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Algorithmic generation of empirical life-stress models with statistical methods

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Life-stress models are used to express the relationship between the applied stress and the resulting lifetime of a product. There are several life-stress models which are widely known and have been widely applied for decades. The most prominent examples are arguably the Arrhenius relationship, the Eyring model, and the Inverse Power Law. While these conventional life-stress models have proven their validity in countless examples, they are at risk of being applied without verification for cases where other models are more suitable. An application case for which conventional life-stress models are potentially not suitable is the presence of several stress variables, as they cannot be integrated in a standard model without further steps. Another example are applications with unknown physics of failure, where it is unclear whether the presumptions made in the derivation of a conventional life-stress model are valid or not. For such cases, the algorithmic development of empirical life-stress models is considered in this paper. The suggested algorithm derives such models by combining different transformations of stress factors, which effectively creates a set of life-stress candidate models from scratch. These candidate models are then fitted to empirical data and iteratively assessed and modified using statistical methods. The resulting empirical models are compared to the conventional models in terms of their accuracy and plausibility. The suggested methodology is applied to experimental data from capacitors, which have been exposed to thermal and electrical stress factors. The results verify the effectiveness of the suggested algorithm in finding well-fitting empirical models.

Keywords: Life-stress models, acceleration model, accelerated testing, statistical evaluation, capacitor lifetime.

1. Introduction

The usage of life-stress models (LSMs), which define a relationship between the lifetime of a product and the stress applied to it, is indispensable in modern reliability testing. The main reasons for this are found both in the product development process and in the field application: in the development phase, products are commonly subjected to higher stress than in the field, in order to be able to reach sufficiently short test durations (weeks to months) which still demonstrate required high field runtimes (years). In the application, products are never subjected to just one single stress level over their entire lifetime, but to a multitude of stress levels (i.e., a load spectrum), each for an individual total duration. To estimate the product lifetime in the field for a given load spectrum, it is necessary to account for the impact of different stress levels on the lifetime.

Mathematically, an LSM is the functional relationship

$$\tau = f(V) \tag{1}$$

between a lifetime characteristic τ – e.g., in years, hours or number of cycles – and a vector of stressors V, which contains one or more physical quantities – e.g., temperature, voltage or strain. While the *real* stressor V is generally complex, consisting of several physical influences, typically only a few or even only one stress variable is of *significant* effect. For this reason, the most frequently applied LSMs consider only a single stress variable, and hardly any models with more than two stress variables exist outside specialised cases with known physics of failure (PoF).

In complex cases with unknown PoF and multiple stresses, it is tedious to find a suitable class of LSM. Additionally, it has to be decided which of the potential stress variables are the most significant and should thus be used in the LSM. On an objective basis, this is possible through the application of statistical methods from the field of Design of Experiments (DoE) in the evaluation of related lifetime data. The integration of DoE techniques in the evaluation of ALT (accelerated life testing) data offers considerable advantages. First, the selected stress variables as well as their integration in the LSM is statistically justified in terms of objective measures of significance and effect size, instead of just being chosen based on subjective assumptions on the failure behavior. Second, the model error in terms of the excluded influences (other potential stress variables or interactions) can also be quantified.

In this paper, such statistical methods are used in a novel algorithm for the generation of empirical LSMs from experimental data. The target application cases are situations with unknown or not completely understood PoF. The performance of the generated LSMs is compared to the performance of several well-known LSMs with one or two stress variables. A selection of these well-known models is presented in Section 2, while Section 3 introduces the suggested algorithm for empirical LSM generation. As application example, experimental data from accelerated capacitors tests is used, which is presented in Section 4. The resulting LSMs are compared in Section 5.

2. Life-stress models

This section gives an overview of the most common LSMs with one stress variable (Section 2.1), or two or more stress variables (Section 2.2):

(1) Arrhenius relationship (1 stressor)
(2) Eyring Model (1 stressor)
(3) Inverse Power Law (1 stressor)
(4) Eyring Model (2+ stressors)
(5) General Log-Linear Model (2+ stressors)

An overview over these – and further – LSMs can be found in Nelson (2004); O'Connor and Kleyner (2011); Rinne (2008); Yang (2007); Srivastava (2017), which have been used to derive the following overview. For the sake of brevity, only additional relevant sources are mentioned in the rest of this section.

Failure times are assumed to be Weibull distributed in this paper. Thus, as lifetime quantity τ, the Weibull scale parameter η is used, while the Weibull shape parameter β remains independent of the stress Modarres et al. (2017); Rinne (2008).

2.1. *LSMs with one stressor*

The three most common LSMs with just a single stress variable are the Arrhenius relationship, the Eyring model, and the Inverse Power Law.

The Arrhenius relationship is derived from the influence of temperature on reaction kinematics Arrhenius (1889a,b); Glasstone et al. (1941). Thus, it is used to model the effect of constant thermal stress. The rate of a chemical reaction v increases with absolute temperature ϑ via

$$v = B \exp\left(-\frac{E_a}{k_B \vartheta}\right), \tag{2}$$

where B, E_a, k_B are constants. While the model coefficient B and the activation energy E_a are reaction-specific parameters of the LSM, the Boltzmann constant k_B is a physical constant,

$$k_B = 1,380649 \cdot 10^{-23} \text{ J/K}. \tag{3}$$

For the purposes of ALT, it is convenient to combine E_a and k_B into a single model parameter A. Replacing the reaction rate with the lifetime η as its reciprocal and redefining B, the LSM

$$\eta = B \exp\left(\frac{A}{V}\right) \tag{4}$$

is obtained, where the general stress variable V is used instead of temperature ϑ. Taking the logarithm of both sides of (4) shows a linear relation between the log of the lifetime and the reciprocal of the temperature,

$$\ln(\eta) \propto \frac{1}{V}. \tag{5}$$

For this reason, the Arrhenius relationship is often plotted in a graph with $1/\vartheta$ vs. $\ln(t)$.

The Inverse Power Law (IPL) is used for non-thermal influences, e.g. mechanical stress (as part of the so called *Woehler curve*) or voltage stress on dielectrics. It is defined

$$\eta = \frac{B}{V^A} = BV^{-A} \tag{6}$$

for a general stress quantity V. Other than for the Arrhenius relationship, the log lifetime is not proportional to the reciprocal stress, but to the log of the stress,

$$\ln(\eta) \propto -\ln(V). \tag{7}$$

Thus, the IPL is linear in a log-log diagram.

The Eyring model is considered an extension of the Arrhenius model and is derived from quantum mechanics Glasstone et al. (1941). While it also comes in a generalized form for multiple (usually two) stress parameters, the single stress form is considered first. As for the Arrhenius relationship, the considered physical stressor usually is temperature. A second term is added multiplicatively, representing indirect influences of temperature via other quantities (e.g., humidity), which are constant themselves. This logic can also be applied for stresses other than temperature. The Eyring model with a single stress parameter is

$$\eta = \frac{B}{V} \exp\left(\frac{A}{V}\right), \tag{8}$$

where Boltzmann's constant and the activation energy are subsumed in the model coefficient A like in (4). When considering the proportionality with log lifetime,

$$\ln(\eta) \propto \frac{1}{V} - \ln(V), \tag{9}$$

the Eyring model can be considered a combination of the Arrhenius relationship and the IPL.

2.2. *LSMs with two or more stressors*

There also exists a generalized version of the Eyring model presented in the previous section. With two stressors V_1 and V_2, it is

$$\eta = c_0 V_1 \exp\left(c_1 V_1 + c_2 V_2 + c_3 V_1 V_2\right), \tag{10}$$

where the coefficients are now labeled c_i and the stress interaction $V_1 V_2$ is included optionally. Usually, the reciprocal temperature is used as first stress quantity, $V_1 = \vartheta^{-1}$ just like in the Arrhenius relationship and the single-stress Eyring model. The second stress can be assigned freely, e.g. relative humidity or voltage. Relabeling (10) with $V := V_2$ gives

$$\eta = \frac{c_0}{\vartheta} \exp\left(\frac{c_1}{\vartheta} + c_2 V + c_3 \frac{V}{\vartheta}\right), \tag{11}$$

which is the variant of the Eyring model usually used in practical application and also in the rest of this paper. Many well-known LSMs for specific PoF with (possibly transformed) stressors can be sorted into the Generalized Eyring model class. Particular examples are

- models for temperature and humidity by Peck (1986) and by Intel Corp. (1987),
- the electromigration models for temperature and current density by Black (1969b,a) or Shatzkes and Lloyd (1986),
- the creep rupture models for temperature and mechanical stress by Zhurkov (1984) or Larson and Miller (1952).

From a more abstract perspective on lifetime influences, the General Log-Linear Model (GLLM) implements the fact that most stressors negatively affect the log lifetime. Thus, the GLLM models the log lifetime as being linear in the stressors,

$$\begin{aligned} \eta &= c_0 - \exp\left(\sum c_i V_i\right) \\ \Rightarrow \quad \ln(\eta) &\propto -\sum c_i V_i. \end{aligned} \tag{12}$$

For comparison with the Generalized Eyring model for two stressors and their interaction in (10), the respective GLLM would be

$$\eta = c_0 - \exp\left(c_1 V_1 + c_2 V_2 + c_3 V_1 V_2\right). \tag{13}$$

Other than the Generalized Eyring model, the GLLM is more typically used for empirical LSMs which don't rely on well understood PoF.

3. Algorithmic LSM generation for empirical data

The LSMs presented in the previous section have several shortcomings.

First, there are LSMs which have been developed just for one specific physical stress variable. The most prominent example is the Arrhenius model, which is derived from thermodynamic considerations and thus considers temperature as stress. Even though it is conceivable to use another stress variable which indirectly exerts a thermal influence (e.g., electrical voltage), the straight PoF derivation of the model is lost, especially for multiple stressors.

Second, if a product exposed to several stress variables is modeled with an LSM which is not limited to a particular physical stress variable, like the IPL, there is no phenomenological reasoning allowing to favour one of the stress variables over another. This could tempt one to choose the stressor due to subjective arguments. A better option, however, is to statistically evaluate all modeling options, as one would do in an empirical model.

Lastly, and especially regarding the models with multiple stress variables, many model variants with different stress variable combinations, transformations and possibly interactions are known (some of which have been presented in the previous section). These – at least partly empirical – LSMs known from literature are often only applicable in a limited, but loosely defined case, rendering the application in differing experiments questionable. In consequence, an LSM specially tailored for the current situation might be more suitable than an LSM derived for a different situation.

In response to these issues, empirical life-stress modeling has been developed Yang (2007); Meeker and Escobar (1998); Nelson (2004). The main idea is to find the acting influences not based on a pre-made model, but based solely on the empirical data at hand. There is, however, no generally accepted algorithm for finding an optimum empirical LSM. In practice, this can lead to unsystematic trial-and-error approaches, carrying the risk of either not finding a sufficiently powerful model (underfitting), or of overfitting models to the data.

In light of these shortcomings, an algorithm for generating, modifying, and assessing potential empirical LSMs based on statistical measures is developed. It is based on a backward model elimination (BME) algorithm, which is extended by a transformation of the physical influences before it, and a second model estimation step after it. The algorithm is depicted in Fig. 1 and explained in detail in the following.

In a BME process, the measured physical variables (which may or may not be true stressors) are used as influences to estimate a model on the target quantity. Iteratively, the model is assessed statistically, the least relevant influence is removed, and the modified model is estimated again (turquoise in Fig. 1). This is repeated until only influences fulfilling all objective criteria remain. The name stems from this progressing elimination of model influences. Subsequently, the relevant parameters of the whole algorithm are presented in detail.

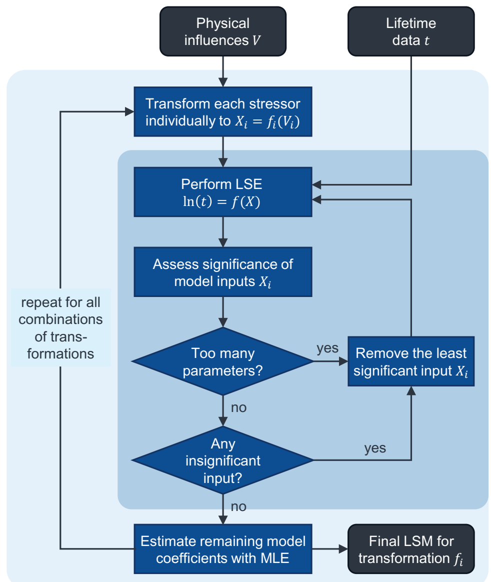

Fig. 1. LSM generation algorithm. The outer loop (light blue) considers all combinations of input transformations. The inner loop (turquoise) represents the BME procedure: a model is estimated for all transformed stressors, and, based on objective criteria, inputs are removed. The inputs remaining in the end are used to estimate the LSM via MLE.

Initial model size. The initial model is made up of $k = 5$ stressors and one constant term, giving $p = 6$ model coefficients to be estimated. This number of coefficients is sufficiently high to still allow influences to be removed, as it can reasonably be assumed that in most cases, no more than 2 or 3 physical quantities are of significant influence.

Constant term. While in some modeling approaches, it is obligatory for a constant term to be included in the final model, no such restriction is imposed on the BME algorithm here. If the constant term fulfills the elimination criterion and thus the data suggests that no constant term is to be kept in the model, it is removed just like any other influence. As justification of this data-driven decision, consider the Generalized Eyring model in (11), which also includes no term independent of the influences.

Estimation algorithm. For any given set of influences X, the model $f(X)$ has to be estimated by a reliable and time-efficient algorithm. Both maximum likelihood estimation (MLE) and least squares estimation (LSE) fulfill these requirements. Due to ease of computation and better comparability with other DoE approaches, LSE is chosen inside the BME loop (turquoise in Fig. 1). However, the suggested algorithm would also work with MLE in principle. Either way, the final model of each set of transformed inputs is estimated via MLE.

Target quantity. The scale parameter η of the Weibull distributed lifetime is chosen as stress-dependent quantity. Stressors in typical LSMs affect the lifetime on a log scale, cf. (6) and (8). As LSE instead of MLE is used inside the BME loop, the natural log of the recorded lifetime is thus used as target quantity.

Elimination criterion. To determine which of the model influences is to be eliminated by the BME algorithm, all influences in the current model are statistically assessed in terms of their significance. To this end, the p-value of a t-test is used, which is a common procedure in DoE Montgomery (2013). Then, the least significant influence (the one with the highest p-value) is removed from the model and the next iteration starts.

Termination criterion. The iterative modeling and elimination of inputs is stopped when only significant inputs remain *and* the predefined maximum number of model inputs is not exceeded anymore. If all model inputs are found to be insignificant, no model remains.

Interactions and hierarchy. First level interactions between pairs of influences are not included from the beginning. Otherwise, the number of interactions to be considered would increase drastically, leading to inefficiently high computation time and overdetermined models.

Model inputs. Performing this algorithm with a set of physical influences V_i as inputs X_i to the model is insufficient to find suitable LSMs in case of unknown PoF. The reason for this is that for most failure mechanisms, it is necessary to transform the physical influences V_i. This is the case in all the standard LSMs in Section 2, as (5), (7) and (9) prominently show.

To employ the algorithm with the ability to find LSMs in case of unknown PoF, a set of transformations, which are common in existing physical LSMs, is defined. For each physical quantity V, the transformations

$$X(V) = \Big(V, 1/V, V^2, \sqrt{V}, \ln(V)\Big)^T \tag{14}$$

are considered as possible model influences. A second iteration loop is built around the existing algorithm (shaded light blue in Figure 1). In each of those iterations, one model input $X_i(V_i)$ is changed to the next transformation f_i. This is repeated until all combinations of transformed model inputs have been used. For the given five transformations, this means that the defined BME algorithm is repeated $5^5 = 3125$ times. The previously mentioned decision for the time-efficient LSE method and for the exclusion of interactions have to be seen in light of this additional computational effort.

If several models with the same influences V_i – yet differently transformed – are found, only the best of those models is kept. The comparison of the models is performed with the Bayesian Information Criterion (BIC) as performance metric. As the final model for each combination of transformations is calculated using MLE, ℓ is easily available for this comparison (cf. Figure 1). BIC is preferred over AIC, as it prevents overfitting more effectively by penalizing additional model coefficients more heavily. The ultimate comparison between all found models is also carried out with BIC as performance metric.

4. Application example

The algorithm for empirical LSM generation suggested in the previous section is applied in an exemplary case. For this purpose, capacitors are chosen, which have been subjected to thermal and electrical stress to emulate realistic usage conditions. The exact physical variables which have been varied were

- temperature T [°C],
- relative humidity H [%],
- unipolar PWM voltage U [V],
- PWM pulse frequency f [kHz], and
- total pulsed voltage TPV[kV/s].

As failure criterion, a capacitance loss of 5 % compared to the initial value was defined. Due to the comparably high stress and the chosen failure criterion, failure times below 200 h were obtained. The considered capacitors are commercially available multi-layer ceramic capacitors (MLCCs) with a nominal capacitance of 10 nF and 445 V rated (peak) voltage. The MLCCs have been tested in a climate chamber under unipolar PWM excitation and are a homogeneous subset of capacitors tested in a larger research project, where their data was used to fit empirical degradation models Mell and Dazer (2025); Mell et al. (2026). In total, 28 capacitors have been tested to failure. The exact stress parameters to which they were subjected are summarized in Table 1.

As this data is a subset of data obtained for different modeling purposes, the allocation of capacitors to stress level combinations doesn't follow the strict requirements of a DoE test plan Mell et al. (2026). This is a realistic situation, as in typical component tests, both in industry and in research, ideal DoE test plans are rarely implemented due to ignorance, physical boundaries or unexpected changes of the test program.

A stress-independent Weibull analysis estimates a shape parameter of $\beta = 1.28$ with $(1.07, 1.54)$ as 80 % confidence interval, which indicates wear-out behaviour. As capacitors sharing the same vendor, technical properties and failure mode were chosen, it can be assumed that β is approximately identical under all stress combinations.

5. Results

The algorithm suggested in Section 3 is applied to the data presented in Section 4. Table 2 shows the best results from both the empirical LSMs and the standard LSMs from Section 2. The results of the standard LSMs, which serve as benchmark, are discussed first.

For the single stressor LSMs, all five parameters are chosen and tested separately. The results show that voltage is the only stressor able to give a stress-dependent Weibull distribution with better performance than a stress-independent Weibull fit. Thus, only models $\eta = f(U)$ are given in Table 2. The best single-stressor model, the IPL, is

Table 1. Stress conditions under which a total of 28 capacitors have been tested.

T [°C]	H [%]	U [V]	f [kHz]	TPV [kV/s]	#(units) [−]
20	20	485	0.5	243	1
20	20	485	5.0	2425	2
20	20	870	2.5	2175	2
20	20	900	0.5	450	2
20	90	850	0.5	425	3
20	90	865	2.5	2163	3
90	20	670	5.0	3350	1
90	90	220	2.5	550	3
90	90	350	0.5	175	1
90	90	350	2.5	875	3
90	90	870	0.5	435	3
90	90	870	2.0	2175	3
90	90	870	5.0	4350	1

Table 2. Performance of selected Weibull fits without LSM, with standard LSMs, and with the suggested empirically found LSMs. Loglikelihood ℓ and BIC are used as performance metrics.

LSM	Stressor(s)	ℓ	BIC
none	-	-132.3	271.3
Arrhenius	U	-127.1	264.2
Eyring	U	-124.7	259.3
IPL	U	-124.3	258.7
GLLM	$1/T, U$	-121.7	260.0
Empirical	U^2, H	-115.8	241.6
Empirical	$U^2 \ln(TPV)$	-116.8	240.3

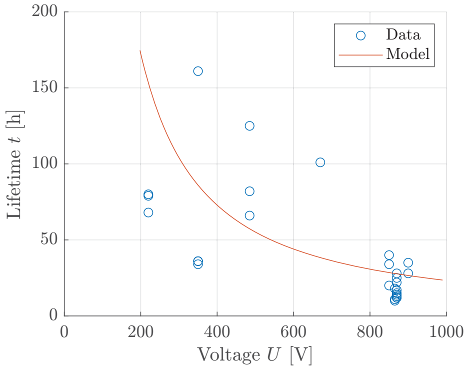

Fig. 2. The IPL with voltage as stressor is the best fitting standard LSM

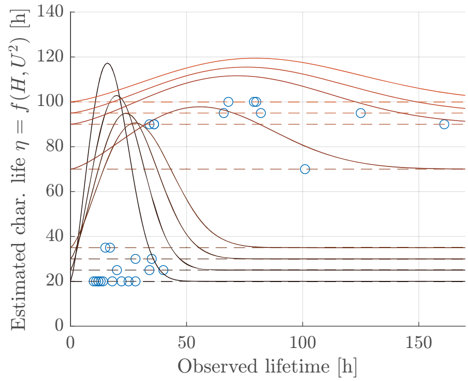

Fig. 3. The found empirical LSM $\eta = f(U^2, H)$. On each distinct stress-dependent level of η (dashed line), the resulting Weibull pdf is plotted (solid line) and compared to the experimental data (blue).

depicted in Figure 2. While a graphical analysis shows that the general behaviour of the life-stress relationship is correctly reflected by the model, a high share of unexplained variance remains.

The best two-parameter model is based on the GLLM (13) and achieves a higher loglikelihood than the standard single-stressor LSMs. In terms of the relevant metric BIC, however, it is inferior due to the increased number of parameters (cf. Table 2). In theory, it could be the case that no better fit than a single-stressor LSM is possible. However, as Figure 2 indicates otherwise, it is more likely that a better fitting combination of stressors is not included in the standard LSMs.

Thus, the suggested algorithm for empirical LSM generation is applied. As described in Section 3, no interactions are considered in the first step. Several models with either two or three stressors are found, which nearly always include H and transformations of U. Temperature only appears as influence if no constant term is part of the model. The fact that humidity and voltage appear consistently, and the fact that voltage also appeared in the standard LSMs, confirm the plausibility of the found models. By comparison in terms of the BIC, the models with two stressors and a constant term perform optimally. The LSM

$$\eta = 124.2 - 0.1968\frac{H}{\%} - 114.0\left(\frac{U}{\mathrm{kV}}\right)^2 \qquad (15)$$

is found to be ideal. It is depicted in Figure 3, where the resulting Weibull distribution for each stress level is plotted. The model performance is clearly above that of the standard models, as the BIC documented in Table 2 shows.

In the second step of the suggested algorithm, the process is repeated with first-level interactions between the stressors. To limit the computational effort, only a subset of stressors and transformations, which were found to be relevant in the previous step, are used. Among other less-convincing model candidates, one LSM with higher performance is found. It features two stressors, U and TPV, in form of an interaction term (cf. Table 2). While this model has a slightly better BIC than the one in (15), its stressors are less consistent with the other found model candidates. Thus, the model (15), depicted in Figure 3, is chosen as the ideal model. For a more thorough discussion of this ambiguity, further tests are advised.

6. Summary and conclusion

In this paper, an algorithm for the generation and evaluation of empirical life-stress models has been suggested. It was applied to exemplary data from capacitors in an accelerated life test. The results show that the algorithm is able to find LSMs, which fit the experimental data considerably better than standard LSMs, as a comparison by objective statistical criteria shows. Due to the not yet understood PoF, no physical justification can be given for either the standard LSMs, or the empirical LSMs. However, the consistently appearing influences are a strong argument for the plausibility of the empirical models, besides the higher performance.

To advance the algorithm, model estimation and feature selection via MLE instead of LSE should be considered in the future. Furthermore, different structures for the general lifetime model, e.g. based on the Generalized Eyring model, should be considered. Lastly, regarding the application example at hand, it should be considered whether the consideration of absolute humidity – which effectively integrates temperature information into the humidity variable – increases modeling performance.

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