# Forecasting Component Service Life by Gentelligent Components

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**Summary:** This article examines the development of a methodology to predict the remaining service life of gentelligent components. The methodology refers to the wear type of fatigue and is based on a maintenance control cycle developed in the sub-project N3 of the Collaborative Research Centre 653. Component conditions are evaluated over the entire life cycle and stored in a database. The stored data serve as experience and knowledge for monitoring the condition of a current component and enable the prediction of the remaining service life. For this purpose, the stresses to which the monitored component has been subjected to date are compared with the stress data of empirical knowledge. If the database contains information about components which were exposed to a similar stress profile during their life cycle, these will be used for the forecast. The statistical analysis of these stress profiles enables the limitation of the future stress on the monitored component and thus an estimate of the remaining service life. Knowledge about the remaining service life is an essential basis for the selection of a possible maintenance measure.

Keywords: Collaborative Research Centre 653, Gentelligent Components, Maintenance, Fatigue, Condition Monitoring

# 1. Collaborative Research Centre 653 – Gentelligent components

The forecast of the component service life is the central content of the sub-project N3 "Component status-driven maintenance". The methodology of component status-driven maintenance (GI maintenance) is being developed by Collaborative Research Centre 653 (CRC 653). The objective of CRC 653 is the development of gentelligent components (GI components). Gentelligence is made up from the words 'genetics' and 'intelligence', and refers to the ability of components to be both "knowing" and "feeling". Components are enabled to absorb information from their environment, process it further and pass it on to subsequent component generations [1].

Sub-project N3 uses the recorded information, such as component stresses, to determine suitable maintenance measures. A significant deciding factor is the forecast service life of the component. This article will examine the forecast methodology in greater detail.

# 1.1. Component-inherent sensors

Sensors are required to record component stresses. Previously used sensors such as strain gauges have no significant place in the monitoring of component stresses due to their high complexity in use. They are used mainly in laboratory trials for component design. Micro-sensors offer one possibility for the permanent monitoring of stresses during operation. These represent an alternative, but much like strain gauges have to be integrated on or in the components.

Sub-projects of CRC 653 however are developing component-inherent sensors. This requires the use of sensitive materials. They enable the registration of the component stresses over the entire life cycle of a component, and thus provide the information needed for component status-driven maintenance.

The sub-project E2 of CRC 653 is developing a novel magnetic magnesium alloy as the sensitive material. For the measurement of the stress, the Villari effect is used, by which the

flux density of the alloy is dependent on the strain and varies depending on the tractive or compression stress. The flux density is measured by means of an eddy current signal [2]. Other subprojects deal with the measurement of the inherent stress in the component surface [3], and the measurement of Martensite content of austenitic steels. Both of these properties vary depending on the component stresses [4].

# 1.2. Control cycle of component status-driven maintenance

The methodology of component status-driven maintenance can be illustrated by a control cycle. This consists of a knowledge basis, a comparison, diagnostic and forecasting module [5], as well as modules for the derivation of a reaction strategy and maintenance, as shown in Figure 1.

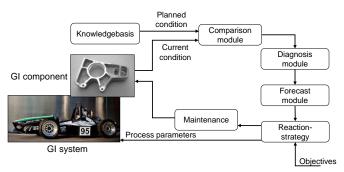


Figure 1. Control cycle of GI maintenance.

The control cycle shown in figure 1 demonstrates the GI maintenance on a racecar (GI system) with a wheel carrier as an exemplary GI component.

The stress information of the wheel carrier can be readout during a pit stop. This information is used as input parameters of the comparison module which compares the current condition of the wheel carrier with the expected condition. The diagnosis module diagnoses between possible failure causes and the forecast module predicts the future condition of the wheel carrier. The results of comparison, diagnosis and forecast module are in turn input parameters of the reaction strategy. The suitable reaction strategy is made by a Bayesian network. On the basis of the input parameters the Bayesian network determines an appropriate maintenance measure.

The focus of this article is the forecast of the component service life, which takes part in the forecast module.

#### 2. Component condition and service life forecast

The current condition and the future probability of failure are important factors for the selection of a suitable maintenance strategy. The condition is based on the fatigue of the component that arises as a result of recurrent stresses. It is possible to measure these stresses with the previously introduced sensors of CRC 653.

One method of quantifying the current component damage is linear damage accumulation. By this means the stress experienced can be converted into the collective stress with the aid of counting procedures, and the partial damage then calculated. The accumulation of damage is the most widely used method of service life calculation of components at risk from fatigue. However, the method has several weaknesses, such as the simplification of stresses in terms of level or the neglect of highly scattered service lives. The new development of a methodology for condition-based monitoring of GI components is therefore necessary to fully exploit the possibilities of GI technology. The basic elements of the methodology are presented in Figure 2.

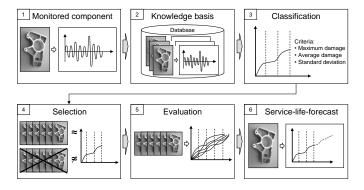


Figure 2. Basic elements of the service life forecast.

The identification of the condition of the component begins in the first step with the conversion of the measured stress into a time-related collective stress. This evaluation of the stress is still carried out according to the Rainflow method, while the preparation of the result centres not on the frequency of the individual stresses, but the time of a stress. In this way, the information about the time of the stress is maintained in the collective stress. The collective stress enables the calculation of the course of the damage with the aid of linear damage accumulation.

# 2.1. Knowledge basis and classification

The second step involves the development of the knowledge basis. Each monitored component must be created as a data set. This stores the essential information such as the location or the stress experienced. These are retained following the end of the life cycle of the component and serve as empirical knowledge for all following components. Figure 3 shows an example excerpt from the database. Once a sufficient number of records exists, the third step begins. This includes the classification of the damage patterns. Firstly of the monitored component itself and secondly of identical components that are stored in the database as empirical knowledge. The classification determines the criteria maximum individual damage of a stress ( $D_{max}$ ), the average damage ( $D_a$ ) at a defined interval, and the standard deviation ( $S_d$ ) of the damage. The classification therefore enables the identification of excessive stresses, average stresses and the distribution of the stresses.

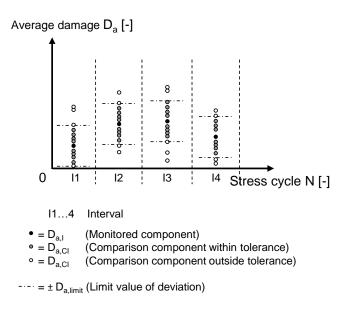
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Figure 3. Database as knowledge basis for GI maintenance.

#### 2.2. Selection and evaluation of comparison components

Once the classification features of the components are identified in the database, those components can be selected from the existing records whose damage pattern is closest to that of the monitored component. For this purpose, the damage pattern is divided into individual areas (Interval I1... I4, figure 4) and the deviation of the average damage in each of these areas is checked. The selection is narrowed down to those components (comparison components) whose damage pattern lies within the tolerance range around the pattern of the monitored component. Figure 4 shows the check of the average damage  $(D_a)$ .

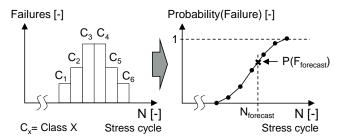
After the comparison components have been selected, the evaluation of their data follows in the fifth step. For the comparison components, the complete life cycle up to the time of replacement is known. Their complete damage pattern is therefore also known. This provides information about the stresses experienced by the comparison components and the total damage sustained. These can be evaluated statistically in order to be able to determine the future stress on the monitored component and the remaining service life.



**Figure 4.** Example classification of the average damage and check of the tolerance range.

# 2.3. Service life forecast

For this purpose, the failure times of the comparison components are summarised in the sixth step in a histogram. The future failure probability of the monitored component can therefore be calculated. Figure 5 illustrates a exemplary histogram with six classes ( $C_x$ ) and the increasing probability of failure (P(F)) with progressive stress of the component. This is based on the empirical knowledge of past components and enables the forecast of the failure probability for a selected number of stress cycles (N<sub>forecast</sub>).



Class X: Number of failures of the comparison components over a period of time

Figure 5. Forecast failure probability.

# 3. Outlook for diagnosis and reaction

The further work of the sub-project N3 includes the development of a diagnostic module, in which fault causes are determined, and a reaction module. This uses the condition information obtained, the knowledge of the cause of the fault and the forecast of the service life, in order to assist maintenance personnel in the selection of appropriate measures by means of a decision-making model. This makes use of the methodology of the Bayesian networks. The above findings on the condition, cause and forecast are input variables of the Bayesian network and have an impact on the commercial viability of maintenance, such as duration and cost. The sum of the utility values forms the

basis of the further decision-making methodology for the selection of appropriate maintenance measures.

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