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Monitoring the Degradation of a Linear Axis with the Aid of a Dynamic Bayesian Network Model

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Abstract: In this a paper an approach for monitoring the degradation of a guiding system as a component of a linear axis will be presented. The degradation process is modeled with the aid of a dynamic Bayesian network, which is capable to represent stochastic processes and Markov chains in particular. By periodically recording the values of selected parameters, which serve as indicators for potential wear-out of the regarded component, it is possible to predict the degree of deterioration. It will be shown which results the model is producing under various boundary conditions like with or without stress, with or without observations as well as with or without maintenance activities. It will further be shown that these results seem to be plausible and adequately reflect the real condition of the linear axis.

Keywords: Degradation, Dynamic Bayesian Networks, Reliability

1. Introduction

Unexpected machine failures in manufacturing can cause downtimes and thus substantial financial loss. Therefore, it would be useful to have a model which predicts potential failures before they actually occur. To develop such a model, we may consider that degradation eventually leads to a weakness that can cause failure. Thus, if it is possible to measure degradation, this might provide more information about the reliability of systems and components than time-to-failure data. Consequently, a relationship between observations and degradation has to be found, as well as a relationship between degradation of components and potential failure. Once these relationships are established, it is possible to estimate how the actual degree of degradation of a component is and how to predict failure and time-to-failure based on observable data.

A degradation model based on the theory of dynamic Bayesian networks was developed for a guide rail of a linear axis, which is used for pick and place tasks. To test the model in respect of correctness and plausibility of results, different scenarios have been developed to reflect real situations in industrial applications. The simulated data and observations for each of the scenarios were fed into the model and the resulting assessments and predictions of the model were evaluated.

2. Background

2.1 The Role of Degradation in Reliability

Using lifetime data to assess the reliability of highly reliable product is often problematic (Birolini, 2014). For a practical testing duration, few or perhaps no failures may occur. Furthermore, if most or all of the observations are censored, they provide little information about reliability for a warranty period that may be orders of magnitude longer than the testing duration.

Degradation data provide a superior alternative to highly censored data, which provide little information, or accelerated data for which identifying an acceleration relationship can be difficult. Most of the failures arise from a degradation process at work, such as the progression of a chemical reaction or the propagation of a crack, which may or may not be observable (Meeker & Escobar, 1998). When there are one or more observable characteristics that degrade or grow over time, one has to relate them to failure.

2.2 Modeling Degradation Processes with the Aid of Dynamic Bayesian Networks

A Bayesian network (Pearl, 1988), (Darwiche, 2014) is a probabilistic graphical model that simplifies a probabilistic representation by exploiting the marginal and conditional independence relations in the respective domain. Simply speaking, a Bayesian network is a pair *(G,**P**)*, where *G=(**V**,**E**)* is a directed acyclic graph (DAG) over a set of random variables ***V*** and ***E*** is a set of directed edges that represent probabilistic relationships between variables in ***V***. ***P*** is a set of conditional probability distributions (CPDs) that quantify the strength of the relations induced by ***E***. Specifically, ***P*** contains for each *V* in ***V***, the CPD *P(V|pa(V))*, where *pa(V)* is the set of parent variables of *V* in *G*.

A Bayesian network supports both diagnostic and prognostic reasoning by computing the posterior probability *P(H|e)* of an unobservable hypothesis *H* given observed evidence $e=\{e_1,..,e_m\}$, where each e_j is the observed state of the variables $E=\{E_1,..,E_m\}$. The calculations are based on the chain rule (Jensen & Nielsen, 2007):

$$P(X_1,...,X_n)=\prod_{j=1}^{n}P(X_j \mid pa(X_j)) \qquad (1)$$

Dynamic Bayesian networks (Kjaerulff & Madsen, 2014) are Bayesian networks which have also a temporal component. They consist of a sequence of slices, each of which contains the same regular Bayesian network. These slices are connected by directed links from nodes in slice *i* to nodes in slice *i+j*. Each slice of a dynamic Bayesian network can have any number of state variables $\boldsymbol{X_t}$ and evidence variables $\boldsymbol{Y_t}$. The variables and their links are exactly replicated from slice to slice and the dynamic Bayesian network represents a nth-order Markov process, so that each variable can have parents only in its own or the n preceding slices.

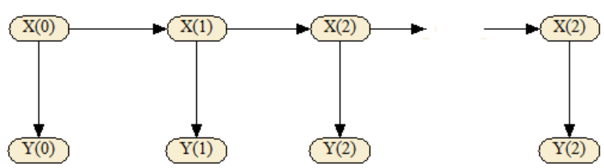

Figure 1. Example of a Dynamic Bayesian Network

Figure 1 shows a simple example of such dynamic Bayesian network representing a first-order Markov process. It consists of one state variable *X(j)* and one evidence variable *Y(j)*. To construct such a dynamic Bayesian network, one has to specify three kinds of information: the prior distribution over the state variables $\boldsymbol{P(X_0)}$, the transition model $\boldsymbol{P(X_{j+1}|X_j)}$, and the sensor model $\boldsymbol{P(Y_t|X_t)}$, in the example in figure 1 $P(X_0)$, $P(X_{j+1}|X_j)$ and $P(Y_j|X_j)$ respectively.

Dynamic Bayesian networks can be interpreted as a generalization of Markov process models, which have frequently been applied for the modeling of degradation (Straub, 2009). Markovian degradation processes are characterized by the fact that for a given condition at time t_1, the condition at any future time $t_2 > t_1$ is stochastically independent of the condition at any past time $t_0 < t_1$.

2.3 The P-F Curve

The P-F curve has become an essential component to any reliability centered maintenance program (Moubray, 2012), and it can help extend the lifespan of systems and components. The basic concept of the P-F curve (see figure 2) consists in modeling the typical behavior of mechanical components in practical applications. It involves the P-F interval, which is the time between when a prospective failure identifies itself (potential failure point P) and when we can no longer use the equipment because its performance degrades to an unacceptable level (functional failure point F).

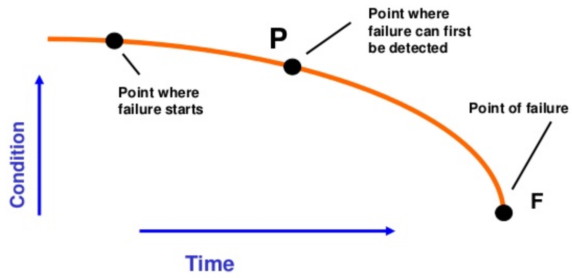

Figure 2. The P-F Curve (Moubray, 2012)

As figure 2 shows, the considered component or system degrades very slowly in the beginning of the operating time. There is, however, a certain point where the degradation of the component or system starts becoming increasingly worse, and finally degrades very rapidly. For example, when a linear axis was in operation for a long time, the surface of the guide rails starts getting cracks and small slivers of metal may develop. In the end more and more slivers are sheared off. Small particles get into the oil, and craters with edges appear on the surface of the rails. The particles, the edges of the craters and the craters themselves accelerate the degradation process.

3. Monitoring the Degradation of Linear Axes

3.1 The Degradation Model for the Guiding System

The degradation model for the guiding system of the linear axis was built up on the basis of a model developed by Lorenzoni and Kempf (2014). It models the P-F curve as introduced above, the operating conditions of the pick and place process, the degradation variable itself as well as indicators for degradation. The topological structure of the model is pictured in figure 3. The green nodes representing the observable indicator variables have been defined by experts for the guiding system.

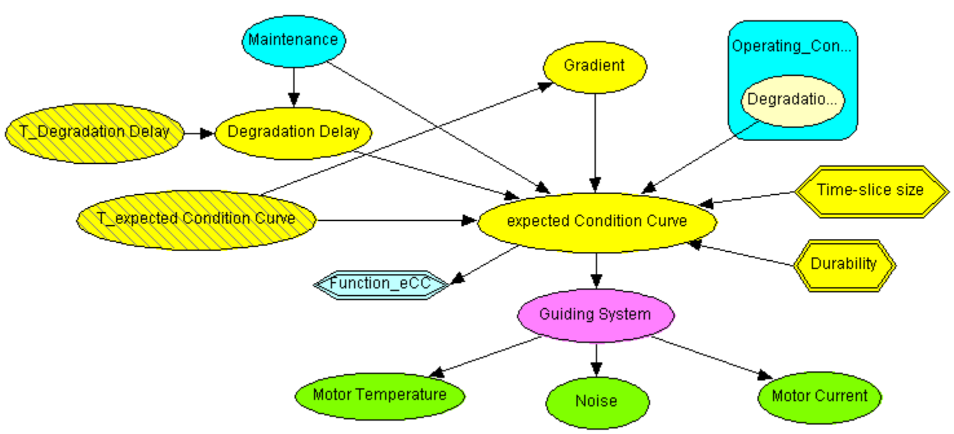

Figure 3. Degradation Model for the Guiding System of the Linear Axis

Besides the structure of the network, the quantitative part, namely the conditional probability distributions have to be specified. These probabilities have been elicited together with a number of experts, who are experienced with this specific type of linear axis and have exhaustive knowledge about the dependencies of the indicator variables and the level of wear-out of the considered guiding system.

3.2 Application of the Degradation Model

The lifetime of the linear axis ranges from 30,000 to 60,000 hours depending on the actuating variables like velocity, acceleration or load. The guiding system in particular has an expected lifetime of 15,600 hours or 650 days at a velocity of 2.1 meters per second. Variables like motor temperature and motor current, which are modeled as observable variables with green nodes in our model in figure 3, are recorded periodically in the second range by the controlling system. These data were summarized appropriately and transferred to the degradation system together with the information whether there was abnormal noise during the last day or not.

Figure 4 shows the normal behavior of the model, namely if no observations have been recorded. It has quite a similar shape than the P-F curve presented before. This curve reflects what the degradation model predicts when no observations are collected.

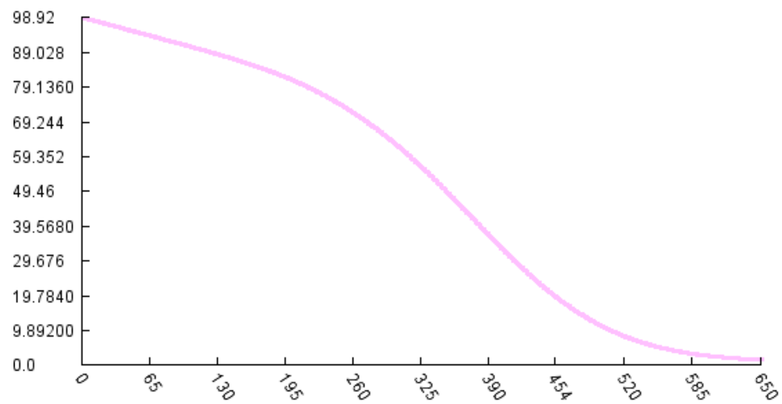

Figure 4. Condition Curve of the Guiding System with No Observations

In the next scenario the recorded values of the indicator variables are all in very good ranges, i.e. there is no indication that something went wrong with the guiding system so far (see figure 5). Obviously the degradation process is progressing quite slowly and it seems that this particular guiding system will probably survive much longer than the average one.

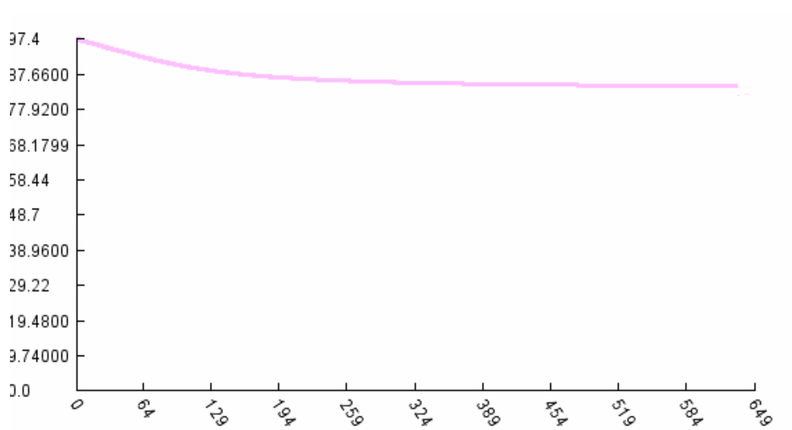

Figure 5. Condition Curve of the Guiding System with Perfect Readings of the Indicator Variables

Figure 6 illustrates a situation where everything works perfectly, until all of a sudden, around day 350, extremely poor values of the indicator variables occur. As these values do not recover anymore the condition curve decreases quickly and according to the model it wears out within about one month.

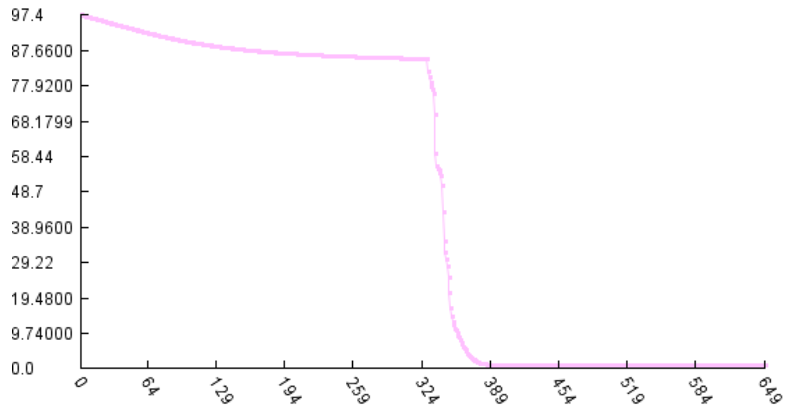

Figure 6. Condition Curve of the Guiding System with Extremely Poor Indicator Variables from Day 350

After realizing that the condition of the guiding system is becoming worse and worse, it is possible to perform maintenance actions. For example one could clean the guide rails from slivers and particles and apply some lubrication. What the degradation curve look like after such a maintenance action is pictured in figure 7.

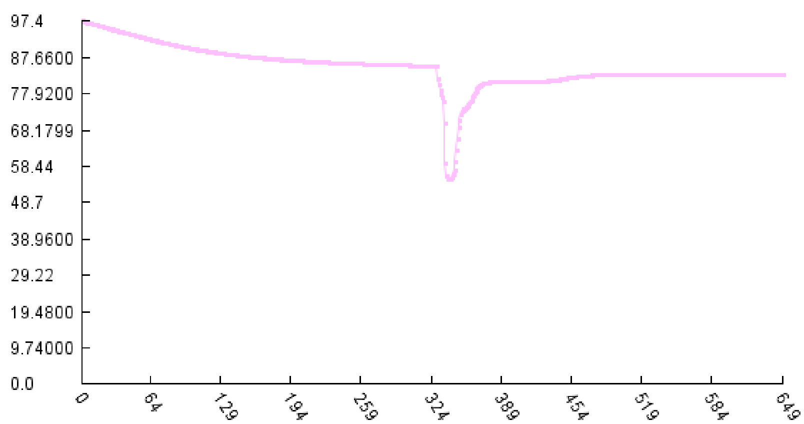

Figure 7. Condition Curve of the Guiding System after a Maintenance Action

Alternatively, instead of performing maintenance, it is possible to replace the guiding system which will result in a behavior illustrated in figure 8.

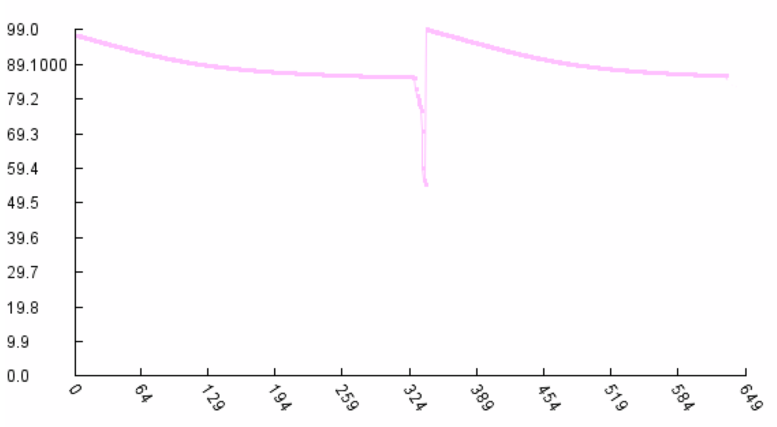

Figure 8. Condition Curve of the Guiding System after Replacement

4. Conclusion

Assessing reliability with degradation data has a number of advantages. One does not have to wait for failures to occur and does not have to use acceleration methods to collect the data. Beyond that, analyzing degradation data gives us a deeper understanding of the degradation mechanisms and can often tell us how to improve the reliability of a component.

The degradation model for the guiding system of a linear axis was tested and validated with the aid of selected applications scenarios. The behavior of the model seems to be plausible and reflects the real mechanical process adequately to monitor the linear axis appropriately by predicting potential failures from wear-out. In a next step it has to be tested in a real industrial environment.

5. References

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