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Using Operational Data to represent Machine Components Health and derive Data-driven Services

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Abstract. A highly competitive global market and rapid technological changes have induced a transformation in the manufacturing industry. In order to stay competitive, companies are intensifying the collection of life cycle data from their products in order to add customized digital services. The resulting digitally-enabled Product-Service Systems (PSS) can boost differentiation, but concrete business opportunities and their implementation often remain vague. An example is the data-driven assessment of machine components health status. While such information could be used to generate services like predictive maintenance or remanufacturing, the necessary data and algorithms to predict the remaining useful life and ways to convey the value to the customer are often unclear. This paper illustrates the engineering of a predictive maintenance service base on operational machine data. Furthermore, possible PSS offerings and the related business models are analysed. The results are tested in a use case from the manufacturing industry and finally implications for digitally-enabled PSS are discussed.

Keywords: Product-Service System, Engineering of data-driven Services, Digital Twin, Industrial Case Study

1 Introduction

A highly competitive global market and rapid technological changes have induced a transformation in the manufacturing industry. In order to stay competitive, companies are intensifying the collection of life cycle data from their products in order to add customized digital services that customers increasingly demand [1, 2]. This has led to the introduction of digitally-enabled Product-Service Systems (PSS), describing the integrated development, realization and offering of specific data-driven product-service bundles as a solution for the customer. Such PSS can boost differentiation, but concrete business opportunities and their implementation often remain vague [3].

An example is the data-driven assessment of machine components health status. System components experience wear and tear over their period of use and their service life

is designed based on the operational loads. Each component has certain functional capabilities that usually decrease during operations, this is referred to as the wear reserve [4]. Before usage, a component has a wear reserve of 100 %, which decreases with the duration, frequency and strength of the occurring loads. This wear reserve can, however, be restored or delayed by maintenance measures [5]. General conditions and disturbances in the utilisation phase often lead to unplannable wear and tear of components, leading to machine failures. In order to make this behaviour predictable, machine and plant construction is increasingly relying on proactive action through monitoring. Suitable sensor technology in combination with IT infrastructure monitors system components during operation and under the name of predictive maintenance, systems are used today whose goal is to maximise the service life of technical systems. Individual component conditions are recorded and evaluated here, which means that maintenance measures can be planned at an early stage and components can be replaced in good time before they fail. As the system complexity and uncertainties increase, knowledge-driven approaches based on expertise on failure modes and physics are replaced by data-driven approaches applying machine learning algorithms on operational data [6].

However the necessary data and algorithms to predict the remaining useful life and ways to convey the value to the customer are often unclear [7]. When monitoring a technical system, the focus should be on the function-critical and failure-critical components. A prediction of their remaining service life requires the determination of their current condition, applied loads and prevailing environmental influences [8]. Therefore, an approach is needed to assess the initial service life of a component, a classification of the relevant types of wear, the identification of impact factors for wear, suitable sensors to detect such impacts and a prognosis model for the remaining service life [9]. Thus, the aim of this paper is to develop an indirect condition description via component loads, types of wear and the identification and monitoring of relevant parameters. The approach is applied in a reaction casting unit use case. The resulting information enables engineering a predictive maintenance service base on operational machine data. Possible digitally-enabled PSS and related Business Models are discussed.

2 Approach for Machine Component Health Assessment

The challenge to determine a machine components health, with a prognosis of the remaining service life, shall be achieved with a temporary recording of special condition data of the component. The process of a prognosis always consists of different work steps that can be arranged chronologically. Basically, it is always a target/actual comparison within the framework of a condition diagnosis. Design data and knowledge about operational use are compared with information derived from condition monitoring and condition analysis. [10]

Loads on components in operation are usually dynamic and time-dependent. If the loads are determined by measurements or calculations, they can be represented as a function over time. When considering service life, load collectives can be included via the damage accumulation theory, which states that load levels that are higher than the

fatigue strength lead to wear of the component [11]. At the beginning of its service life, a component has a certain performance related to its condition, which in turn is based on physical, chemical and other characteristics. These are influenced by process conditions, environmental influences and extraordinary impacts, and this is referred to as technical wear and tear [12]. A classification can be made according to the different wear mechanisms:

Abrasion means the progressive loss of material on the surface of a solid body, caused by mechanical causes. *Corrosion* means the destruction of the material surface by chemical or electrochemical reaction with its environment. *Material fatigue* describes the reduction of material strength depending on the magnitude and direction of constantly changing stress. The internal processes in the material structure of a component, which occur independently of its stress and lead to wear, fall under the term *aging*. The determination of the actual condition of a component that has already been subjected to load cycles results from the as-new condition minus any technical wear that may have occurred. For each of the types of wear presented, different influencing variables can be identified that contribute to component wear. During tests, the question is answered as to what type and level of effect the influencing variables have on the component service life. It makes sense to consider the influencing variables that make the greatest contribution to wear. It must also be possible to measure the selected influencing variables in a targeted and reproducible manner, as the extent of their influence depends on their intensity. [13]

Suitable sensor technology can help to monitor the operating condition of components during operation. The characteristics of the previously identified influencing factors are recorded as measured variables. The changes in the measured variables can be directly or indirectly attributed to wear of the components. For example, the increasing intensity of a measured variable (e.g. temperature) can indicate increasing wear (e.g. material removal through friction) on a component. However, the collection of corresponding measurement data is not sufficient for a service life prediction. In order to determine the degree of wear and thus the remaining service life of the components from the recorded measured variables, the application of a prognosis model is necessary. [14]

The determination of the remaining service life of the components is to be carried out with the help of a prognosis model, which predicts potential wear processes on the basis of determined component data and known correlations. The characteristics for the wear of the components and the influencing variables responsible for this are recorded in a time-discrete manner with the selected sensor technology. For the implementation of this requirement, the monitoring of the components and the automated analysis and evaluation of the recorded data are necessary. For prognosis, the supervised machine learning approach can be used to determine the remaining useful life of critical components [15, 16]. The selected sensors provide the data for learning the model. The algorithms used identify correlations and unknown patterns from the available data. The model is able to evaluate the recorded condition of the components and to predict a remaining service life.

3 Use Case: Spindle Bearing of a Reaction Casting Unit

The approach for assessing machine component health is tested on a reaction casting unit, which includes a mixing screw with spindle and associated bearing (see Fig. 1). Within the unit, polyol is mixed with isocyanate in a chamber with the aid of the screw in order to obtain a reactive mixture that foams up within a mould. The spindle bearing was identified as a critical component, as its failure or impairment of its original function causes machine downtimes. Currently, the machine condition is qualitatively assessed and communicated by the operator. In particular, the expertise of the operating personnel is used to document whether, for example, unusual behaviour such as vibrations and disturbance variables have been detected.



Fig. 1. Housing with the spindle bearing and the mixing screw of the injection unit

In general, the service life of a spindle is determined by the number of injection processes. Furthermore, the service life depends on the additional loads to which the components have been subjected and the prevailing environmental conditions. Therefore, these conditions as well as operating data such as speed, operating hours and load variables must be compiled. The spindle itself can be described as fatigue resistant, while the bearings are designed for approx. 5,000 operating hours. An average duration for one injection cycle is 18 s, which means the rolling bearings must withstand $\approx 1,000,000$ load cycles.

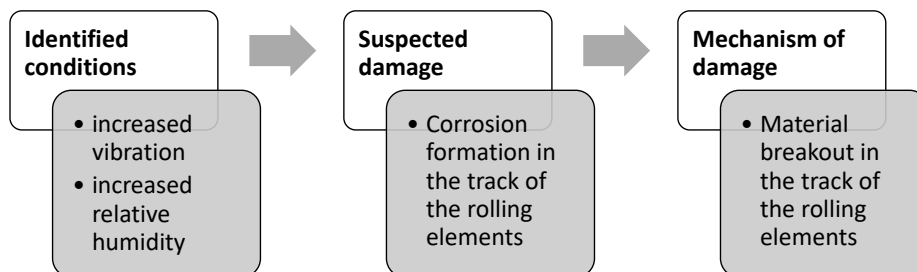


Fig. 2. Example of a Damage Chain for Bearings

Based on knowledge from construction and operation, damage descriptions, damage patterns, damage mechanisms and characteristics were identified for the bearings. This forms the basis for deriving the required sensor technology and calculating the factors for determining the remaining useful life of the bearing. The disturbance influences acting on the reaction casting unit can have different causes and dependencies. This is illustrated by an exemplary damage chain (see Fig. 2):

The sensors for recording the measured values were selected on the basis of the expected types of wear. Furthermore, a constructive implementation must be possible. For the bearing, it is expected that characteristic values change with increasing material removal due to corrosion, as the track of the rolling elements becomes more irregular, resulting in increased friction and imbalance due to the rolling over of unevenness. Sensors for vibration and acoustics can provide physically measurable results that indicate such a change. Since the humidity in the environment is of great importance for the formation of corrosion, an air humidity sensor is included.

Thus, a sensor box has been developed accordingly (see Fig. 3). Ethernet (industrial standard) is used for the connectivity of the sensor box. This interface enables the box to be connected to a network that is usually available and already transmits operating data from the shop floor system.

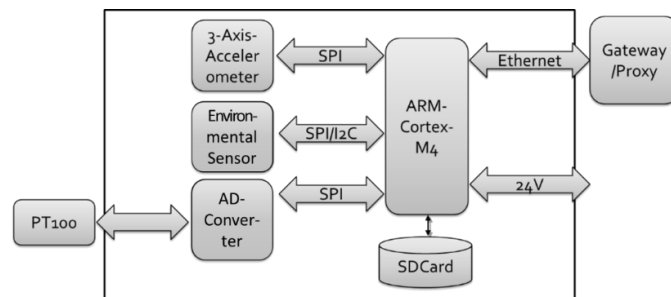


Fig. 3. Sensor implementation

The collected data, sensor box and operating data, are transferred to a cloud as JSON files. An NTP server provides the current time stamps so that the recorded data can be synchronised. For data exchange, REST interfaces were defined and implemented according to the OpenAPI standard. An engine receives the data stream and performs the analysis of the data and the enrichment of the data stream with derived forecasts.

The mathematical approach for quantifying component wear combines data-driven and physical models into a hybrid modelling approach. It relies on a target-performance comparison of relevant measured process parameters. For the use case, those input parameters consist of reliable component condition indicators for abrasion, i.e. load cycles and vibration. Through test runs and historical data of the use case processes, empirical courses of the parameters were identified and linked to the wear and condition of the spindle bearing. For the lifetime prognosis, a Bayesian network assesses the difference between the empirical and the actual course of the parameters, identifies the potential deviation (whether the wear is proceeding faster or slower than expected) as a conditional probability and predicts the remaining time to failure based on this gap.



Fig. 4. Spindle wear quantification and lifetime visualization

The application visualises the evaluation (see Fig. 4), i.e. the detection of events on the basis of the forecasts. This can mean, for example, that a threshold value for the expected remaining useful life of a component has been undershot. It can also indicate that the remaining useful life can be extended if the machine utilisation is reduced. When stating the remaining service life, it is important to note that the result is subject to certain uncertainties and cannot be absolutely reliable. This is due to the fact that both the correction factors and the designed load cycle number are statistical values that are subject to certain probability distributions.

4 Discussion

For a practical lifetime prediction, a proven relationship between field tests, test bench tests and calculations is required. Likewise, the evaluation and assessment of recorded data in order to ultimately be able to represent an effective tool is important. The aim of product development is to develop products in such a way that they achieve the required service life under specified loads. Wear and tear lead to shortened service life expectations, which must be countered with suitable strategies. An option is the integration of data-driven services to create a digitally-enabled PSS. These can be service life calculations, as well as maintenance measures and sensor-based monitoring of operating conditions. Based on this, maintenance measures can be derived as well as new business models, as a service offer can be improved with a prognosis system and, in addition, new opportunities can be opened up.

The presented approach requires the provision of data for model development and to provide the service of prognosis. Since some enterprises are reluctant regarding the provision of data, reference business models are required to reduce this reluctance. Theoretically it is possible to save data that enables conclusions regarding the productivity of the operator of the machine. Hence, such data should be anonymised (hide time stamp for a data set or use decoding methods). The effort to gather data that is required for the later application of the prognosis service depends on the technical realisation of the measuring device. The effort can be low, if the device and the sensors are already integrated in the system and can be accessed automatically. But the measurement can

also require activities by personnel for installation of the test bed and the actual measurement. This has to be evaluated for the particular case.

The main sources of benefits and the corresponding recipients are on the one hand avoidance of unplanned downtimes that are caused by breakdowns of the module or late availability of spare parts brings benefit for the machine operators and thereby for the enterprise. On the other hand, input for a further optimisation of the machines to increase customer satisfaction and competitiveness. Today, new business models must also be viewed in the context of sustainability. If it can be proven that there are advantages for all partners involved, a high level of acceptance can be expected.

5 Conclusions and Future Work

The collection of operational, machine and environmental data offers new possibilities for improved maintenance planning, which enables more reliable processes. By determining the remaining service life, the functionality of components can be better utilised, which saves resources and costs. The created database in connection with a continuous recording of component conditions can also be used to predict preventive maintenance and, if necessary, replacement measures more accurately, to deliver necessary replacement components to the place of use in good time and to plan the service deployment. Replaced components can then be checked to see whether they can be used again in less demanding applications and/or within the framework of other legal requirements for the installation of new components. In this way, it should also be possible to determine a useful life that can be reliably predicted for used components.

For the approach presented here, detailed knowledge of the wear processes in the affected components is necessary. This can be used to determine a suitable sensor system with which the relevant or correlating measured values that indicate wear can be recorded directly or indirectly. In addition, system configurations are required for each application, as the systems to be monitored each have specific characteristics and features that make it necessary to adapt the model presented. For example, the probabilistic influence model used in the form of a Bayesian network must be adapted depending on the sensor data required in the application. In addition, a technical data connection, historical measurement data and a quantification of wear processes are required in order to be able to create the most accurate remaining service life forecast possible.

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