Improved product reliability quantification methodology making use of physics of failure based prognostics

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ABSTRACT

Quantifying accurate reliability at (sub-)system level is not an easy task. Despite the availability of different tools allowing reliability estimation, e.g. reliability handbooks as MIL217-F, the accuracy of the obtained results is not guaranteed. For instance, the data used in these handbooks are outdated, referring to old technologies and assuming stresses that are not always realistic. Other methods exist which should allow a more accurate reliability estimation e.g. the physics of failure prognostics. However, for an industrial end user, following such an approach at (sub) system level is too expensive. Typical steps to obtain reliability data of one component following physics of failure prognostic approach would require (i) understanding a given failure mechanism and developing its corresponding physics of failure model, (ii) identifying stress accelerators of this failure mechanism, and (iii) planning and implementing an accelerated life test to collect failure data in order to validate the model. A typical accelerated life test would require failures of components collected during the test time (in the order of months) at different stress levels. Another approach to get more accurate reliability at (sub-)system level is collecting and analyzing field data. However, this would require a complete process within an organization, by tracking the products in the field and collecting failure information for many years.

In order to overcome these limitations for companies, we propose a methodology allowing to obtain quick and accurate estimations of the (sub-) system reliability by combining component's reliability information from different sources, e.g. using physics-of-failure models for some critical components where test data are historically available, and / or using reliability prediction handbook for proven in use components, and / or using field data if available.

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LIST OF ACRONYMS

ALT	Accelerated Life Testing
BOM	Bill Of Materials
FTA	Fault Tree Analysis
HALT	Highly Accelerated Life Testing
LDA	Life Data Analysis
MLE	Maximum Likelihood Estimator
MR	Median Rank
MTBF	Mean Time Between Failures
PoF	Physics of Failure
RBD	Reliability Block Diagram

1. INTRODUCTION

The reliability of (sub-)systems is of huge importance to manufacturers for many reasons e.g. it results in advantages in relation to their competitors (more reliable than a competitor), it influences the reputation of a company (a company is liable if their system is reliable), it allows to motivate the price of the product (a slightly higher price is justified by enhanced reliability), it is a support in obtaining the necessary certificates for safety critical systems (the quantification of the prescribed safety integrity level depends on the reliability). Therefore, manufacturers need a way to estimate their product's reliability (Porter, 2001) (Lu, 2000) (Barnard, 2008).

Many state-of-the art methods to estimate (sub-)system reliabilities are inaccurate (e.g. by using old reliability books) and/or time consuming or costly (e.g. by collecting field data). Therefore, there is a general need for methods to estimate the reliability of systems in a cost and time efficient way without losing accuracy of the estimates. This is a challenging task especially for long-life systems. For example, it is not cost-effective to collect test data for products with a lifetime of over 20 years (Wohlgemuth, 2011).

On the other hand, having multiple sources of estimating reliability could be seen as an advantage from engineering point of view allowing the development of a cost-effective and accurate methodology for reliability estimation.

An engineering asset could be seen as a combination of different sub-systems, which in their turns are composed by components. Such a decomposition could be covered in reliability by logical models such as Reliability Block Diagram (RBD) modeling or / and quantitative Fault Tree Analysis (FTA). These kind of models associate a block to a specific sub-system or components that has a specific reliability. At that stage, we can deal with separate sub-systems / components. The next stage would be to estimate the accurate reliability values for these sub-systems / components. The approach we propose will make use of Physics of Failure (PoF) modeling to get more accurate reliability values. Such an approach consists of understanding physically how a failure mechanism would occur in a component / sub-system. This can be modeled by taking into account material, dimensions of the components, model of the stresses influences on the lifetime, modeling of stress propagation within a sub-system / components, etc. In this paper, we present a methodology to get enhanced and hence more realistic estimations of (sub-) system reliability. A special attention will be given to the Physics of Failure modeling underlying every technique in that methodology, illustrated with some examples. The performance of the methodology is evaluated by comparing it to the state-of-the-art approaches and is validated on industrial cases.

The originality of this work lies in the proposed methods for reliability assessment which allow to reduce needed time / resources for such an assessment and increase accuracy of reliability estimate. Furthermore, the methodology can be seen as a framework that can be quickly and easily used in the reliability assessment process with some easy-to-access supporting tools. The estimates from the different methods can also be integrated in one system's level reliability modeling, for instance, through a reliability block diagram.

The paper is organized as follows, section 2 gives an overview of state of the arts methods for reliability estimation and their limitations. In section 3, the improved methods are presented and their improvements are highlighted. Section 4 discusses the added value of using reliability block diagram modeling to combine reliability data from multiple sources. Conclusions are given in section 5.

2. STATE-OF-THE-ART

The state-of-the methodologies for quantitative estimation of the reliability of products which will be discussed further are: (i) prediction handbooks, (ii) Life Data Analysis (LDA) or Weibull analysis, and (iii) accelerated life testing (ALT). Figure 1 illustrates the difference between these methodologies in terms of cost and complexity. As could be seen in the graph, cost is related to needed efforts but also to accuracy. Higher cost means higher accuracy, while complexity is linked to the integration maturity (concept, prototype, integration in final systems).
Prediction handbooks are classified in the left bottom part of the graph (low-complexity/low-cost). This methodology is often applied in the concept phase of the project since no prototype is needed. On the other hand, less preparation is needed as there are prediction tools that can be easily set by using the existing Bill of Materials (BOM).
The accelerated life tests are somewhere in the middle of the complexity-cost graph. To conduct such tests, you need existing prototype / production samples and you need to prepare the tests (test chambers, failure capturing system, and analysis of the data). The Life (field) data analysis is set in the top-right corner of the graph (high-complexity / high-cost). This will definitely give the most accurate reliability estimate because the components / sub-systems are working on the final end use system where the exact stresses are seen. However, getting such data would require a complete process (maintenance policy and people, data collection database, returns analyses, etc.). In the following section, we will give more information about state of the arts of these different techniques and show their limitations.

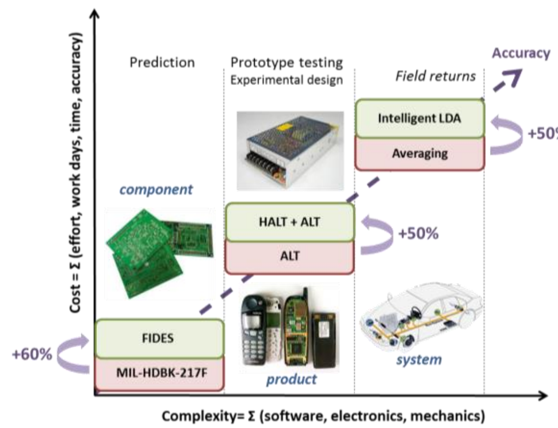

Figure 1: Methodologies for estimation of the reliability of (sub-)systems shown in relation to their complexity and cost. Recommendations or developments made by Flanders Make are shown on top of the state-of-the art approaches. The respective improvements relative to the state-of-the-art are indicated by the arrow. For each methodology, an application and the applicability is shown.

2.1. Prediction handbooks

Although not accurate, prediction handbooks are still attractive to industries because minor efforts have to be spent to do reliability analysis if we compare it to field data analysis and / or reliability testing.

For instance, the military handbook MIL-HDBK-217F [MIL-01] composed by the American defense department is still the most widely used handbook for reliability estimation (of electronics) despite of some major concerns in relation to the quality of the results. These concerns mainly result from the empirical nature of the models used to calculate the reliability based on the sum of the weighted failure rate λ:

$$\lambda = \sum_{m=1}^{M} N_m \ \lambda_m \ \pi_{Q_m} \tag{1}$$

with m = 1…M the number of categories, N_m the number of parts within a category m, λ_m the generic failure rate of a category m, and π_{Q_m} quality-related factors for a category m taking into account stress factors. It is assumed that the percentage of failure is constant and hence the distribution model is exponential. In many cases however, this assumption is inappropriate, e.g. connectors fail mostly as a consequence of fatigue which does not follow an exponential distribution. Failure mechanisms are not taken into account, hence the estimation is an underestimation of the field performance, neither are the main stress factors and product defects taken into account in a relevant way. Moreover, the book is obsolete: the models are based on data collected over 20 years ago, hence it ignores the new technologies. In the end, estimations based on the MIL-217F handbook do result in a worst case scenario rather than providing a realistic estimation. An alternative to perform reliability prediction taking into account modern electronics technologies (semi-conductors, lead-free, processing units, etc.) is to use Physics of Failures insight to understand failure mechanisms and to predict failures under different stress types (for instance under vibration stress which is one of the dominant stresses in may applications). We elaborate on this in section 3.

2.2. Life data analysis (LDA)

LDA estimates the reliability based on data collected from a product at end users (field). For such an analysis, the operational time, the observed failure time and the number of failed / non-failed units are required. Typically, Mean Time Between Failures (MTBF) is determined based on the ratio between the total operational hours (t) and the number of observed failures (N):

$$MTBF = \frac{\sum_{n=1}^{N} \ t_n}{N} \tag{2}$$

This simplistic estimate does not converge to the true reliability if for instance failure rate of the components are changing versus time. A better way to deal with modeling life data is to change the formulae by considering statistical distribution. Weibull model would be explained in section 3.

2.3. Accelerated life testing (ALT)

ALT aims at estimating the probability of failure of a (sub-) system at a given normal user circumstances based on observations under higher levels of stress (Lu, 2000). The estimation of the lifetime is based on structural and stochastic models.

A structural model describes the relation between the lifetime and the stress level. The model description depends on the type of stress. The Arrhenius model (eq. 3) is a well-known example of a structural model that describes the acceleration factor, AF, between the 'normal user' temperatures (T_{use}) and the 'high stress' temperatures (T_{ALT}):

$$AF = \ e^{\left(\frac{\Delta H}{T_{use}} - \frac{\Delta H}{T_{ALT}}\right)} \tag{3}$$

ΔH is the activation energy which depends on the failure mechanism and the materials involved. Hence, this parameter describes how the distribution depends on the stress level.
A stochastic model describes the probability of failure given a stress level. The model parameters determine the behavioral characteristics of the system. The Weibull model is a frequently used stochastic model of which the scaling parameters depend on the stress level. As a consequence, the predicted lifetime (plus the uncertainty) given normal stress levels, also depends on the choice of the model structure.
When conducting an ALT, the main question would be at which stress level to test. This has a direct economic impact on the test. Higher AF would lead to a quicker test but can also bring the system to a test zone where non-linear behavior would occur which is not correlated to the normal use. In section 3 we will propose some guidelines to increase the AF while still staying at the relevant range to generate normal failures.

3. IMPROVED RELIABILITY ESTIMATION METHODS

The two main problems arising in the state-of-the art approaches for the estimation of (sub-)system reliability are (i) the approaches do not result in realistic estimates (accuracy), and (ii) the approaches are not cost efficient (high needed preparation effort, long test time). To increase accuracy and decrease cost, as typically required from industries, a systematic and integrated methodology has been proposed which enables companies to increase reliability and safety evaluation of their (sub-)system. The methodology is schematically represented in figure 2. The following sub-sections only describe the different building blocks of the framework related to reliability. Safety evaluation is out of scope in this paper. A summary of the results is presented in table 1.

3.1. Prediction handbooks: FIDES rather than MIL-217F

Amongst others, two more recent prediction handbooks have been identified, which have been selected for further evaluation: IEC TR 62380 [IEC] and FIDES [Fides].

Although IEC TR 62380 is more recent than MIL-217F, it has not been maintained since 2003. As a consequence, the models for the physics of failure are not adapted for the new technologies.

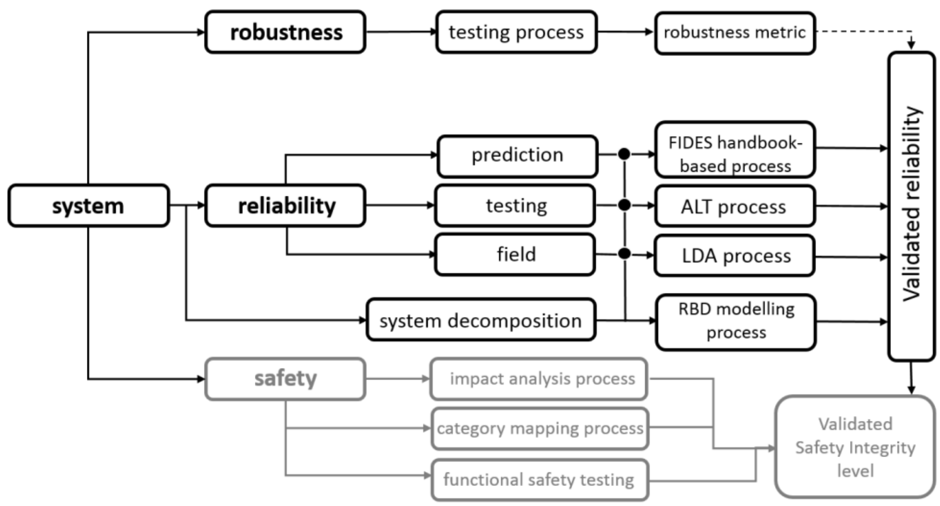

Figure 2: Schematic representation of the systematic and integrated methodology developed and validated for system reliability estimation within Flanders Make.

Also, IEC TR 62380 does not take the complete life cycle of the product into account in the reliability evaluation. Where MIL-217F results in worst case scenario's, IEC TR 62380 results in too optimistic estimations (Marin, 2005). FIDES prediction handbook, which latest edition has been released in 2009, include reliability information of more recent technologies and considers the full life cycle in the reliability evaluation of a product. It also makes use of different physics of failure models to describe failure mechanisms. Altogether, we opted to obtain predictions from the FIDES handbook: a pilot project where more than 5000 electronic units have been observed in the field for 2 years proved that estimation from FIDES handbook, when process parameters are properly chosen, is much closer to the observed values in the field (~1.2 ratio of observed failure rate estimated by FIDES compared to ~7.9 ratio observed estimated by MIL-217). The spread for some observed units is shown in figure 3. This rationale is supported by literature (Charpenel, 2003) (Bayle, 2010) while (Marin, 2005) compared failure rates between FIDES and MIL-217F for a selection of electronic devices. For a 12V power supply they report a relative difference in failure rate of over 30% (FIDES relative to MIL-217F).

To predict reliabilities, FIDES uses following model:

$$\lambda = \lambda_{physical} \prod Manufact \prod Process \tag{4}$$

In contrast to equation 1, the prediction relies on a combination of (i) the sum of the physical contribution $\lambda_{physical}$ (due to thermal, mechanical,…stress), and (ii) the quality of the components ($\prod Manufact$) and the quality of the complete product cycle process ($\prod Process$).
Additionally, FIDES provides (freeware) tools to assess system reliabilities.

As an example, from FIDES, the model of a ceramic capacitor, the factors contributing to $\lambda_{physical}$ are thermo-electrical stress $T_{thermo\text{-}electrical}$, mechanical stress $\Pi_{Mechanical}$ and thermal cycling stress Π_{TCy}. The respective stress models are function of voltage, temperature, vibration and time-related parameters. This is shown in figure 4. A typical Physics of Failure (PoF) prognostics models to study the thermo-electrical effect, when varying the electric stress, and the PoF prognostics model when varying mechanical stress are shown in figure 5.

Table 1: Overview of observed improvements in either accuracy of the estimated prediction of the respective method or the time reduction by applying the respective method.

	Improved accuracy for reliability estimates		Reduced test time
FIDES handbook	X		
ALT			X
LDA		X	
Improvements	**Up to 60% compared to MIL-217F**	**Up to 50% compared to averaging**	**Up to 50% compared to traditional testing**

In order to validate the reliability prediction using FIDES handbook, we performed an estimation of the reliability of the machine controller of a heavy-load vehicle. The improvement in accuracy of the estimated reliability in comparison to the MIL-217F handbook is showed in table 1.

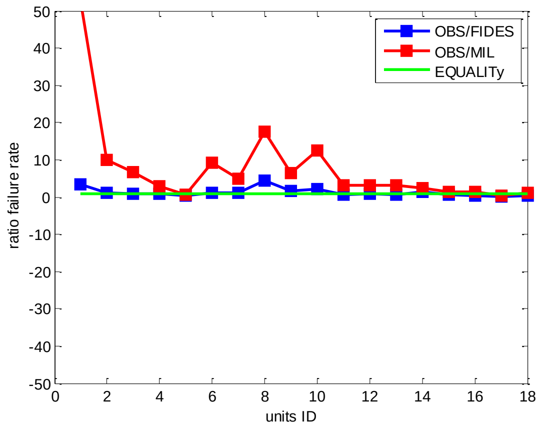

Figure 3. Comparison reliability prediction from FIDES and MIL-217F compared to measured values from the field

3.2. Intelligent LDA rather than real life data averaging

The rationale behind LDA is to estimate the reliability of 'all' (sub-)systems on the observations made for a set of (sub-) systems by fitting a statistical model, a Weibull model, to the observed data instead of using averaging as described in section 2.2. The general formulation of this parametric stochastic model is:

$$f(t) = \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} e^{-(\frac{t-\gamma}{\eta})^{\beta}} \tag{5}$$

where β, γ, and η the shape, location and scale parameters respectively. In general, γ is set to 0. β values could describe the different zones in the lifetime of the product (commonly called 'bathtub' curve). If $\beta < 1$ infant mortality is described meaning that failure rate is decreasing versus time and a consistent failure is occurring leading to early failures in the field. $\beta = 1$ describes an exponential distribution where the failure rate is constant versus time. This is typically the assumption made in prediction handbooks. $\beta > 1$ describes wear-out zone at end of lifetime where failure rate systematically increases versus time.

As also described in some literature (Jiang, 2011), using a wrong model would result in estimation inaccuracies. Figure 6 illustrates the inaccuracies introduced in reliability estimates if non-proper model is used. For instance, using exponential distribution for a wear-out failure. The exponential model results in an inaccurate prediction of reliability (extrapolation of the model to the point that 63.2% of the (sub-) systems failed corresponding to Mean-time-to-failure).

$\Pi_{Thermo\text{-}electrical}$	In an operating phase: $\gamma_{TH-EL} \times \left(\frac{1}{S_{reference}} \times \frac{V_{applied}}{V_{rated}}\right)^{3} \times e^{11604 \times Ea \times \left[\frac{1}{293} - \frac{1}{(T_{board-ambient}+273)}\right]}$ In a non-operating phase: $\Pi_{Thermo\text{-}electrical} = 0$
Π_{TCy}	$\gamma_{TCy} \times \left(\frac{12 \times N_{annual\text{-}cy}}{t_{annual}}\right) \times \left(\frac{\min(\theta_{cy}, 2)}{2}\right)^{\frac{1}{3}} \times \left(\frac{\Delta T_{cycling}}{20}\right)^{1.9} \times e^{1414 \times \left[\frac{1}{313} - \frac{1}{(T_{max-cycling}+273)}\right]}$
$\Pi_{Mechanical}$	$\gamma_{Mech} \times \left(\frac{G_{RMS}}{0.5}\right)^{1.5}$

Figure 4. Ceramic failure model as proposed in FIDES prediction handbook, respectively for thermo-electrical stress model $\gamma_{TH\text{-}EL}$ is the is the base failure rate at nominal thermos-electric stress, $S_{reference}$ is a reference level of electrical stress, $V_{applied,rated}$ applied and rated voltages, Ea the activation energy, $T_{board,ambient}$ the board and the ambient temperature. γ_{TCy} is the failure rate at nominal thermal cycle stress, $N_{annual\text{-}cy}$ is the annual number of thermal cycles, t_{annual} is the annual operation hours, θ_{cy} is the cycle duration, $\Delta T_{cycling}$ the amplitude of a thermal cycle phase, $T_{max\text{-}cycling}$ maximum temperature in a cycle, γ_{Mech} the base failure rate at nominal mechanical stress, G_{RMS}, the applied random vibration stress amplitude.

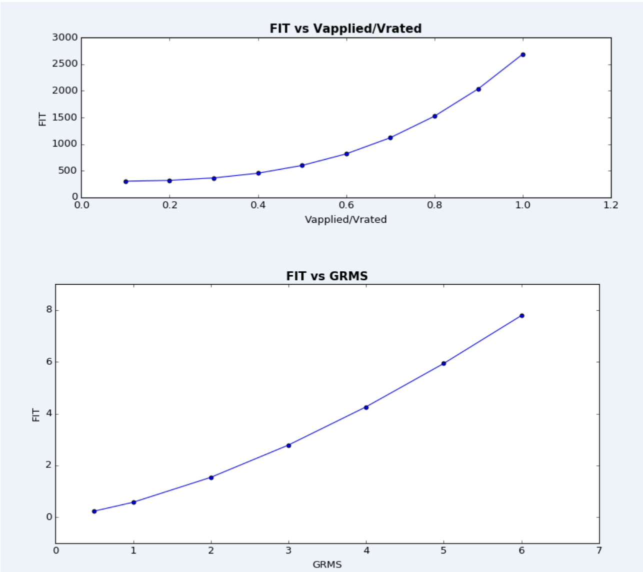

Figure 5. PoF prognostics model based on FIDES prediction handbook: (top) for electrical stress: Failures in Time (FIT) is plotted versus $V_{applied,rated}$ applied and rated voltages; (bottom) for mechanical stress: FIT is plotted versus G_{RMS}, the applied random vibration stress amplitude.

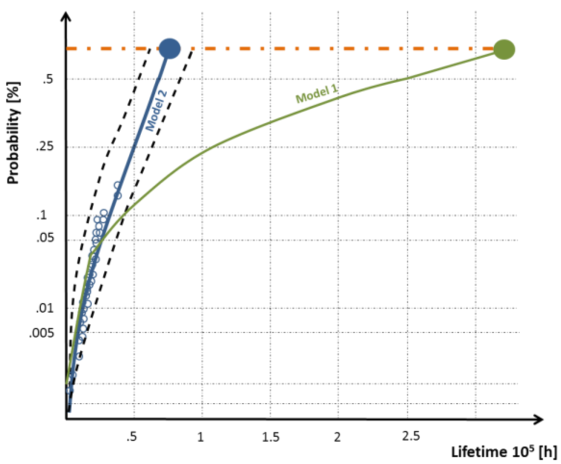

Figure 6: Model 1 describes the exponential distribution of the data. The model provides an inferior fit of the data. Model 2 describes a parameterized Weibull distribution of the data. The model provides a better fit of the data. The model determines the estimate of the MTBF (at 63.2%, indicated by the horizontal line).

Data averaging has been shown not to be an appropriate method to accurately estimate a product's lifetime (Ryu, 2005). To overcome the problem of overestimating the lifetime of a (sub-)system due to the application of simplified models as is illustrated in figure 6, we start the LDA analysis by collecting field data for the selected component. Next, we classify based on the type of failure and per time to failure. Finally, we fit the data with a relevant model, here a 2-parameter Weibull model. (Jiang, 2011) already reported the importance of the model parameters and its effect on e.g. time to failure and residual lifetime.

|In order to check the accuracy of the LDA analysis, two optimization algorithms for median rank (MR) fit were investigated. These methods are maximum likelihood estimator (MLE) and polynomial fit (polyfit). The results were also compared to the averaging method. The MR/polyfit algorithm gives the best accuracy (2%), followed by MR/MLE (6.6%) while averaging is lagging much more behind (19%).

Table 2: Comparison of different tools to obtain MTBF based on life data. In the methods column indicates MLE Maximum Likelihood Estimator, MR Mean Radian, polyfit a polynomial fit using least-square method; these methods refer to the way the tool deals with collected data from devices which did not yet reach the end of their lifetime. η is the scale parameter of the Weibull distribution, β is the shape parameter of the Weibull distribution. Weibull++ is part of Reliasoft software, Dfittool is part of the Statistics Toolbox of Matlab, the reference tool is according to (Abernethy, 2006).

Tool	Method	η	β	MTBF
Weibull++	MR/MLE	87,95	3,01	78,56
Matlab/Dfittool	MR/MLE	87,95	3,01	78,56
LDA-Tool	MR/polyfit	96,88	1,93	85,93
Traditional	Operation hours/ Number of failures	100,4	1	100,4
Reference	MR/graph fit	95	2,02	84,17

3.3. [HALT + ALT] rather than ALT

Highly accelerated life testing, HALT, is appropriate to determine relative robustness of products or systems. For example, a newest version of a product would be considered more robust than a previous version if it survives longer HALT test time. Although commonly used by industries in the development phase of a product to evaluate its robustness, HALT does not allow to establish the correlation between the robustness results and the field failures of a product.

In some literature (Ashburn, 2008) HALT refers to use PoF models at higher stress than normally used. This is different from our HALT terminology. HALT test in this paper refers to performing a test in a HALT chamber where 6DoF pneumatic hammer is used combined with a temperature chamber where temperature rate could reach 30ºC/min. On the other side our terminology of ALT refers to moderate stress levels where PoF models can still be applied.

Other literature (McLean, From HALT results to an accurate field MTBF estimate, 2010) claimed that they could estimate reliability of a product based on HALT-chamber based test. After contacting the authors, it revealed that they developed a methodology where they perform HALT tests on electronic modules and they observe the same designs in the field. After some years, they could find a correlation between HALT data (using a specific test profile) and the field data. Although this is possible, by correlation analysis (Coit, 2005), the assumptions made, as McLean *et al.* do, need to be clearly understood.

Observations we made from previous HALT tests proved it is difficult to establish the link with field data. However, HALT test is a very useful tool to learn the user about destruct limits of the tested product. By taking proper safety margins below these destruct limits (McLean, HALT, HASS and HASA explained, 2009), it would be possible to optimize the maximum stress levels for an ALT test. As a consequence, a lot of test tine is gained (Shi, 2009). A typical stress-life curve is shown in figure 7. The estimation of the reliability results from clustering the times to failure per failure mechanism. Modelling is equivalent to the description in section 2.3. The obtained time gain for our industrial case is given in table 1.

In order to validate this method, we designed and implemented an ALT for commercial power supplies where we identify (i) first, the thermal destruct limits of these power supplies and (ii) second, use these limits in the design of ALT. A typical step stress curve to detect this stress levels is shown in figure 8. Starting from ambient temperature, the stress level decreases in a step-wise to low values to detect the lower limit. The same procedure is then followed by increasing temperature until the high stress limit is identified

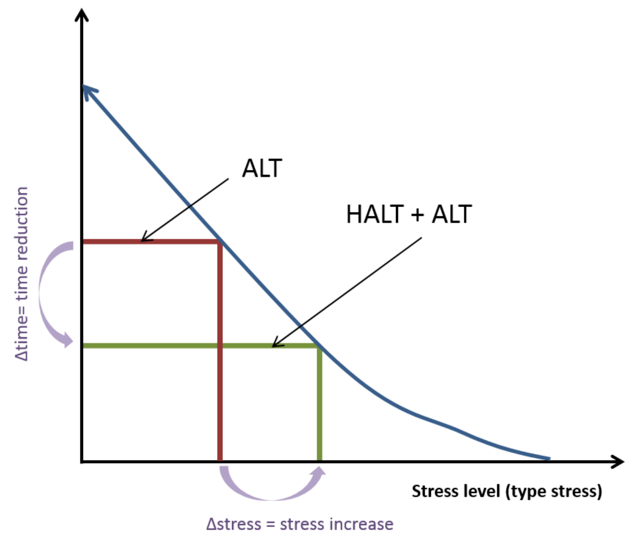

Figure 7: Illustration of the time gain using HALT+ALT testing in reliability prediction versus using only ALT

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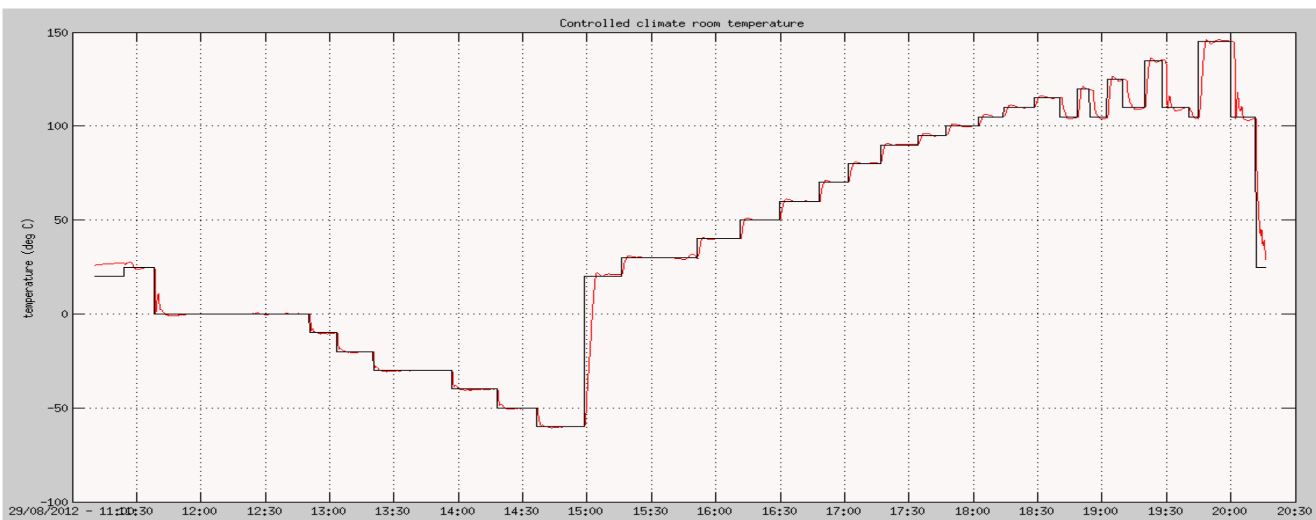

Figure 8. Step stress to identify thermal stress limits (black line: set temperature, red line: measured temperature)

After this step, an ALT test is designed at specific safety margins from these limits. A model was developed to predict the failure rate under a specific condition as depicted in figure 9. Form figure 9, it can be concluded that conducting a test at 100ºC for 2000h (~84 days) would results in 20% failure rate (imaging that we put 100 units in the test chamber, 20 of them would fail after this test period). However, to get the same failure rate (20%) at a test temperature of 50ºC, a test duration of more than 10000 (~417 days) would be needed. Hence, combining HALT+ALT could result in an acceleration factor of ~5 compared to traditional reliability testing (without using HALT information). The real test results prove these predictions.

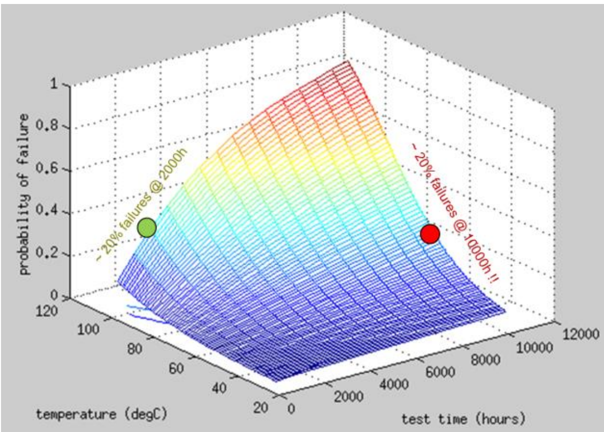

Figure 9. prediction of failure rate versus time for an ALT under thermal stresses

4. RELIABILITY BLOCK DIAGRAM TOOLS AND FAULT TREE ANALYSIS FOR COMPLEX SYSTEMS

Complex systems (e.g. cars) could be modeled using Reliability Block Diagram (RBD) and / or quantitative Fault Tree Analysis (FTA) (Wang, 2004). A typical RBD decomposition model looks like shown in figure 10.

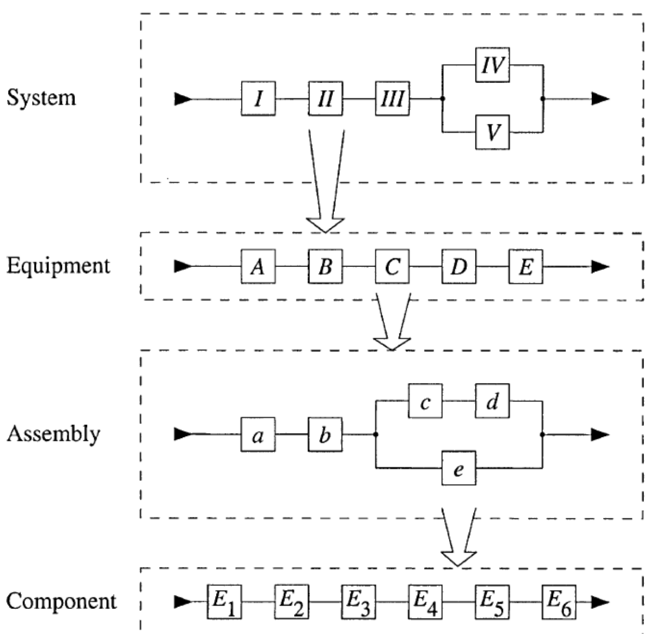

Figure 10. RBD decomposition of a system

The level decomposition can stop where acceptable reliability information is available. For example, sub-systems *I,III,IV,V* reliability data is known from field data. Equipment's *A,B,D,E* reliability data are known from tests from suppliers, assembly *a,b,c,d* reliability data is available from a designed HALT+ALT tests, while reliability of components *E1, ...,E6* are predictable from FIDES handbook.

This multi-source information is perfectly possible to combine in an RBD model and estimate the system's reliability.

5. CONCLUSION

We presented in this paper an improved product reliability quantification methodology where physics of failure based prognostics modeling were highlighted. This methodology is a combination of mainly three improved methods based on (1) improved prediction handbook (2) improved accelerated life testing (3) improved life data analysis. The reported improvements compared to state of the arts and common practices are quite high and reach at least 50%. These improvements are immediately understood when you compare the parameters / assumptions of current methods to the ones we proposed. Often non-correct assumptions are made (for example constant failure rate), and / or methods for outdated technologies or processes are applied. By means of PoF modeling, proposed in the improved methods, we introduced more physical insight in the analyses yielding better reliability prediction estimates.

However, the PoF models used in the proposed methodologies are approximates to the use cases we investigated and will always contain parameters that need to be tuned by guidelines (e.g. process guidelines proposed by FIDES) or by getting more experiences with the product studied (e.g. material parameters used in life-stress models). Having a generic PoF model that would take all details of product construction and interaction of components is practically very difficult, if not impossible, to get.

This methodology was developed with the mindset to serve industrial processes. Therefore, a set of practical user friendly tools were developed and which some of have been presented in this paper.

The reliability monitoring is an interesting topic to save market shares and liability of manufacturing companies, therefore it needs the right tools to allow accurate and economical estimates for such a monitoring. We believe this presented methodology has the potential to contribute to achieve these goals.

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Abdellatif Bey-Temsamani received his master in engineering from University of Mons in 1996. He received a PhD in engineering at Free University Brussels (VUB) for the dissertation entitled ‘Parametric modeling and estimation of ultrasonic bounded beam propagation in viscoelastic media’. He is (co) author of different journal and proceedings papers in the field of non-destructive testing, condition monitoring, maintenance optimization, and data mining. His current research interests are in condition monitoring hardware / software, smart systems, decision making in industrial processes, reliability and safety of industrial systems.

Stijn Helsen was born in 1966 in Belgium. He graduated as a Mechanical Engineer in 1989 and Engineer in Mechatronics in 1990. After working in an independent industrial company for 15 years, he started as a project engineer at FMTC, which became Flanders Make in 2015.

Steven Kauffmann is a research engineer skilled in embedded software development. He graduated in 2006 as a master of Electronics-ICT at the UC Leuven-Limburg (former KHLim). For 9 years, he is now active at Flanders Make as a project engineer, assisting companies in software related topics. In recent research projects he worked on systems engineering, functional safety, model-based development and reliability prediction of electronics components.

Anke Van Campen obtained a PhD degree in Mechanical engineering (KU Leuven). Her research was mainly involved with experimental design, model identification, and numerical optimization. Recently she joined Flanders Make as a validation engineer