shape, color, surface morphology, rate of formation, intensity and increase, material composition, etc.

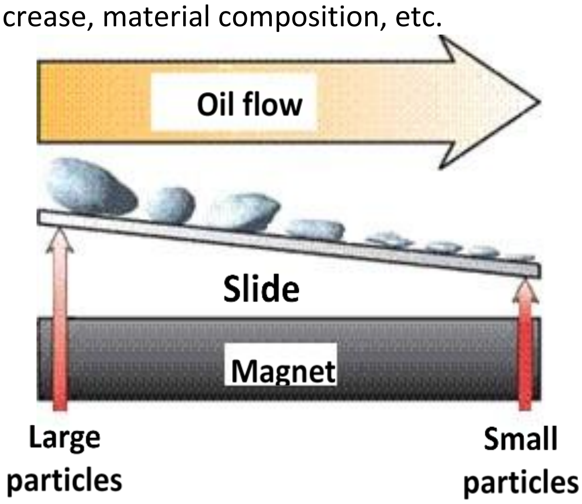


Figure 1. Principle of ferrography

The issue of diagnosing wear particles and fragments has been addressed by ferrography for a relatively long time, Fig. 1 [9]. However, the interpretation of the results was somewhat subjective, which very often depended on the knowledge and especially the experience of the operator. This method allowed for ferrodensometric or ferroscopic clarification of the ferrogram [3], calculation of the wear intensity index I_0, evaluation of the density of the ferrographic trace F_d, or expression of the standardized wear index J_S, assuming a normal distribution of the deposition density of large D_L and small particles D_S, when

$$J_S = \left(\frac{x-\mu_x}{\sigma_x}\right)^2 + \left(\frac{y-\mu_y}{\sigma_y}\right)^2, \qquad (1)$$

where μ_{xy}… is the mean value and σ_{xy}^2… is the variance. In doing so, we describe the result of diagnostic measurements assuming a normal distribution. $X \sim N(\mu, \rho^2)$. As a quantitative measure for densometric evaluation of the ferrogram PLP, characterizing the proportion of large particles in the taken sample of lubricating medium, when the following applies

$$PLP = \frac{D_L}{D_L + D_S} \cdot 100\ [\%]. \qquad (2)$$

The specific concentration of wear particles in a unit volume of the investigated lubricating (hydraulic, turbine) medium V is

$$WPC = \frac{D_L + D_S}{V} \cdot 100\ [\%]. \qquad (3)$$

Currently, analytical ferrography is gradually being replaced by new methods, but it is still used in practice. This contribution briefly shows possible tools for eliminating the subjective influence of the operator and replacing it with tools for automatic classification of particles into classes corresponding to wear mechanisms. The replacement of analytical ferrography includes a methodology for sophisticated particle analysis of lubricating media, hydraulic fluids and turbine mixtures. An example is a laser counter, particle classifier and a device for tracking ferroparticles $> 25\ \mu$m allowing distribution according to their size (Spectro LaserNetFines Q200, etc.), Fig. 2.

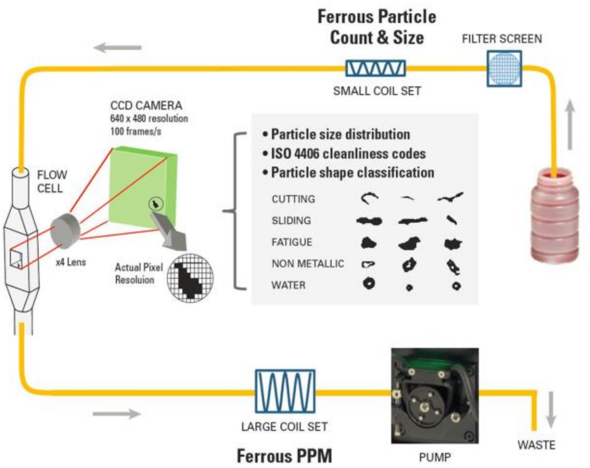


Figure 2. Schematic of a laser counter, particle classifier and ferroparticle tracking device

This device allows classification of abnormal abrasion, counting of particles of size 4 - 100 μm, with a saturation limit of up to 5 million particles/ml (with minimal error $< 2\%$), the viscosity range is according to ISO15 to ISO320 (without dilution), allows error correction for the presence of free water (ppm) and air bubbles, distinguishes contaminants (silicates), and gives the possibility of illuminating dark samples (containing up to 2% soot) with automatic laser control. The device allows counting particles and codes for the following standards: ISO 4406, NAV 1638 NAVAIR 01-1A-17, ASMT D6786, SAE AS 4059 and other user-defined parameters. The device uses modern data export formats including Automatic storage management, as well as backup at the extent level (mirroring), file distribution on multiple disks (striping), allows changing configurations (balancing), etc. This modern method, in addition to the number of particles, abrasion modes, non-metals, fibers, etc., displays silhouettes of metal particles, which, however, are only informative and are the result of averaging real images (shape, size) using a CCD camera (resolution 640x480 pixels). This fact allows using these shapes (silhouettes) in a similar way as when analyzing ferrography results [4-5]. An important issue is the mechanisms of wear of mechanical systems, which generally include the following types: adhesive, abrasive, erosive, corrosive, cavitation, fatigue, vibration and their combinations [6].

2. PARTICLES CLASSIFIED ACCORDING TO THEIR FORMATION MECHANISMS

The shapes of wear particles and their predominant origin are given in Table 1. Adhesive wear is characterized by the separation and displacement of particles as a result of relative movement due to intermolecular attractive forces (chemical and physical), while surface layers are broken, plastic deformations and thermal micro-joints are formed. The particles are "one-dimensional", their width and thickness are approximately identical, they usually have an elongated shape, often with an irregular grooved edge, jagged edges, the size exceeds 25 - 50 μm, sometimes plates, flakes or scales. They are characteristic of the wear of steel parts; therefore, they have good magnetic properties. The genetic origin is in the Beillby layer from which they gradually peel off and are washed away by the lubricant. Their number and size characterize the intensity of wear. Adhesive particles larger than 15 μm indicate increased stress on the friction pair. Abrasive (cutting) wear involves the separation of particles from the functional surface by the action of a hard (rough) surface of another body or the penetration of a harder material into a softer one. Abrasive particles are characteristic of an incorrect mode of the diagnosed system. Grooves are formed, their number is inversely proportional to the size of the abrasive particles. The particles have an elongated shape and resemble chips, spirals or cocoons in shape [5], [7]. However, they have smooth edges and surfaces. Abrasive particles formed during the running-in mode of the system have the shape of crescents or swords with sharp protrusions at the ends. The size ranges from 50 to 300 μm, with a relatively small thickness of about 0.25 μm. Fatigue particles are formed during cyclic stress by gradual accumulation of defects usually on the surface of functional surfaces. Fatigue wear has a rolling character in the area of fatigue of the Beillby layer. The area of microcracks gradually spreads, pitting (round-shaped pits) or spalling (peeling of the surface layer) appears. The particles have the shape of spheroids (balls), or their rolling (as a result of multiple passes through the machine system) creates thin flat flakes, micro-chips (chunks), high-temperature abrasion (scuffing), pebbles, canopies and flats. The dimensions of the spheroids are about 2 - 50 μm. The shape of the spheroids is regular, the edges and surface are smooth, or cracked, the color is bright. It has been experimentally verified that a single rolling element produces 6 - 7 million spheroids until its failure occurs. As a result of redistribution processes in the lubrication systems of machines, laminar particles are formed. Repeated passage of the lubricating medium leads to plastic deformation and rolling of three-dimensional particles and spheroids formed by various wear mechanisms into thin flat flakes, 20-50 μm long, 10-50 μm wide, irregular in shape, with jagged edges and a grooved, cracked surface, sometimes with holes, bright in color. Abnormal (borderline, emergency) particles usually arise during massive abrasion or seizure. Their cause is the mechanical disruption of the Beillby layer, under excessive load. At the point of contact of the friction pair, this layer does not have the necessary load-bearing capacity. The result is three-dimensional particles with a characteristic sharp edge and dimensions of 30 - 70 μm. The shape is irregular, the edges are jagged, the surface is grooved and the color is bright. Non-ferrous particles are formed, for example, by the interaction of steel and non-ferrous metal alloys, usually in adhesive wear. Vibration wear is caused by mutual oscillating tangential displacements of functional surfaces under normal load, which is usually accompanied by the formation of iron oxides. Iron oxides, e.g. Fe_3O_4 (magnetite) are formed at high temperatures and pressures, usually in the event of insufficient lubrication. The particles have a black, smooth surface, pebble shape, and a size of about 5 μm. Furthermore, Fe_3O_4 (hematite) usually signals corrosion of functional surfaces. The particles are pink to red. Corrosive particles can be formed secondarily by the chemical reaction of free metal particles with acidic components of the lubricating medium. They have a green color, translucent edges and a red core. Other particles include non-metallic particles, usually of secondary origin. These include, for example, dust particles (silicates), spherical or prismatic in shape, clear (translucent), size up to 30 μm. Fibers usually made of filter materials (cotton, synthetic materials), loop- shaped or straight, with significant light refraction at the ends. Tribopolymers with a thin steel core and organic matter, usually have the form of spherical particles or cylinders. Cavitation wear involves the separation of particles at the points of collapse of cavitation bubbles during turbulent flow in hydraulic systems. Cavitation involves places where the velocity of the flowing liquid increases, resulting in a decrease in pressure, the formation of bubbles and their imposition , resulting in a shock wave, the pressure of the liquid reaches the order of 103 MPa and temperatures up to hundreds of ^{o}C. The surface of the system is bombarded by molecules of the liquid (water in cooling systems), resulting in shocks, vibrations, erosion and noise, which massively damage the material and in extreme cases lead to failure of the entire system.

Table 1. Wear particle shapes and their probable origin [4-5]

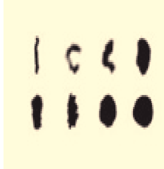
Typical shape	Particle category	Possible origin
	sphere	fatigue particles (spheroids)
	ellipsoids deformed, smooth	dust particles (SiO_2 etc.)
	plates, flakes, scales	adhesive particles (amorphous)
	pebbles, tops and flats	fatigue, pitting corrosion etc.
	scrolls	delamination Beilby layers
	spirals and cocoons	cutting (abrasive) wear
	chains and fibers	fiber additives, silicones, cotton, etc.

3. OPTIMIZATION OF WEAR PARTICLE CLASSIFICATION

A proven possibility based on the morphological parameters of particles is a method using particle shapes that are exactly mathematically described. These are an equivalent circle (diameter with the same area as the particle), circularity (deviation from the circle in the interval $< 0, 1 >$where the value 1 exactly corresponds to a circle), aspect ratio, cardinality, minimum distance between two vertical and horizontal parallels, maximum and minimum distance between parallels that border the particle, diameter of the smallest circumscribed circle, diameter of a circle that has the same circumference as the particle, length of a line that divides the particle into halves, height and width of the smallest circumscribed rectangle, length and width of a rectangle that has the same area and length as the particle. Details in [1-3], [6-8]. An important area of optimization of wear particle classification are machine learning techniques. Machine learning is a sub-part of artificial intelligence that deals with algorithms that allow a computer system to "learn". By learning we mean changes in the internal state of the system, optimizing the ability to adapt to changes in the surrounding environment. These techniques include procedures that allow us to create a model for classification classes (wear mechanisms from which the obtained particles originate) from the so-called training data set (in our case, particle images) so that new results of image analysis are assigned to the appropriate class. These techniques allow us to search for hidden knowledge in data that in our case has an image form. The entire classification process consists of assigning the image of wear particles, which is described by symptoms, to the appropriate class. The first step is to divide the data into a training and test set. In doing so, we teach the classifier to recognize individual particle images based on known practices of verified expert evaluations of the actual wear mechanisms from which the respective particle images originate. There are data (particle images) available that we know how to classify, and through gradual processing, the classifier learns to recognize the class for unknown data. Classification is generally divided into binary (i.e. belongs or does not belong to a given class) and multi-criteria (probability of being assigned to one of several monitored classes) [9]. There are a relatively large number of machine learning techniques, one of the most frequently used of which is neural networks. For example, a laser counter, a particle classifier and a device for tracking ferroparticles work on their principle, which allows the use of suitable training patterns (particle images). An important prerequisite for successful use is the selection of a suitable neural network, however, this problem is not the subject of the presented contribution, since it was solved at the level of AI specialists. Specifically, a feedforward network with backpropagation of error was used. Training data (normalized particle images) were input and the output was compared with the desired output (which are known images that, according to experts, come completely unambiguously from defined wear mechanisms), and the error was then calculated [10-12]. Normalization is the conversion of the particle image to a uniform size and rotation along their main axis. By setting the input weights of the neuron, the error is minimized, the process is repeated with the neurons of the previous layers up to the input layer, while adjusting the neuron weights to minimize the learning error. The error for a given classifier setting is the ratio of incorrectly classified samples *TN* (True Negative), correctly classified samples *TP* (True Positive) to the total number of samples, it is valid

$$err = \frac{FP+FN}{TP+TN+FP+FN}. \quad (4)$$

The Real AdaBoost algorithm was used as a wear particle classifier [13-14]. This algorithm uses decision trees and updates their weights after each iteration based on the error rate function. The algorithm is mainly focused on weakly classified results (Haar symptoms), and generally serves to create a strong classification function using several weak classifiers. The algorithm is a powerful machine learning technique that improves the accuracy and performance of a predictive model [7]. An example of particle images before normalization Fig. 3, images after normalization Fig. 4 and images of particles entering the classifier are shown in Fig. 5 [2], [4-5]. Fig. 6 [9] shows selected output information from the laser counter and particle classifier (total number of particles, particle diameter and maximum size, number by origin mechanism, amount of soot, current and past measurements, etc.).

		
Figure 3. Particle images before norm.	**Figure 4.** Particle images after norm.	**Figure 5.** Particle images entering the classifier

4. CONCLUSION

The presented contribution cannot provide an exhaustive overview of the possibilities of using automatic classification of wear particles and fragments in specific applications nor does it describe in detail the solution of specific tasks. The wear process can be considered as an open system in which very complex physical-chemical processes usually take place on the surface of individual bodies.

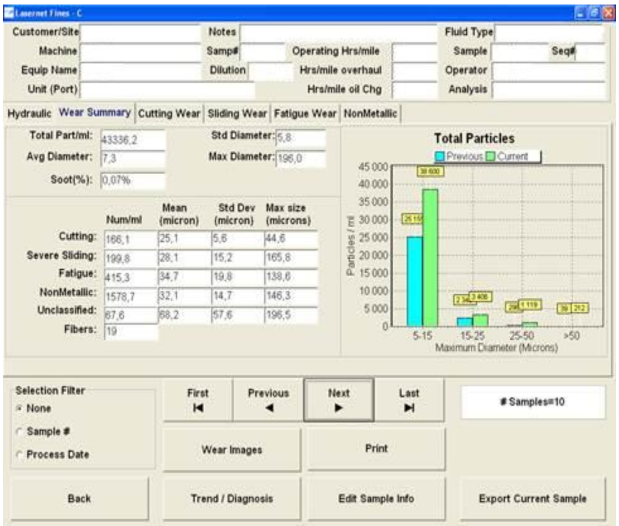


Figure 6. Selected information from the laser counter and particle classifier

It is a complex process that is a function of many factors simultaneously occurring in real time. The mechanism itself cannot be described by means of classical mechanics, because the contact surfaces of friction surfaces are composed of discrete flats and are therefore not homogeneous isotropic bodies, and the volume of material transmitting the load is not constant either. The basic object that can be the subject of modeling the wear process of an internal combustion engine is a data sequence , which is a set of samples between two subsequent oil changes in a specific engine. A set of sample sequences derived from one engine describes the engine from a tribological point of view within its operation. Tribological data then form a hierarchical structure. Analysis of wear particles and fragments represents the realization of a random variable $X(t)$, which has a non-stationary character, when $E[X(t)] = f(t, p)$, where f is a generally non-decreasing function depending on the vector of parameters p . The author's intention is to draw attention to a rapidly developing industry that allows a wide range of applicability in diagnostic practice. The experiments used showed a relatively small error rate of up to 15%, which brings a significant improvement compared to the results of subjective assessment. Further use assumes a focus on improving the quality of the classifier, e.g. using an extension of the AdaBloost algorithm, or using real time approach, accelerating the calculation of features (integral image), with the WaldBloost algorithm [15].

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