Health Assessment and Prognostics of Automotive Clutches

Agusmian Partogi Ompusunggu[1,2], Steve Vandenplas[1], Paul Sas[2], and Hendrik Van Brussel[2]

[1] *Flanders' MECHATRONICS Technology Centre (FMTC), 3001 Heverlee, Belgium*
agusmian.ompusunggu@fmtc.be
steve.vandenplas@fmtc.be

[2] *Katholieke Universiteit Leuven, Department of Mechanical Engineering, Division PMA, 3001 Heverlee, Belgium*
paul.sas@mech.kuleuven.be
hendrik.vanbrussel@mech.kuleuven.be

ABSTRACT

Despite critical components, very little attention has been paid for wet friction clutches in the monitoring and prognostics research field. This paper presents and discusses an overall methodology for assessing the health (performance) and predicting the remaining useful life (RUL) of wet friction clutches. Three principle features extracted from relative velocity signal measured between the input and output shaft of the clutch, namely (i) the normalized engagement duration, (ii) the normalized Euclidean distance and (iii) the Spectral Angle Mapper (SAM) distance are fused with a logistic regression technique into a single value called the health index. In logistic regression analysis, the output of the logistic model (*i.e.* the health index) is restricted between **0** and **1**. Accordingly, the logistic model can guide the users to assess the state of a wet friction clutch either in healthy state (*e.g.* health index value of (close to) 1) or in failed state (*e.g.* health index value of (close to) 0). In terms of prognostics, the logarithm of the odds-of-success g defined as $g = \log[h/(1-h)]$, where h denotes the health index, is used as the predicted variable. Once a history data is sufficient for prediction, the weighted mean slope (WMS) method is implemented in this study to adaptively build a prognostics model and to predict the trajectory of g until it crosses a predetermined threshold. This way, the remaining useful life (RUL) of a clutch can be determined. Furthermore, an experimental verification of the proposed methodology has been performed on two history datasets obtained by performing accelerated life tests (ALTs) on two clutch packs with different friction materials but the same lubricant. The experimental results confirm that the proposed methodology is promising and has a potential to be implemented for real-life applications. As was expected, the estimated RUL converges to the actual RUL and the uncertainty interval decreases over time that may indicate that the prognostics model improves as more evidence becomes available.

1. INTRODUCTION

Wet friction clutches are mechanical components enabling the power transmission from an input shaft (connected to engine) to an output shaft (connected to wheels), 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 that cleans the contacting surfaces and gives smoother performance and longer life. However, the presence of the ATF in the clutch reduces the coefficient of friction (COF). In applications where high power is necessary, the clutch is therefore designed with multiple friction and separator discs. This configuration is known as a multi-disc wet friction clutch as can be seen in Figure 1, in which the friction discs are typically mounted to the hub by splines, and the separator discs are mounted to the drum by lugs.

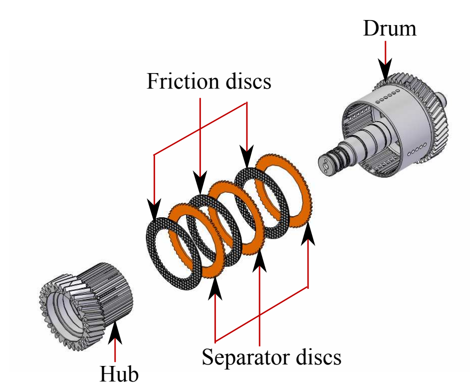


Figure 1. Exploded view of a wet friction clutch.

Today's vehicles have become widely equipped with automatic transmission (AT) systems, where wet friction clutches are one of critical components that play a major role on the transmission performance. In the beginning of its life, a clutch is designed to transmit certain power under a smooth and fast engagement with minimal shudder. But, due to the unavoidable degradation, the clutch frictional characteristics change, thus altering its initial performance and consequently affecting the performance of the vehicles. As the degradation proceeds, failure can unexpectedly occur, which eventually leads to the total breakdown of the vehicles. An unexpected breakdown can put human safety at risk, possibly cause long term vehicle down times, and result in high maintenance costs. Hence, integration of a maintenance strategy into AT systems can significantly increase safety and availability/reliability as well as reduce the maintenance cost of the vehicles.

The maintenance strategy should be performed in an optimal way, in the sense that degrading clutches need to be replaced with the new ones at the *right time*. Here, the right time can be referred to as the "optimal" end of life of the clutch, at which the clutch is no longer functioning as it should be. Notice that the end of the clutch lifetime does not necessarily mean the condition where the catastrophic failure occurs. Regarding the optimal maintenance strategy, the information concerning the end of clutch lifetime (or remaining useful clutch life) therefore becomes important aspect in order to minimize the vehicles downtime. Condition Based Maintenance (CBM), which is also known as Predictive Maintenance (PdM), is a right-on-time maintenance strategy which is driven by the actual condition of the critical component of systems. This concept requires technologies and experts, in which all relevant information, such as performance data, maintenance histories, operator logs and design data are combined to make optimal maintenance decisions (Mobley, 2002). In general, the key technologies for realizing the PdM strategy rely on three basic elements, namely (i) *condition monitoring*, (ii) *diagnostics* and (iii) *prognostics*. PdM has been in use since 1980's and successfully implemented in various applications, such as in oil platforms, manufacturing machines, wind turbines, automobiles, electronic systems, (Basseville et al., 1993; Bansal, Evans, & Jones, 2004; Garcia, Sanz-Bobi, & Pico, 2006; Srinivas, Murthy, & Yang, 2007; Bey-Temsamani, Engels, Motten, Vandenplas, & Ompusunggu, 2009b, 2009a).

Despite critical components, to authors' knowledge, very little attention has been paid to wet friction clutches in the area of PdM research. Several methods have been proposed in literature for assessing the condition of wet friction clutches based on the quality of the friction material, namely (i) Scanning Electron Microscope (SEM) micrograph, (ii) surface topography, (iii) Pressure Differential Scanning Calorimetry (PDSC) and (iv) Attenuated Total Reflectance Infrared spectroscopy (ATR-IR) (Jullien, Meurisse, & Berthier, 1996; Guan, Willermet, Carter, & Melotik., 1998; Li et al., 2003; Maeda & Murakami, 2003; Nyman, Mäki, Olsson, & Ganemi, 2006). Generally, the implementation of these existing methods is very time consuming and possibly not pragmatic for real-life applications, owing to the fact that the friction discs have to be taken out from the clutch pack and then prepared for assessing the degradation level. In other words, an online monitoring and prognostics system can not be realized by using these existing methods

As the central role of wet friction clutches relies on the friction, a natural way to monitor and assess the condition of these components is by monitoring and quantifying the frictional characteristics. The use of the mean (averaged) coefficient of friction (COF) for a given duty cycle as a principle feature for condition monitoring of wet friction clutches has been popular for many years (Matsuo & Saeki, 1997; Ost, Baets, & Degrieck, 2001; Maeda & Murakami, 2003; Li et al., 2003; Fei, Li, Qi, Fu, & Li, 2008). However, this is normally performed in laboratory tests, namely durability tests of clutch friction materials and ATF, where the used test setup (*i.e.* SAE#2 test setup) is fully instrumented. For real-life applications, the use of the mean COF for clutch monitoring is possibly expensive and not easily implementable, due to the fact that *at least two sensors* are required to extract it, namely a torque and a force sensor, which are commonly difficult to install (typically not available) in today's transmissions.

Regarding clutch health assessment and prognostics, only a few publications were found in literature. Yang *et al.* (Yang, Twaddell, Chen, & Lam, 1997; Yang & Lam, 1998) developed a physics-based prognostics model by considering that the degradation occurring in a clutch is only due to thermal effect taking place in the friction materials. The model was developed based on the cellulose fibers concentration, where the change of the fibers concentration is assumed to be likened to a simple chemical reaction. They found that, the ratio between the instantaneous concentration of cellulose fibers $\mathscr{W}$ and the initial concentration of cellulose fibers $\mathscr{W}_0$, *i.e.* weight loss ratio $\frac{\mathscr{W}}{\mathscr{W}_0}$, likely follows a zero-th order reaction in isothermal condition. The degradation rate constants are obtained by performing dedicated (separate) Thermal Gravimetric Analysis (TGA) experiments on the friction material samples taken out from clutch packs at different interface temperatures. To predict the degradation level and RUL of friction material under dynamic engagement, the temperature history of friction material as a function of time and axial locations are of importance in this approach. Since the interface temperature of the friction material during a clutch engagement is difficult to measure, they (Yang, Lam, Chen, & Yabe, 1995; Yang & Lam, 1998) developed a comprehensive and detailed mathematical model to predict the temperature at the interface, as well as the temperature distribution as a function of time and different locations. Hence, the accuracy of the existing clutch prognostics method is strongly determined by the accuracy of temperature prediction. Since the degradation mechanism occurring in the clutch friction material is not only due to thermal effect but also another major mechanism namely adhesive wear (Gao, Barber, & Chu, 2002; Gao & Barber, 2002), the assumption made in this prognostics method is too oversimplified. When the complete design data of a wet friction clutch is not available, this prognostics method would be possibly difficult to implement.

Considering the above discussed literature survey, one may conclude that the available clutch monitoring and prognostics methods are not pragmatic and flexible to implement for real-life applications. Nowadays, there is still a need for automotive industries (*e.g.* our industrial partner) to realize a clutch monitoring and prognostics system which is easy to implement and flexible to adapt. In addition to this, the development of such a system must be based on typically available sensors in AT systems, such as rotational velocity, pressure and temperature sensors. Hence, research in this direction is still of great interest.

Recently, some potential monitoring methods which can serve as bases for clutch prognostics have been investigated and reported in previous publications. The preliminary evaluations of a clutch monitoring method based on the *post-lockup* torsional vibration are discussed in (Ompusunggu, Papy, Vandenplas, Sas, & VanBrussel, 2009; Ompusunggu, Sas, VanBrussel, Al-Bender, Papy, & Vandenplas, 2010). Since it is reasonable to assume that the ATF has no significant effect on the clutch post-lockup torsional vibration, this method is suitable to monitor only the clutch friction material degradation. A more complete description concerning the feasibility and practical implementation of this method will be discussed in another communication. Furthermore, a clutch monitoring method based on the *pre-lockup* torsional vibration is evaluated in (Ompusunggu, Sas, VanBrussel, Al-Bender, & Vandenplas, 2010), where a high resolution rotational velocity sensor is required in order to capture the high frequency torsional vibration. Another clutch monitoring method based on tracking the change of the relative rotational velocity between the input and output shaft of a clutch is proposed in (Ompusunggu, Papy, Vandenplas, Sas, & VanBrussel, 2012). Since the relative velocity can be seen as the representative of the clutch dynamic behavior during the engagement phase, which are strongly influenced by the combination of friction material and ATF, the latter method can be used to monitor the global state of a clutch. Nevertheless, the prognostics aspect was not tackled yet in those publications. An attempt to develop a systematic methodology for health assessment and prognostics of wet friction clutches is the main objective of this paper. For this purpose, the latter condition monitoring method described in (Ompusunggu et al., 2012) is extended in this paper towards a prognostics methodology.

The remainder of this paper is organized as follows. After introducing the objective and motivation, the methodology proposed in this paper is presented and discussed in Section 2. To verify the proposed method, life data of some commercially available clutches obtained from accelerated life tests (ALTs) carried out on a fully instrumented SAE#2 test setup are employed. The details of the experimental aspects are described in Section 3. The results obtained after applying the proposed method to the clutches' life data are further presented and discussed in Section 4. Finally, some conclusions drawn from the study that can be a basis for future work are presented in Section 5.

2. Methodology

The overall methodology proposed in this paper is described in the flowchart depicted in Figure 2. As can be seen in the figure, the methodology consists of four steps. In the first step, capturing the signal of interest from raw pressure and relative velocity signals is discussed. In the second step, three primary features are computed once the signal of interest has been captured, where the verification of the three features has been addressed in another publication (Ompusunggu et al., 2012). In the third step, the features are fused into a single value, namely health index, using a logistic regression technique. The output of the logistic model is restricted between 0 and 1 such that the health or performance of a wet friction clutch can be easily assessed. Finally, the algorithm to predict the remaining useful life (RUL) using the fused features as the predicted variable is presented and discussed. Since the knowledge of the evolution of the proposed features during clutches' lifetime is still limited, a data-driven prognostics approach is investigated in this paper.

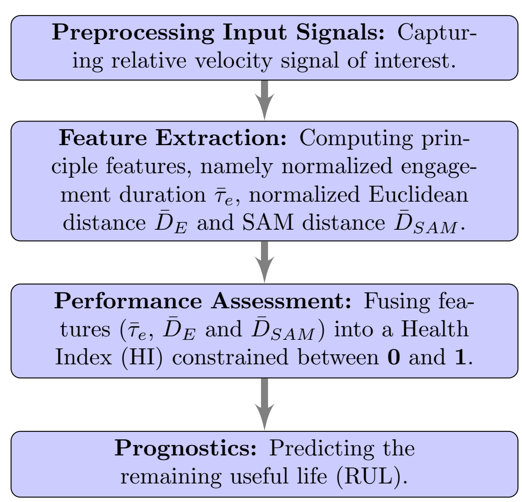


Figure 2. Flow chart of the proposed methodology.

2.1. Relevant Signals Measurement

Prior to computing principle features as will be discussed in the next subsection, the raw signals obtained from measurements first need to be preprocessed. Figure 3 graphically illustrates the signal preprocessing step, namely the procedure to capture the **relative velocity signal of interest** based on two raw measurement signals: (i) the *relative rotational velocity* and (ii) *applied pressure* signals. In the following paragraphs, the procedure is briefly discussed.

Let the signal of interest be captured at a given (arbitrary) duty cycle with a predetermined time record length τ, and suppose that the time record length is kept the same for all duty cycles. For the sake of consistency, the signal must be captured at the *same* reference time instant. It is reasonable to consider that the time instant when the ATF pressure applied to the clutch pack $p(t)$ starts to increase from zero value t_f as the reference time, which can be mathematically formulated as:

$$t_f = \min \{\forall t \in \mathbb{R} : \quad p(t) > 0\} . \tag{1}$$

While the applied pressure is increasing, contact is gradually established between the separator and friction discs. As a result, the transmitted torque increases that consequently reduces the relative velocity $n_{rel}(t)$. Eventually, the clutch is fully engaged when the relative velocity reaches zero for the first time at the lockup time instant t_l that can be formulated in similar way to Equation (1) as:

$$t_l = \min \{\forall t \in \mathbb{R} : \quad n_{rel}(t) = 0\} . \tag{2}$$

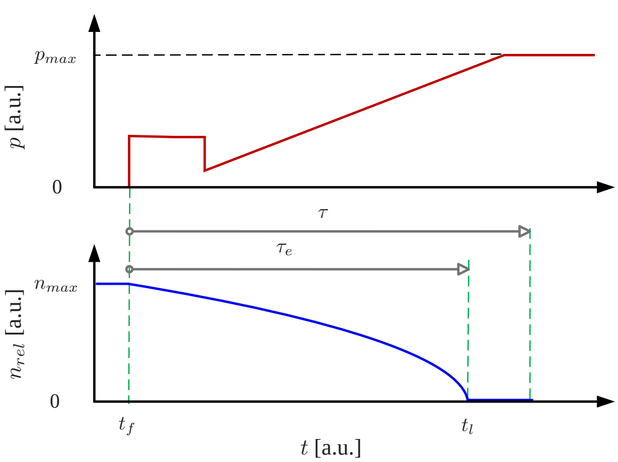


Figure 3. A graphical illustration of how to capture the relative velocity signal of interest. The upper and lower figures respectively denote the typical applied pressure p and the raw relative velocity signal n_{rel}. Note that a.u. is the abbreviation of arbitrary unit.

2.2. Feature Extraction

Formal definitions of the developed features (engagement duration, Euclidean distance and Spectral Angle Mapper distance) and the mathematical expressions to compute them are discussed in this subsection. The first two features are dimensional quantities while the third one is dimensionless. The first two features are normalized such that they become dimensionless quantities and are in the same order of magnitude as of the third feature.

2.2.1. Engagement Duration

The engagement duration τ_e is referred to as the time interval between the lockup time instant t_l and the reference time instant t_f, as graphically illustrated in Figure 3. Once both time instants t_f and t_l have been determined, the engagement duration τ_e can then be simply computed as follows:

$$\tau_e = t_l - t_f . \tag{3}$$

Without loss of generality, τ_e can be normalized with respect to the engagement duration measured at the initial condition (healthy state) τ_e^r, according to the following equation:

$$\bar{\tau}_e = \frac{\tau_e - \tau_e^r}{\tau_e^r}, \tag{4}$$

where $\bar{\tau}_e$ denotes the dimensionless engagement duration.

2.2.2. Dissimilarity Measures

A dissimilarity measure is a metric that quantifies the dissimilarity between objects. For the sake of condition monitoring, the dissimilarity measure between an object that represents an arbitrary condition and the reference object that represents a healthy condition, can be treated as a feature. Thus, the dissimilarity measure between two identical objects is (close to) zero; the dissimilarity measure between two non-identical objects on the other hand is not zero. Here, the object will be referred to as the relative velocity signal n_{rel}. Two dissimilarity measures, namely the Euclidean distance and the Spectral Angle Mapper (SAM) distance, are considered in this paper because of their computational simplicity (Kruse et al., 1993; Paclik & Duin, 2003).

The main motivation behind the dissimilarity approach is that the measured signals of interest are treated as vectors. Let $\mathbf{X}$ be a K dimensional vector, $x_i, i = 1, 2, \ldots, K$, denoting the discrete signal of the relative velocity measured in a normal (healthy) condition and $\mathbf{Y}$ be a K dimensional vector, $y_i, i = 1, 2, \ldots, K$, denoting the discrete signal of the relative velocity measured in an arbitrary condition. The vector $\mathbf{X}$ representing a healthy condition is referred to as the "baseline".

The dimensional Euclidean distance D_E between the vectors

$\mathbf{X}$ and $\mathbf{Y}$ is defined as:

$$D_E(\mathbf{X},\mathbf{Y}) = \sqrt{\sum_{i=1}^{K}(x_i - y_i)^2}. \tag{5}$$

For convenience, D_E can also be normalized in accordance with the following equation:

$$\bar{D}_E(\mathbf{X},\mathbf{Y}) = \frac{D_E(\mathbf{X},\mathbf{Y})}{x_1\sqrt{K}}, \tag{6}$$

where $\bar{D}_E$ denotes the dimensionless Euclidean distance and $x_1 > 0$ denotes the initial value of the *baseline*.

By definition, the SAM distance is a measure of the angle between two vectors and is therefore dimensionless. The SAM distance $\bar{D}_{SAM}$ between the vectors $\mathbf{X}$ and $\mathbf{Y}$ is mathematically expressed as:

$$\bar{D}_{SAM}(\mathbf{X},\mathbf{Y}) = \cos^{-1}\left(\frac{\sum_{i=1}^{K} x_i y_i}{\sqrt{\sum_{i=1}^{K} x_i^2}\sqrt{\sum_{i=1}^{K} y_i^2}}\right). \tag{7}$$

Recall that the distance from an object to itself is zero and that a distance is always non-negative.

2.3. Health Assessment

Health assessment constitutes a dichotomous problem, namely determining the state of of a unit (system) of interest (UOI) whether in healthy or failure state. Intuitively, health can be represented by a binary value, *e.g.* **0** or **1**, where this categorical value may be seen as a health index. For health assessment purposes, it is natural to assume that the health index of (close to) 1 represents a healthy state, while the health index of (close to) 0 represents a failure state. This formulation implies that the degradation occurring in a UOI is indicated by the progressive change of the health index from 1 to 0. It should be noted that the health index is sometimes called "confidence value" in literature.

In practice, feature values are not necessarily restricted between 0 and 1, which cannot allow a direct justification on the health of a UOI. Despite reflecting the actual condition of a UOI, principle features extracted from measurement data cannot be directly used to assess the health of the UOI unless the *relative distances* to the corresponding values which represent the end of life of the UOI (*i.e.* thresholds) are known. To this end, the feature values evolving from a healthy to failure state need to be transformed to the health indices.

In this study, health assessment based on a logistic regression technique is investigated. As will be shown later, logistic regression can be seen as a process with a two-fold objective: (i) fusing multiple features (independent variables) into a single value (*i.e.* health index) and (ii) restricting the health index between 0 and 1. As discussed in (Lemeshow & Hosmer, 2000), logistic regression is appropriate technique for dichotomous problems, where the predicted variable (*i.e.* health index) must be greater than or equal to zero and less than or equal to one. Unlike linear regression which is inappropriate for dichotomous problems (Lemeshow & Hosmer, 2000), in logistic regression, only data representing healthy and failure states are required to estimate the regression coefficients. Thus, a logistic regression technique is suitable to problems with limited number of history data. Moreover, it has been reported in the literature that logistic regression technique is a powerful tool for health assessment modeling of some systems based on extracted high dimensional features (Yan, Koc, & Lee, 2004; Yan & Lee, 2005).

Let us consider a simple **logistic function** $P(F)$ defined as:

$$P(F) = h = \frac{1}{1+e^{-g(\mathbf{F})}} = \frac{e^{g(F)}}{1+e^{g(F)}}, \tag{8}$$

where $F = \{F_1, F_2, \ldots, F_L\}$ denotes a set of L extracted features, h denotes the health index of an event (*i.e.* healthy or failure) given a set of features F and $g(F)$ is the **logit function** which is mathematically expressed as:

$$g(F) = g = \log\left(\frac{P(F)}{1-P(F)}\right) = \sum_{i=0}^{L}\beta_i F_i, \tag{9}$$

where $F_0 = 1$, β_i denotes the logistic model parameters to be identified and g denotes the logarithm of the "odds-of-success". In a more compact way, Equation (9) can be rewritten as:

$$g = \boldsymbol{\beta}^{\mathrm{T}}\mathbf{F}, \tag{10}$$

with

$$\boldsymbol{\beta} = [\beta_0 \quad \beta_1 \quad \beta_2 \quad \ldots \quad \beta_L]^{\mathrm{T}}$$

and

$$\mathbf{F} = [1 \quad F_1 \quad F_2 \quad \ldots \quad F_L]^{\mathrm{T}},$$

where the superscript T denotes a transpose operation.

Note that the logistic function expressed in Equation (8) can be seen as a kind of probability function (cumulative distribution function) because it ranges between 1 (healthy) and 0 (failure). In addition to this, the logit function expressed in Equation (10) constitutes a linear combination of features extracted from measurement data $F_1, F_2, \ldots, F_L$. This implies that the logarithm of the odds-of-success g preserves the nature of features to be extracted from measurement signals.

Here, the main objective of the logistic regression is to identify $(L+1)$ parameters $\boldsymbol{\beta}$ in Equation (10) such that the logistic model is readily implementable for the health assessment of a UOI. In this context, the parameter identification is normally performed using the maximum-likelihood estimator, which entails finding the set of parameters for which the probability of the observed data is maximal (Czepiel, n.d.). This is done off-line where two sets of features, F_{health} and $F_{failure}$ respectively representing healthy and failure states, are used as training data.

2.4. Prognostics Algorithm - Data Driven Approach

The prognostics algorithm proposed in this paper is based on a data-driven approach. The variable to be predicted is the logarithm of the odds-of-success g. The main reason for this consideration is that this predicted variable g still preserves the nature of features extracted from the measurements (the linear combination of features). Basically, the algorithm consists of four main steps, namely (i) determining the first time instant to start prediction t_p^1 such that the history data available at t_p^1 are sufficient, (ii) building a prognostics model from the available data, (iii) predicting the trajectory of the predicted variable g to the future based on the built prognostics model and (iv) estimating the remaining useful life (RUL). When new data are available, the steps (ii) - (iv) are performed and this procedure is periodically repeated until a certain time instant useful to do prediction. Thus, the prognostics model is updated once new data are provided and it is expected that the model converges because more evidence accumulates over time. These steps are discussed in more detail in the subsequent paragraphs.

In this paper, t_p^1 is proposed as the time instant when the health index h is equal to 0.75. At this value ($h = 0.75$), theoretically, it is reasonable to assume that a UOI has passed about 25% of its total lifetime and the history data to build a prognostics model are practically available. In the domain of the predicted variable g, the aforementioned health index $h = 0.75$ corresponds to $g = 1.098$.

The weighted mean slope (WMS) method proposed in (Bey-Temsamani et al., 2009b) is used in this paper to adaptively build a prognostics model for given history data. This method is easy to implement and based on a data-driven approach where the model to be built is updated periodically when new data come in. In this method, all the local slopes of a time series are first computed. Afterwards, the slope at the end of the time series (*i.e.* at the arbitrary time instant to do prediction t_p) is computed by summing up all the local slopes weighted by a certain function, where the weighting factor of the most recent data is the greatest. Let $g = \{g_1, g_2, \ldots, g_N\}$ and $t = \{t_1, t_2, \ldots, t_N\}$ be respectively the history of the logarithm of the odds-of-success and the corresponding time sequence at t_p. The WMS b_w at this particular time instant t_p is calculated according to the following equation:

$$b_w = \sum_{n=2}^{N} \omega_n b_n, \tag{11}$$

with

$$\omega_n = \frac{n}{\sum_{n=2}^{N} n}, \tag{12}$$

and

$$b_n = \frac{g_n - g_{n-1}}{t_n - t_{n-1}} \quad \{n = 2, 3, \ldots, N\}, \tag{13}$$

where b_n and ω_n respectively denote the local slope and the corresponding weighting factor. The standard deviation σ_b of the WMS at time instant t_p is calculated according to the following equation:

$$\sigma_b = \sqrt{\sum_{n=2}^{N} \omega_n \left(b_n - b_w\right)^2}. \tag{14}$$

For 95% confidence interval, the lower bound b_w^{lower} and upper bound b_w^{upper} of the WMS can be calculated as follows (Meeker & Escobar, 1998):

$$b_w^{lower} = b_w - 1.96 \frac{\sigma_b}{\sqrt{N-1}}, \tag{15}$$

$$b_w^{upper} = b_w + 1.96 \frac{\sigma_b}{\sqrt{N-1}}, \tag{16}$$

As will be shown later in Section 4, the three features $(\bar{D}_E, \bar{D}_{SAM}, \bar{\tau}_e)$ evolve linearly during the lifetime of the tested clutches. It is therefore reasonable to assume that the trend of the predicted variable g is also linear since the nature of the features is preserved. Hence, the value of the predicted variable at time instant $t_p + t_h$, namely $g_{t_p+t_h}$, is given by:

$$g_{t_p+t_h} = g_{t_p} + b_w t_h, \tag{17}$$

where $g_{t_p} = g_N$.

Suppose that the failure threshold (RUL threshold) g_{limit} is known in advance. The expected RUL r at an arbitrary time instant t_p can be computed as:

$$r = \frac{g_{limit} - g_{t_p}}{b_w}. \tag{18}$$

Based on the lower and upper bound of the WMS expressed in Equations (15) and (16), the uncertainty of prognostics (the lower bound Δr^{lower} and the upper bound Δr^{upper} of the RUL) can be estimated according to the following equations:

$$\Delta r^{lower} = r - r^{lower}, \tag{19}$$

$$\Delta r^{upper} = r^{upper} - r, \tag{20}$$

with

$$r^{lower} = \frac{g_{limit} - g_{t_p}}{b_w^{upper}}, \tag{21}$$

$$r^{upper} = \frac{g_{limit} - g_{t_p}}{b_w^{lower}}. \tag{22}$$

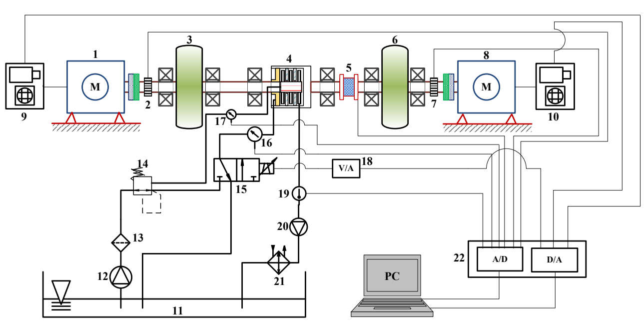
3. Experiment

Service life data of wet friction clutches are required for the evaluation of the developed health assessment and prognostics method. In order to obtain the clutch service life data in a reasonable period of time, the concept of an accelerated life test (ALT) is applied in this study. For this purpose, a fully instrumented SAE#2 test setup designed and built by our industrial partner, Dana Spicer Off Highway Belgium, was made available. In this respect, an ALT can be realized by means of applying a higher mechanical energy to a tested clutch compared to the amount of energy transmitted by a clutch in normal operation. The energy level is normally adjusted by changing the initial relative velocity and/or the inertia of input and output flywheels. In this study, the ALTs were conducted on different commercial wet friction clutches using the fully instrumented SAE#2 test setup. During the tests, all the clutches were lubricated with the same Automatic Transmission Fluid (ATF). The test setup and the ALT procedure are discussed in the following subsections.

3.1. SAE#2 test setup

The SAE#2 test setup used in the experiments, as depicted in Figure 4, basically consists of three main systems, namely: driveline, control and measurement system. The driveline comprises several components: an AC motor for driving the input shaft (1), an input velocity sensor (2), an input flywheel (3), a clutch pack (4), a torque sensor (5), output flywheel (6), an output velocity sensor (7), an AC motor for driving the output shaft (8), a hydraulic system (11-20) and a heat exchanger (21) for cooling the outlet ATF. An integrated control and measurement system (22) is used for controlling the ATF pressure (both for lubrication and actuation) to the clutch and for the initial velocity of both input and output flywheels as well as for measuring all relevant dynamic signals.

(a)



(b)

Figure 4. The SAE#2 test setup used in the study, (a) photograph and (b) scheme, courtesy of Dana Spicer Off Highway Belgium.

3.2. Test specification

The general specification of the test scenario is given in Table 1. Two clutch packs with different lining materials of the friction discs were tested. It should be noted that all the used friction discs, separator discs and ATF are commercial ones which can be found in the market. In all the tests, the inlet temperature and flow of the ATF were kept constant, see Table 1. Additionally, one can see in the table that the inertia of the input flywheel (drum-side) is lower than that of the output flywheel (hub-side).

Number of clutch packs to be tested	2
Number of friction discs in the clutch assembly	8
Inner diameter of friction disc (d_i) [mm]	115
Outer diameter of friction disc (d_o) [mm]	160
ATF	*John Deere J20C*
Lubrication flow [liter/minute]	18
Inlet temperature of ATF [°C]	85
Output flywheel inertia [kgm^2]	3.99
Input flywheel inertia [kgm^2]	3.38
Sampling frequency [kHz]	1

Table 1. General test specification.

3.3. Test procedure

Before an ALT is carried out to a wet friction clutch, a run-in test (lower energy level) is first conducted for 100 duty cycles in order to stabilize the contact surface. The run-in test procedure is in principle the same as the ALT procedure, but the initial relative rotational velocity of the run-in tests is lower than that of the ALTs. Figure 5 illustrates a duty cycle of the ALT that is carried out as follows. Initially, while both input flywheel (drum-side) and output flywheel (hub-side) are rotating at predefined respective speeds in opposite direction, the two motors are powered-off and the pressurized ATF is simultaneously applied to a clutch pack at time instant t_f. The oil thus actuates the clutch piston, pushing the friction and separator discs towards each other. This occurs during the filling phase between the time instant t_f and t_a. While the applied pressure is increasing, contact is gradually established between the separator and friction discs which results in an increase of the transmitted torque on the one hand and a decrease of the relative velocity on the other hand. Finally, the clutch is completely engaged when the relative velocity reaches zero at the lockup time instant t_l. As the inertia and the respective initial speed of the output flywheel (hub-side) are higher than those of the input flywheel, after t_l, both flywheels rotate together in the same direction as the output flywheel, see Figure 5. In order to prepare for the forthcoming duty cycle, both driving motors are braked at the time instant t_b, such that the driveline can stand still for a while.

The ALT procedure discussed above is continuously repeated until a given total number of duty cycles is attained. For the sake of time efficiency in measurement, all the ALTs are per-

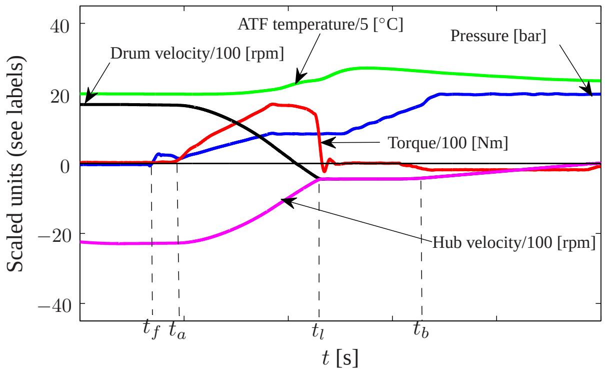


Figure 5. A representative duty cycle of wet friction clutches. Note that the transmitted torque drops to zero after the lockup time instant t_l because there is no external load applied during the test.

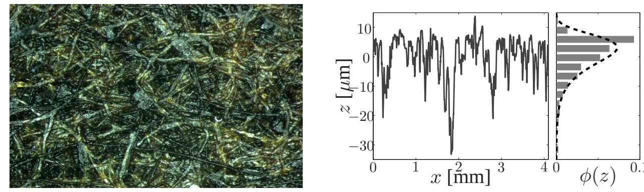
formed for 10000 duty cycles. The pressure applied to the clutches is kept constant during the tests and the ATF is continuously filtered, such that it is reasonable to assume that the used ATF has not degraded during the tests.

4. Results and Discussion

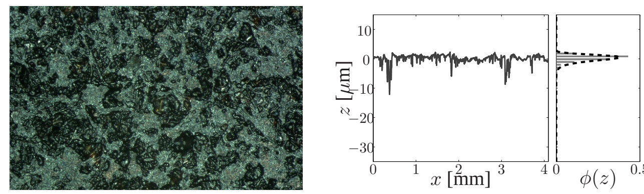
Figure 6 shows the optical images and the surface profile of the friction material before and after the ALT, taken from the first clutch pack. The images are captured using a **Zeiss microscope** and the surface profiles are measured along the sliding direction using a **Taylor Hobson Talysurf** profilometer. It can be seen in the figure that the surface of the friction material has become smooth and glossy and the clutch is therefore considered to have failed. The change of the color and the surface topography of the friction material is known as a result of the glazing phenomenon that is believed to be caused by a combination of adhesive wear and thermal degradation (Gao et al., 2002; Gao & Barber, 2002).

4.1. Capturing the Signal of Interest

Figure 7 shows 3D plots of the relative velocity signals of interest obtained from the first ALT (clutch pack#1) and second ALT (clutch pack#2). All the signals are captured at the same reference time instant t_f with the same time record length τ of 2.5 s. As can be seen in the figure, the reference time instant t_f is set to zero. Furthermore, it is evident from the figure that the profile of the relative velocity signal deviates from its initial profile, as the clutch degradation progresses (pointed out by the arrow). This deviation is indicated by two major patterns, namely (i) the changing shape and (ii) the shifting lockup time instant t_l to the right hand-side with respect to the reference time instant t_f. This observation confirms the experimental results reported in the literature (Fei et al., 2008).

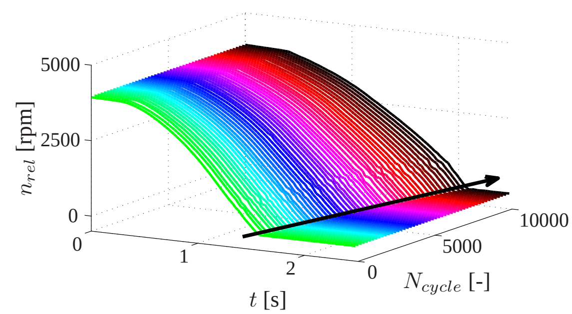


(a)

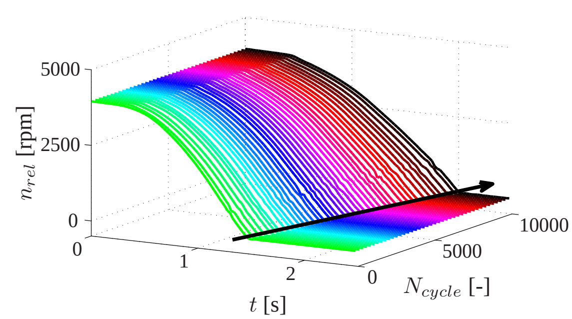


(b)

Figure 6. Comparison of the friction material before and after the ALT of 10000 duty cycles. (a) optical image (left) and the corresponding surface profile (right) of the friction material *before* the test, (b) optical image (left) and the corresponding surface profile (right) of the friction material *after* the test. Note that z denotes the displacement of the profilometer stylus in Z-axis (perpendicular to the surface), x denotes the displacement of the profilometer stylus in X-axis (along the sliding direction) and $\phi(z)$ denotes the probability distribution function of the surface profile.



(a)



(b)

Figure 7. Evolution of the relative velocity signals of interest obtained from (a) the *first* ALT and (b) the *second* ALT.

4.2. Extracted Features

The features introduced in Section 2 are extracted from the relative velocity signal of interest as shown in Figure 7 based on Equations (4), (6) and (7). Figure 8 shows the evolution of the features in function of the clutches service life. It is remarkable to mention that the trends of all the features are linearly increasing with relatively small variations.

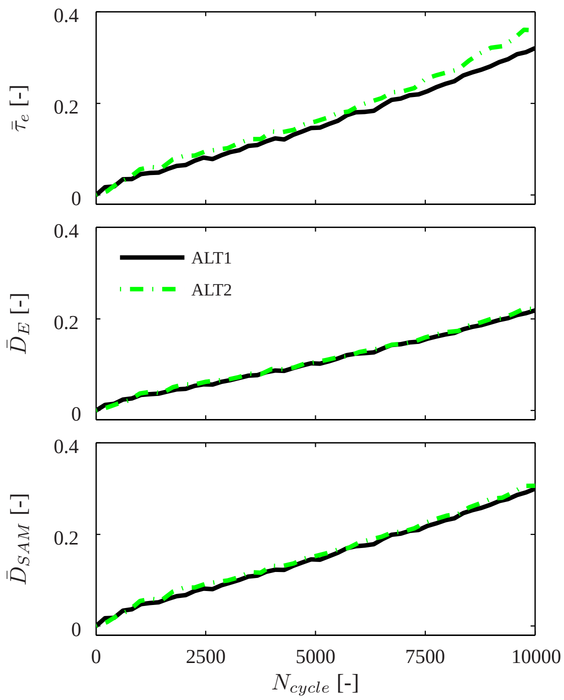


Figure 8. Evolution of the features obtained from the first and second ALT.

4.3. Logistic Model

In order to build a logistic model for clutch health assessment, a number of sets of the features, $F_{health} = \{\bar{\tau}_e^{\mathrm{i}}, \bar{D}_E^{\mathrm{i}}, \bar{D}_{SAM}^{\mathrm{i}}\}$ and $F_{failure} = \{\bar{\tau}_e^{\mathrm{f}}, \bar{D}_E^{\mathrm{f}}, \bar{D}_{SAM}^{\mathrm{f}}\}$, respectively representing healthy and failure states are required. Note that the superscripts i and f respectively denote the healthy and failure state. Table 2 lists the sets of features used for logistic regression for different observations on the features extracted from the measurement data as shown in Figure 8. The health index h assigned for the healthy and failure states are respectively 0.95 and 0.05. It should be mentioned here that these two values are heuristically derived since there are no enough history data.

Using the training data listed in Table 2, the parameters obtained from the logistic regression can be written as:

$$\boldsymbol{\beta} = [3.09 \quad 2.07 \quad -35.96 \quad 3.57]^{\mathrm{T}}.$$

Based on the identified parameters, the logistic model represented as the health index h in function of the clutch duty cycles N_{cycle} can be expressed in the following equation:

$$h(N_{cycle}) = \frac{e^{g(N_{cycle})}}{1 + e^{g(N_{cycle})}}, \tag{23}$$

with

$$g(N_{cycle}) = 3.09 + 2.07\bar{\tau}_e - 35.96\bar{D}_E + 3.57\bar{D}_{SAM}. \tag{24}$$

Figure 9 shows the evolution of the health index h of the two tested clutches. As was expected, the health index decreases progressively during the service life of the clutches. Since the index is restricted between 0 and 1, this figure can thus ease the users to justify the health status of the clutches. When the index value is close to 1, one can directly justify that the clutches are healthy, while the index approaches 0, one can easily justify that the clutches are going to fail.

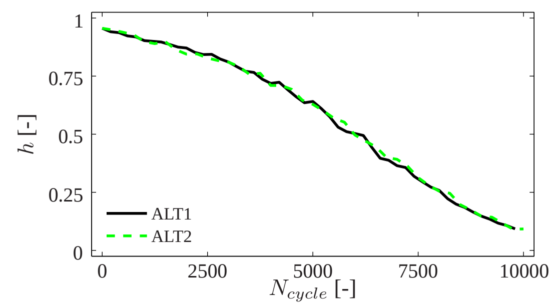


Figure 9. The health index h evolution of both tested clutches.

4.4. Prognostics Performance

In this subsection, the performance of the proposed prognostics algorithm is demonstrated. Figure 10 shows the evolution of the logarithm of the odds-of-success g which has been specified as the predicted variable. When $g = 1.098$ (*i.e.* crossing the upper horizontal line) the algorithm is triggered for the first time to build a prognostics model (at 3000^{th} cycle) and the trajectory of g indicated by the gray dashed line is consecutively predicted until it crosses the predefined threshold (the lower horizontal line). The RUL threshold g_{limit} is set at the value of -2.197 which corresponds to the health

	Observation	$\bar{\tau}_e$	$\bar{D}_E$	$\bar{D}_{SAM}$
Healthy state ($h = 0.95$)	1	0	0	0
	2	0.0033	0.0034	0.0051
	3	0.017	0.0122	0.017
	4	0.0109	0.0069	0.0109
Failure state ($h = 0.05$)	1	0.3	0.2	0.27
	2	0.32	0.22	0.29
	3	0.3205	0.2186	0.2995
	4	0.3593	0.2216	0.3062

Table 2. Sets of features used for logistic regression analysis

index of 0.1. At this particular value ($g_{limit} = -2.197$), it is reasonable to assume that the tested clutches have passed about 90% of their expected total lifetime. For a comparison, the prediction at 7000^{th} cycle is also shown in the figure. As can be seen, the predicted trajectory of g at the latter cycle (shown by the solid black line) gets closer to the measurement data indicating that the model has been updated.

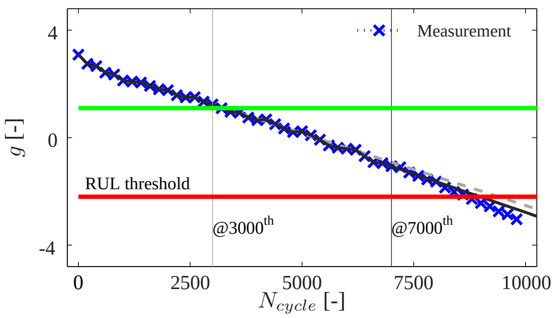


Figure 10. Representative evolution of the logarithm of the odds-of-success g.

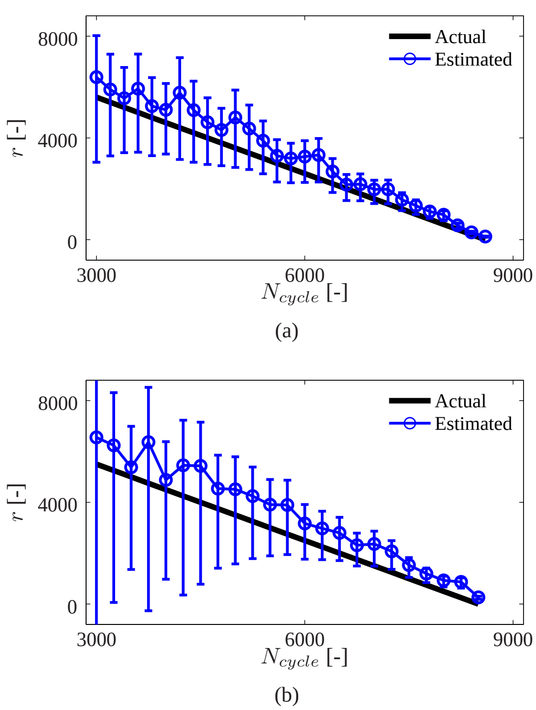


Figure 11. Comparison of the estimated and actual RULs of: (a) the first clutch pack and (b) the second clutch pack.

The RUL estimations of both clutches are depicted in Figure 11. As can be seen in the figure, the error between the estimated RULs and the actual RULs, and the corresponding uncertainty interval are quite large in the beginning of the prediction because limited amount of data are available to build the prognostics model. When more evidence becomes available, it is evident from the figure that the estimated RULs tend to converge to the actual RULs and the uncertainties tend to decrease over time, implying that the prognostics model improves over time.

5. Conclusion and Future Work

In this paper, an attempt to develop a health (performance) assessment and prognostics methodology for wet friction clutches has been presented and discussed. For health assessment purposes, all the extracted features are fused into a single variable called the health index h which is restricted between 0 and 1, based on a logistic regression solved with the maximum likelihood estimation technique. In this way, a logistic model can be built that allows a direct justification on the health of wet friction clutches. In terms of prognostics, the logarithm of odds-of-success, *i.e.* $\log(h/(1-h))$ is assigned as the predicted variable. The weighted mean slope (WMS) method, which is simple and easy to implement, is used to predict the trajectory of the predicted variable and consecutively to predict the remaining useful life (RUL) of clutches. The proposed methodology has been experimentally evaluated on two commercially available clutch packs with different friction materials. The experimental results confirm that the methodology proposed in this paper is promising in aiding the development a maintenance strategy for wet friction clutches.

The experiments carried out in this study were under controlled environment. More data will be collected in the future where some variations of loading, operational temperature and applied pressure during the duty cycles are present. Furthermore, some prospective algorithms need to be evaluated in future work in order to determine the most optimal one, in regard to the accuracy, convergence rate and the practical implementation.

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NOMENCLATURE

t	time
$\mathscr{W}$	instantaneous concentration of cellulose fibers
$\mathscr{W}_0$	initial concentration of cellulose fibers
n_{rel}	relative velocity
p	pressure
t_f	reference time instant
t_l	lockup time instant
t_p^1	time instant for first prediction
t_p	arbitrary time instant for prediction
τ	time record length
X	vector denoting a discrete relative velocity signal measured in an initial (healthy) condition
Y	vector denoting a discrete relative velocity signal measured in an arbitrary condition
$\bar{\tau}_e$	normalized engagement duration
$\bar{D}_E$	normalized Euclidean distance
$\bar{D}_{SAM}$	normalized SAM distance
F	a set of features
h	health index
g	logarithm of the odds-of-success
g_{limit}	RUL threshold
b_n	local slope
ω_n	weighting factor
b_w	weighted mean slope
σ_b	weighted standard deviation
r	remaining useful life (RUL)
N_{cycle}	number of duty (engagement) cycles

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BIOGRAPHIES

Agusmian Partogi Ompusunggu is a project engineer at Flanders' MECHATRONICS Technology Centre (FMTC), Belgium. His research focuses in condition monitoring, prognostics, vibration testing and analysis and tribology. He earned his bachelor degree in mechanical engineering (B.Eng) in 2004 from Institut Teknologi Bandung (ITB), Indonesia and master degree in mechanical engineering (M.Eng) in 2006 from the same technological institute. He is currently pursuing his PhD degree in mechanical engineering at Katholieke Universiteit Leuven (K.U.Leuven) Belgium.

Steve Vandenplas is a program leader at Flanders' MECHATRONICS Technology Centre (FMTC), Belgium. He received his Master's Degree of Electrotechnical Engineer in 1996 from the Vrije Universiteit Brussel (VUB), Belgium. In 2001, he received a PhD in Applied Science and started to work as R&D Engineer at Agilent Technologies for one year. Thereafter, he decided to work as a Postdoctoral Fellow at the K.U. Leuven in the Department of Metallurgy and Materials Engineering, in the research group material performance and non-destructive testing (NDT). He has been working at Flanders' MECHATRONICS Technology Centre (FMTC) since 2005, where he is currently leading FMTC's research program on "Monitoring and Diagnostics". His main interests are on machine diagnostics and condition based maintenance (CBM).

Paul Sas is a full professor at the Department of Mechanical Engineering of Katholieke Universiteit Leuven (K.U.Leuven), Belgium. He received his master and doctoral degree in mechanical engineering from K.U.Leuven. His research interest comprise numerical and experimental techniques in vibro-acoustics, active noise and vibration control, noise control of machinery and vehicles, structural dynamics and vehicle dynamics. He is currently leading the noise and vibration research group of the Department of Mechanical Engineering at K.U.Leuven.

Hendrik Van Brussel is an emeritus professor at the Department of Mechanical Engineering of Katholieke Universiteit Leuven (K.U.Leuven), Belgium. He was born at Ieper, Belgium on 24 October 1944, obtained the degree of Technical Engineer in mechanical engineering from the Hoger Technisch Instituut in Ostend, Belgium in 1965 and an engineering degree in electrical engineering at M.Sc level from K.U.Leuven. In 1971 he got his PhD degree in mechanical engineering, also from K.U.Leuven. From 1971 until 1973 he was establishing a Metal Industries Development Center in Bandung, Indonesia and he was an associate professor at Institut Teknologi Bandung (ITB), Indonesia. He was a pioneer in robotics research in Europe and an active promoter of the mechatronics idea as a new paradigm in machine design. He has published more than 200 papers on different aspects of robotics, mechatronics and flexible automation. His research interests shifted towards holonic manufacturing systems and precision engineering, including microrobotics. He is Fellow of SME and IEEE and in 1994 he received a honorary doctor degree from the 'Politehnica' University in Bucharest, Romania and from RWTH, Aachen, Germany. He is also a Member of the Royal Academy of Sciences, Literature and Fine Arts of Belgium and Active Member of CIRP (International Institution for Production Engineering Research).