

# Establishing a Wear-Related Deterioration Model Based on Experimental Data

Nejra Beganovic, Sandra Rothe, Dirk Söffker

► **To cite this version:**

Nejra Beganovic, Sandra Rothe, Dirk Söffker. Establishing a Wear-Related Deterioration Model Based on Experimental Data. Le Cam, Vincent and Mevel, Laurent and Schoefs, Franck. EWSHM - 7th European Workshop on Structural Health Monitoring, Jul 2014, Nantes, France. 2014. <hal-01021048>

**HAL Id: hal-01021048**

**<https://hal.inria.fr/hal-01021048>**

Submitted on 9 Jul 2014

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

## ESTABLISHING A WEAR-RELATED DETERIORATION MODEL BASED ON EXPERIMENTAL DATA

Nejra Beganovic, Sandra Rothe, Dirk Söffker

*Chair of Dynamics and Control, University of Duisburg-Essen, Lotharstrasse 1-21, 47057, Duisburg*

nejra.beganovic@uni-due.de

### ABSTRACT

System modeling with respect to reliability function is of increasing importance, since knowledge about reliability function enables its integration in control affecting the control strategies. Suitable operating strategies will lead not only to extended lifetime, but also give a possibility for predictive maintenance. The assessment of reliability function relies often on probabilistic theory. From probabilistic point of view it consequently involves mathematical assumptions, but physically mainly relies on knowledge about system's state-of-deterioration. This implies that statements about the state-of-deterioration, about predictive maintenance, as well as the ability to control the system's extended lifetime assume knowledge about the relation between system's load (applied to the system), system's stress (appearing within the system), and the resulting behavior of systems to the loads applied. This contribution establishes a parametric model from the experimental data generated from wear experiments, and compares the results to those results obtained for individual system generating data.

**KEYWORDS :** *life-cycle analysis, probabilistic and stochastic modelling, damage accumulation, reliability*

### INTRODUCTION

The importance of increased reliability and availability, as well as enhanced safety comes in focus in today's mechatronic systems. The assessment of reliability function allows prediction of the states in a system, and thus have found numerous usages, including forecasting life cycle cost, safety analysis, failure modes, and comparison of design and products [1]. Summarized from literature, the system components and system itself is subject to time variable complex loadings. Damage increases due to applied loading and stress appearing within the system [2]. The knowledge about the reliability function enables estimation of beforehand mentioned point in time at which system fails, and simultaneously also remaining useful lifetime. Inferred by Banjevic [3], remaining useful lifetime is denoted as the time between estimated end-of-lifetime and considered lifetime, in which it assumes the system survived. The ultimate goal of achieving reliability function is to modify control strategies in such a way that the extension of component lifetime is obtained, but simultaneously operating and maintenance cost reduced through timely (scheduled) maintenance, and enhanced safety. Variety of techniques are used to carry out prognostics, starting from probabilistic techniques, over statistical techniques to artificial intelligence models. In accordance with [4], all mentioned prognostic approaches are divided into data- and model-based approaches. While data-based approaches take into account statistical and artificial intelligence techniques, model-based approaches consider mathematical description of physical processes present in the system [4–6]. Primary intention of this paper is to establish a generic model that describes the relationship between the accumulated damage and system's expended lifetime. For prognostic of system's lifetime as the point in time at which the failure criterion is fulfilled, a number of lifetime models are known. Problem statement and an overview of known lifetime models are addressed in section 1. In section 2 the problem of wear-related deterioration in tribological system is detailed, as well as the introduction of test rig. Demonstration of generic

concept modeling follows in section 3, with results and discussion on results presented in section 4. At the end, advantages and disadvantages of proposed method are summarized in conclusion.

## 1. PROBLEM STATEMENT

The various processes, occurring under loading and consequent aging of materials, effect on reducing the lifetime of components. These processes are taken into account in lifetime modeling and included in mathematical expressions describing lifetime model. As well known, often system operates under different loading profiles whose character and intensity varies with the type of system (mechanical, electrical). Varying character of loads applied to a system, including mechanical, electrical loads, as same as the impacts from the environment, such as temperature and humidity, have necessitated the development of lifetime models in several directions. Lifetime models, considered in this chapter, illustrates different approaches in model estimation and highlights key aspects in terms of practical application of models. The lifetime models observed here require data for model parameter estimation. The accuracy of parameter estimation depends on experimental data and causes specific model selection. For lifetime model parameter estimation providing the experimental data that reflect the conditions as close as possible to conditions in normal system operation is of crucial interest.

### 1.1 Overview of known lifetime models

The Arrhenius model [7], describing effect of temperature on lifetime of electrical system in exponential form, has been available for several years and is widely used with a number of modified descriptions. Applications are known from non-mechanical systems, mainly describing chemical system processes and its effects on lifetime. The activation energy, as one of the parameters in Arrhenius model, present minimum energy required in terms of taking participation in processes related to failure mechanisms. Eyring model represents a sort of extension of Arrhenius model in terms of involving additional stresses. With each additional stress, eventually taken in consideration with Eyring model, model is extended with two additional unknown parameters, which should be estimated. The both, Eyring and Arrhenius models, are applicable to stresses of constant amplitude [8]. Inverse-power model connects the variables related to electrical stress (voltage) and temperature, describing in such a way combined thermal and electrical effects on lifetime. Inverse-power model is derived on base of Eyring model. Simoni [9, 10] introduced a combined-stress lifetime model applicable to insulation materials taking in consideration thermal and electrical stresses. The intension of authors was to introduce the general model, valid for any type of insulation material. Description of aging processes and cracks in metals are proposed by Coffin-Manson's model. The lifetime is calculated by taking in consideration temperature cycles and its effects on the crack growth in metals. Considering the derivation of lifetime models for mechanical systems and taking into account that the load changes with the change of time are not always known, a number of methods that allow estimation of lifetime under varying loads are developed. Loading profile, temperature, and humidity are some of the factors that greatly affect the growth of damage in mechanical systems. Primarily developed hypotheses have basically discussed the deterministic approach, and considered the presumption that the loading profiles under a certain level do not affect the growth of damage. S-N curve, describing the relation between nominal stress and the number of cycles within the failure appears, shows this effect as an endurance limit under which the material theoretically has infinite lifetime. Palmgren and Miner proposes the method for damage calculation based on assumption that the S-N curve and associated damage accumulation is established as introduced in Eqn 1. Regarding to Miner [11], damage increment is represented by the ratio of the current number of cycles and the maximum number of cycles to failure under constant stress. Accumulated damage is thus simply expressed as a sum of incremental damages. Beforehand mentioned assumptions do not reflect the situation in practice, where the damage propagates even in case of lower level of the loading profile (under endurance limit), and

where mechanical part is exposed to a complex loadings with random sequence of appearance. The deviation between experimental data and calculated damage is thus enormous as a consequence of neglected damage propagation for loading profiles under endurance limit, as well as neglected the actual state-of-deterioration and load sequence [11, 12] as

$$D_j = \sum_{i=1}^j d_i \text{ and } d_i = \frac{n_i}{N_i}. \quad (1)$$

In accordance to achieving the good results regarding to experimental data, the number of modifications of Palmgren-Miner rule are proposed. Modifications proceeded by Henry [13], Marco and Starkley [14], Gatts [15], and Subramanyan and Srivatsavan [16, 17] considers modification of Palmgren-Miner with an intension to adapt the rule to specific problems. The common idea for the most of proposed modifications is introducing nonlinearities in model. So that, modification proposed by Marco and Starkley introduces nonlinear model dependent of current load and its amplitude through power rule. Modification, proposed by Henry in 1955 considers changes related to endurance limit, and recommends the endurance limit changes with the increased damage. Gatts's proposal on modifications regarding linear Palmgren-Miner rule is based on the tests relating to steel specimens. On such base author introduces the endurance limit in form of initial endurance limit appeared with the first applied load. Submayan and Srivatsavan threated variable amplitude loading in the lifetime predictions considering a set of isodamage lines. The disadvantage of all deterministic approaches is the fact that they do not consider the stochastic nature of damage accumulation, which is reflected in different characteristics of materials. Stochastic nature of damage caused development of stochastic hypothesis taking into account the load as a random variable or the damage as a random process. The most of them relies on the probabilistic theory in description of damage propagation in system. Parzen tried to explain the stochastic nature of damage using renewal theory. Renewal theory as specialized field of probability theory was able to handle with variable amplitude of loads, as well as randomness of the material characteristics [18]. Modeling of damage process proposed by Bogdanoff is related to description of damage accumulation, primarily wear and fatigue, with respect to load cycle. Bogdanoff considered damage accumulation assigned to one load cycle as a discrete Markov-Process [19, 20]. Kutt und Bienek proposed cumulative damage rule studying the fatigue of metals under varying stress. Among the four identified challenges related to damage accumulation models, authors deal with two of them and presents the stochastic model of fatigue damage of metals, as well as the cumulative damage rule [21].

In comparison with the deterministic approaches, the stochastic approaches describe damage progression more accurate taking in consideration variable loading profiles, as well as the randomness of material behavior through probabilistic theory.

## 2. GENERIC CONCEPT TO OPTIMIZATION-BASED MODELING

As already emphasized, damage in system has progressive character and propagates over the time showing monotonical increase. By observing the incomes at discrete moments of time and by using the label DA for damage accumulation, the damage accumulation observed at an unspecified point  $n$  in time can be denoted as  $DA(n)$ . Comparing with income at an unspecified point  $n-1$  its value will be increased by  $\Delta DA$ . Since the system's end of lifetime is defined as state in which the damage accumulation reaches predefined limit, by increasing DA in such a way the system is with each income closer to its end of lifetime. Consequently expended lifetime is increased, while remaining lifetime is decreased. Considering propagation of damage accumulation over the time, system representation through a difference equation is imposed as one of the possible solutions. Difference equation allows calculation of expended lifetime based on current damage accumulation, as

$$LT(n) = \sum_{k=1}^n a_{n-k} \cdot DA(n-k) + \sum_{k=1}^{n-1} b_{n-k} \cdot LT(n-k). \quad (2)$$

With such a representation it becomes possible to calculate expended lifetime, and furthermore also remaining useful time. In the phase of model training,  $a_k$  and  $b_k$  parameters have to be estimated in terms of the best fitting with used training experimental data. On the assumption of such a model, mitigating factor is a linear relationship between  $a_k$  and  $b_k$  parameters, as

$$\begin{aligned} suma_{n-1} &= \sum_{k=1}^{n-1} a_{n-k-1} \cdot DA(n-k-1), \quad sumb_{n-2} = \sum_{k=1}^{n-2} b_{n-k-1} \cdot LT(n-k-1), \\ a_n &= \frac{LT(n) - suma_{n-1} - b_n \cdot LT(n-1) - sumb_{n-2}}{DA(n)}, \\ b_n &= \frac{LT(n) - a_n \cdot DA(n-1) - suma_{n-1} - sumb_{n-2}}{LT(n-1)}. \end{aligned} \quad (3)$$

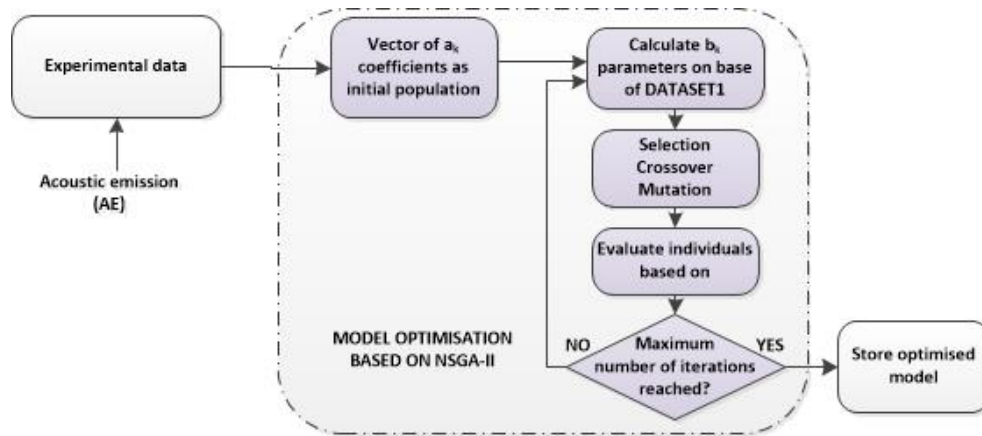


Figure 1 : Optimization of model parameters based on NSGA-II

Assuming more than one dataset from tribological system operating under identical conditions is available,  $a_k$  parameters can be randomly chosen and furthermore  $b_k$  parameters calculated, and vice versa. In practice it means that a large set of solutions for describing one dataset by calculating the parameters can be found. The resulting task is to define those set of  $a_k$  and  $b_k$  coefficients, able to describe a number of experimental data from the system operating under identical conditions. The problem can also be interpreted as a multi-objective optimization problem. Non-dominated sorting algorithm can be used to define a suitable solution in terms of the optimization of model parameters. As depicted on Figure 1, one experimental dataset is used for calculation of parameters, while the second dataset for parameter optimization through minimizing the deviation between considered two datasets. The algorithm can simply be extended by including more than one dataset in training phase, guaranteeing a large degree of congruency. Optimization of model parameters using a suitable number of datasets for model parameter assessment in training phase increases the degree of congruency also with experimental training data. The implementation of non-dominated sorting algorithm follows the algorithm description detailed in [22] and is implemented in MATLAB by Song [23].

### 3. WEAR-RELATED DETERIORATION IN TRIBOLOGICAL SYSTEM

Tribology, as a science describing the behavior of metallic surfaces and its interaction with respect to their relative motion, covers friction analysis from the aspect of wear-related deterioration processes

in tribological systems. Over the time and variable operating conditions, wear effects become noticeable, including adhesive wear at the beginning, following by abrasive wear, surface fatigue, fretting, and erosive wear at the end. In the literature adhesive wear, abrasive wear, and surface fatigue are identified as a main wear mechanism [24]. These processes can be monitored through the three clearly distinguished deterioration phases: the run-in phase, permanent wear and wear-out phase, which differ in failure rates. Within the wear-out phase tolerable limit of damage accumulation is exceeded and the system can be considered as failed [25–27].

### 3.1 Test rig and experimental data

Tribological system, as discussed in this contribution, uses several different sensors for monitoring tribological effects and deterioration progression. As depicted in the sketch in Figure 2, application example consists of two wear plates [27]. Wear plates (also called contact partners) are of different sizes with surface areas in ratio 1:5, sliding against each other under variable friction and lubrication conditions. The contact partner with larger surface area is fixed and has no movement, while the other one performs linear motion by applying normal force, causing thereby tribological effects [28].

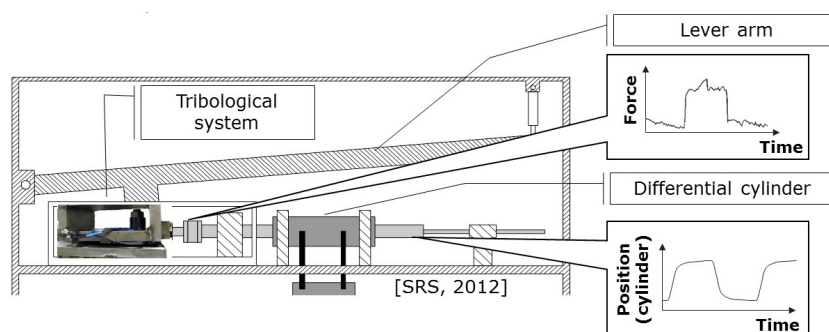


Figure 2 : Test rig for wear examination, Chair of Dynamics and Control, SRS, U DuE

Contact partner, performing linear motion, is equipped with a piezoelectric sensor. Using the sensor and the measurement chain, it is possible to measure acoustic emissions, phenomena where transient elastic waves are generated as a result of rapid release of energy. It is proved that acoustic emission signals can indicate different effects related to material changes, including aging, material displacement, and wear [29]. From the other side, due to interaction between contact partners, friction appears within the system. Since the force is not directly measurable, representation of force goes through the hydraulic pressure, which is proportional to the applied force. Proceeding with diagnosis-oriented data filtering, applied to hydraulic pressure measurements, is necessary to generate the characteristic values for all considered load-cycles. Arithmetic mean of one load-cycle is calculated by using sliding window technique, and then the arithmetic mean of means gives the characteristic value of one load-cycle [28]. Any of these two signals can be used for establishment mathematical representation of damage accumulation and system's expended lifetime.

## 4. EXPERIMENTAL RESULTS AND DISCUSSION ON RESULTS

Assuming expended lifetime as the time elapsed from the system start-up, the relationship between the accumulated damage and expended lifetime for two experiments with identical operating conditions from tribological system, is depicted in Figure 3. Here illustrating one measured experimental result is given and discussed without loss of generality. The different test runs are denoted as  $Z_{xy}$ , here results from  $Z_{15}$  and  $Z_{20}$  are shown as example. Damage accumulation is normalized to 1, while the expended lifetime is normalized to 100.

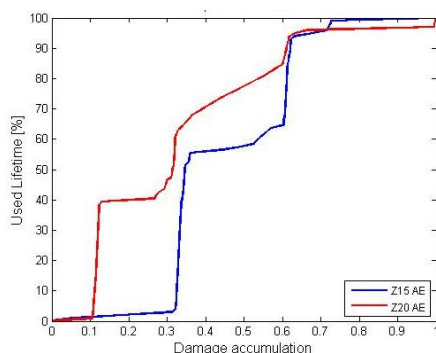


Figure 3 : Damage - Lifetime relation based on experimental data (two experimental data sets)

In order to obtain the coefficients  $a_k$  and  $b_k$  of the generic model introduced in chapter 2, one dataset is used (depicted as Z15 in figures), and thus the degree of congruity of such a model with the first dataset is high, as evidenced by Figure 4 on the left side. Random selection of  $a_k$  coefficients is used, while the  $b_k$  coefficients are calculated. The problem that occurs here is a finite but depending on the number of parameters to be defined large number of possibilities choosing  $a_k$  coefficients, all suiting good the dataset used for calculation, but not equally well suiting experimental data used for validation. Necessity of model optimization in a terms of choosing the most appropriate set of ( $a_k$ ,  $b_k$ ) coefficients is obvious. In other words, assuming a large number of datasets for estimation of coefficients  $a_k$  and  $b_k$  the results become more accurate in terms of a larger degree of model congruity with the experimental data, so the model becomes able to reflect changes with respect to deterioration in the system.

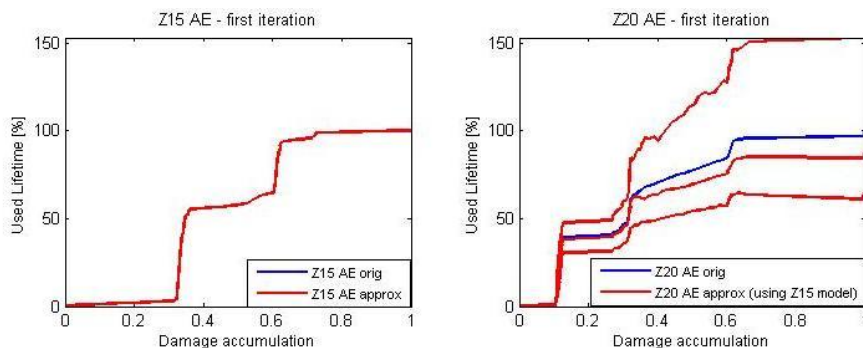


Figure 4 : Generic model behavior with respect to randomly chosen  $a_k$  coefficients

Comparing the model behavior with three different sets of  $a_k$  and  $b_k$  coefficients it is noticeable that the degree of congruity with the first data set (Z15) for all three ( $a_k$  and  $b_k$ ) sets is high, what is expected since the coefficients are calculated based on the first dataset, while the degree of match with second dataset (depicted as Z20 in figures) varies, as shown on the right side of Figure 4. This behavior shows that the model optimization with a number of datasets representing the system behavior under identical operating conditions is necessary. In lack of experimental data the second dataset is used in non-dominated sorting algorithm in form of objective function trying to minimize the deviation of experimental data and parametric model derived on base of the first dataset. The results, depicted on Figure 5, proves that such an approach gives good results in terms of model training/optimization with respect to set of training data representing the damage accumulation in system and its effect on system's lifetime. Despite model application to set of data (Z15, Z20), Figure 6 represents the results of the identical procedure applied to set of data (Z11, Z13).

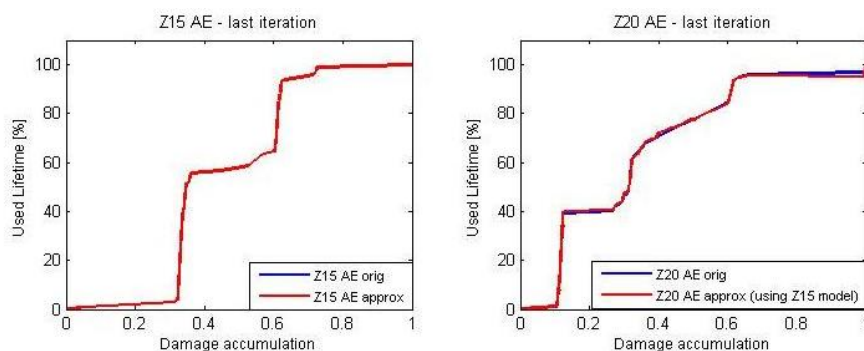


Figure 5 : Model approximation results using generic model optimization for Z15 and Z20 datasets

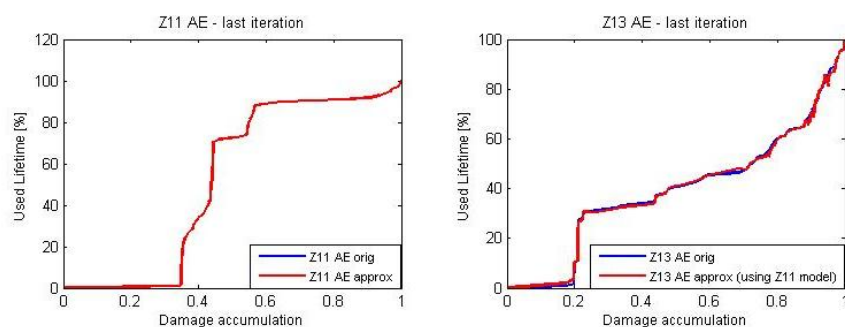


Figure 6 : Model approximation results using generic model optimization for Z11 and Z13 datasets

Primary intension was to show that the model proposed in 2 trained appropriately (with appropriate training datasets) gives the high degree of congruity with the experimental data, implying the ability to describe damage progression in tribological system. The model shows high sensitivity on errors in estimation, since takes in consideration previous values of damage accumulation, what is equal to current state of system deterioration. If the error is present in the initial stages, it is also accumulated in the next stages, thus the errors in damage estimation should be avoided, especially in the initial stage.

## CONCLUSION

This contribution primarily gives an overview of lifetime models known from literature and used in analysis. As shown, the - from an application point of view - important challenge of theoretical lifetime models is to be adapted to the real damage propagation of real stressed systems. Also due to the nonstochastic character of the models the theoretical models can not be realistic. In this contribution another strategy is implemented. Here a generic model for damage estimation based on knowledge about current state-of-deterioration in tribological system is proposed. Using a large number of model parameters leading to more degrees of freedom for model adaption, and thus more possibilities for model optimization. This implies that the training of model belonging to parameter estimation has to be well designed. It relates primarily to the set of experimental data used for model training, which should represent the key features of system from one side, and to be enough diverse to show different system's behaviors despite the identical operating conditions. Experimental data, used for model identification, are generated from wear experiments. Presented results corroborate the need for the enough diverse dataset used for parameter estimation. Despite the fact that a small number of datasets is used for parameter estimation the results are satisfactory.



## REFERENCES

- [1] STANDARD IEEE. 1413-1998 - IEEE Standard Methodology for Reliability Prediction and Assessment for Electronic Systems and Equipment. August 2002.
- [2] K. Dettmann and D. Söffker. Adaptive modeling of reliability properties for control and supervision purposes. *Int. J. of Applied Mathematics and Computer Science (AMCS)*, 21:479–486, September 2011.
- [3] D. Banjevic. Remaining useful life in theory and practice. *Metrika*, 69:337–349, January 2009.
- [4] Q. Miao, L. Xie, H. Cui, W. Liang, and M. Pecht. Remaining useful life prediction of lithium-ion battery with unscented particle filter technique. *Microelectronics Reliability*, 53:805–810, June 2013.
- [5] J. Gu, D. Baker, and M. Pecht. Prognostics implementation of electronics under vibration loading. *Microelectronics Reliability*, 47:1849–1856, December 2007.
- [6] M. Pecht and R. Jaai. A Prognostics and health management roadmap for information and electronics-rich systems. *Microelectronics Reliability*, 50:317–323, February 2010.
- [7] S. Arrhenius. On the reaction rate of the inversion of non-refined sugar upon souring. *Zeitschrift für Physikalische Chemie*, 4:226–248, 1889.
- [8] S. Glasstone, K.J. Laidler, and H.E. Eyring. *The theory of rate processes*. McGraw Hill, NY, 1941.
- [9] G.C. Montanari and L. Simoni. Aging phenomenology and modeling. *Electrical Insulation*, 28:755–776, Oktober 1993.
- [10] L. Simoni, G. Mazzanti, G.C. Montanari, and L. Lefebvre. A general multi-stress life model for insulating materials with or without evidence for thresholds. *Electrical Insulation*, 28:349–364, June 1993.
- [11] M.A. Miner. Cumulative damage in fatigue. *Applied mechanics*, 12:159–164, 1945.
- [12] A. Palmgren. Lifetime of ball bearing. (*In German*), *VDI-Z*, 68:339–341, 1924.
- [13] D.L. Henry. A theory of fatigue-damage accumulation in steel. *Trans. of the ASME*, 77:913–918, 1955.
- [14] S.M. Marco and W.L. Starkley. A concept of fatigue damage. *Trans. of the ASME*, 76:627–632, 1945.
- [15] R.R. Gatts. Application of a cumulative damage concept to fatigue. *Trans. of the ASME*, 83:529–540, 1961.
- [16] S. Subramanyan. A cumulative rule based on the knee point of the S-N curve. *Journal of Engineering Materials and Technology*, 98:316–321, 1976.
- [17] R. Srivatsavan and S. Subramanyan. A cumulative damage rule based on successive reduction in fatigue limit. *Journal of engineering materials and technology*, 100:212–214, April 1978.
- [18] E. Parzen. On models for the probability of fatigue failure of a structure. *AGARD report*, April 1959.
- [19] J.L. Bogdanoff. A new cumulative damage model, Part I. *J. of Appl.Mech.*, 45:246–250, 1978.
- [20] J.L. Bogdanoff. A new cumulative damage model, Part II. *J. of Appl.Mech.*, 45:251–257, 1978.
- [21] Tiiu V. Kutt and M.P. Bieniek. Cumulative damage and fatigue life prediction. *AIAA Journal*, 26:213–219, 1988.
- [22] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan. A fast and elitist multiobjective genetic algorithm NSGA II. *Evolutionary Computation*, 6:182–197, July 2002.
- [23] L. Song. <http://www.mathworks.com/matlabcentral/fileexchange/31166-ngpm-a-nsga-ii-program-in-matlab-v1-4>. Access date: 20.02.2014.
- [24] C. Sly. Tribologist attacks wear and friction from the inside. *Practical Failure Analysis*, 2:9–10, April 2002.
- [25] D. Baccar and D. Söffker. Classification of wear by means of acoustic emission and signal processing techniques. *6th Europ. Workshop on SHM*, Dresden, Germany, July 3-6, 2012.
- [26] K.U. Dettmann, D. Baccar, and D. Söffker. Examination of wear phenomena by using filtering techniques for FDI purposes. In: Chang, F.K. (Ed.). *Structural Health Monitoring 2011*, pages 1037–1044, 2011.
- [27] K.U. Dettmann and D. Söffker. Classification of wear phenomena by specific ultrasonic emission detection for prognostic purpose. *Proc. Int. Conf. Prognostics and Health Monitoring*, San Diego, USA, Oktober 2009.
- [28] D. Söffker, S. Rothe, S. Schiffer, H. Aljoumaa, and D. Baccar. Smart, tough, and successful: Three innovative approaches for diagnosis and prognosis of technical systems. In: Chang, F.K. (Ed.). *Structural Health Monitoring 2013*, pages 81–88, 2013.
- [29] S.M.C. van Bohemen, J. Sietsma, M.J.M. Hermans, and I.M. Richardson. Analysis of acoustic emission signals originating from bainite and martensite formation. *Philos. Magazine*, 85:1791–1804, 2005.