Proceedings of the 3rd Annual World Conference
of the Society for Industrial and Systems Engineering,
San Antonio, Texas, USA
October 20-22, 2014

Degradation model constructed with the aid of Dynamic Bayesian Networks

Anselm Lorenzoni, Michael Kempf

Department of Sustainable Production and Quality Management
Fraunhofer Institute for
Manufacturing Engineering and Automation (IPA)
Nobelstrasse 12
70569 Stuttgart, Germany

Corresponding author's Email: Anselm.Lorenzoni@gmx.de

Author Note: Anselm Lorenzoni is working as a research assistant at Fraunhofer IPA in the field of predictive maintenance and repair strategies. He is currently about to finish his master thesis on degradation modeling to predict potential failures of machinery and equipment. Michael Kempf is engaged in quality management as well as product development. His research focuses on statistical methods in the fields of reliability engineering, process optimization and risk minimization.

Abstract: This paper develops a generic degradation model based on Dynamic Bayesian Networks (DBN) which predicts the condition of a technical system. Besides handling bi-directional reasoning, a major benefit of modeling this degradation model by means of a Dynamic Bayesian Network is its capability to adequately model stochastic processes as well as Markov chains. We will assume that the behavior of the degradation can be represented as a P-F-curve (also called degradation or life curve). The model developed here is able to combine information from condition monitoring systems, expert knowledge and statistical uncertainties. Furthermore it can include 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. That's why 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 process

1. Introduction

Unexpected downtime from machine failure in manufacturing causes critical loss of production and financial loss (Hirschmann, 2007). 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 (Lu & Meeker, 1993). 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 (Robinson & Crowder, 2000). Therefore, it would be useful to have a predictive model which prognosticates failures before they happen. To develop such a model, we may consider that degradation eventually leads to a weakness that can cause failure. Therefore, if it were possible to measure degradation, this could provide more information than time-to-failure data about the reliability of production systems and the causes of their failure. Consequently, a relationship between live observations and degradation has to be found, as well as a relationship between degradation of components/systems and failure. Once both relationships are established, it is possible to estimate how badly the component/system is degraded, as well as to predict failure and the time-to-failure based on live sensor data.

This approach would allow the reliability of manufacturing equipment to be enhanced by providing information on the condition of the different components and systems during the lifetime of a product line, and whether it is possible to use them again in new product lines. Therefore, this would be highly profitable.

2. Background

2.1 The P-F-curve

Here, it is assumed that the condition of a component/system is diametrically related to its degradation: if a component/ system is half degraded, its condition is expected to be half as good as new. Hence, this paper uses the term 'condition' of a component more frequently than the term 'degradation'. 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(Moubray, 1997). 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 construction fault or operating error causing failure to occur earlier (or later) than expected.

Initially, the condition of a component will remain good for a certain period (performance is without any 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 has the characteristics of a P-F-curve (also called the "life curve" (Sugier & J., 2010) or degradation curve (Nelson, 1998)) from J. Moubray (Moubray, 1997). "Fig [1] is called the P-F-curve, because it shows how a failure starts, deteriorated to the point at which it can be detected (e.g. vibrations could be detected) until it reaches at the point of functional failure" (Moubray, 1997).

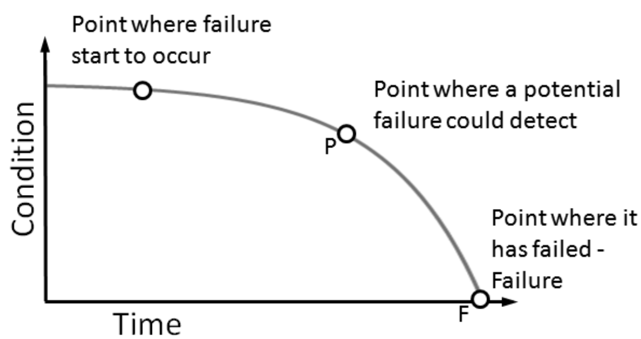


Figure 1: Classical P-F-curve

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" (Moubray 1997).

2.2 Bayesian Networks

"A Bayesian Network (BN) is a graphical model for probabilistic relationships among a set of variables". (Heckermann, 1995). 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) (Weidl, Madsen, & Israelson, 2005). Fig. 2 shows an example of a simple Bayesian Network. In the GUI of a network are only two different symbols: Arcs and nodes. "An arc between two nodes indicates a direct probabilistic dependence between them, while the absence of an arc indicates a conditional independence relation" (McNaught & Chan, 2011).

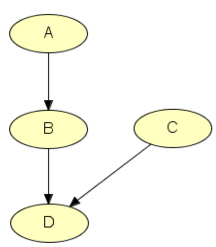


Figure 2: Example of a Bayesian Network

A very good summary of Bayesian Networks is given by R.F. Jensen (Jensen & Nielsen, 2007):

- "A set of variables and a set of directed edges [arcs] between variables"
- "Each variable has a finite set of mutually exclusive states"
- "The variable together with the directed edges form a DAG […]"
- "To each variable B with parents A1, …, An, a conditional probability table (CPT) $P(B \mid A_1, ..., A_n)$ is attached"

2.3 Dynamic Bayesian Networks

Bayesian Networks are useful when the state is static. Time is irrelevant. But to extend a Bayesian Network into a time dimension, a Dynamic Bayesian Network (DBN) can be used to model such dynamic systems (Hulst, 2006). 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" (Hulst, 2006). Fig. 3 shows an example of a DBN.

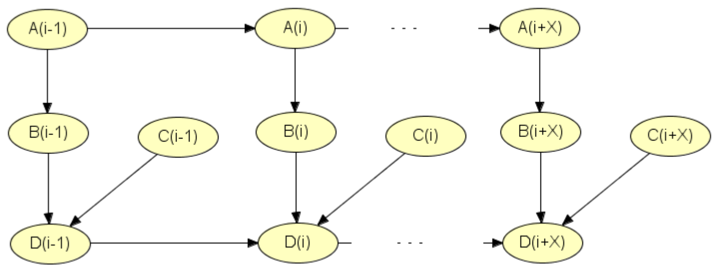


Figure 3: Example of a Dynamic Bayesian Network

"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" (Kjærulff, 1995)
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" (Jensen und Nielsen 2007).

2.4 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 (Yin & Zhang, 2013). 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. $x_m(t=m)=r$ 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" (Upton, Graham J. G & Cook, 2008). "The past has no impact on the future given the present" (Jensen & Nielsen, 2007)

3. The Degradation Model

3.1 Reversed exponential function as a Markovian Polygon

The basic concept of the degradation model in this paper is based on the work of D. Straub, who described the process of deterioration depending on time, a set of time-variant and time-invariant parameters (root causes) as well as observations (Straub, 2009). The set of time-variant parameters is given by the P-F-curve, the time-invariant parameters are given as influencing factors of degradation and finally, the observations made are given as available sensor data as well as from human inspections. In the following, the integration of the parameters/observations in a DBN will be explained. The first task will be to develop a curve which has the same curve progression as a P-F-curve. The reversed exponential curve is very similar to the P-F-curve, which could be expressed as follows:

$$eC(\mathrm{t}) = \begin{cases} 101 - e^{\ln(101)*\frac{t}{D}} & ,t < D \\ 0 & ,t \geq D \end{cases} \tag{1}$$

The problem with this function is that time is used – but it is not possible to use a continuous time variable in DBNs. Also, it is not helpful to have such a "static" process in a DBN. As (Moubray, 1997) says: "Many failure modes are not age-related, most of them give some sort of warning that they are in process of occurring or are about to occur". For example, if there is an observation/parameter which indicates that a probable failure will occur, the degradation process has started - and if the degradation process has already started, the condition of a component/system often rapidly deteriorates. Thus, the condition of a component/system clearly depends on its condition one time step before. Therefore, a stochastic process which has the Markov property has to be sought, one which exhibits the same trend. A very easy way to accomplish this is a polygon function from the reversed exponential function.

A polygon function consists of polygonal lines. Because of memory capacity and computational speed, 5 polygonal lines are chosen here. In other words, for every 20% change of the condition of a component/system, the polygonal line changes. It is advantageous to implement linear polygonal lines in DBNs. Fig. 4 shows how the polygon looks:

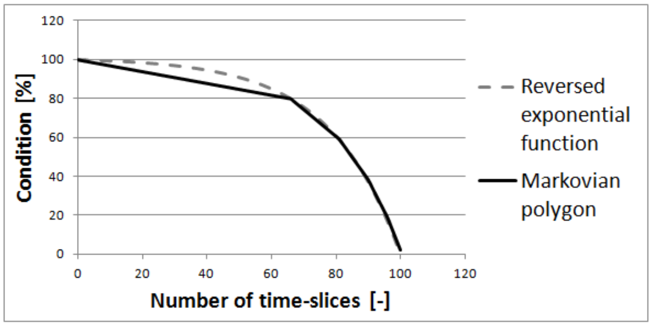


Figure 4: Polygon reversed exponential function with a degradation process in 100 time-slices

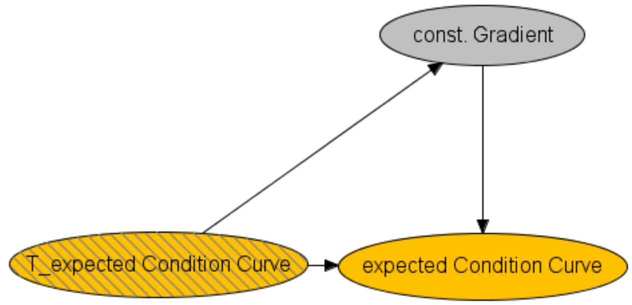


Figure 5: P-F-curve modelled in HUGIN 8.1

The formula of the expected condition [eC] curve (P-F-curve) appears as follows:

$$eC(s) = \begin{cases} eC(s-1) - 20 * \dfrac{c}{G(s)} & , eC(s) > 0 \\ 0 & , eC(s) \geq 0 \end{cases} \tag{2}$$

With Gradient:

$$G(s) = \begin{cases} 0.65968 & , eC(s-1) > 80 \\ 0.14497 & , eC(s-1) > 60 \\ 0.0861 & , eC(s-1) > 40 \\ 0.06144 & , eC(s-1) > 20 \\ 0.04781 & , eC(s-1) > 0 \end{cases} \tag{3}$$

And for the time-slice length t_{Slice} and Durability D:

$$\frac{t_{Slice}}{D} = c \tag{4}$$

3.2 Implementation of a dynamic environment and maintenance activities

Influences depending on operational conditions cannot be excluded - operational issues and the environment might well be expected to influence wear over time. If the component/system is not being used, obviously the Degradation level [Dl] becomes 0 (no stress). If the component/system works under normal circumstances Dl = 1 (normal stress). If the environment is imperfect for the component/system (for example, very dirty, hot or high humidity) or the operating conditions exceed those for which the component/system was designed, Dl could be 2 (high stress) or in very unusual circumstances Dl = 3 (very high stress).

Maintenance will also have an influence on the degradation process. The definition of Maintenance from (European Standard) is: “Combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function.” There are two different kinds of maintenance which have to be distinguished: 1) maintenance like re-lubrication or re-tensioning; 2) replacements of components of the system. This implies that after, for example, re-lubrication or re-tensioning, the degradation process will be slower than before maintenance. The condition of the component is not improved after re-lubrication or re-tensioning but the degradation process is delayed. To keep the model simple, implementation of only three different maintenance actions is included here:

1. None — No maintenance action
2. Reset — re-tensioning, re-lubricating (maintenance without any replacement)
3. Replace — replacement of the whole component/system

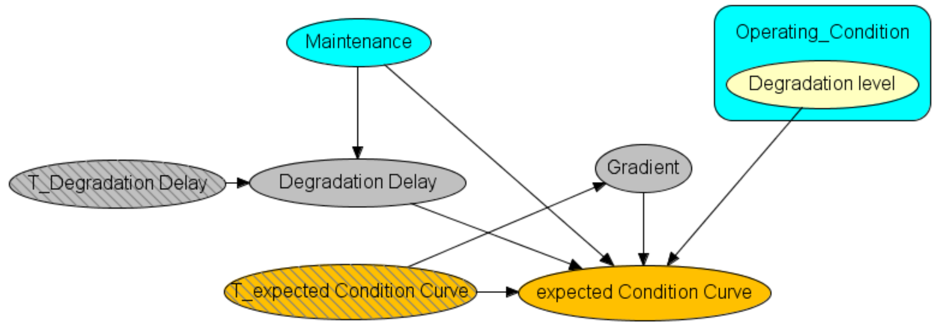


Figure 6: Degradation model which includes dynamic environment and maintenance activities

3.3 Implementation of the condition states and the observations

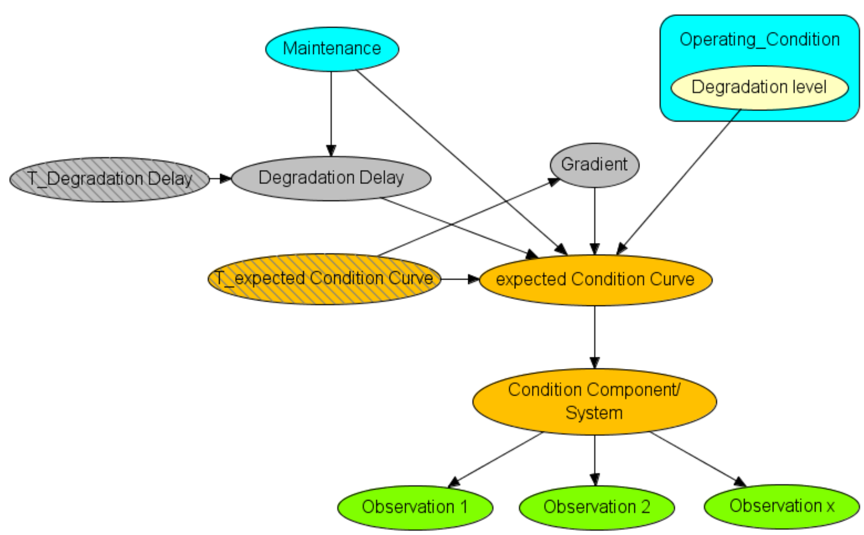
After modeling the P-F-curve as an expected Condition curve in HUGIN 8.1 there are two problems: 1) the number of states in the node expected Condition curve is very high (50) and thus very difficult to interpret; 2) because the curve as well as the durability is estimated it is useful to integrate an uncertainty. Additionally, the accuracy of sensor data and observations also implies a degree of uncertainty.

To simplify the conceptualization of the continuous degradation of a component/system a so called damage-index is introduced. This paper refers to the examples of (IEEE Trondheim PowerTech, 2011) and (McNaught & Zagorecki, 2009). Both use 5 states to define the condition of a component/system, as follows. If we have a new replacement component, there will be no indication for degradation (state 1). The component is as good as new. After some time, the condition of the component will again decline to the next state, state 2. Now there will be some indications of degradation. An observation for this could be, for example, vibration or particles in the oil. The next state, state 3, is accompanied by serious degradation, as indicated in this example by noise or stronger vibrations. Progression to state 4 is then very rapid, the condition of the component becomes critical, and, for example, high temperatures and smoke might now be observed. If the condition of the component reaches state 5 the probability of a failure is very high. To implement this, we need a new variable which gives notice of the Condition [C] of the component/system. The 5 states of this variable are [0-20, …, 80-100]. But HUGIN 8.1 requires a normal distribution to be used for the border values -∞ and ∞. Because of this the states are [-∞-20, …, 80-∞]. The formula for the Condition is now:

$$P(C(s)) = Normal(eC(s), v) \quad (5)$$

The variance [v] depends on the knowledge of the experts assessing the system.

The sensor data/observations depend on the condition of the subsystem. For example, if the bearings of a motor are not in a good condition, the probability is high that there will be noise. In the general model it is possible to include as many observations as required. With the Observation, a defect or abnormality could be detected (and with that a potential failure) at an early stage. Possible failure modes and the remaining life-time should now be effectively predictable (Qiu, Lee, Lin, & Yu, 2003).



3. Conclusions

In this paper, a degradation model is presented which is based on Dynamic Bayesian Networks (DBN). The model is divided into four separate parts. There is a time-invariant part which includes maintenance activities as well as the operating conditions (which also include stress and environmental variables). In this model, the time-invariant parameter is a P-F-curve which describes a typical degradation process. The second part consists of the time-variant parameters the P-F-curve. The P-F-curve is modeled as a reversed exponential function including the Markovian property. The third part is the damage-index which describes the state of the component/system, including an uncertainty (because of the sensor accuracy and the estimated values). Finally, observations (life data) are implemented as the final part. These four parts are combined in one single net. Because of the ability of DBNs to incorporate bi-directional reasoning, it is possible to very precisely estimate the condition of a component/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 and advantages in doing so. It can be used in a dynamic environment: there are different operating conditions as well as different environments considered. This is an advantage for components/systems which are used in critical operating conditions or in countries with extreme climates. Moreover it can take maintenance activities into account. By including observations, initial failures can be detected early and avoided, this saves time and money. Also it is possible to extrapolate and predict failures of the component/system before it occurs with this model. Finally the model considers multiple failure modes and has the ability to detect wear of the part which would be the reason for the failure of the whole system.

References

Heckermann, D. (1995). *A Tutorial on Learning with Bayesian Networks*: Microsoft Corporation; Microsoft Research.

Hirschmann, J. *Ein Beitrag zur Fehlerfrüh- und Fehlerdiagnose von elektromechanischen Antriebseinheiten in der Automatisierungstechnik* (IPA-IAO-Forschung und Praxis).

Hulst, J. (2006). *Modeling physiological processes with dynamic Bayesian networks* (Thesis). Delft Universtity of Delft, Delft.

IEEE Trondheim PowerTech. (2011). *IEEE Trondheim PowerTech: Trondheim, Norway, 19 - 23 June 2011*. Piscataway, NJ: IEEE.

Jensen, F. V., & Nielsen, T. D. (2007). *Bayesian networks and decision graphs* (2nd ed.). *Information science and statistics*. New York: Springer.

Kjærulff, U. (1995). dHugin: a computational system for dynamic time-sliced Bayesian networks. *International Journal of Forecasting*, *11*(1), 89–111. doi:10.1016/0169-2070(94)02003-8

Lu, C. J., & Meeker, W. Q. (1993). Using Degradation Measures to Estimate a Time-to-Failure Distribution. *Technometrics*, *35*(2), 161. doi:10.2307/1269661

McNaught, K., & Chan, A. (2011). Bayesian networks in manufacturing. *Journal of Manufacturing Technology Management*, *22*(6), 734–747. doi:10.1108/17410381111149611

McNaught, K. R., & Zagorecki, A. (2009) Using dynamic Bayesian networks for prognostic modelling to inform maintenance decision making. In *2009 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)* (pp. 1155–1159).

Moubray, J. (1997). *Reliability-centered maintenance* (2nd ed). Oxford: Butterworth Heinemann.

Nelson, W. (1998). Statistical Methods for Reliability Data. *Technometrics*, *40*(3), 254–256. doi:10.1080/00401706.1998.10485526

Qiu, H., Lee, J., Lin, J., & Yu, G. (2003). Robust performance degradation assessment methods for enhanced rolling element bearing prognostics. *Advanced Engineering Informatics*, *17*(3-4), 127–140. doi:10.1016/j.aei.2004.08.001

Robinson, M. E., & Crowder, M. J. (2000). Bayesian methods for a growth-curve degradation model with repeated measures. *Lifetime data analysis*, *6*(4), 357–374.

Straub, D. (2009). Stochastic Modeling of Deterioration Processes through Dynamic Bayesian Networks. *Journal of Engineering Mechanics*, *135*(10), 1089–1099. doi:10.1061/(ASCE)EM.1943-7889.0000024

Sugier, J., & J., G. (2010). Modelling Equipment Deterioration vs. Maintenance Policy in Dependability Analysis. In A.-D. Ali (Ed.), *Computational Intelligence and Modern Heuristics* . InTech.

Upton, Graham J. G, & Cook, I. (2008). *A dictionary of statistics* (2nd ed., rev). *Oxford paperback reference*. Oxford, New York: Oxford University Press.

Weidl, G., Madsen, A. L., & Israelson, S. (2005). Applications of object-oriented Bayesian networks for condition monitoring, root cause analysis and decision support on operation of complex continuous processes. *Computers & Chemical Engineering*, *29*(9), 1996–2009. doi:10.1016/j.compchemeng.2005.05.005

Yin, G., & Zhang, Q. (2013). *Continuous-time Markov chains and applications: A two-time-scale approach* (2nd ed). *Stochastic modelling and applied probability: Vol. 37*. New York: Springer.