# When AE (Acoustic Emission) meets AI (Artificial Intelligence) for wear states and loading conditions detection

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**Abstract.** Wear is a type of surface damage commonly observed in industrial components in relative motion and in contact with other solid surfaces. The majority of wear occurs progressively in a given contact starting from an initial running-in period followed by a steady-state period. Being able to accurately classify the running-in and steady-state periods allow reducing significant production or damage costs of complex machines, in particular when the load varies during operation. Production cost can be addressed by optimizing the running-in time. In contrast, significant damages can takes place if the machine are of set to full production capacity before the running-in time is finished. To address these two problems, we use a real-time monitoring system to differentiate between running-in and steady-state periods as well as classify the loading conditions simultaneously based on AE signals using a multi-label Convolutional Neural Network (CNN).

Reciprocating sliding tests are performed at two loads (200 and 500 g). The tribopair used is a steel ball sliding against steel plates under dry conditions. The tribotest is divided into two different states, running-in and steady-state based on the obtained friction curves. A pico-acoustic sensor is attached on the steel plate's surface, the fix body, to acquire AE signals during the friction test. Raw AE signals are processed and directly analyzed using a multi-label CNN to simultaneously classify the running-in and steady-state periods as well as the loading conditions. This machine learning method accurately classifies the running-in and steady-state as well as the loading conditions with a 99% average accuracy.

## Introduction

To save money and energy, industries need to optimize the wear states of particular tribo-systems [1]. The majority of the friction-related mechanical contact processes consist of an initial running-in period (friction coefficient fluctuates as initial wear occurs due to large surface contact) even in lubricated conditions followed by a steady-state period (where the friction coefficient remains more or less constant until failure) [2,3]. The running-in is a complex period at the beginning of the friction process, which is often expensive from an industrial point of view. This period can be time-consuming (the machine is not operating at full capacity) or difficult to identify along with the other wear states [2,3]. Therefore, identifying the transient between the running-in and steady-state stages allows saving significant production time and minimize the risk of damage. In other words, being able to accurately determine this running-in period in situ, without having to stop the machine and in a non-destructive way, will significantly reduce the cost for the industries. Productivity can be increased by being able to have full production capacity earlier. Also, in many complex machines, the load is not fixed. In these machines, the procedure to perform the running-in is based on experience and often, to minimize the risk of damage, is much longer than necessary [4]. This approach has two major drawbacks. Firstly, if the running-in is achieved before the end of the procedure, there is a loss of productivity of the machine. Second, there is no guarantee that the running-in is finished at the end of the procedure. In such cases, putting the machine at full capacity would lead to severe damage. To address both problems, there is a need to have a monitoring system able to differentiate between running-in and steady-state. However, monitoring the running-in of machines with variable loads is complex and not addressed in the literature. Hence, this study is supplement to and enrichment of existing studies on running-in diagnosis associated with potential damage and is the goal of this contribution.

Acoustic Emission (AE) is a powerful non-destructive tool to monitor and examine material behavior in different friction-related processes; e.g. tool wear and abrasive belt grinding [4,5]. In moving mechanical systems, acoustic waves are mainly related to high frequency elastic waves generated from the materials subjected to stresses [6,7]. Under such conditions, AE sensors detect the high frequency elastic waves and convert them into electric signals [9]. For industrial applications, various types of AE sensors can be coupled with the stationary counterpart. The sensor output is amplified through a low noise pre-amplifier, filtered to remove noise. Besides, AE signals can be processed and analyzed to gain insights into the physics of friction processes [9,10]. AE has been used to monitor various types of wear such as scuffing, rolling contact fatigue, abrasive wear [11-13].

Large amounts of AE data are generated even for a short duration tribotest. The most important data related to the process physics is only 1-2 % of the signals. Thus, AE has been used with various machine learning (ML) methods such as Convolutional Neural Network (CNN), Support vector machine (SVM), Logistic regression for real-time monitoring of mechanical wear processes [14–19]. In these studies, features related to specific tribological behaviors such as cracks initiation, propagation, wear states are extracted from the AE signals. These extracted features are the inputs of the ML algorithms during the training operation. The ML algorithms then use these features to detect, classify, and predict those behaviors or the remaining lifetime of a component [21]. In this work, the raw AE signals (instead of extracted AE features) are fed directly into a multi-label CNN to simultaneously classify the wear states – running-in and steady-state – and the loading conditions.

## Experimental Setup

Tribotests were conducted on a High Frequency Reciprocating Rig (HFRR) from PCS instruments. It has a computer controlled ball-on-plate reciprocating system used to assess the performance of lubricants and materials under lubricated and non-lubricated conditions. It can operate under low stroke length mode (characteristic of fretting wear) or high stroke length mode (abrasive wear), depending on the amplitude used during testing.

The tribotests were carried out for a duration ranging between 15 and 20 mins at 30°C. In this study, the amplitude selected to induce wear was 200 μm, which corresponds to the high stroke length mode. The stroke frequency was 200 Hz giving a maximum velocity of 40 mm/s. Two applied loads of 200 g and 500 g, approximately 2 N and 5 N, respectively, were selected to simulate different loading wear states. Hence, the theoretically estimated maximum Hertzian contact pressures in these contacts were 826 MPa and 1'122 MPa. The tests was repeated at least two times to ensure the reproducibility.

The tribo-pair consisted of a ball sliding against a plate in dry condition. The body and counter-body were made of the same material, an AISI 52100 steel (100Cr6). The elastic moduli were also identical with a value of 210 GPa. The ball had a diameter of 6 mm with a roughness *Ra* of 15 ± 5 nm. The plate had dimensions of 15 x 7 x 2 mm with a roughness *Ra* of 20 ± 5 nm.

A standard Vallen acquisition system was used to record the AE signals in a continuous mode during the friction experiment's complete duration. A commercially available pico-miniature sensor (PICO HF-1.2), lightweight AE broadband sensor purchased from Physical Acoustics was employed to acquire the AE data from the friction test. This sensor was fixed directly on the stationary steel plate to minimize signal losses. The sensor has a broadband frequency response ranging from 500 to 1'850 kHz. The Vallen system consists of a bandpass filter which filters the undesired generated in the signals. The sampling rate used is 2 MHz. The distance between the sensor and the sliding contact was 1-2 cm. We use this experimental configuration as it is known from the literature that mechanical wear mechanisms such as abrasive wear occurs in the frequency range of 500 – 1'000 KHz [12]. The experimental setup used for the tribotest and the AE sensor is shown in Fig. 1.

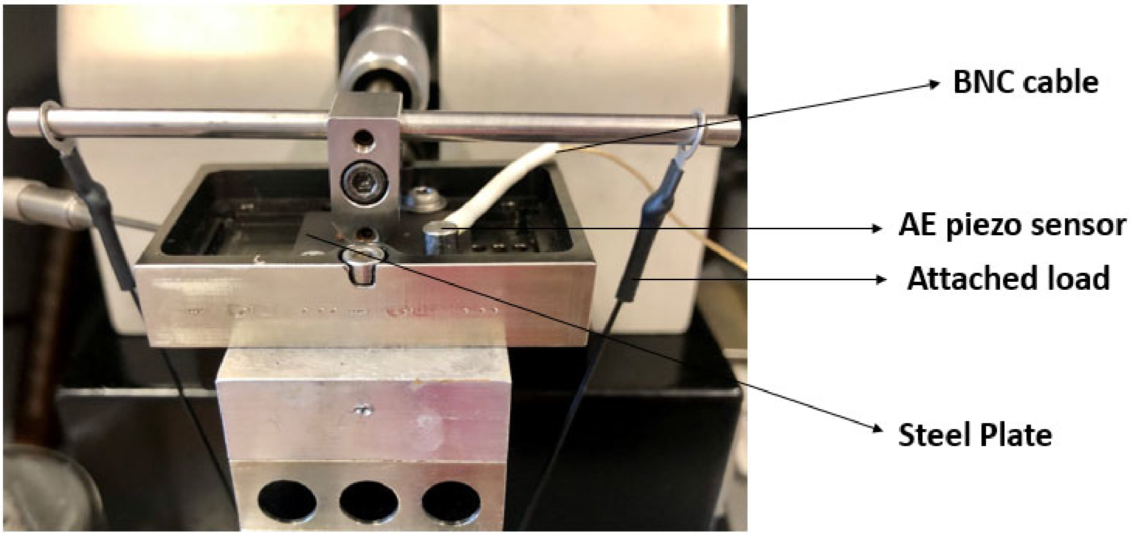


Fig. 1. HFRR (high frequency reciprocating rig) for fretting / abrasive wear test from PCS Instruments UK.

## Results and Discussions

Typical friction curves for a steel ball sliding against a steel plate at loads of 200 g and 500 g are shown in Fig. 2. From this figure, it is observed that the average friction coefficients for both experiments are similar and in the range of 1. Furthermore, the friction curves can be divided into two major wear states – initial running-in followed by a steady-state. For the 200 g load experiment, the friction coefficient increases rapidly up to a value of 1.6 before decreasing until the steady-state is reached after around 100 s. The running-in behavior of the 500 g load is significantly different. It does not have a peak value, but increases to the steady-state plateau after approximately 40 s. The majority of the wear occurs in the running-in period due to severe solid-solid contact and removal of the material from the surface of both bodies. After the running-in, the wear and friction coefficient becomes more or less stable in the steady-state period. During this period, abrasive wear occurs continuously so that the amount of wear increases steadily [22].

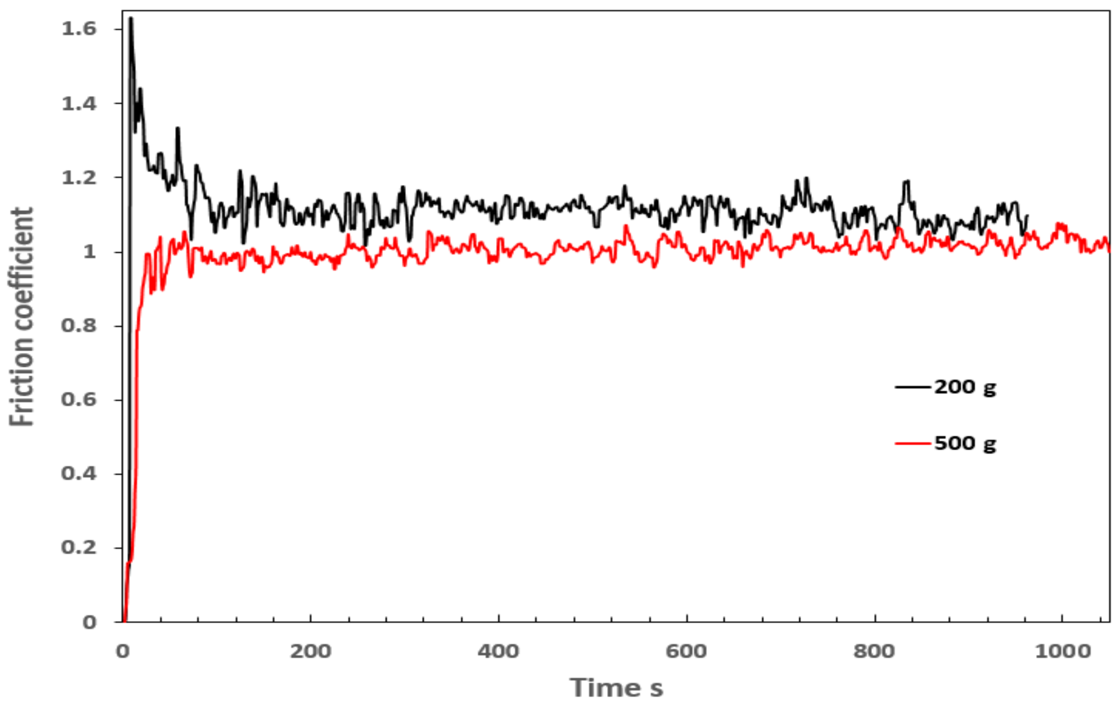

Fig. 2. Friction coefficient vs time curves for steel ball against steel plate at 200 g and 500 g applied loads.

To analyze the signals, we split the raw AE signals into fixed-width sliding windows of 2.5 ms. Taking into account that the sampling rate was 2 MHz, these sliding windows consist of 5'000 data points. From the entire test duration, a total of 27'996 windows were selected for all four conditions. In other words, 6'999 consecutive windows were extracted for each condition for a time 17.49 seconds. The selected raw AE signals corresponding to each wear state (running-in and steady-state) and loading condition (200 g and 500 g) were presented in Fig. 3 for visualization. From this figure, it can be observed that the AE signals are significantly different between the running-in and steady-state periods for both tests, irrespective of the load. This can be attributed to the physics of the process; the changes in the contact pressure and changes in wear severity. In addition, stronger AE signals are observed during both the running-in and steady-state periods for the test with 500 g as compared to the one at 200 g. This could also be due to more wear occurring in steel – steel contact at 500 g during the running-in period. Though the visualization of complete raw AE signals indicates discrete amplitude values ranges for the different wear states and loading conditions, there are overlaps between the signals due to the small window size considered, which cannot be distinguished without state-of-the-art signal processing algorithms. Visualization of the raw AE signals indicates an increase in amplitude from running-in to steady-state period in the 200 g test case. In contrast, there is a decrease in amplitude from running-in to steady-state period in case of 500 g test. This indicates the presence of strong signals relating to severe mechanical contact during the running-in period at 500 g.

Generally, time, frequency and time-frequency domain features are extracted in order to use them as input for various machine learning algorithms to classify or predict the wear states [14,22,23]. However, in this study, an alternative approach is considered where the wear states (running-in or steady-state period) and the loading conditions (200 g or 500 g) are classified simultaneously using directly the raw acoustic fixed-width sliding windows. If successful, this multi-label classification approach will give the tribology community two major advantages. Firstly, it will detect the wear state, whether the friction test is in running-in or steady-state period. Secondly, it will also allow the loading conditions used for a particular test to be identified. This knowledge is of utmost importance in many industries as it will allow controlling the friction process.

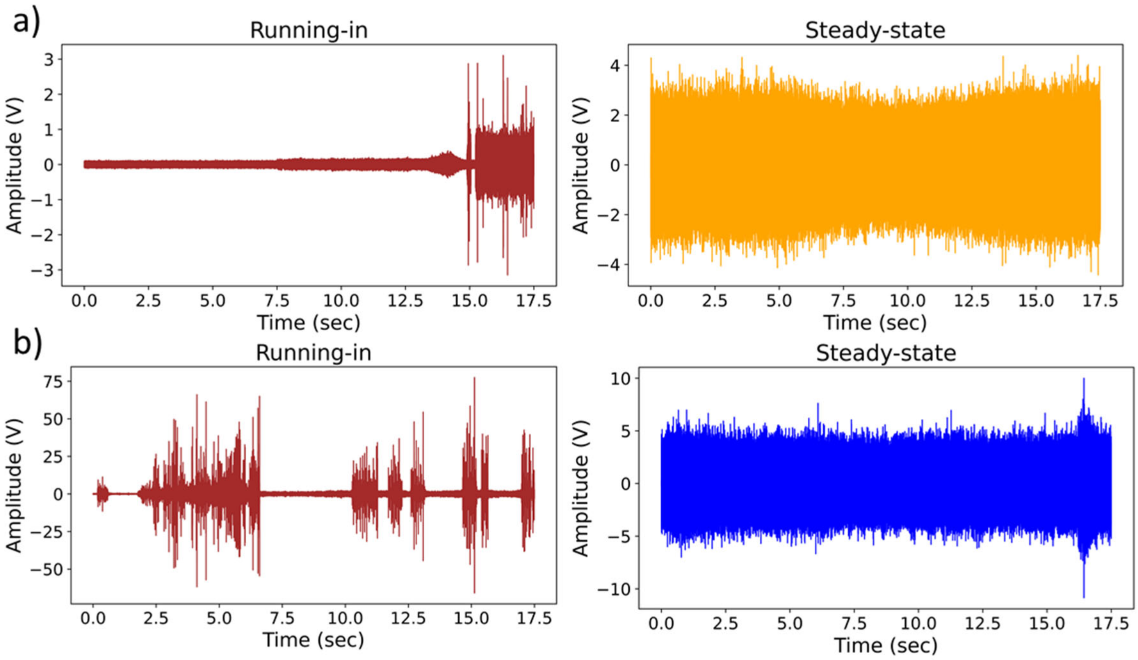


Fig. 3. Selected raw AE signals corresponding assembled together for visualization of the wear state (running-in and steady-state) for (a) 200 g loading condition and (b) 500 g loading condition. Please not that different scales have been used.

To classify the wear states and the loading conditions at the same time on a given signal window, a multi-label CNN architecture is proposed in Fig. 4. The framework includes four convolution layers with kernel sizes of 500, 251, 41 and 21, respectively. The last fully connected layer is divided into two linear layers, one classifies the wear states (running-in and steady-state) and the other the loading conditions (200 g and 500 g).

When the networks were trained, weights were updated by back-propagating the cross-entropy loss. Fig. 5 shows that the multi-label CNN network's accuracy increases with training when classifying wear states and the loading conditions. Based on this figure, the networks were trained for 50 epochs using the PyTorch library and a Titan RTX Nvidia GPU.

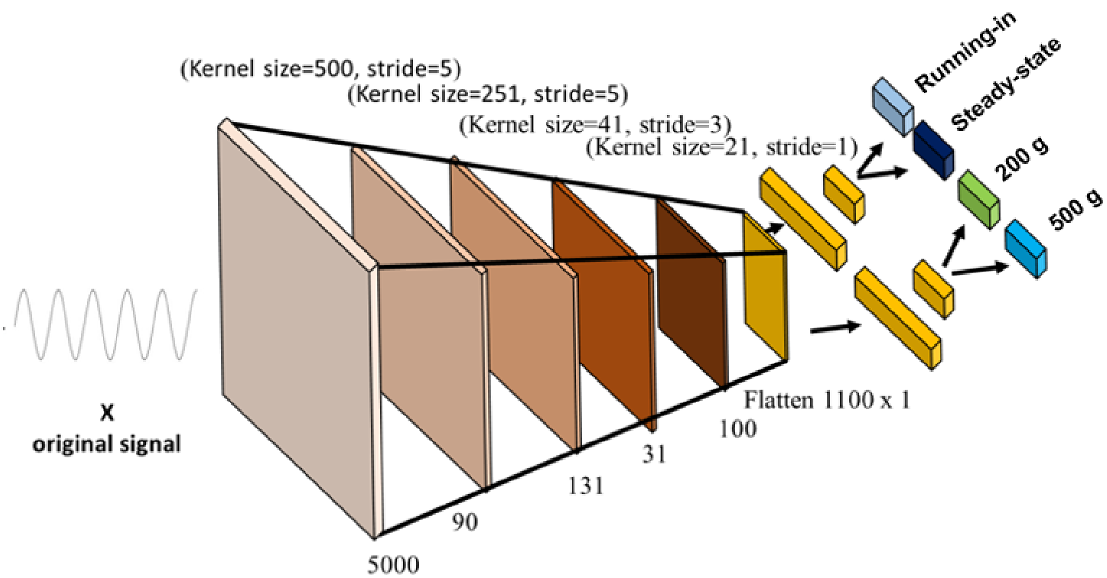


Fig. 4. Schematic of multi-label CNN architecture.

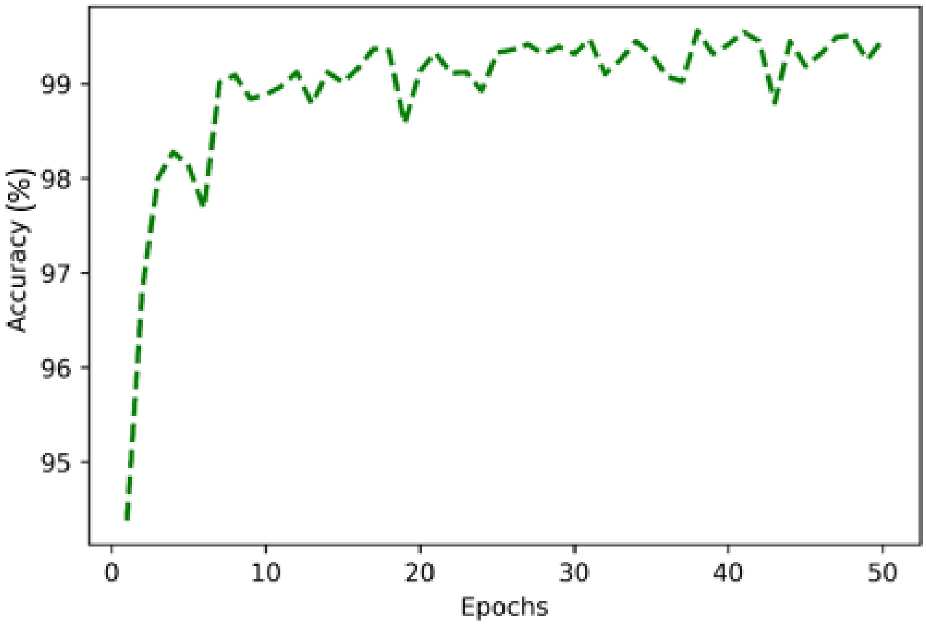


Fig. 5. Training accuracy (%) with number of epochs

The total dataset consisted of 27'996 rows of 2.5 ms windows corresponding to two classes, i.e. steady-state and running-in and all classes were balanced. Then, 70% of the total dataset was exploited as the training set whereas the last 30% formed the test set. Table 1 shows the 2 by 2 confusion matrices for the simultaneous classification of the wear states and loading conditions.

The first confusion matrix (Table 1a) shows the wear states' classification into running-in and steady-state. The running-in period is classified with 99% accuracy, and the steady-state period is classified with 100% accuracy. The second confusion matrix (Table 1b) shows the loading conditions classification (200 or 500 g test). Similarly to Table 1a, the classification accuracy observed is very high. It is 99% for the 200 g load and 100% for the 500 g load. The overall multi-label CNN accuracy is close to 100% in performing both classifications simultaneously. This very high classification accuracy obtained with multi-label CNN indicates that raw AE signals can be directly used instead of extracting AE features from processed AE signals. This demonstrates that our approach is a promising solution to reduce production and damage costs related to putting complex machines working under various loading conditions into operation.

**Table 1.** Confusion matrices for the multi-label classification of (a) wear states (running-in and steady-state periods) and (b) loading conditions (200 g and 500g).

**(a) Wear states**

| **Ground truth** / **Predicted label [%]** | ***Running-in*** | ***Steady-state*** |
|---|---|---|
| ***Running-in*** | **99.0** | 1.0 |
| ***Steady-state*** | 0.0 | **100.0** |

**(b) Loading conditions**

| **Ground truth** / **Predicted label [%]** | ***200 g*** | ***500 g*** |
|---|---|---|
| ***200 g*** | **99.0** | 1.0 |
| ***500 g*** | 0.0 | **100.0** |

## Conclusions

In this contribution, Acoustic Emission (AE) has been used to monitor the wear states and loading conditions during a ball-on-plate reciprocating sliding test conducted on a high frequency reciprocating rig (HFRR) in dry condition. The wear states considered were the running-in and steady-state regimes. The two loading conditions were 200 g and 500 g. The counterparts were made of steel with mirror-polished surface quality. These experimental conditions were selected to produce abrasive wear in the contact area. However, the amount of wear is related to the applied loads. The overall friction coefficient behavior is found to be similar in both cases. However, the running-in behavior is significantly different between both applied loads, whereas the steady-state ones show higher similarities. These results suggest that the dissimilar wear rate occur between both the running-in and steady-state periods as well as for the loading conditions. AE signals were recorded using a pico-miniature sensor (PICO HF-1.2 from PAC). The raw signals showed peculiar and quite different signature for the different wear states and loading conditions. Machine learning (ML) algorithm of multi-label Convolutional Neural Network (CNN) accurately classified both the wear states and loading condition. Actually, the classification accuracy for both the running-in and steady-state periods were 99% and 100%, respectively. The simultaneous classification of loading conditions for 200 g and 500 g showed similar high classification accuracy of 99% and 100%. Therefore, it is suggested that a two-step classification using multi-label CNN from raw AE signals of classifying the wear states (running-in and steady-state) and the loading conditions (200 g and 500 g) is a successful method to monitor wear in a wide range of operating conditions. Additional work is still required for further classification of wear states.

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