Statistical feature extraction of pre-lockup torsional vibration signals for condition monitoring of wet friction clutches

A.P. Ompusunggu¹, P. Sas¹, H. Van Brussel¹, F. Al-Bender¹, S. Vandenplas²

¹ K.U.Leuven, Department of Mechanical Engineering, Division of PMA
Celestijnenlaan 300 B, B-3001, Heverlee, Belgium
email: agusmian.ompusunggu@mech.kuleuven.be

² Flanders’ Mechatronics Technology Centre (FMTC)
Celestijnenlaan 300 D, B-3001, Heverlee, Belgium

Abstract
Wet friction clutches play a critical role in vehicles equipped with automatic transmissions. It is unavoidable that they progressively degrade and eventually break down while the vehicles are under operational condition. To avoid unexpected failures, a proper condition monitoring tool extended with a lifetime prediction method should be implemented. In order to achieve this, appropriate parameters delivering any information about the failure modes and levels must be determined. This paper presents an experimental investigation on a set of statistical parameters generated from the zeroth- and first-order derivative of time domain pre-lockup torsional vibration signals, to determine the appropriate parameters, often called relevant features, for condition monitoring of wet friction clutches. The torsional vibrations are measured by using two Ferraris sensors installed on both input and output shaft of the clutch. The determination of the relevant features is based on an evaluation of the historical trends of the parameters. Clearness and fluctuation level of the historical trends are considered as criteria for selecting relevant features from the generated statistical parameters. The trends of the parameters are extracted from lifetime data obtained from an accelerated lifetime test on a paper-based wet clutch, using a SAE#2 test setup. This study reveals that the RMS value and Shannon entropy extracted from the first-order derivatives of the pre-lockup torsional vibration signals, and the kurtosis extracted from the zeroth-order derivatives of the pre-lockup torsional vibration signals, can be used as relevant features for condition monitoring of wet friction clutches.

Keywords: Condition monitoring, wet friction clutch, torsional vibration, high order derivative signal, Taylor series based digital differentiator and accelerated lifetime test.

1 Introduction

Wet friction clutches are mechanical components enabling to transmit power from an input to an output shaft, based on the friction occurring in lubricated contacting surfaces. The clutch is lubricated by an automatic transmission fluid (ATF) having a function as a cooling lubricant cleaning the contacting surfaces and giving smoother performance and longer life. However, the presence of the ATF in the clutch reduces the friction coefficient. Therefore, in applications where high power is needed, the clutch is commonly designed with multiple friction and separator discs. This configuration is known as a multi-disc clutch as can be seen in Figure 1, wherein the friction discs are mounted to the input shaft (drum) by splines, and the separator discs are mounted to the output shaft (hub) by lugs. The friction disc is commonly made of a steel disc with a friction material bonded on both sides, and the separator disc is made of plain steel. Nowadays, widely used friction materials for wet clutch applications are paper-based and sintered bronze types.
Wet friction clutches play a critical role in vehicles equipped with automatic transmissions (ATs). It is unavoidable that they progressively degrade while the vehicles are under operational condition. If they unexpectedly fail, the vehicles will eventually breakdown. An unexpected breakdown of the vehicles can put human safety at risk, cause long term vehicle down times, and result in high maintenance costs. To avoid an unexpected breakdown, a proper condition monitoring system, extended with a remaining useful lifetime (RUL) prediction method, also known as a health prognostic system, has been considered. In order to achieve this, appropriate parameters delivering relevant information about the failure modes and levels must be determined. In the remainder of the paper, the appropriate parameters will be referred to as relevant features.

The friction coefficient has long been considered as a relevant feature for condition monitoring of wet friction clutches. Monitoring of the friction coefficient can be performed online by measuring the transferred torque and applied normal force. Many studies on the characteristics of the friction coefficient during the service-life of wet friction clutches have been carried out since many years, e.g. in refs. ([1],[2],[3]). In general, these studies show that the friction coefficient progressively decreases monotonously. Nevertheless, the drawback of using this approach for monitoring of the clutch is that at least two sensors are needed to obtain the friction coefficient. As a consequence, a price to be paid to implement the approach is possibly prohibitively high. Moreover, in real-life applications both sensors are difficult to install in a transmission.

Alternatively, in previous works ([4],[5]), we have proposed and validated that the dominant torsional natural frequency and its corresponding modal damping ratio can be used as relevant features for condition monitoring of paper-based wet friction clutches. The aforementioned features are extracted from the post-lockup torsional vibration signal obtained on the SAE#2 test setup, using a pre-filtered Hankel total least squares time domain method. A post-lockup signal is defined here as a signal recorded just after the lockup time instant. The lockup time instant is formally defined as the time after which the relative velocity between friction and separator discs (v) becomes zero for the first time.

We believe that there is more useful information related to the clutch degradation that can be extracted from the pre-lockup torsional vibration signal. The reasoning behind of this hypothesis is based on the fact that, the Stribeck curve representing the steady state friction characteristic which is the relation between the friction coefficient (μ) and the relative velocity (v), changes with respect to the degradation level as has been reported in several references ([1],[6]). A common pattern which can be identified on the Stribeck curve is that the slope changes with respect to the degradation level. Depending on the combination of friction material and ATF and operational conditions, the slope can change from a high to a low value, or vice versa. By a simple vibration analysis, one can show that a changing slope leads to a changing overall damping of a transmission. This consequently changes the torsional vibration characteristics, particularly in the pre-lockup phase where the relative velocity is not zero. Moreover, if the Stribeck slope is negative, as a result, the overall damping of a transmission can be possibly negative which may introduce a self-excited vibration (shudder) in the transmission.

This paper aims at a statistical analysis of time-domain pre-lockup torsional vibration signals for determining relevant features for condition monitoring of wet friction clutches. Here, statistical parameters
widely used in condition monitoring of machines, such as root mean square (RMS) value, kurtosis, skewness, crest factor and Shannon entropy, are investigated to determine the relevant features for monitoring of wet friction clutches.

The rest of the paper is organized as follows. In Section 2, signal processing prior to feature extraction is presented and discussed. The statistical feature extraction is described in Section 3. Furthermore, the experimental aspects concerning the description of the SAE#2 test setup, measurement system, duty cycle, and testing procedures are presented in Section 4. The results obtained from the experiments are presented and discussed in Section 5. Finally, some concluding remarks and recommendations for the future works are given in Section 6.

## 2 Signal processing

For a given duty cycle which will be discussed later on in the experimental section, all relevant signals are measured and recorded by a multi-channel data acquisition system with sampling frequency $f_s$ of 12.8 kHz. The signals are recorded for 5 seconds resulting in 63,999 data samples for each measured signal.

Attention is mainly focused here on the angular accelerations of the input and output shaft. The angular accelerations of both shafts are independently measured by two Ferraris sensors. These particular sensors have a limited frequency bandwidth up to 1 kHz. In principle, a Ferraris sensor measures a relative angular acceleration between a moving part and the sensor head. The working principle of a Ferraris sensor is fully described in [7].

In this section, relevant signal processing methods applied prior to feature extraction of the pre-lockup torsional vibration are presented and discussed in the following subsections. The pre-lockup angular acceleration is first detected and captured from a raw angular acceleration signal measured at a given duty cycle. Next, the pre-lockup angular acceleration is reprocessed in order to obtain the pre-lockup torsional vibration only. In short, a block diagram describing the steps of the signal processing is shown in the following figure.

![Figure 2: Block diagram representing the signal processing steps](image)

### 2.1 Pre-lockup signal detection

Let $\alpha(t)$ and $\nu(t)$, be the raw angular acceleration and the relative angular velocity signal for a given duty cycle, respectively. The representation of both signals obtained from the measurement can be seen in Figure 3.
The formal definition of the lockup time has been given in the previous section, as the time instant when the relative velocity $v(t)$ reaches a zero value for the first time. By this definition, the lockup time $t_l$ can thus be mathematically written as follows:

$$t_l = \min\{\forall t \in \mathbb{R}: |v(t)| = 0\}$$

(1)

Moreover, the figure above also shows that the lockup time $t_l$ can be derived from the angular acceleration signal by the fact that the angular acceleration reaches a maximum value at the lockup time. Hence, the lockup time $t_l$ can also be written as

$$t_l \in \mathbb{R}: \alpha(t_l) = \max\{\alpha(t)\}$$

(2)

Let $L$ be the pre-determined data length of the pre-lockup acceleration signal $\alpha_{pre}$ extracted from the raw acceleration signal $\alpha(t)$. Based on Figure 3(b), the pre-lockup acceleration signal $\alpha_{pre}$ with a data length of $L$ samples can thus be written as follows:

$$\alpha_{pre} = \alpha(t_o < t \leq t_l)$$

(3)

where $t_l = t_o + L T_s$, $t_o$ denotes the initial time of the pre-lockup signal and $T_s$ is the sampling period (the inverse of the sampling frequency $f_s$, $T_s = 1/f_s$).

In this study, $L = 19,200$ samples which is equivalent to 1.5 seconds is selected. Using the detection procedures given by Equations (1) – (3), the pre-lockup angular acceleration signal $\alpha_{pre}$ detected from the raw signal is given in Figure 4.

The pre-lockup acceleration signal $\alpha_{pre}$ depicted by Figure 4 can be split into two components. The first is a piecewise ramp component indicated by the dashed line $\alpha_m$, and the second one is a dynamic component representing the torsional vibration $\alpha_d$. 

Figure 3: (a) The raw angular acceleration signal, (b) relative angular velocity signal for a given duty cycle
Since our interest has been addressed on the pre-lockup torsional vibration, the piecewise ramp component in the pre-lockup acceleration signal needs to be removed. In this paper, the ramp component is removed by means of a digital high-pass filtering and numerical differentiation. The removal techniques are presented and discussed hereunder.

2.2 Capturing the torsional vibration

The digital high pass filter used here is a 3\textsuperscript{rd}-order Butterworth filter which is designed by using a Matlab toolbox. The cut-off frequency of the filter must be selected such that the piecewise ramp component diminishes. There is no a strict procedure to select the cut-off frequency for this particular case. Here, the selection is based on trial and error leading to the cut-off frequency of 20 Hz. A zero-phase forward and reverse digital filtering technique is implemented in order to obtain the filtered signal with zero phase distortion. The signal resulting from the high-pass filtering of the pre-lockup acceleration signal is depicted in Figure 5. The figure clearly shows that after the high-pass filtering, the ramp component has disappeared.
2.2.2 Numerical differentiation

Differentiation of a signal consisting of a ramp and a dynamic component in one hand will turn the ramp component into a DC-offset, and on the other hand will amplify the high frequent contents of the dynamic component which is advantageous for the accuracy of the feature extraction from the vibration signal.

The central difference method based on a higher-order approximation of a Taylor series proposed by Khan and Ohba [8] is used in this study to numerically calculate the first derivative of the pre-lockup angular acceleration signal.

It is proved that the first derivative of an uniformly sampled signal, \( y(n) \), where \( N \) is the number of data samples, can be written in a closed form as follows:

\[
y^{(1)}(n) = \frac{1}{T_s} \sum_{i=-K}^{K} d_i y(n+i)
\]

with

\[
d_0 = 0,
\]

\[
d_i = \frac{(-1)^{i+1}(K)^2}{i(K-i)(K+i)}, \quad i = \pm 1, \pm 2, \ldots, \pm K
\]

where \( y^{(1)}(n) \) denotes the value of the first derivative of \( y(n) \) at an arbitrary time index \( n \), \( T_s \) is the sampling period and \( K \) is the order of the Taylor series approximation.

Let \( n = m - K \) and \( i = j - K \), by substituting these two terms into Equation (4), one can rewrite this equation as follows:

\[
y^{(1)}(m-K) = \frac{1}{T_s} H[y(m)]
\]

with

\[
H[y(m)] = \sum_{j=0}^{2K} d_{j-K} y(m-[2K-j])
\]

The mathematical operation given in Equation (7) constitutes a finite-impulse-response (FIR) filtering process. This means that the presented differentiation method can be treated as a FIR filter. Hereafter, the presented differentiation method is called as the Taylor Series Based FIR Digital Differentiator (TSB-FIRDD).

In general, a FIR filtering process can be written as follows:

\[
z(m) = \sum_{l=0}^{M} b_l u(m-l)
\]

where \( u(m) \) is an arbitrary input signal, \( z(m) \) is the corresponding output signal, \( b_l \)'s and \( M \) are respectively the coefficients and the order of the FIR filter.

By comparing the structure of Equation (7) and (8), it can be concluded that the order of the TSB-FIRDD is \( 2K \), and the coefficients \( d_l \)'s given in Equation (5) can be treated as FIR filter coefficients \( b_l \)'s with the following relationship:

\[
b_l = d_{K-l}, \quad l = 0, 1, 2, \ldots, 2K
\]

The accuracy of the TSB-FIRDD can be evaluated based on its magnitude response as depicted in Figure 6. The figure highlights the comparison between the magnitude response of an ideal differentiator and the TSB-FIRDD with different value of \( K \). It can be seen that the higher \( K \) is, the more accurate the TSB-FIRDD is. Moreover, the figure also shows that, for \( K \geq 5 \), the accuracy of the presented differentiator is guaranteed as long the frequency of interest \( f_{int} \) is less than or equal to 0.25 times of the sampling frequency \( f_s \) (\( f_{int} \leq 0.25f_s \)).
It is unavoidable that noise is always present in measurement signals. Due to this fact, differentiation of a noisy signal will also amplify the high-frequency noise. As a result, this particular noise may bury any relevant information related to the clutch degradation. In order to suppress the high-frequency noise and the offset due to the differentiation, a band pass filtering can be applied to the first derivative of the pre-lockup angular acceleration signal. The low cut-off frequency of the band pass filter is set to 20 Hz and the high one is set to 1 kHz which is the maximum frequency bandwidth of the used Ferraris sensors. The digital band pass filter used for this purpose is a 3rd-order Butterworth filter which is designed using a Matlab toolbox. Again, a zero-phase forward and reverse digital filtering technique is implemented in order to obtain the filtered signal with zero phase distortion.

The first derivative of the pre-lockup acceleration signal $\alpha_{\text{pre}}^{(1)}$ is shown in Figure 7. The derivative signal prior to the band pass filtering is shown in Figure 7(a), and after the band pass filtering is shown in Figure 7(b). By comparing both figures, it can be seen that the high-frequency noise is quite significant by the fact that the signal energy after the filtration, which can be seen from the signal amplitude, is approximately half of the signal energy prior to the band pass filtering.
3 Feature extraction

Let \( y(n), n = 1,2,\ldots,N \), be a discrete-time signal of interest. The statistical parameters to be extracted from the discrete signal \( y(n) \) are RMS value, kurtosis (\( Ku \)), skewness (\( Sk \)), crest factor (\( CF \)), and Shannon entropy (\( H \)). They are mathematically expressed as follows:

\[
RMS = \sqrt{\frac{\sum_{n=1}^{N} y(n)^2}{N}} \quad (10)
\]

\[
Ku = \frac{1}{N} \sum_{n=1}^{N} \left[ y(n) - \bar{y} \right]^4 \sigma^4 \quad (11)
\]

\[
Sk = \frac{1}{N} \sum_{n=1}^{N} \left[ y(n) - \bar{y} \right]^3 \sigma^3 \quad (12)
\]

\[
CF = \frac{\max\{y(n)\}}{RMS} \quad (13)
\]

with

\[
\bar{y} = \frac{1}{N} \sum_{n=1}^{N} y(n) \quad (12)
\]

and

\[
\sigma = \frac{1}{N} \sqrt{\sum_{n=1}^{N} \left[ y(n) - \bar{y} \right]^2} \quad (13)
\]

Let \( M \) be the number of events in a signal, and \( p_i \) be the probability of every event in the signal, where \( i = 1,2,\ldots,M \). The Shannon entropy of the signal \( H_s \) is defined as [9]:

\[
H_s = -\sum_{i=1}^{M} p_i \ln(p_i) \quad (14)
\]

To estimate the Shannon entropy from a discrete signal \( y(n), n = 1,2,\ldots,N \), the signal is first classified into \( M \) classes. Here, one class represents an event in the signal. For practical purposes, one can choose \( M = \lceil \sqrt{N} \rceil \), where \( \lceil \cdot \rceil \) denotes a ceiling operator. Let the frequency of occurrence of the \( i^{th} \) class, \( i = 1,2,\ldots,M \), be \( m_i \). The naive probability of the \( i^{th} \) class \( \hat{p}_i \) can be estimated as a ratio between the frequency of occurrence of the \( i^{th} \) class \( m_i \) and the total frequency of occurrence of all classes \( \sum_{i=1}^{M} m_i = N \), which can be written as follows:

\[
\hat{p}_i = \frac{m_i}{\sum_{i=1}^{M} m_i} = \frac{m_i}{N} \quad (15)
\]

The use of the naive probability \( \hat{p}_i \) to estimate the Shannon entropy, as a consequence, results in a systematic error (bias) [10]. The biased entropy \( \hat{H} \) can be expressed as follows:

\[
\hat{H} = -\sum_{i=1}^{M} \hat{p}_i \ln(\hat{p}_i) \quad (16)
\]
Furthermore, Miller [11] proposes a correction term added into Eq.(16) leading to the unbiased Shannon entropy $H^*$:

$$H^* = - \sum_{i=1}^{M} \hat{p}_i \ln(\hat{p}_i) + \frac{M - 1}{2N} \tag{17}$$

4 Accelerated Lifetime Test (ALT)

As was previously stated, a feature can be considered to be relevant if it shows a distinct trend during the service-life of an operating system. To determine whether the presented statistical parameters can be used as relevant features for the clutch monitoring, as a consequence, lifetime data are absolutely needed. In this paper, the concept of ALT is applied in order to obtain the lifetime data in a reasonable period. The ALT’s were carried out on the SAE#2 test setup as will be discussed in the following sub-sections.

4.1 SAE#2 test setup

The SAE#2 test setup, depicted in Figure 8, consists of three main systems: driveline, control, and measurement system. The driveline is composed of nine components: AC motor for driving the input shaft (1), input velocity sensor (2), input flywheel (3), multi-disc clutch package (4), torque sensor (5), output flywheel (6), output velocity sensor, AC motor for driving output shaft (8), and a hydraulic system (11-21). Control systems (22) are used for both controlling the input oil pressure to the clutch and the velocity of input- and output-shafts. A multi-channel measurement system (22) is used to measure all relevant dynamic signals.

![Figure 8: Scheme of the SAE#2 test setup (top view)](image)

4.2 Duty cycle

Initially, while both flywheels are rotating at the same speed in opposite direction, the motors are powered-off and the pressurised oil is simultaneously applied to the clutch package at time $t_f$. The
pressurised oil actuates the clutch piston, pushing the friction and separator discs towards each other. This occurs between time \( t_f \) and \( t_e \), and is called the filling phase. Consecutively, contact is established between separator and friction discs. As a result, the transmitted torque starts to increase at time \( t_e \). This is known as an engagement phase wherein the relative speed between the input and output shaft decreases due to the generated friction. The heat dissipated in this phase results in an increase of the ATF temperature. Finally, the clutch is completely engaged when the relative speed reaches zero at the lockup time \( t_s \). Typical signals recorded during a representative duty cycle are shown in Figure 9.

![Figure 9: Representative recorded signals of one duty cycle](image)

### 4.3 Test description

In order to realize the ALTs, the energy level applied onto the clutch in this study is relatively high compared to the one in normal operational conditions. The ALTs are continuously carried out for 10,000 duty cycles. After the first 10,000 cycles, the test is temporarily stopped and the clutch is inspected and evaluated. If the friction materials of the clutch are not completely failed, the test is continued with a higher energy level than before, for the next 10,000 duty cycles. The procedure is repeated every 10,000 duty cycles. The test is completely stopped when the friction material is considered to have completely failed. In addition, prior to the ALTs, continuous run-in tests are performed up to only 100 duty cycles. The energy level applied to the clutch during the run-in tests is relatively low compared to the one of the ALT. The data are captured every 200 duty cycles.

In addition, the friction material type of the clutch used in this study is paper based. There are 10 friction discs used in the clutch. The clutch is lubricated by an ATF called Texamatic 7045.

### 5 Results and discussion

Figure 10 - Figure 17 show all historical trends of the presented statistical parameters which are extracted from the pre-lockup torsional vibration signals measured on the input and output shaft using the Ferraris sensors. Each figure shows two historical trends indicated by the square and round legend. Both legends respectively denote the historical trends of the statistical parameters of the torsional vibration captured from the pre-lockup angular acceleration signal using high-pass filtering (\( n = 0 \)) and numerical differentiation method (\( n = 1 \)). Hereafter, the torsional vibration signals captured from the pre-lockup angular acceleration signals using the former and latter method are respectively called the zeroth-order and first-order derivative signal. The dashed lines on the figures are the reference lines denoting the parameter
values obtained from the first measurement which represent the healthy condition of the clutch. Note that the historical trends are obtained from one lifetime dataset of a paper-based wet friction clutch. The clutch is considered to fail after 27,400 duty cycles.

The figures generally show that the historical trends of the statistical parameters extracted from the first-order derivative signal (n = 1) show larger fluctuations than the ones extracted from the zeroth-order derivative signal (n = 0), except for the historical trends of the RMS value and Shannon entropy. For readability reasons, both statistical parameters are scaled by dividing them by their values obtained from the first measurement, as can be seen in Figure 10 - Figure 11. Moreover, the RMS value and Shannon entropy extracted from the first order-derivative signal (n = 1) show clearly increasing trends and relatively small fluctuations during the lifetime. It can also be observed that both parameters obtained from the signal measured on the input and output shaft show relatively similar behaviour. Therefore, the RMS value and Shannon entropy can be considered as relevant features. Nevertheless, there is an exception on the left panels of Figure 10 and Figure 11 where one can notice the fluctuations indicated by the ellipses. Here, the fluctuations can be possibly considered as outliers.

Among the presented statistical parameters extracted from the zeroth-order derivative signals (n = 0), kurtosis (Ku) can only be considered as a relevant feature which shows clear trends and relatively small fluctuations during the lifetime, as can be seen in Figure 12 and Figure 13. Moreover, the figures show that the kurtosis extracted from the zeroth-order derivative signals exhibits a monotonically decreasing trend, which are observed on both input and output shaft.

![Figure 10: The historical trends of RMS value of the zeroth and first order derivative signal. The left and right panels respectively denote the RMS values measured on the input and output shaft.](image1)

![Figure 11: The historical trends of Shannon entropy of the zeroth and first order derivative signal. The left and right panels respectively denote the entropy measured on the input and output shaft.](image2)
Figure 12: The historical trends of kurtosis of the zeroth and first order derivative signal measured on the input shaft. The left and right panels respectively denote the global and detailed view.

Figure 13: The historical trends of kurtosis of the zeroth and first order derivative signal measured on the output shaft. The left and right panels respectively denote the global and detailed view.

Figure 14: The historical trends of skewness of the zeroth and first order derivative signal measured on the input shaft. The left and right panels respectively denote the global and detailed view.
Figure 15: The historical trends of skewness of the zeroth and first order derivative signal measured on the output shaft. The left and right panels respectively denote the global and detailed view.

Figure 16: The historical trends of crest factor of the zeroth and first order derivative signal measured on the input shaft. The left and right panels respectively denote the global and detailed view.

Figure 17: The historical trends of crest factor of the zeroth and first order derivative signal measured on the output shaft. The left and right panels respectively denote the global and detailed view.
6 Conclusions and recommendations

An experimental investigation on statistical parameters extracted from lifetime data of pre-lockup torsional vibration signals which can be potentially as relevant features for condition monitoring of wet friction clutches has been presented. The pre-lockup torsional vibration signals are captured from the angular acceleration signals which are measured using Ferraris sensors installed on both input and output shaft of the clutch. A set of statistical parameters widely used in condition monitoring is generated. In order to determine relevant features from the set of parameters, the historical trends of the parameters are evaluated based on proposed criteria: the clearness and fluctuation level of the historical trends. This means that a parameter can be selected as a relevant feature if it shows a clear historical trend and relatively low fluctuation level. The evaluation is performed here by a visual inspection on the trends. Based on the criteria, the RMS value and Shannon entropy extracted from the first order derivatives of the pre-lockup torsional vibration signals, and the kurtosis extracted from the zeroth-order derivatives of the pre-lockup torsional vibration signals can be possibly used as relevant features for condition monitoring of wet friction clutches.

In order to quantitatively evaluate the performance of a parameter which can be considered as a relevant feature, the criteria proposed in this study should be mathematically formulated. Moreover, since the historical trends presented here are obtained from one lifetime dataset, further investigation on more lifetime datasets must be performed in order to evaluate the robustness of the proposed relevant features under different operational conditions.

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