Degradation processes modelled with Dynamic Bayesian Networks

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Abstract — **In this paper a generic degradation model based on Dynamic Bayesian Networks (DBN) which predicts the condition of technical systems is presented. Besides handling bi-directional reasoning, a major benefit of using DBNs is its capability to adequately model stochastic processes. We assume that the behavior of the degradation can be represented as a P-F-curve (also called degradation or life curve). The model developed is able to combine information from condition monitoring systems, expert knowledge and any kind of observations like sensor data or notifications by the machine operator. Thus it is possible to even take the environment and stress into account under which the component or system is operating. Thus it is possible to detect potential failures at an early stage and initiate appropriate remedy and repair strategies.**

Keywords — ***Degradation, dynamic Bayesian networks, P-F-curve, stochastic processes***

I. Introduction

Unexpected downtime from machine failure in manufacturing causes critical loss of production and costs [1]. To mitigate these effects, it is important to develop procedures for predicting component failures. Traditional life tests record the time to failure, but it is difficult to give a statement about the durability of a single component and accurately predict failures before they occur [2]. This is because only failure times are taken into account, but products might just as well have construction faults, operating errors, or there may be other reasons which can cause initial failure. Moreover, when products are highly reliable, the accumulation of failure time data can be expensive and impractical due to the long time it takes for any component to fail [3]. Since degradation eventually leads to a weakness that can cause failure, it would be useful to have a predictive model which prognosticates failures before they happen.

A great benefit of modelling this degradation model by means of Dynamic Bayesian Networks (DBN) is to be able to include stochastic processes and the Markov property. An added value of DBNs is that bi-directional reasoning is possible. Nowadays, most reliability calculations use estimated values with statistical uncertainties. It will be assumed that the behaviour of the degradation can be represented as a P-F-curve (also called degradation or life curve). The model developed here, on the other hand, is able to combine condition monitoring, expert knowledge, mathematical laws and statistical uncertainties.

After describing the foundations of wear-out processes as well as the theory of Bayesian belief networks, a DBN based approach for degradation modelling will be presented. This approach allows the reliability and availability of manufacturing equipment to be enhanced by providing information on the condition of the different components and consequently on the whole system during the lifetime of a production line. After introducing the model its functionality will be illustrated with the help of different application scenarios.

II. Background

A. *Degradation and condition of systems*

It is important to understand how we define the condition of a component and its relation to degradation. It is known that materials in a product will often degrade during use. If there is enough degradation, the product element (component) will stop functioning altogether [4]. Ferreira et.al. assert that failure occurs when the amount of degradation for a unit (component / system) exceeds a certain level [5].

For this degradation model there is no need to know the physical behaviour of the degradation. It is more important to know how the components' degradation behaves over time.

Therefore, this paper assumes that the condition of a component is diametrically related to its degradation (fig. 1). If, for example, a component is half-degraded, its condition is expected to be half as good as new.

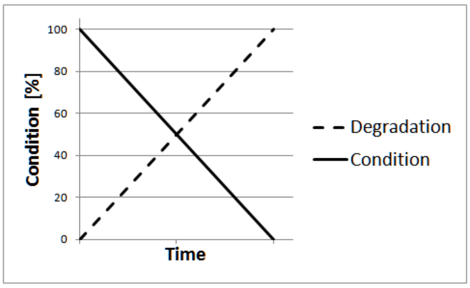

Figure 1: Characteristics of degradation and condition

Hence, this paper uses the term *condition* of a component more frequently than the term *degradation*. If a component is new there is no degradation (D) but the condition (C) of the component is perfect, i.e. in percentages it is 100%. However, when the degradation is so high that the component does not work anymore the condition of the component is 0%. At the same time degradation is on its highest possible point, i.e. 100%. In formula:

$$C = 100\% - D \quad (1)$$

However, the characteristics (linear trend) of the function in Fig. 1 do not match reality which in most cases. Therefore, a P-F curve has to be integrated.

B. *The P-F-curve*

Most failure modes provide some sort of warning of incipient failure. Often, evidence that something is in the final stages of failure can be discerned [6]. This is very helpful for creating a degradation model because it is possible to estimate in which state a component/system is on the basis of several observations. Observations of failures appear often in defined stages of the condition of a component/system. Clearly, there is a relationship between the chronological age of a component/system and its failures, but this relationship is not necessarily linear, for example in the case of a defect or operating error failure occurs earlier than expected.

Initially, the condition of a component will remain good for a certain period (performance is without significant changes). However, at a certain point, where an observation indicating a potential failure emerges as likely, the condition of the component as well as its performance decreases precipitously. Typical degradation behavior over time has the characteristics of a P-F-curve (also called the life curve [7] or degradation curve [8]) from J. Moubray [6]. Fig. 2 shows the P-F-curve. It illustrates when a failure starts, the way it deteriorates to the point at which it can be detected (e.g. by observing vibrations) until it reaches at the point of functional failure [6].

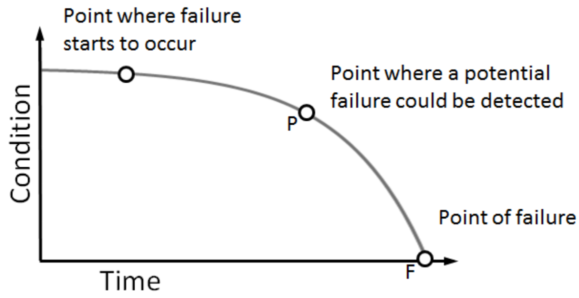

Figure 2: Classical P-F-curve

It is very useful to integrate this curve into degradation models. At the beginning of the operating time, the degradation of a component/system is very slight, but there comes a certain point where the degradation of the component or system starts and "degradation accelerates in the final stages of most failures" [6].

C. *Bayesian Networks*

A Bayesian Network (BN) is a graphical model for probabilistic relationships among a set of variables [9]. A BN consists of several nodes which represent random variables, a set of arcs which connect the nodes to form a directed acyclic graph (DAG) and a set of conditional probability distributions (CPD) [10]. Fig. 3 shows an example of a simple Bayesian Network. In the graphical user interface (GUI) of a network are only two different symbols: Arcs and nodes. An arc between two nodes indicates a direct probabilistic dependence between them [11].

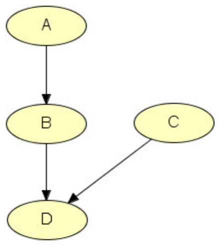

Figure 3: Example of a Bayesian Network

A good informal definition of Bayesian Networks is given by F. V. Jensen and T.D. Nielsen [12]:

- A set of variables and a set of directed edges (arcs) between variables
- Each variable has a finite set of mutually exclusive states
- The variables together with the directed edges form a directed acyclic graph (DAG)
- A conditional probability table (cpt) $P(B \mid A_1,..,A_n)$ is attached to each variable B with parents $A_1,..,A_n$

D. Dynamic Bayesian Networks

Regular static Bayesian Networks are useful when time is irrelevant. To model dynamic systems a time dimension can be added to a Bayesian Network yielding a Dynamic Bayesian Network (DBN) [13]. The structure of the network does not change dynamically but one can model a dynamic system with it. A DBN is a directed a-cyclic graphical model of a stochastic process. It consists of time-slices (or time-steps), with each time-slice containing its own variables [13]. Fig. 4 shows an example of a DBN.

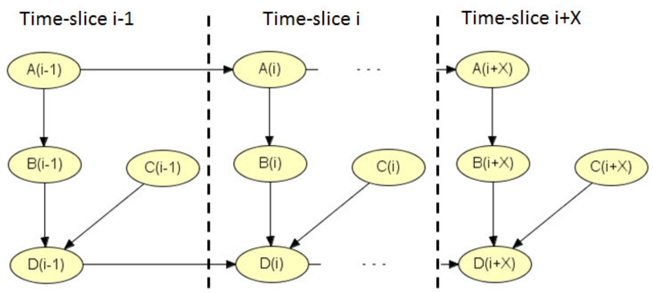

Figure 4: Example of a Dynamic Bayesian Network

The time-slices of a DBN are assumed to be chosen such that the DBN obeys the Markov property: the future is conditionally independent of the past given the present [14].

It is also possible to have a stationary DBN. This is the case if the probability distributions are time-invariant between the time slices. A dynamic Bayesian network is first-order Markovian when the variables at time step [time-slice] i+1 are d-separated from the variables at time step [time-slice] i-1 given the variables at time step i [12].

DBNs in HUGIN 8.1 look a bit different. Instead of repeating the same network and linking it with temporal arcs a temporal clone of each node is made with the Markov property.

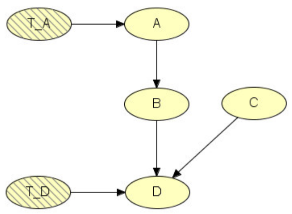

Figure 5: Example of Dynamic Bayesian Network in HUGIN 8.1

Fig. 5 shows the same DBN as in Fig. 4, but modelled in HUGIN 8.1. The hatched nodes are the temporal clones. The conditional probabilities table (CPT) of the temporal clone (T_A)[1] includes the probabilities from node A one time-slice before (see fig. 6).

[1] Temporal clones are labelled with a "T_" before the name of the node.

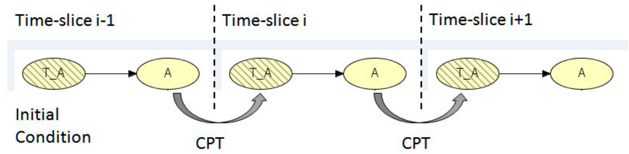

Figure 6: Dynamic Bayesian Networks in HUGIN 8.1

The advantage of this technique is that there is no necessity to define the number of time-slices beforehand. The only number that needs to be defined is the number of required future time-slices. It saves computing time to predict and fix this number beforehand.

E. Markov Process

Some basic rules are given here in order to better understand the DBNs. A Markov process is a special stochastic process which is named after A.A. Markov who developed the concept in 1907 for discrete time processes with finite-state spaces [15]. In a discrete-time Markov chain, random variables (x_1, x_2,...) are dedicated to time. At any given time, the variables have a defined state. $x(m)=r$ means that the variable x is at time m in state r. The Markov property implies that the state occupied at time point m is dependent on the state occupied at time point (m−1) but not on the state occupied at any previous time point [16]. The past has no impact on the future given the present [12].

III. The Summary of the Degradation Model

In this paper we focus on the results of the degradation model (see fig. 7) we developed with the aid of selected application scenarios rather than providing details of the model itself. The states in fig. 7 represent random variables with a finite number of states. For a detailed description thereof refer to [17].

The degradation model consists of four different main parts:

1. Causes for degradation processes like maintenance activities and operating conditions (dynamic environment) → implemented as time-invariant parameters (blue)
2. A P-F-curve which pictures the degradation process over time (in this case a reversed exponential function) → implemented as a time-variant parameters (yellow)
3. Uncertainty by a Gaussian normal distribution with well defined states → damage index (purple)
4. Observations like sensor data in combination with expert knowledge → observations (green)

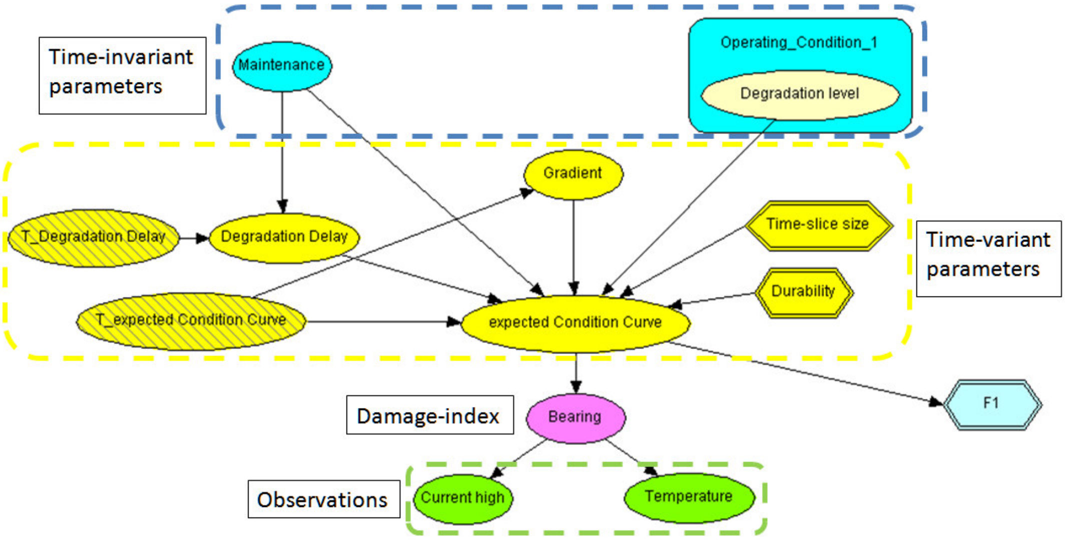

Figure 7: Degradation model based on Dynamic Bayesian Network

The hatched nodes in fig. 7 are the temporal clones which are explained in the section 2, D. The node *F1* is not relevant for the model itself. This paper concentrates on the behavior of the P-F-curve (in the picture the node *expected condition curve*). Different scenarios will be illustrated in the following section.

IV. SIMMULATING DIFFERENT SCENARIOS

To simulate the results of the degradation model based on Dynamic Bayesian Networks a simple example is given. A component (e.g. a bearing) has a durability of 10000 hours (value of the node). The time-slice size is 100 hours. That means that after each time-slice 100 hours are passed. Finally after 100 time-slices the durability of the component is reached. Using a function node (fig. 7 Node *F1*) which is used to perform post-inference custom calculations [18] the conditions of the component can be calculated.

Following the papers [19] and [11], we introduce 5 states to describe the condition of a component:

1. **No indication of degradation** → The component is as good as new
2. **Some indication of degradation** → After some time the condition of the component declines. Indications for this behavior are observations like high current or a high temperature.
3. **Some serious degradation** → . Observations in connection with this could be noise or stronger vibrations. The higher the degradation is the faster the component degrades i.e. the time interval to the next state is very small.
4. **Critical degradation** → For example, high temperatures and sometimes smoke could be observed.
5. **Failure Probability extremely high** → As shown in fig. 8, after 10000 hours the component is in a worn out state.

Simulating the model for the bearing example yields the following results (fig. 8). The degradation of the bearing shows the normal behavior without any observation, under normal operating conditions and no maintenance activities. The depicted line corresponds to the above discussed P-F-curve proposed by [6], [7], [8]. After 10000 hours the state *failure probability is extremely high* is reached. A validation of the model with actual degradation data is still to be performed.

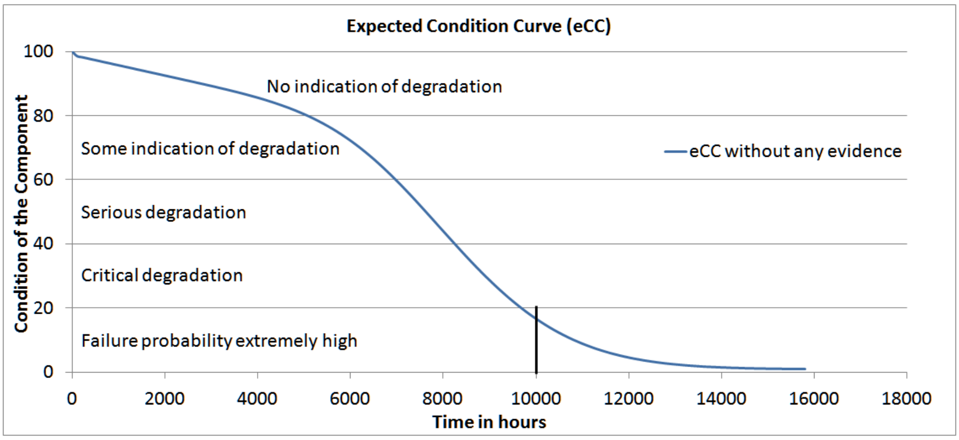

Figure 8: With the DBN simulated degradation curve for the component

A. Maintenance activities

BS EN 13306:2010 [20] describes preventive maintenance as a kind of maintenance with predetermined intervals or following prescribed criteria to reduce the degradation of the functioning component. One should distinguish between two kinds of maintenance: on the one hand, maintenance could mean activities like re-lubrication or re-tensioning, and on the other hand, replacements of components of the system. It is assumed that after replacement the condition of the replaced component is new (100%; see green dashed curve in fig. 9). After re-lubrication or re-tensioning the degradation process decelerates. We assume that the condition does not improve after re-lubrication or re-tensioning, but that the degradation process is delayed (see purple dashed curve in fig. 9).

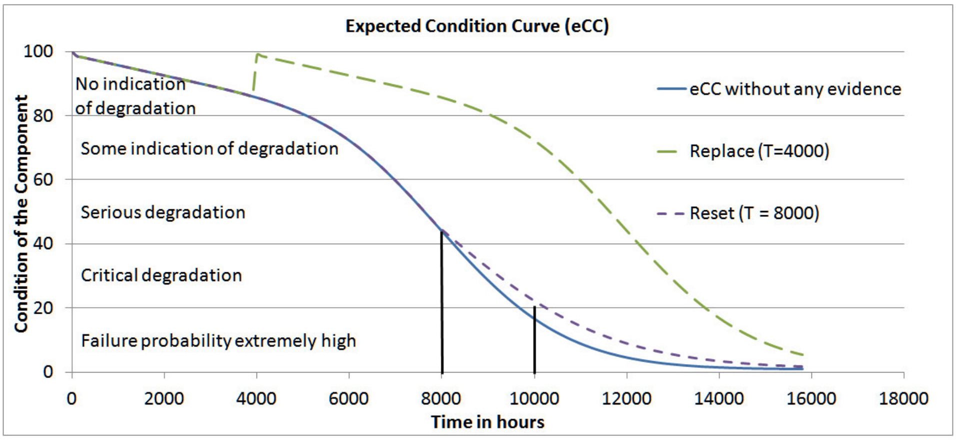

Figure 9: Modified degradation curve after different maintenance activities

B. Including operating conditions and observations

A dynamic environment can be included in this model, as the following example shows. Frequently, sensor data like acceleration, velocity and load are measured or they are predetermined by the working process. The model differentiates between four different dynamic environments, which are expressed as so called degradation levels. If the component is not in operation and the environment is not harmful the degradation level Dl is 0 (no stress). If the component works under normal circumstances Dl is 1 (normal stress). If the environment is not perfect for the component, if it is very dirty, very hot or very humid, or if the operating conditions are exceeding what the component is designed for, the Dl could be 2 (high stress) or in very marginal cases Dl = 3 (very high stress). If for example in time-slice 50 the component will be overloaded because of a mistake of the operator, the degradation level will be set to Dl = 3. In fig.10 the results of the model are shown.

The model is also able to include observations. The causes for the observations are the condition of the component. The sensor data/ observations depend on the condition of the component. For example, if the bearings of a motor are in a suboptimal condition the probability of high current or a high temperature is rather high. For example if there is an unexpected high temperature at the bearing it can be expected that the durability of the bearing is much shorter than expected. In fig. 10 this very hazardous observation is depicted. Observations like this are usually only possible when the component is close to fail. The observation was made in

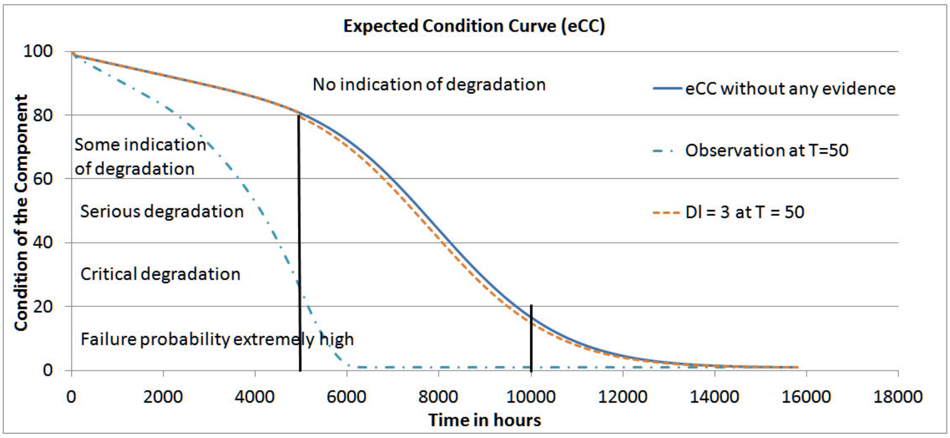

Figure 10: Condition curve with observations and different degradation levels

time-slice 50 and from this observation the condition of the component is in the state *Failure probability extremely high*.

V. Conclusion

In this paper a DBN based degradation model was presented, which is divided into four separate parts. There is a time-invariant part which includes maintenance activities as well as the operating conditions. The P-F-curve and related time-variant parameters describe a typical degradation process and make up the second part of the model. The third part is the damage-index which describes the state of the component or system together with a given uncertainty covering the inaccuracy of measurements. Finally, observations are implemented in the final part. With the help of these four parts, which are combined in one single DBN, it is possible to reliably estimate the condition of a component or system, because the influence of maintenance activities, operating conditions, expected degradation processes and observations as well as their interactions can be taken into account.

As shown above, there are numerous different possibilities for using this model. It can be used in a dynamic environment with different operating as well as environmental conditions. This is an advantage for components/systems which are used in a critical operating environment or in countries with extreme climates. Moreover it can take maintenance activities into account. Not only the presented P-F-curve can be modelled. Also it is possible to simulate linear or differently shaped degradation processes. By including observations, initial failures can be detected early and avoided, which saves time and money. Also it is possible to extrapolate and predict failures of the component/system before they occur. Finally the model considers multiple failure modes and has the ability to detect wear of the component which would be the reason for the failure of the whole system.

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