Remaining Lifetime Prediction for Reliability-based Dry Clutch Control

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ABSTRACT

Increasing requirements for reliability of modern powertrains can be achieved by predictive maintenance and reliability-based control based on lifetime prediction. This contribution presents lifetime prediction for a dry clutch, being an essential component of automated manual transmissions. Model-based development of lifetime prediction requires knowledge of dry clutch wear, which was identified in previous experiments. The derived wear model allows estimation of characteristic wear-dependent values, like friction lining material losses and friction coefficient changes. Based on these estimated values the presented lifetime prediction was developed by fusing these estimated values into a health index (HI) describing the systems healthiness. Furthermore, the remaining useful lifetime (RUL) becomes predictable from observations of health index trend using an exponential weighted moving average. Whereby, this method is limited to linear wear trends. Eventually, the presented lifetime prediction was implemented and tested on real-time operating hardware similar to common transmission control units. In order to control the system lifetime in normal operation, target trends for health index and predicted remaining useful lifetime were defined. Based on trend deviations, a fuzzy-logic based control strategy was realized, which sets the optimization target for a reliability-based control. Thus, the optimization target can be varied between comfort-optimized or wear-optimized clutch engagements. Finally, an outline of reliability-based control concepts is given.

1. INTRODUCTION

The demand for reliability throughout the modern powertrain is steadily increasing. Unexpected failures usually cause intolerable costs and can endanger vehicle occupants. In order to meet these increasing requirements, the application of reliability improving concepts, like predictive maintenance and reliability-based control, is necessary. Usually, these approaches require estimation and prognosis of system healthiness and remaining lifetime.

Lifetime prediction is a common research topic for different mechanical systems. In general, prediction of remaining useful lifetime can be done either data-driven or model-based. Data-driven approaches are useful when wear influences at least one measured quantity. However, existing system sensors are mostly not usable for data-driven wear prediction due to inaccuracy. Therefore, additional sensors, for example, vibration sensors for bearing monitoring, need to be integrated into the mechanical system. This results in two disadvantages: the physical wear behaviour might be interpreted incorrectly from sensor signals, because the physical wear behaviour is unknown, and application of additional sensors increases costs. As an alternative, model-based approaches can be used for remaining useful lifetime prediction. Model-based prediction requires identification of a wear model by measurements on a component test bench. By identification, a detailed physical insight is generated on the one hand. On the other hand, the identification process costs much effort.

An application of lifetime prediction for clutches by a data-driven approach was shown in (A. P. Ompusunggu, Vandenplas, Sas, & van Brussle, 2012). Wear of a wet clutch was predicted from three features, which were extracted from measured speed and clutch actuator pressure. These features were fused in a system health index. Remaining useful lifetime was predicted based on this health index by a weighted moving average. Another data-driven approach for dry clutches

was presented in (Ramalingam, Prasad, Regalla, & Srinivasa Prakash, 2017). Lifetime prediction by using measured clutch actuator position was illustrated, but a proof of concept was missing. A general approach for model-based lifetime prediction for a dry clutch was shown in (Watson, Byington, Edwards, & Amin, 2005). The cumulative wear was estimated by an Archard model and lifetime prediction was done by a double exponential smoothing. The Archard model in (Watson et al., 2005) requires knowledge of the wear coefficient, which needs to be identified by experiments.

Based on the lifetime prognosis, a reliability-based control can be realized. The aim of a reliability-based control is to control system lifetime, leading to a guaranteed required lifetime. In literature, reliability-based control was investigated for different systems. An approach for an electrical machine was presented in (Hu, Foitzik, Chi-Thuan, & Guhmann, 2009). The accumulated wear was estimated model-based and was subsequently used for health index calculation. In consequence, the decision for the intervention of reliability-based control was done by evaluation of health index and its derivative. In (Hu et al., 2009) and in (Gokdere, Bogdanov, Chiu, Keller, & Vian, 2006) a fuzzy system was proposed to determine intervention of the reliability-based control. The reliability-based control can guarantee the required lifetime by changing the controller reference, as presented in (Hu et al., 2009), or by changing the controller parameters, as illustrated in (Gokdere et al., 2006). As an alternative adjusting of cost function weights of an optimal controller, like model predictive controller (MPC), was investigated in many applications. For example in (Salazar, Nejjari, & Sarrate, 2014) an MPC with integrated wear model was used for reliability-based control of a twin rotor system. In (Sanchez, Escobet, Puig, & Odgaard, 2017) a reliability-based control was realized using a MPC for a wind turbine system with linearisation of calculated load.

Finally, the literature review reveals two open research issues: a model-based approach for lifetime prediction with identified model parameters and reliability-based control for clutches. Both topics will be addressed in this contribution.

The remainder of this paper is structured as follows. Section 2 presents the applied methods of wear modelling, lifetime prediction and reliability-based control strategy followed by the results in section 3. In section 4 the presented results are discussed. This contribution concludes with a summary and an outlook on future work.

2. METHODS

For realisation of the proposed reliability-based control four subsystems are required: the wear model (section 2.1), the health assessment (section 2.2), the lifetime prediction (section 2.3) and the reliability-based control strategy (section 2.4). The total structure is shown in figure 1. At first, the wear model is used for wear estimation from known process
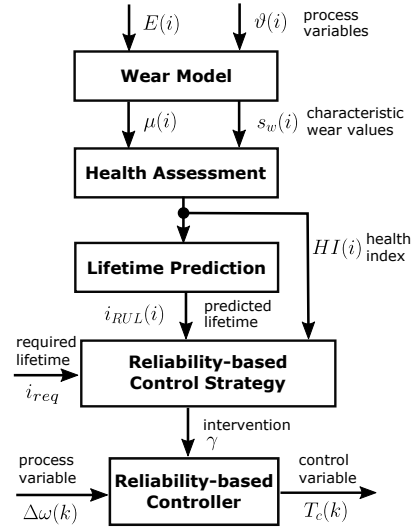

Figure 1. Block scheme for reliability-based control

variables. Afterwards, the characteristic wear-dependent values are fused into the health index by the health assessment. The health index trend allows predicting the remaining useful lifetime. In the end, the control strategy calculates required intervention in the clutch control from health index and remaining useful lifetime. Thus, the required system lifetime can be guaranteed by the clutch control.

2.1. Wear Modeling

The dry clutch is a tribological system, where wear is caused by abrasion of friction lining. In contrast to other mechanical systems, the clutch can endure wear as well as thermal stress to a certain limit. The friction lining surface is degraded by abrasion. As a result, a new underlying surface with similar friction characteristics is uncovered. Thus, wear do not change system performance significantly, as long as friction lining height limit is not reached or friction lining surface is not damaged by thermal overload. Wear of dry clutches can be described macroscopically by Archard's Law (Archard, 1953).

$$V_w = k_w F_N s \qquad (1)$$

According to Eq. (1) the volume loss V_w is calculated from wear coefficient k_w, applied normal force F_N and sliding distance s. The proof of this thesis as well as the identification of the wear coefficient k_w were done by previous experiments (Strommenger, Gühmann, & Knoblich, 2017). The required wear model can be build by applying the Law of Archard to dry clutches, which will be described in the following.

A universal approach for wear modelling consists of two steps. Firstly, tribological loads shall be determined and calculated. For a dry clutch these are friction energy E and surface temperature ϑ of friction linings. E is calculated from clutch torque T_c and differential speed $\Delta\omega$, which is defined as dif-

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ference between engine speed ω_e and clutch speed ω_c. Friction energy is generated only during slipping. The slipping time is defined as t_{slip}.

$$E = \int_0^{t_{slip}} T_c \Delta \omega dt \qquad (2)$$

The other tribological load ϑ is not measurable by common vehicle sensors. In general, ϑ can be estimated by a thermal model as presented in (Strommenger, Gühmann, Knoblich, & Beilharz, 2017). Hence, ϑ is assumed as known.

As second step, the relationship between load and wear need to be identified. In order to identify this relationship, various test bench experiments were performed to gain a deep insight to dry clutch wear behaviour (Strommenger, Gühmann, & Knoblich, 2017). These investigations allowed the derivation and validation of a wear model stimulated by friction energy and clutch temperature. All tests were planned according to design of experiments (DoE) methods (Strommenger, Gühmann, & Knoblich, 2017). Eventually, the wear behaviour is described by wear coefficient k_w depending on friction energy E and temperature ϑ of friction lining surface. As a result, dry clutch material loss is calculated per cycle, whereby each engagement is assumed as a cycle i, according to Eq. (3) by applying Archard's Law from Eq. (1). Material loss is defined as reduction of friction lining height Δs_w divided by bearing area A_R (Strommenger, Gühmann, & Knoblich, 2017).

$$\Delta s_w(i) = k_w \frac{E(i)}{A_R} \qquad (3)$$

Consequently, the accumulated material loss describes the total wear of a dry clutch by friction lining height s_w.

$$s_w(i) = s_{w,max} - \sum_{j=1}^{j=i} \Delta s_w(j) \qquad (4)$$

Whereby, the height of a new friction lining is defined as $s_{w,max}$ and of a worn friction lining as $s_{w,min}$.

The friction lining height s_w describes aging of dry clutches. However, s_w cannot explain additional damage caused by overload. Thermal overload causes a rapid reduction of friction coefficient μ, called Fading. This effect is reversible, if overload is applied for a short time. In this case the friction surface will regenerate by abrasion of the damaged surface layers. By continuous application of overload, the damage will be irreversible and the friction coefficient μ will not regenerate. Hence, the friction coefficient will be used in addition to describe overload related damages. Furthermore, the friction coefficient μ is assumed as estimable from measured clutch position and estimated clutch torque. For $\mu > \mu_0$ the friction lining is considered as healthy, for $\mu_{min} < \mu < \mu_0$ it is considered as partially damaged and for $\mu < \mu_{min}$ it is considered as irreversible damaged.

2.2. Health Assessment

Lifetime prediction always requires a health assessment of the system. For that reason a health index HI needs to be defined, which allowing an easy assessment of health or performance for dry clutches. All characteristic wear-dependent values are fused into the health index, as in (A. P. Ompusunggu et al., 2012). Therefore, friction lining height s_w and friction coefficient μ are combined to HI. For the presented wear model from Eq. (3) and Eq. (4), the first part of HI can be described by assuming thresholds for new ($HI = 1$) and worn ($HI = 0$)

$$\begin{aligned} HI_{s_w} &= 1 \text{ for } s_w(i) = s_{w,max} \\ HI_{s_w} &= 0 \text{ for } s_w(i) = s_{w,min} \end{aligned} \qquad (5)$$

and by assuming a linear relation between HI_{s_w} and s_w to model expected wear behaviour.

$$HI_{s_w}(i) = \frac{s_w(i) - s_{w,min}}{s_{w,max} - s_{w,min}} \qquad (6)$$

The second part of HI can be described as a nonlinear relation between HI_μ and μ by a sigmoid function to model expected wear behaviour.

$$\begin{aligned} HI_\mu(i) &= \frac{1}{1+e^{a(\mu(i)-b)}} \\ a &= \frac{-2ln(99)}{\mu_0 - \mu_{min}} \\ b &= \frac{\mu_{min} + \mu_0}{2} \end{aligned} \qquad (7)$$

In Eq. 7 the sigmoid function was defined, that HI_μ will fulfil the following conditions.

$$\begin{aligned} HI_\mu &= 0.99 \text{ for } \mu(i) = \mu_0 \\ HI_\mu &= 0.01 \text{ for } \mu(i) = \mu_{min} \end{aligned} \qquad (8)$$

Finally, HI can be fused by multiplication as an mathematical *and*.

$$HI(i) = HI_{s_w}(i) \cdot HI_\mu(i) \qquad (9)$$

2.3. Lifetime Prediction

The presented wear model allows a continuous material loss estimation, which grants the opportunity of lifetime prognosis by predicting the trend of HI. The presented lifetime predic-
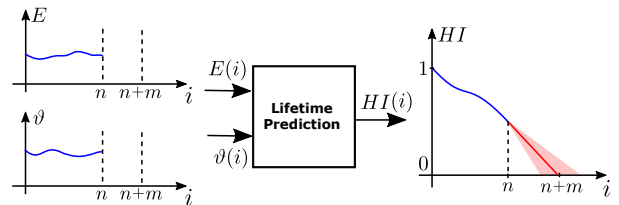

Figure 2. Principle of lifetime prediction

tion is illustrated as a block scheme in following Figure 2.

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Trend prediction can be done by different methods. For choosing an appropriate method it is necessary to determine whether the wear trend is linear or nonlinear. According to Eq. (3) and Eq. (4), the wear model is assumed as linear. Hence, a linear method for lifetime prediction of dry clutches is chosen.

A simple approach for linear prediction is the weighted moving average (WMA). The WMA can predict steady trends well but is not able to predict monotonically increasing trends. Thus, the WMA is applied to the change of health index ΔHI, which has a steady trend, instead of HI having a monotonically decreasing trend.

$$\Delta HI_{WMA}(i) = \sum_{i=n-N}^{i=n} \alpha(1-\alpha)^{(i-1)}\Delta HI(i) \qquad (10)$$

The WMA averages $\Delta HI(i)$ from all observed values inside rolling window $i = n - N$ to current cycle $i = n$. Newer values have greater influence on calculated average due to exponential weights by $\alpha(1-\alpha)^{(i-1)}$. Eventually, prediction is done by assuming $\Delta HI_{WMA}(i = n, ..., n + m) = \Delta HI_{WMA}(i = n)$ for all future values $i = n + m$ inside a prediction horizon m. For practical implementation the WMA will be used in its recursive form.

$$\Delta HI_{WMA}(i) = \alpha\Delta HI(i) + (1-\alpha)\Delta HI_{WMA}(i-1) \quad (11)$$

In practical applications, the prognosis uncertainty needs to be considered. According to (A. P. Ompusunggu et al., 2012) the standard derivation σ of the WMA can be calculated by the following equation.

$$\sigma = \sqrt{\sum_{i=n-N}^{i=n} \alpha(1-\alpha)^{(i-1)}(\Delta HI(i) - \Delta HI_{WMA}(i))^2}$$
$$(12)$$

Hence, the 95 % confidence interval $\Delta HI_{WMA,b}$ of the WMA can be calculated as follows.

$$\Delta HI_{WMA,b} = 1.96\frac{\sigma}{\sqrt{N-1}} \qquad (13)$$

Additionally to the 95 % confidence interval, the estimation uncertainty of the presented wear model has an influence on the lifetime prediction accuracy. In (Strommenger, Gühmann, & Knoblich, 2017) the uncertainty of the wear model $s_{w,b}$ was determined to be about 10 %.

By using the WMA to predict wear from current cycle n until HI reaches 0 inside the prediction horizon m, the remaining useful lifetime (RUL) i_{RUL} can be determined as follows.

$$i_{RUL}(i) = \frac{HI(i)}{\Delta HI_{WMA}(i)} \qquad (14)$$

By considering the confidence interval of the WMA from Eq. (13) and uncertainty $HI(s_{w,b})$ derived from the wear model, the uncertainty of prognostics $i_{RUL,b}$ can be estimated by two assumptions. Firstly, the uncertainty of prognostics is derived by division of two uncertainties and can be calculated according to (Berendsen, 2011) by Eq 15. Secondly, the covariance is neglected.

$$i_{RUL,b} \approx i_{RUL}\sqrt{\left(\frac{HI(s_{w,b})}{HI}\right)^2 + \left(\frac{\Delta HI_{WMA,b}}{\Delta HI_{WMA}}\right)^2} \qquad (15)$$

2.4. Reliability-based Control Strategy

As a result of the lifetime prediction, the RUL describes expected time to system failure. This grants the possibility to realize predictive maintenance. By predictive maintenance the repair of vehicle components can be planned before damage will occur. However, the lifetime prediction does not allow any evaluation, whether current RUL is acceptable. For example, the system could be actuated with overload, which decreases the system lifetime drastically. In this case, overload should be prevented by clutch control algorithms. This concept is named reliability-based control, which shall guarantee a required lifetime by preventing critical overloads.

Reliability-based control requires a control strategy, which decides whether intervention by load reduction is necessary or not. This control strategy is illustrated as a block scheme in Fig. 3 and will be explained in this section.
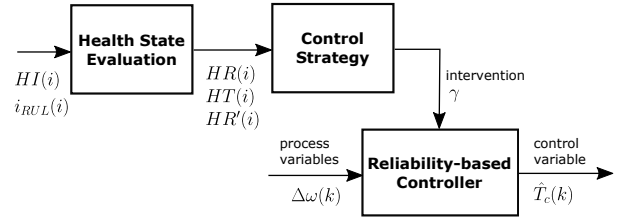

Figure 3. Principle of reliability-based control

Furthermore, the reliability-based control shall be integrated into the system control. In case of a clutch, the reliability-based control is part of clutch engagement control. Whereby, the application for vehicle launch is crucial because most of the wear will be generated during engagement. Concepts for reliability-based controller will be concretized at the end of this contribution as a research outlook.

The control strategy is based on three inputs: health rate HR, Health Trend HT and Health Tendency HR'. The health rate HR evaluates current health index HI in relation to current cycle i and required lifetime i_{req}. (Hu et al., 2009)

$$HR(i) = \frac{HI(i)}{1 - \frac{i}{i_{req}}} \qquad (16)$$

Thus, $HR > 1$ describes an acceptable health state for current lifetime, which means that required lifetime will proba-

bly be achieved. Otherwise, for $HR < 1$ the required lifetime will probably not be achieved. Furthermore, the tendency for HR can be described by its derivative HR' as difference quotient.

$$HR'(i) = \frac{\Delta\, HR(i)}{\Delta\, i} \qquad (17)$$

HR' describes whether the system is currently operated with light load for $HR' > 0$ or with high load for $HR' < 0$. Whereby, for $HR' = 0$ the system is operated with appropriate load to achieve the required lifetime i_{req}. However, HR and HR' did not consider prediction. To consider predicted i_{RUL}, the health trend HT is defined as ratio of expected lifetime i_{EoL} to required lifetime i_{req}.

$$HT(i) = \frac{i_{RUL}(i) + i}{i_{req}} = \frac{i_{EoL}(i)}{i_{req}} \qquad (18)$$

HT gives information, if the health rate HR will probably improve for $HT > 1$ or worsen for $HT < 1$ in current operation scenario. In other words: the system will achieve for $HT > 1$ the required lifetime in current operation scenario without intervention. In contrast, this will be not achievable for $HT < 1$.

By using these values for the evaluation of lifetime prediction, the required intervention by clutch control can be defined colloquially as in Table 1. A fuzzy-system with 9 rules is used

Table 1. Required intervention of reliability-based control for evaluated lifetime prediction

HR	HT	HR'	intervention
> 1	> 1	> 0	none
> 1	> 1	< 0	none
> 1	< 1	> 0	none
> 1	< 1	< 0	low
< 1	> 1	> 0	none
< 1	> 1	< 0	low
< 1	< 1	> 0	medium
< 1	< 1	< 0	high
$\ll 1$	$*$	$\ll 0$	high

to realize the reliability-based control strategy. All inputs are fuzzified by trapezoidal-shaped membership functions. HT is divided in 2 cases. HR and HR' are divided in 3 cases. The output γ is defuzzified with 4 triangular-shaped membership functions. The principal block scheme of this fuzzy system is shown in Fig. 4. All functions of this fuzzy system are shown in Table 2. For better understanding, fuzzification by a trapezoidal-shaped membership function is shown principally for HR as an example in Fig. 5. HR is divided into three cases: *healthy*, *unhealthy* and *ill*. The case *ill* is defined additionally to handle overload more aggressive. All cases are overlapping each other to ensure output continuity. The intervention aggressivity can be adjusted by the gradient between two cases. Additionally, a tolerance for no reaction is defined by assuming unhealthy state for $HR < 1 + \epsilon$ instead of $HR < 1$. Hence, the intervention will not be set for noisy
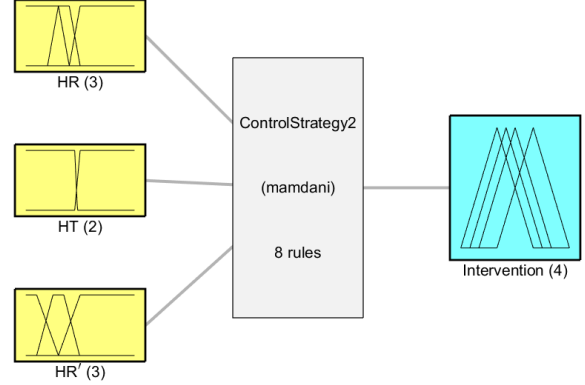

Figure 4. Fuzzy-System for calculating intervention of reliability-based control

Table 2. Fuzzy functions for control strategy

Function	Method
And	Multiplication
Or	Probabilistic (Algebraic Sum)
Implication	Minimum
Aggregation	Probabilistic (Algebraic Sum)
Rules	Mamdani
Defuzzification	Centroid of area

HR values around 1, if noise is smaller than ϵ.

A similar strategy is used for HT and HR'. Mathematically the input membership functions are expressed by Eq. 19. Whereby, $trapmf()$ is a Matlab notation for trapezoidal-shaped membership function and $trimf()$ for triangular-shaped membership function.

$$
\begin{aligned}
\gamma\ (\text{none}) &= \text{trimf}(-1, 0, 1) \\
\gamma\ (\text{less}) &= \text{trimf}(-0.75, 0.25, 1.25) \\
\gamma\ (\text{mean}) &= \text{trimf}(-0.5, 0.5, 1.5) \\
\gamma\ (\text{high}) &= \text{trimf}(0, 1, 2)
\end{aligned}
\qquad (19)
$$

The input membership functions are expressed by Eq. 20.

$$
\begin{aligned}
HR\ (\text{healthy}) &= \text{trapmf}(0.8, 1.2, 3, 3) \\
HR\ (\text{unhealthy}) &= \text{trapmf}(0.4, 0.6, 0.8, 0.95) \\
HR\ (\text{ill}) &= \text{trapmf}(-1, -1, 0.6, 0.8) \\
HT\ (\text{go-healthy}) &= \text{trapmf}(0.9, 1, 3, 3) \\
HT\ (\text{go-ill}) &= \text{trapmf}(-1, -1, 0.9, 0.95) \\
HR'\ (\text{low-load}) &= \text{trapmf}(-4, 0, 300, 300)/100 \\
HR'\ (\text{high-load}) &= \text{trapmf}(-8, -5, -3, -0.1)/100 \\
HR'\ (\text{over-load}) &= \text{trapmf}(-100, -100, -8, -4)/100
\end{aligned}
$$

$$(20)$$

Finally, the presented fuzzy system is able to calculate an intervention value γ for the reliability-based control based on three evaluation values, which are derived from HI and i_{RUL}. The intervention value can vary between $\gamma = 0$ (no intervention) to $\gamma = 1$ (full intervention), whereby $\gamma = 0$ is interpreted as comfort-optimized engagement and $\gamma = 1$ as
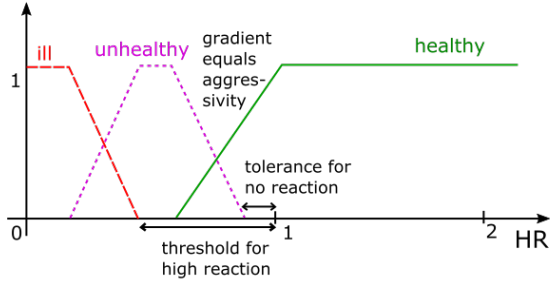
Figure 5. Principally membership function of fuzzy-system for control strategy

wear-optimized engagement.

3. RESULTS

The presented methods were simulated on real-time prototype hardware by randomized stimuli. Friction energy is varied from 5 kJ to 45 kJ and temperature from 40 °C to 140 °C. The resulting wear is illustrated in Fig. 6 by reduction of friction lining height and reaches its limit at 120,000 cycles.

The required lifetime in the example is chosen as 125,000 cycles, which is not achieved. In this example, overload is prevented, therefore the friction coefficient μ is neglected. According Eq. 11 and Eq. 14 HI and i_{RUL} are estimated and illustrated in Fig. 7. i_{RUL} is estimated after 30,000 cycles. Because of rolling window length $N = 30,000$ cycles, the WMA estimates a valid i_{RUL} after $i \geq N$. Thus, the i_{RUL} is set equal to the target trend for $i < N$. The exponential weighting value α is chosen as 0.002. Additionally, the target trends for HI and i_{RUL} are shown in Fig. 7. If HI and i_{RUL} meet their target trends, the evaluation represented by HR, HT and HR' will stay at their targets too.

The resulting lifetime evaluation by HR, HT and HR' is shown in Fig. 8. At least the intervention γ in Fig. 8 was calculated by the presented fuzzy-system for the reliability-based control strategy. As the system is operated without reliability-based control, the intervention does not have any influence on lifetime. This open loop scenario shows, that the control strategy works correctly. For example, the intervention γ increases, if HR decreases. Intervention γ is amplified, if HT, HR and HR' are far away from their target trends.

4. DISCUSSION

The presented method for lifetime prediction is based on two assumptions. Firstly, the health index is calculated from two characteristic wear-dependent values. The presented health assessment is expendable for systems with more characteristic wear-dependent values if the physical background is known. In other cases, all characteristic wear-dependent values need to be fused into the health index by different methods. One opportunity was proposed in (A. P. Ompusunggu et al., 2012), where a logistic regression model was introduced for health
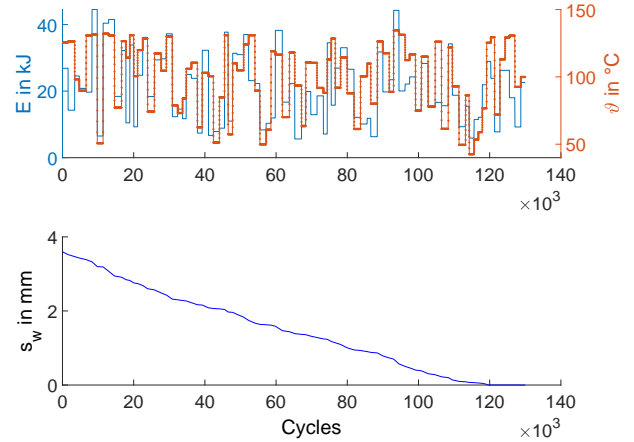

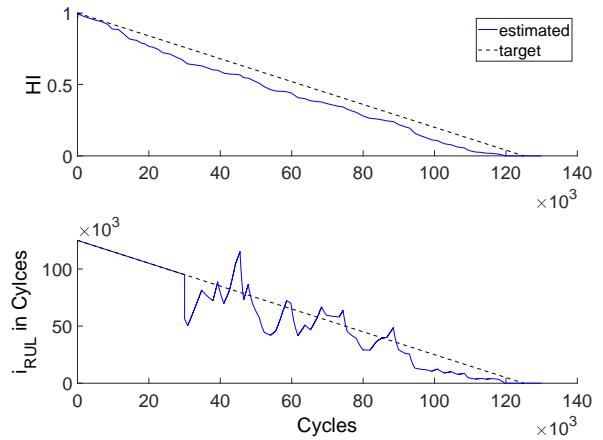Figure 6. Estimated wear s_w for randomized stimuli

Figure 7. Estimated HI and predicted i_{RUL} for randomized stimuli

index calculation. This solution is quite useful for data-driven approaches with higher number of features.

Secondly, the presented approach for lifetime prediction of dry clutches is based on the assumption of a linear wear trend. Therefore, WMA is used for a linear prediction of the remaining useful lifetime. Hence, this approach works only for linear wear behaviour. The linearity of the wear model was ensured by experiments in (Strommenger, Gühmann, & Knoblich, 2017). Thus, this prediction method is not applicable, if wear behaves nonlinearly. In this case nonlinear prediction methods should be used. One example of a nonlinear prediction method is a Kalman filter with an exponential wear model as presented in (A. Ompusunggu, Papy, & Vandenplas, 2015). This method can be used for nonlinear as well as for linear prediction, which offers a more general usage.

Due to the fact, that the presented lifetime prediction shall be integrated on a real-time-hardware, the WMA is preferred, because of its short execution time. Usage in real-time hardware is one major requirement for the presented approach.
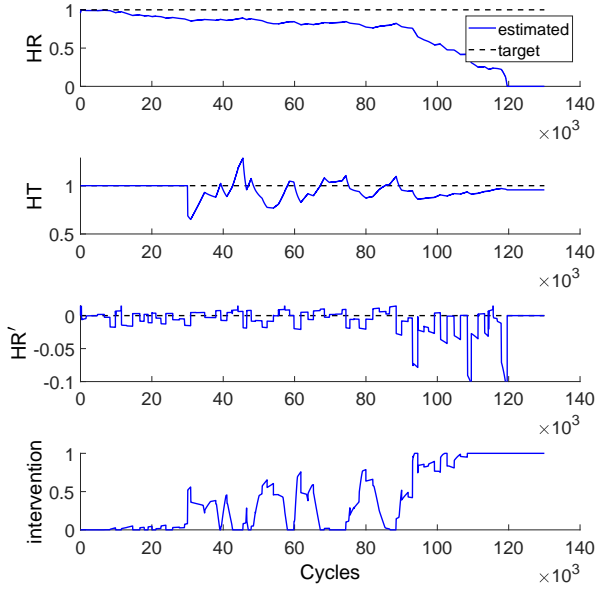
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Figure 8. Estimated health state evaluation HR, HT and HR' and required intervention γ for randomized stimuli

All methods are integrated on a dSPACE Microautobox II with Matlab 2016b and tested on a transmission test bench, described in (Nowoisky, Knoblich, & Gühmann, 2012). This setup guarantees a later usage of all methods in a transmission control unit of a real vehicle. As execution time 10 ms are chosen, but all event discrete methods will be executed once per engagement cycle and will be idle until next engagement cycle occurs.

The uncertainty of presented lifetime prediction is considered in Eq. 15, but is not shown for clarity in the results section. Compared to wear model uncertainty, the uncertainty of the WMA, which is below 1 %, can be neglected. Hence, the wear model uncertainty of 10 % cause an prediction uncertainty of 10 % according to Eq. 15. Due to a constant relative uncertainty, the absolute uncertainty is increasing over time. In contrast, the absolute prediction error e_{pred} is decreasing over time, because of decreasing time distance between prediction cycle n and i_{EoL}.

$$e_{pred}(i) = i_{RUL}(i) + i - i_{EoL} \qquad (21)$$

This means, the difference between $i_{RUL} + i$ and i_{EoL} will decrease over time, which makes prediction results more trustworthy if prediction cycle n and i_{EoL} are close to each other. Additionally, the WMA will deliver no trustful results, if current cycle i is smaller than window length N. During this initial learning phase the uncertainty of lifetime prediction will decrease according to Eq. 12 and 13 until it reaches the mentioned WMA uncertainty below 1 %.

Besides the considered model uncertainties, additional input uncertainties and operating environment uncertainties need to

be considered. Input uncertainties are dependent on the initial state of damage, manufacturing variability and measurement noise. The initial state of damage will be assumed as zero for a new clutch. No uncertainty need to be assumed in this case. In contrast, the reinitialization of current wear is crucial for wear estimation due to the fact, that new wear is estimated from cumulated old wear according to Eq. 4. Hence, for usage in vehicles, old wear values shall be saved continuously to grantee a valid reinitialization in every case. By this measure, uncertainty due to the initial state of damage can be neglected. Uncertainties caused by manufacturing variability and measurement noise were not determined in this contribution. These uncertainties need to be determined for a specific dry clutch system in the later application. The influence of resulting input uncertainty on the uncertainty of lifetime prediction need to be determined for example by a Monte Carlo simulation.

In contrast to input uncertainties the operating environment uncertainties have an higher impact on lifetime prediction results. Operating environment uncertainties are dependent to unforeseen future loads and variability of history data. According to Eq. 12 and 13 increasing variability causes higher lifetime prediction uncertainty. The influence of variability can be handled by choosing appropriate values for window length N and exponential weight α of the WMA. Assuming, that these can be chosen from field data with a variability similar to the real application. If this is not valid, additional measures for determination of the WMA parameters according to the current data variability need to be considered. The influence of unforeseen future load was not considered for the presented lifetime prediction. Hence, unforeseen future loads and variability of history data are open issues, which should be investigated in further research.

The presented reliability-based control strategy is based on a fuzzy logic, which grants two benefits. Firstly, it allows an easy interpretation of evaluated lifetime prediction and resulting intervention. Secondly, it avoids unsteadiness of intervention γ, which could cause stability problems of the reliability-based control. In comparison to existing approaches like (Hu et al., 2009) or (Gokdere et al., 2006) the presented reliability-based control strategy shows additional benefits. Both approaches were based on models, whereby (Hu et al., 2009) used a wear model to estimate health index and (Gokdere et al., 2006) used a model for considering desired working conditions. Though, none of them used lifetime prediction results for reliability-based control strategy. By using prediction, unnecessary intervention can be reduced. Instead of a control strategy based on an additional model, a MPC-controller with integrated wear prediction model was investigated by (Salazar et al., 2014). This approach considers prediction but needs much computational effort. Thus the presented fuzzy-based control strategy has two advantages in comparison to existing approaches: it considers prediction and can be used on real-time-hardware.

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5. OUTLOOK

The presented reliability control strategy can be used to vary the aim of the engagement controller between wear-optimized or comfort-optimized if intervention value γ is integrated into clutch control. Common clutch controllers are based on calibrated trajectories (Wehbi, Bestle, & Beilharz, 2016). Therefore the intervention can easily be integrated as an additional input of a lookup-table. Hence, the controller aim can be set for each engagement by choosing trajectories from a lookup-table as it is illustrated in Fig. 9 depending on intervention γ and operation scenario. The operation scenario depends on engine torque T_e and load torque T_L. The control variable $T_{c,ref}$ will be set as a reference for underlying actuator control. An alternative approach is the integration of intervention
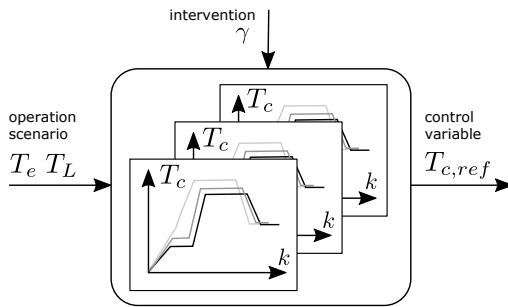

Figure 9. Reliability-based controller concept by trajectories

value γ inside a cost function of an optimal controller. In general, MPC is suggested for an optimal clutch control (Dolcini, Béchart, & Canudas de Wit, 2010), which can consider intervention as a weight for two partial cost functions for comfort J_c and wear J_w.

$$minJ = \gamma J_w + (1 - \gamma)J_c \qquad (22)$$

Both approaches will be investigated in further research.

6. CONCLUSION

In summary, the presented approach can be used to predict health index and remaining useful lifetime based on estimated wear for dry clutches. A WMA was used to perform lifetime prediction based on health index trend. The presented lifetime prediction is limited to linear wear trends. The uncertainty analysis of the proposed method reveals that lifetime prediction uncertainty is mainly influenced by wear model uncertainty. Besides the limitation to linear trends, the lifetime prediction is not trustful at initial learning phase. Additional uncertainties arising from manufacturing variability, measurement noise as well as variability of history data and future load were not determined in this contribution. Hence, the uncertainty analysis shall be extended to these open issues in further research to achieve a reliable lifetime prediction for real application.

Furthermore, the resulting health index and remaining use-

ful lifetime were evaluated by a fuzzy-logic. By this evaluation, the required intervention for reliability-based control was derived. Usage of fuzzy-logic allows an easy interpretation of lifetime prediction results and avoids unsteadiness of the resulting intervention for the reliability-based control. As a result, the reliability-based control will be able to control system lifetime by varying between comfort-optimized and wear-optimized clutch engagements. Finally, all presented methods were implemented and tested on real-time prototype hardware to guarantee the later usage in real vehicles. In the end, the basis for a reliability-based control was built by the presented lifetime prediction and control strategy. The concretisation of the reliability-based control idea will be an issue of further research.

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