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Using acoustic emission signal categorization for reconstruction of wear development timeline in tribosystems: Case studies and application examples

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ABSTRACT

The purpose of this work is to demonstrate how a new acoustic emission (AE) technique can be used to monitor friction surface degradation in a four-ball tribosystem under different types of lubrication. The AE method is based on a novel signal spectral categorization technique, and it was used to identify concurrent degradation processes in bearing steel. The correlation of AE features with the development of specific microstructural features on the contact surfaces has been used to identify the AE "signature" of specific damage mechanisms, and thus to monitor the progression of wear. The proposed approach enables the construction of a chronology of lubricant and/or contacting material degradation during tribological testing with a high degree of confidence. Furthermore, it provides an efficient means for automated wear monitoring and for real-time, non-supervised interpretation of the state of wear in a given tribosystem.

1. Introduction

Tribological testing is routinely used to evaluate the performance of lubricants and properties of contacting materials. The behavior of lubricants is influenced, among other things, by various external factors such as load, temperature, and environment [1]. One of the primary objectives of tribology is optimization of friction processes leading to a reduction in material and energy losses and to the extension of the failure-free operation of machines and devices. To accomplish this goal, the details of non-damaging and damaging modes of operation of tribological contacts should be understood. More specifically, laboratory testing is often aimed at:

1) establishing the conditions under which the lubricant loses its protective properties; comparing and selecting lubricants
2) describing the stages of friction damage initiation and accumulation;
3) identifying the predominant wear mechanisms and the timing of their occurrence;
4) comparing the degradation behaviors of different contact pairs.

To address these objectives and to assess the behavior of a tribosystem (such as that illustrated schematically in Fig. 1), it is essential to know the time history of damage evolution since its inception to failure. Obtaining this information is challenging due to the inaccessibility of the friction contact area for direct observations during testing. The post-mortem investigation of the worn area yields only limited information, because of the compound effect of multiple damaging processes on the worn surface appearance. Therefore, the roles of individual mechanisms cannot be assessed separately at the end of the test. Alternative conventional indirect methods, such as the measurement of the friction force and temperature as well as interrupted testing for the mid-term visual observation and/or the measurement of the wear scar size are either not applicable, costly, or can adversely affect the results in many, if not most, practical cases. Therefore, novel approaches are required to get a better insight into temporal details of damage evolution in-situ without altering testing conditions or practically adopted standard test schedules.

The acoustic emission method (AE) has long been proven effective in gaining a deeper understanding of friction and wear processes in sliding and rolling contacts [2–7]. AE has often been reported to be more sensitive to damage process and operating conditions than the friction force [8] or vibration measurements [9]. Different ways of AE characterization have been explored, with different levels of success. The count rate, root mean square (*rms*) voltage or envelope were the AE features most frequently used in tribology [8,10–18]. Despite the

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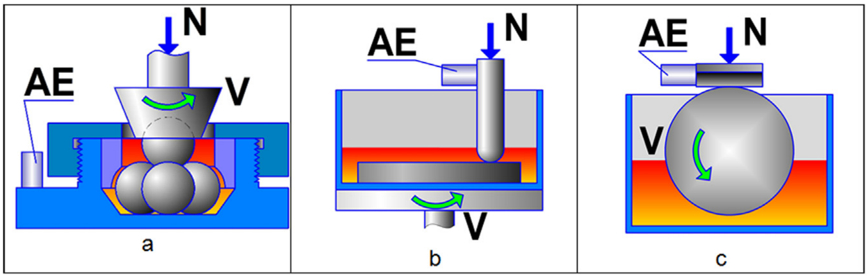

Fig. 1. Schematic illustration of tribology testing methods: (a) four-ball [31,32], (b) pin-on-disk [33], (c) cylinder-on-ring [34], N – stands for load and V for rotation direction.

simplicity of these parameters, the empirical relationships have been found between them and the wear scar volume or the wear rate. However, a robust distinction between different damage mechanisms is hardly possible by means of these integral AE parameters. The recent rapid advent of information technologies and the increasing power of computing have opened new prospects for advanced data mining and machine learning techniques which take a prominent position in modern tribology studies, see, e.g. [3,16,19–21]. The use of spectral (Fourier [22,23] or wavelet [24–27]) transform has shown that the frequency or time-frequency distribution of the AE power (energy) varies depending on friction conditions and this can be used for prediction of scuffing [28]. To increase further the efficiency of the AE spectral analysis, an original AE signal clustering algorithm based on a statistical comparison of AE spectral density functions is employed in the present work.

It has been well-understood that several mechanisms can be involved in a wear process concurrently [29]. Different individual mechanisms can interact in a sequential manner (or in parallel) to form a complex wear progression. The relative importance of individual wear mechanisms can change with the changes in influential parameters including metallurgy factors, testing conditions, and chemical factors. To gain a better understanding and to characterize the wear process in more details it is, therefore, important to distinguish between different modes of damage and to reconstruct the chronology of their occurrence. Thus, the AE method seems to be indispensable for addressing this challenge. In what follows a novel AE-based approach integrating continuous data acquisition, spectral analysis and statistical categorization of AE waveforms is described in the application to friction and wear condition monitoring. The proposed methodology allows to:

– reproduce the chronology of degradation of lubricants and contacting surfaces in tribological tests;
– automate the AE data recording and processing for routine practical testing;
– simplify the presentation of AE results for quick interpretation.

Four main wear situations between the contacting surfaces, which are commonly recognized in the literature, include adhesive wear, abrasion wear, fatigue wear, and tribochemical (corrosive) wear [30]. The present work deals primarily with adhesive wear although the proposed methodology can be adapted easily to other situations.

2. Method implementation

The proposed workflow is shown in Fig. 2. The approach involves a Fourier spectral decomposition followed by statistical categorization (clustering) of individual spectra corresponding to AE sources of different origin. The signal categorization is applied in parallel with the traditional analysis of integral AE features discussed above. The active wear mechanism is associated with one of the pseudo-AE sources prevailing over the others in the sliding contact zone at a given time. In the present work, these sources are confined to the elastic and plastic interaction between asperities, micro-cutting, and scratching, adhesion and scuffing. Several typical examples illustrating the proposed methodology are given below

3. Experimental details

The proposed approach was validated during the investigation of the degradation of several contact materials under controlled lubrication conditions in the standard tribosystems: (1) four-ball [31,32], (2) pin-on-disk [33] and (3) cylinder-on-ring [34] as shown schematically in Fig. 1. For the sake of brevity, the results of the four-ball testing of 100Cr6 steel balls will be mainly discussed in what follows. However, very similar results were obtained for other methods and materials as well.

Contacting materials included 12.7 mm diameter 100Cr6 steel balls (four-ball method); 6.0 mm diameter 100Cr6 steel balls, and 30 × 40 × 5 mm St35 and C45 steel plates (pin-on-disk method), 8 mm diameter 40CrNiMo22 steel, and AlMg3 type aluminum alloy cylinders, 50 mm diameter, 5 mm wide roller made of abrasion resistant Gh190 cast iron (cylinder-on-ring method).

Several lubrication conditions were simulated with different lubricants, such as motor oil and various commercial greases. Their codified designations and properties are summarized in Table 1.

AE recording was performed by using a home-built AE system, operating in the frequency range of 50–1000 kHz. A broadband AE-900S-WB transducer AE was mounted in the closest possible proximity to the sliding contact as shown schematically in Fig. 1. A total gain was set at 40 dB. Machine oil was used as a coupling medium to ensure efficient transfer of elastic waves from the surface to the transducer.

For integral AE characterization, a *waveform envelope* Y was measured by an analog integrator circuit built-in in the pre-amplifier as

$$Y = \frac{1}{T}\int_0^T |U(t)|dt, \tag{1}$$

where $U(t)$ is the voltage at the output of the preamplifier, and T is the integration time constant. The Y value was then recorded by the AE system in parallel with the waveform. The envelope integration time constant was set at 100 ms to eliminate spike-like noise. For the AE signal classification, the continuously recorded AE signal was sectioned into consecutive individual realizations ("frames"). Each frame contained $n = 8192$ readings sampled at 6.25 MHz. The following parameters were computed for each frame: amplitude, energy and median frequency of the power spectral density (PSD). The *energy* (per frame) W is defined as the area below the AE PSD $G(f)$ curve given as a function of frequency f as:

$$W = \int_{f_{\min}}^{f_{\max}} G(f)\, df, \tag{2}$$

where $f_{\min}$ and $f_{\max}$ denote the minimum and maximum frequency in the frequency band of the acquisition system. The *median frequency* f_m of the PSD function is computed by definition as: