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ADAPTIVE MODELING OF RELIABILITY PROPERTIES FOR CONTROL AND SUPERVISION PURPOSES

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Modeling of reliability characteristics typically assumes that components and systems fail if a certain individual damage level is exceeded. Every (mechanical) system damage increases irreversibly due to employed loading and (mechanical) stress, respectively. The main issue of damage estimation is adequate determination of the actual state-of-damage. Several mathematical modeling approaches are known in the literature, focusing on the task of how loading effects damage progression (e.g., Wöhler, 1870) for wear processes. Those models are only valid for specific loading conditions, *a priori* assumptions, set points, etc. This contribution proposes a general model, covering adequately the deterioration of a set of comparable systems under comparable loading. The main goal of this contribution is to derive the loading–damage connection directly from observation without assuming any damage models at the outset. Moreover, the connection is not investigated in detail (e.g., to examine the changes in material, etc.) but only approximated with a probabilistic approach. The idea is subdivided into two phases: A problem-specific relation between loading applied (to a structure, which contributes to the stress) and failure is derived from simulation, where a probabilistic approach only assumes a distribution function. Subsequently, an adequate general model is set up to describe deterioration progression. The scheme will be shown through simulation-based results and can be used for estimation of the remaining useful life and predictive maintenance/control.

Keywords: reliability, parameter estimation, damage accumulation, probabilistic simulation.

1. Introduction

A major challenge in today's systems is to address competing objectives such as enhanced safety, improved reliability, reduced life cycle costs, etc. To compromise for those tasks, the most harmful factors have to be identified and their negative effects compensated by appropriate countermeasures. In today's maintenance decision policy, proper estimation of deterioration due to loading in field usage (e.g., typical environmental conditions, etc.) poses a major challenge. In some industrial sectors and products, traditional maintenance strategies consider worst-case scenarios for operation conditions to reduce the probability of premature failures. Consequently, the system has an oversized safety margin and/or has to be maintained earlier than its planned end of lifetime (in terms of threshold values for kilometers, operation time, cycles, etc.). Those maintenance strategies are commonly used especially for systems where failures lead to a loss of safety and/or immense financial losses. Though highly reliable and safe operation can be guaranteed, the life cycle costs are increased and the availability is reduced due to frequent inspection intervals and down times. For less safety relevant systems the replacement is feasible as close to its (individual) failure as possible. One of the main issues is to make a timely maintenance decision, based on the on-line degradation information. This concept is called Condition-Based Maintenance (CBM). Advantageous, real field operation is considered on-line. The objective of CBM is to calculate relevant information about the actual reliability of a system. In the work of Banjevic (2009), the Remaining Useful Life (RUL) of the system is defined as $X_t = T - t$ (for $T > t$), if the system has survived until time t and T is the time to failure. Other information used for CBM purposes is known in the literature, i.e., actual damage, state-of-health, probability of failure, etc.

The key feature for compromising adaptively for safety, reliability, and costs (e.g., premature maintenance) over the whole life time and during field usage is to estimate the actual (remaining useful) life and/or damage and control the affecting loading profiles (Wolters, 2008). To cope with this challenge, the loading–failure connections have to be known.

The proposed concept details the idea of how to state an appropriate loading–damage relation. In Section 2 the main idea of using mathematical models for damage calculation is discussed and a brief introduction to known damage accumulation models is given. The core idea is illustrated by means of a mechanical system: the novel approach is explained. Especially the process of defining a suitable model with a suitable set of parameters is detailed. In Section 3 the results of calculations are shown. This contribution closes with a discussion of the results and an outlook.

2. Damage estimation

In the literature, loading (as the measurable force/operating condition) and stress (as the individual reaction on the loading applied) are discussed differently. Here, the prerequisite for the novel model is to use only directly measurable signals (loading). Anyhow, in the literature, both terms are often used interchangeably.

The calculation of damage is usually realized using assumptions of underlying damage accumulation laws. A well-known and controversially discussed example for a damage accumulation law is introduced by Wöhler (1870). A large sample size of comparable tensile specimens are cycled under constant, uniaxial loading until failure. The data reveal the nominal stress S (as a consequence of loading), required to cause a failure in N number of cycles. This S–N correlation is used for the most widely spread damage accumulation law developed by Palmgren (1924) and Miner (1945).

The first point of general criticism of this hypothesis is that even a large number of comparable (tensile) tests leads to an ambiguous stress S vs. cycle N relation. The results for S are hardly reproducible and scatter over a range of N.

The second point is that "real structures seldom, if ever, experience constant amplitude loading" (Downing and Socie, 1982). Hence, the transferability of those results to real applications (variable, multiaxial loading) is widely discussed, e.g., by Holmen (1979) using the example of various load histories on the fatigue behavior of concrete.

Although the damage accumulation law is discussed controversially, the idea of identifying fatigue performance experimentally is used in manifold domains, e.g., accumulator testing. Those tests reveal the sensitivity of loading factors (temperature, force, electricity, etc.) on deterioration but are time and cost intensive.

Henceforth, the data base used for this contribution is obtained by simulation. The classical damage accumulation model by Wöhler (1870), Palmgren (1924) and Miner (1945) is considered to represent the loading–damage connection of the reference system. The novel and several classical models are calculated in parallel with the damage accumulation, based on two different loading profiles. The results of damage progression are subsequently compared to the reference one.

2.1. Model structure.

A scheme of a real system with loading as input and damage-equivalent signal as output is shown in Fig. 1. Based on this idea, different models have been developed, to estimate real systems' damage behavior. According to the Miner rule (Palmgren, 1924; Miner, 1945), the damage D can be calculated if the S–N curve and the related damage accumulation model are known. Furthermore, the stress S is assumed to be proportional to the loading L. At the beginning of the 1950s, Henry (1955), Marco and Starkey (1954), as well as Hwang and Han (1986), among others, adapted the Miner rule to specific problems, i.e., special material behavior, maximal tolerable strain borders, etc. The majority of the damage accumulation hypotheses assume that all loading profiles L (above a certain level) cause an incremental damage d, independent of the actual state-of-damage and the load applied (history). All these are similar in that the state-of-damage calculation consists of two phases: first, the incremental damage d for a given interval i of loading is calculated; subsequently, the damage is accumulated to the total damage D. A detailed description of different approaches and models for incremental and accumulated (non)linear damage calculation is given by Wolters (2008).

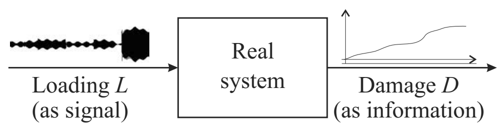

Fig. 1. Schematic input/output relation of a system; sample damage progression due to loading.

As illustrated in Fig. 2, three different calculation paths are followed. The column on the left represents the reference model. The loading–damage correlation used is detailed in Section 2.1.1. The model output is denoted by D_r.

The column "Novel approach" details the idea of the general model, which was not derived from physical effects/observations. This model considers directly stochastic side effects and loading profiles. The calculation results are denoted by D_g.

The last column depicts the classical approach. Due to the prerequisite of the classical models of Palmgren (1924) and Miner (1945), the loading L has to be classified first. Then, the loading L and classified loading L_i

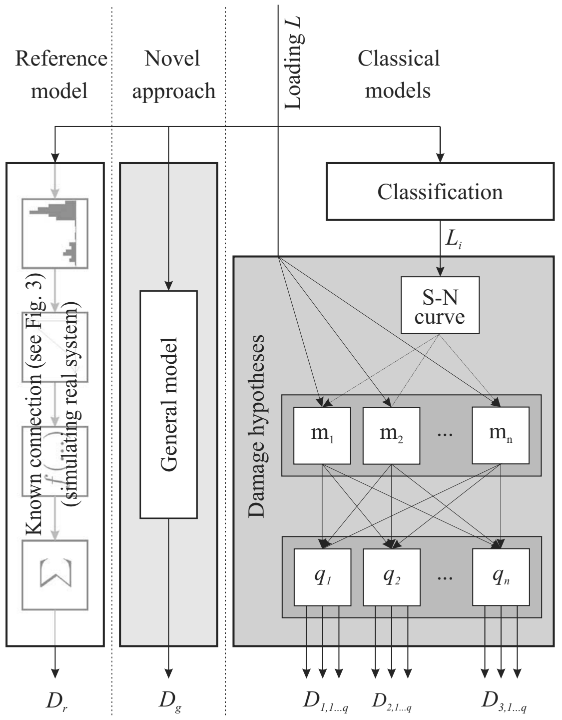

Fig. 2. Overview of the loading → damage model.

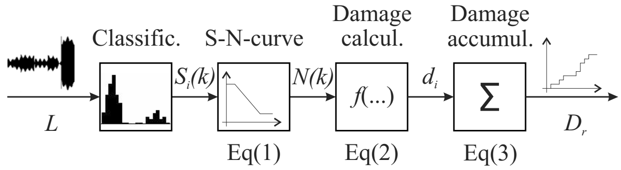

Fig. 3. Calculation of damage D_r of the reference system.

are used for the damage hypotheses. Due to the above mentioned problem of local validity of damage models (adapted to special material behavior, maximal tolerable strain borders, etc.), the incremental and the accumulated damage are calculated in parallel by several models. By using different models with different sets of parameters, the calculation results change significantly. The damage hypotheses consists of two parts: First, the incremental damage d is calculated by n different incremental damage calculation models $m_{1\ldots n}$. Subsequently, q different models $g_{1\ldots q}$ for damage accumulation derive the accumulated damage $D_{1\ldots n,1\ldots q}$ from each incremental damage $d_{1\ldots n}$.

The following section is divided into three parts: First, the mathematical model of the reference system is introduced. All results of $D_{n,q}$ and D_g are compared to the reference damage progression D_r. Then, two mathematical models using classical approaches are detailed. The drawback of deterministic models is pointed out briefly, and the novel method of concluding from failed systems to the actual average damage are discussed in detail.

2.1.1. Reference model. The causal chain from loading to damage is graphically shown in Fig. 3. In order to calculate the damage, the loading L, acting on the system, has to be classified first. Therefore, the loading L is quantized by a classification algorithm and analyzed for containing amplitudes. This can be realized by the rainflow-counting algorithm developed by Downing and Socie (1982). Other classification methods, e.g., range-pair counting, peak-counting, etc., can be implemented; their effect on the calculation result/performance can be measured and compared with those of other algorithms. The loss of information due to classification resulting from this algorithm is not discussed here.

In general, a classification algorithm reduces the spectrum of varying signals to the important set of simple reversals. The rainflow-counting algorithm creates a histogram of cyclic loadings by splitting it into i equidistant intervals. Subsequently, each data block is classified into k different amplitudes, each at its own occurrence. In this contribution, the mean loading level is defined as zero, so only the amplitude distribution is of interest. The results are shown in Fig. 4 for a given load profile.

As stated above, the Miner rule assumes that stress S is proportional to loading L, and every stress S damages the system independently from the moment of application. Hence, the quantized signal for one interval i represents the classified stress S_i.

In the following, the stress is processed with the S–N curve which is derived from material tests with a large sample size of specimen. Those tests reveal characteristic points of the S–N relation, e.g., the low-cycle-fatigue point at (N_1, S_1), and the endurance limit S_D at (N_2, S_2). As preliminarily mentioned, even a large sample size leads to an ambiguous relation between stress S and cycle N. Therefore, the probabilistic nature of failure has to be considered by varying failure rates, cf. the work by Bebbington *et al.* (2007), due to varying mate-

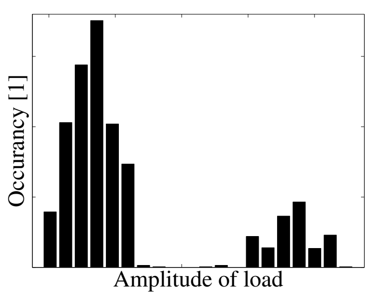

Fig. 4. Rainflow matrix of a load profile, classified into k different amplitudes.

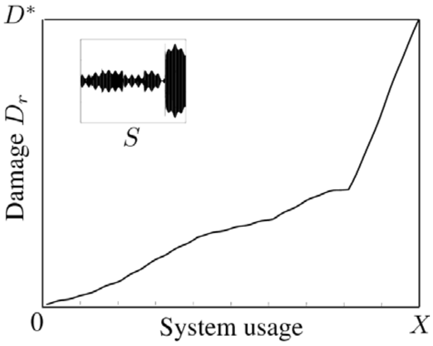

Fig. 5. Calculated damage progression D_r of the reference system.

rial behavior/quality, etc. These probabilistic effects are considered during simulation by varying the characteristic points and hence the S–N relation.

The maximum number of tolerable cycles $N(k)$ for a certain stress amplitude $S_i(k)$ is defined by Wöhler (1870) as

$$\log_{10}(N(k)) = \frac{\log_{10}(S_i(k)) - \left(S_1 - N_1 \dfrac{S_2 - S_1}{N_2 - N_1}\right)}{\dfrac{S_2 - S_1}{N_2 - N_1}}. \tag{1}$$

The Miner rule derives for the incremental damage

$$d_{i,k} = \frac{\Delta N(k)}{N(k)} \tag{2}$$

of the reference system, where $\Delta N(k)$ represents the actual number of load cycles applied for amplitude k.

The accumulated damage D_r is the summarized incremental damage

$$D_r = \sum_i \sum_k d_{i,k}. \tag{3}$$

The loading L is designed such that the calculated value of D reaches the maximum tolerable damage D^* (here assumed as 1) within i steps. Hence, the damage D_r progresses within i steps from $D_r = 0$ (i.e., undamaged) to $D_r = 1$ (i.e., failure). Due to the assumption that loading damages the system continuously, a monotonic increase of damage D_r is obtained.

Instead of using the time as the independent variable, damage progression is calculated over a meta-parameter X, denoting system-specific quantities, e.g., driven kilometers, time of usage, remaining useful life, etc.

In Fig. 5, the simulation result for the damage curve of the reference system is shown.

The degradation D_r represents the damage progression, which is derived from simulation with deterministic (fixed) values. As stated, this assumption is only valid for the average damage progression, derived from a set of comparable systems, operated under comparable loadings. This point will discussed again in Section 2.1.3.

2.1.2. Classical models. The structure of damage calculation, as depicted in Fig. 3, is maintained, but the algorithm for incremental damage calculation is exchanged. Due to the need for classifying the input signal L into amplitude-occurrence classes S_i, the standard Miner rule for damage accumulation as introduced in Eqn. (1) will be kept fixed.

In the sequel, models for incremental damage calculation, substituting Eqn. (2), are introduced.

The approach of Henry (1955) (model $m1$) considers a changing endurance limit S_D and an associated durability N_D. The incremental damage is calculated as

$$d_i = \sum_k \frac{\dfrac{\Delta N(k)}{N(k)}}{1 + \dfrac{1 - \frac{\Delta N(k)}{N(k)}}{\frac{S_i(k) - S_D}{S_D}}}, \tag{4}$$

here $\Delta N(k)$ describes the number of loads applied, $N(k)$ the number of maximum tolerable loads at a certain load level S_i, and S_D the endurance limit of the undamaged system.

The mathematical model $m2$ for incremental damage calculation is suggested by Marco and Starkey (1954), considering nonlinear behavior. The incremental damage d_i is described by

$$d_i = \sum_k \left(\frac{\Delta N(k)}{N(k)}\right)^{c_i}, \tag{5}$$

with c_i as a function of the actual load level $S_i(k)$. The algorithm for damage accumulation is the same.

To reach a high correlation of D_n with the reference damage D_r, the set of parameters of each mathematical model has to be determined and adapted to the special given problem (here material, stress profile, etc). The calculation is very sensitive to wrongly chosen boundaries/assumptions, as mentioned before. As stated by Troć and Unold (2010), "[...] the construction of algorithms letting the parameters adapt themselves to the problem is a critical and open problem [...]". In practice, this task is solved, e.g., by look-up tables for material behavior, if the system constraints are sufficiently known. Here, unknown/insufficiently known parameters but exact knowledge output data over the whole system usage are assumed. This contribution focuses on time-domain parametric models and methods, due to the fact that the experimental data are obtained in time-domain (Nelles, 2001). As all models have parametric form and D_r is known, classical parameter identification tasks are applicable.

2.1.3. Novel approach. The actual damage D of a (mechanical) system at a certain point in system usage x can usually not be measured. Hence, neither certain (intermediate) damage points nor the damage progression itself for an individual system can be determined/measured as assumed above. The only measurable information is binary information if the system is still in operation or already failed. The calculation of a realistic, real damage progression between $D = 0$ and $D = 1$, based only on these two pieces of information (in operation or failed), is hardly possible. Therefore, a related probabilistic approach for identifying damage progression experimentally in combination with appropriate tests will be used instead. The idea is based on early contributions by Wöhler (1870). Comparable systems operating under comparable operating conditions are considered. Hence, only two scenarios for failure are possible: either all systems fail at the same point in system usage X, or all systems fail at individual points x_j. If the former assumption is fulfilled, a simple deterministic model for damage calculation can be stated, based on a single measurement. As known from observation, this scenario is unlikely for most real systems and hence will not be a subject of further investigations. The latter scenario is considered in the following.

A sample size of f systems is operated with comparable load profiles. The number j of failed systems at certain points x_j is counted. Hence, the discrete points x_j of failure are directly measurable, but the damage progression itself is unknown for each system from $D = 0$ (undamaged) to $D = 1$ (failure). To conclude from these discrete points x_j to the damage progression, the distribution of observed failures D_j over system usage x_j can be investigated.

As proposed, a failure is defined as the exceedance of the individual damage D_j of the maximum tolerable damage level D^*. Hence, a premature failure of system j appears at point $(x_j, D_j = D^* = 1)$. That means that the individual points of failure in system usage only vary in x_j, where D_j is at that certain point equal to 1. The distribution of x_j over X revel information about the general distribution of lifetime within the examined set of systems. The probability of failure is assumed as Weibull's, which is a common approach for such (mechanical) applications (Castillo and Fernández-Canteli, 2006).

The probability distribution function (pdf), parameterized by experimentally observed failures, is subsequently used to estimate the average damage D_{av} over each point of failure x_j in system usage. A graphical illustration of the realization is depicted in Fig. 6. The presented four systems of a collective ($f = 10$) failed at individual points in system usage at x_1 to x_4. The Weibull parameters are derived from the distribution of x_j over X (not depicted). This pdf is then used for all observed x_j (F_1 to F_4), where the shaded areas beneath each distribution curve are proportional to the counted number j of

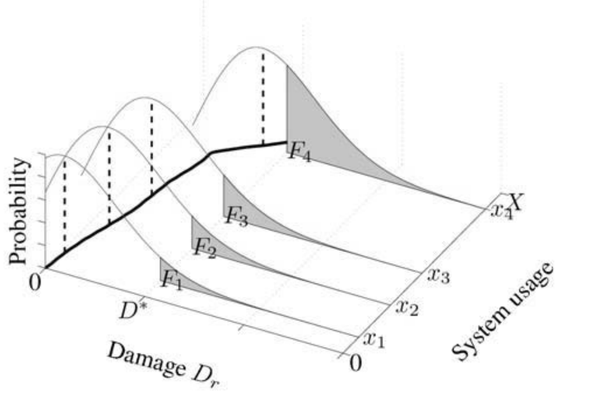

Fig. 6. Conclusion from the number of failed systems to the average accumulated damage via the Weibull distribution.

failed systems at that instant in system usage x_j, e.g., area F_1 represents the failure probability of 10%. Accordingly, the projection of each modal point onto the system usage-damage plane (dotted line) is equal to the average (most probable) actual state-of-damage D at system usage x_j.

To conclude from this discrete information (four modal values, representing the average damage at the shown four points x_j) to a continuous damage progression over system usage X, the following assumption can be stated generally: Due to the loading applied, the average damage progression will increase monotonically. Therefore, a monotonic increasing spline with supporting points at the modal values for each observed failure at x_j is taken and assumed to be very close to the curve of reference damage progression D_r. This spline represents the average system usage–damage curve and is used as an approximation of the reference damage progression from Fig. 5. Hence, the probability of the actual state-of-damage can be calculated for other points in system usage x_j, with $f > 10$.

A general model describing the unknown input–output relation is used in the following. Although Palmgren and Miner suggested a linear damage accumulation hypothesis, no linear general model, e.g., ARX, ARMAX, Box–Jenkins, etc., calculates the damage progression accurately. Thus, a time-delay-neural-network in a nonlinear ARX structure for single input/output (one layer) data is chosen by

$$\hat{D}_g(i) = f(D_g(i-1), \ldots, D_g(i-na), L(i-1), \ldots, L(i-nb)). \quad (6)$$

Here, the output $\hat{D}_g(i)$ is calculated in two steps: first, the input and output signals are delayed to different degrees, second, a nonlinear activation function $f(\cdot)$ (here a static neural network) estimates the output. Nelles (2001) proposes a sigmoid function for the nonlinear activation function, which is used here. Other functions for nonlinear dynamic modeling e.g., Hammerstein models, Wiener models, neural or wavelet networks can also be used. This general nonlinear ARX model is used to calculate the damage progression by identification.

The proposed method is applicable for systems with a sufficiently spreading failure probability, and will not prevent all failures but needs failures to obtain an adequate data base. With an increasing number of usage–failure relations, the observed behavior (damage progression) can be described in greater detail. Correspondingly, this approach estimates the damage progression in the most important (in terms of maintenance, failure prediction, etc.) close-to-failure phase. Due to the importance of this phase, probabilistic information about a premature failure can be stated by the proposed method. The more the state-of-damage spreads, the earlier the algorithm is parameterized. Depending on the observed system and its failure mechanism, this warning is maybe sufficient to avoid premature failures.

3. Simulation results

All models are simulated with two different input signals L^1 and L^2, and the results are discussed. The load profile L^1 leads to the damage progression D^1, where L^2 causes D^2. The indices $m1$, $m2$, and g refer to the model used. The accumulated damage will be evaluated with the reference damage progression of D_r^1 and D_r^2 of the reference model.

3.1. Damage calculation with the loading profile L_1. The results of the classical models $m1$ and $m2$ are depicted in Fig. 7. The solid line denotes the reference damage progression D_r^1, the dotted line is the result calculated by the model $m2$, and the dash-dotted line belongs to the model $m1$. In summary, none of the models reproduces the reference damage progression sufficiently.

The application of the novel model is divided into two steps: First, the neural network is trained with known loading and damage data. A part of the loading profile L^1 and the reference damage progression D_r^1 is used for training purpose. Next, only the loading L_1 is used as input. Accordingly, the estimated damage D_g^1 can be compared to the reference damage D_r^1.

The damage shapes are obtained as depicted in Fig. 8. As can be seen, the reference and the calculated curve shapes fit sufficiently. Hence a prediction can be made based on the calculated parameters and the assumed model.

The influence of the training data size (part of L^1) on the prediction accuracy is discussed in the following. In Fig. 9, different calculated damage accumulations are depicted, where the thick line represents the damage progression D_r^1 of the reference system.

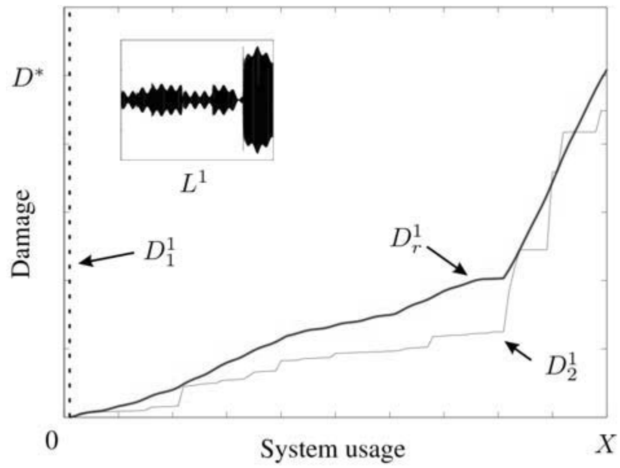

Fig. 7. Comparison of reference damage progression D_r^1 and results of classical models m_1 and m_2.

At the beginning, no information is available about the actual state-of-damage until the first system fails at x_1. Subsequently, the above introduced algorithm computes the most probable damage of the collective of systems. As a result, rough knowledge about the degradation is obtained and the nonlinear ARX model can be trained. It can be seen from Fig. 9 that the nonlinear ARX calculation results (e.g., g_{x_1}), which use a small information base for the training purpose, predict the damage progression insufficiently. With an increasing number j of failed systems at x_j, the identified mathematical models can be calculated in greater detail. For all points x_1 to x_4 of system usage, the nonlinear ARX model is re-trained and the remaining system usage of the examined collective of systems up to the moment/situation X is predicted.

The prediction error reduces with the increasing

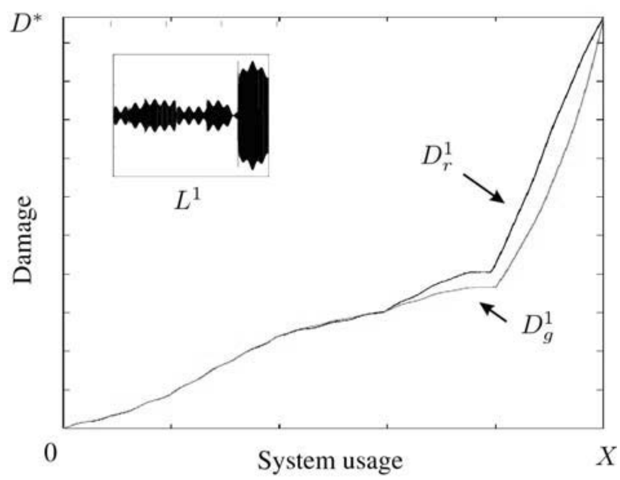

Fig. 8. Comparison of reference damage progression D_r^1 and calculated D_g^1 (nonlinear ARX model).

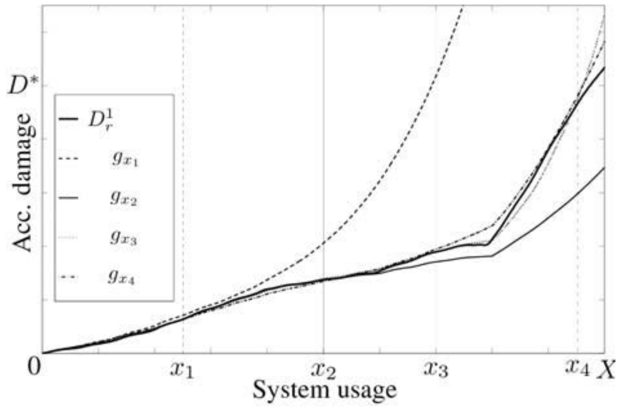

Fig. 9. Reference and predicted damage accumulations.

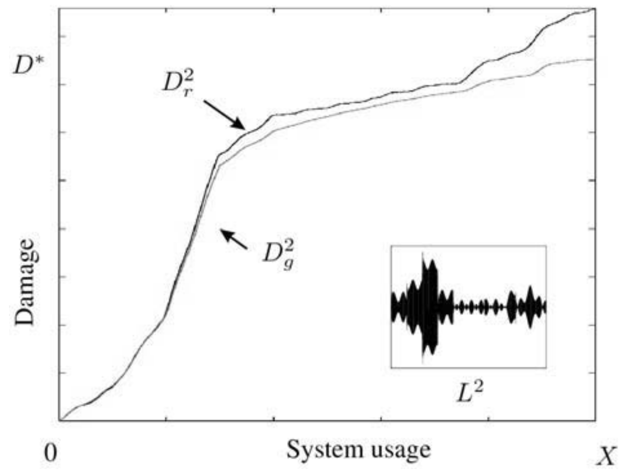

Fig. 10. Comparison of accumulated damage progression calculated with the reference system and m_g with L^2 as the input signal.

number of failed systems, and the curve fits better and better the reference damage curve D_r^1.

3.2. Damage calculation with the loading profile L_2. To assure that the trained model describes the damage progression accurately, a new input signal L^2 is generated and the damage progression D_r^2 is calculated with the identical reference system model from Section 2.1.1. If the primarily received model (mainly the parameters of the Weibull distribution) still describes the damage accumulation adequately, the nonlinear ARX model can be used to define reliability characteristics. No re-training is performed.

By feeding the new L^2 data into the previously derived general model, the damage curve is calculated and shown in Fig. 10. Again, the reference and the calculated damage progression match sufficiently. The curve diverges quantitatively with an increasing prediction horizon from the reference damage. For investigations with the focus on qualitative results, the nonlinear ARX model can be used if, e.g., the influence of an applied stress on the damage behavior of an system is of interest.

The nonlinear ARX model derived from a measured input and a probabilistic approximation of the average damage progression can be used to calculate the damage progression for different input signals. It can therefore be used as a deterioration model for this system. As shown, this cannot be achieved with the classical approaches.

The achieved nonlinear ARX model is able to calculate the damage progression caused by the employed load profile adequately. The most probable state-of-damage and the remaining system usage can be calculated; no assumptions about the classification algorithm, etc., have to be made. Furthermore, the model is independent of the chosen load profiles L^1 and L^2. The information about the actual state-of-damage can then be used for the remaining useful life prediction, the activation of limp home modes, etc.

4. Conclusion

The knowledge about the on-line state-of-damage of a system/component is a central aspect for condition monitoring and predictive control/maintenance. The direct measurement of damage-related states or direct correlations to physical effects is usually not possible, even when the physical effects cause signals being measurable and the signals features allow the direct relation to the damage level or the conclusion to the remaining useful life. State-of-the-art strategies use static knowledge and several assumptions about the environmental/operating conditions to at least realize preventive maintenance. One drawback is that the system is not used up to its maximal possible point of usage.

To improve this, the stress–damage relation is investigated in this contribution. The transfer behavior for an arbitrary mechanical system with stress as input and damage as output is described by the classical damage accumulation hypothesis and is assumed to describe the damaging behavior of a real system. Hence, the damage progression for an input stress signal can be calculated.

In real applications, neither the complex damage accumulation model, nor the parameters can be determined. This central problem is solved in two steps: First, the average actual damage is determined by counting the failing systems and assuming a damage distribution. Then the suggested stress-damage models are parametrized.

The idea developed and proposed in this contribution relates the simulated stress profiles and number of failed systems of a collective to the underlying damage progression law and its parameters.

For this purpose, the failures of a collective of systems operated under comparable operating conditions are counted/observed. By assuming a Weibull distributed failure probability of the countable event (failure before the average end of a lifetime), the most probable average damage of the collective can be derived. This approach is the basis for concluding to the average actual damage of the whole collective.

Subsequently, two different mathematical models known from the literature are used to calculate the damage progression. Additionally, a novel nonlinear approach is realized, which is not based on physical effects. As shown, linear models are not able to describe the damage progression adequately.

In conclusion, the developed general model was used with a different stress signal—related results are shown. The calculated damage progression is sufficiently close to the reference one.

Once the information about the average state-of-damage of a collective is obtained, strategies for extending the average system usage, as proposed by Söffker and Rakowsky (1997), Ławryńczuk (2009), and Ławryńczuk and Tatjewski (2010), become possible.

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