"POLITEHNICA" UNIVERSITY OF BUCHAREST

ETTI-B DOCTORAL SCHOOL

PhD THESIS

- SUMMARY -

Application-Aware Lifetime Estimation of Power Devices

Estimarea Duratei de Viață a Circuitelor Integrate de Putere în Aplicații

by **Ciprian V. Pop**

DISSERTATION COMMITTEE

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Chapter 1

Introduction

Power devices are widely used nowadays, so the assessment of their reliability represents an essential concern for the manufacturers. Because the lifetime testing is a time consuming process and it requires very complex and expensive equipment, a limited amount of reliability data is available.

The general goal of this research is the development of strategies and tools that facilitate the joint use of data from different development/test stages of a product and simulation data, for reliability assessment.

The thesis introduces a comprehensive methodology for application-aware estimation of the power devices' mean lifetime, that receives as inputs the application operating conditions for a power device and provides as output its lifetime, defined as the moment when the chip's performances are out-of-specifications. Also, for a more accurate estimation of the minimum guaranteed lifetime, a methodology for prediction of the lifetime spread is presented. The proposed models are necessary for characterization of power devices' lifetime on wide ranges of application operating conditions of the customers, from many industries. The research is performed on smart power devices comprising double-diffused MOS (DMOS) structures.

1.1 Power Devices Switching Inductive Loads

Switching of inductive loads (e.g. relays, motors, solenoids & valves) is very challenging due to high power dissipation and corresponding heating of the devices. In order to reduce the overvoltages that appear when the devices are switching off the inductive loads the smart power switches typically use integrated clamping circuits. Even so, the power stages are subject to severe stresses due to active cycling (thermal cycling), also called repetitive clamping, affecting the lifetime of the devices.

A typical circuit of a low-side DMOS - based power switch driving an inductive load is presented in Figure 1.1 (a), with the corresponding waveforms of the voltages, load current and power loss within the device (b). Every time the inductive load is switched off the demagnetization energy has to be taken in consideration. It heats up the device causing especially intrinsic failure mechanisms.

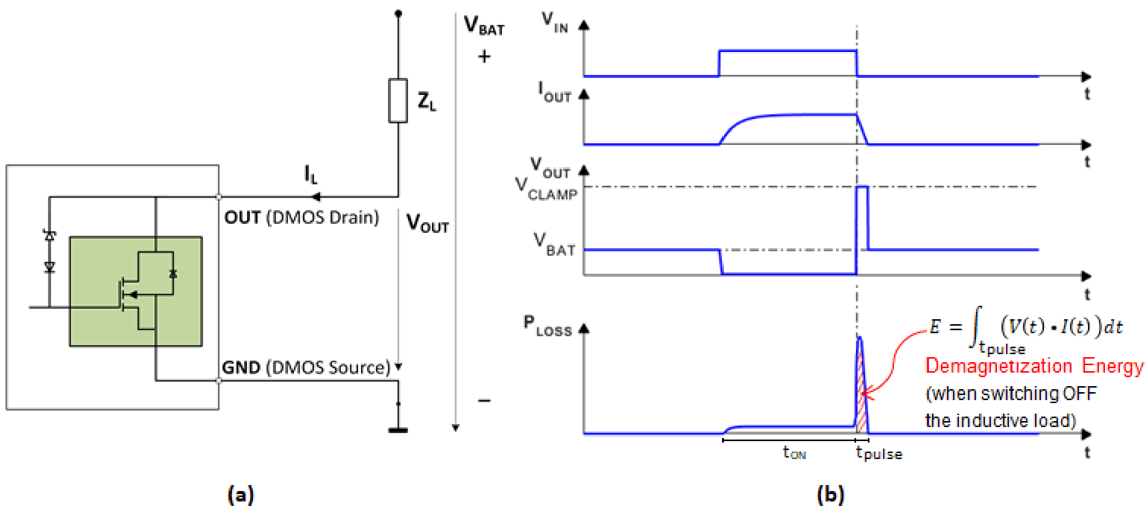

Figure 1.1: (a) A typical circuit of a smart Low-Side Power Switch driving inductive load. (b) The corresponding waveforms of the voltages, load current and power loss.

1.2 Problem Description

The lifetime of a product strongly depends on the conditions it is operated, the load it is exposed to, and other stimuli variations. For example, an electronic switch from a window lifter system is not solicited in the same way as a switch from a fuel injection control system. Consequently, in the semiconductor industry, there is a need to estimate the lifetime of power devices on different application operating conditions.

Lifetime characterization tests are time consuming. In particular, the active cycling of power devices (repetitive switching of inductive loads) requires months of testing for measuring the lifetime at different operating conditions. The parallelization of tests is not an efficient solution, as it is very costly. Also, the stress-tests cannot be accelerated, as the criterion of failure is not the total destruction of the devices, rather the moment when the devices no longer perform in the specifications. For that, continuous measurements are necessary in order to verify the failure condition and discrete inductive loads must be used. Another problem is that, due to the manufacturing process, the measured lifetime comes with a big variance. By using discrete inductive loads, the setup capability allows only a small number of Devices Under Test (DUTs) at a time, so the lifetime spread estimation is poor. The increasing of the measurement capability (the number of simultaneously measured devices) requires a more complex and expensive setup. Consequently, a limited amount of reliability data is available, measured on a few operating conditions scenarios and on a small number of DUTs.

For these reasons, the manufacturers most often provide the lifetime parameters only for a standardized set of operating conditions which ensures coverage on a wide range of applications and the provided values are very conservative.

On the other hand, the customers need reliable and, in the same time, cost-efficient products that properly fit their applications.

1.3 Motivation

As described in the previous section, in the characterization stage of power devices, it is necessary to estimate the lifetime on different application operating conditions and estimate the spread of the lifetime more accurately. The big challenge is to estimate the lifetime as accurate as possible and on a wide space of application operating conditions, having available only a limited amount of reliability data, measured on a few operating conditions scenarios and on a small number of DUTs.

In general, the reliability assessment methods define lifetime as the total destruction of the devices, while in the characterization of power devices, the end of life is considered the moment when the performances of the chip do not satisfy the specification anymore. Most of them consist of empirical models, based on Coffin-Manson law [Man66, JED16], where the estimation of the maximum junction temperature swing within a fast thermal cycle (ΔT) is the key, but also the biggest challenge. They were extended with different parameters, so the models require for fitting large amounts of data. Other approaches are based on physical modeling, describing the creep mechanics in materials under cyclic loads. The main drawbacks are the difficulties of calibration and utilization of these models. There are also methods based on degradation modeling. These can estimate lifetime at a predefined failure level, but the models are validated on a limited number of operating conditions. In conclusion, the existing methods do not fulfill the characterization requirements of power devices.

1.4 Scope of the Research

The main goal of the research is to develop a comprehensive methodology for application-aware estimation of the power devices' mean lifetime, that receives as inputs the application operating conditions for a power device and provides as output its lifetime, defined as the moment when the chip's performances are out-of-specifications. Also, for a more accurate estimation of the minimum guaranteed lifetime, a methodology for prediction of the lifetime spread will be developed. Failure analysis will be performed to confirm the failure mechanisms and modes under active cycling. The methodologies are to be built based on optimal reliability measurement resources. Data will be gathered from both lab tests and electro-thermal simulations. Metamodels and other machine-learning techniques will be used for building prediction models that represent the lifetime as a function of the factors that impact it. This will help scaling the lifetime estimation to many applications with less reliability data required.

To fulfill these requirements, the thesis first presents an approach for estimation of ΔT (the main stress-factor of the lifetime), based on electro-thermal simulation. Also, a data-driven model for prediction of ΔT on different application operating conditions is proposed. It is fitted from data on a grid of electro-thermal simulations based on estimated power profiles over a wide space of operating conditions. With the developed model, dependencies of ΔT with the operating parameters can be observed and ΔT predictions on different application operating conditions can be done.

Furthermore, the classical lifetime model is assessed and extended in order to be applied on different application operating conditions and for a predefined failure criterion (instead of total destruction of devices). The model coefficients are fitted from experimental data. Leave-one-out and bootstrapping methods are used for validation.

The thesis also introduces a methodology for estimation of the lifetime spread (caused by the manufacturing process variation), which overcomes the problem of limited available reliability data, by using data from different stages of product development and tests. First, a global sensitivity analysis (SA) which performs even with a small amount of data is presented. It is used to determine the most relevant electrical parameters (EP), measured before the stress-test, which correlate with the lifetime spread. Because of the complex dependencies between the design and technology properties, usually, there is not a strong relationship between the lifetime spread and only one electrical parameter. Instead, more EP taken together can correlate with the lifetime variation. For that, the developed global SA takes into account not only the direct influences of EP on the lifetime spread, but also their interactions. With the resulted most relevant EP the lifetime spread model is fitted. Eventually, by using the distributions of the most relevant EP from Back-End (BE) stage, where thousands of assembled devices are measured, the model can predict the lifetime distribution.

1.5 Structure of the Thesis

Chapter 2 presents the state-of-the-art methods and related works for power devices lifetime estimation and for lifetime variation estimation. The disadvantages or limitations of these methodologies, in the context of thesis's objectives, are also underlined.

Chapter 3 presents the theoretical fundamentals of machine-learning techniques applied in this thesis. Also, the principle of electro-thermal simulation is described.

Chapter 4 introduces the proposed methodology for modeling of the junction temperature swing (ΔT), the main stress-factor of the lifetime, in the space of operating conditions, based on data from a grid of electro-thermal simulations.

In chapter 5 it is introduced the methodology for application-aware lifetime estimation. The classical Coffin-Manson model is assessed and then extended in order to develop an application-aware lifetime model, which estimates the out-of-specifications time of the power device, in a wide space of operating conditions.

Chapter 6 describes the proposed approach for estimation of the lifetime variation. First, it is presented how the most relevant EP which correlate with the lifetime spread are found based on a specially developed global SA method. Next, it follows the description of the fitting and validation of the lifetime spread model. The methodology ends with the estimations of the lifetime distribution and of the minimum lifetime.

Chapter 7 presents the experimental results. The application of the methodology for ΔT modeling is presented first. Then, the application of application-aware lifetime estimation methodology is provided. The last section presents the application of the methodology for estimation of the lifetime variation.

In chapter 8 the final conclusions are drawn, the main contributions of this thesis are underlined and the future research perspectives are proposed.

Chapter 2

Related Work

2.1 Lifetime Estimation

Empirical Models. The most known empirical method is based on Coffin-Manson law [Man66]. According to it, the lifetime (expressed in cycles-to-failure) depends on ΔT based on the relation (2.1). This simple model is appropriate as long as the cycles peak temperature does not exceed $120°C$ [BTB+11]. Improved models take into consideration additional factors, such as the medium temperature T_m (introduced by means of an Arrhenius term), or the frequency of the temperature cycles [NL69]. The work [BHL+08] introduces one of the most complex extended Coffin-Manson model, based on a large amount of data from different IGBT modules and test conditions.

$$N_f = a \cdot (\Delta T)^{-n} \tag{2.1}$$

where: N_f is the number of cycles to failure, ΔT is the maximum junction temperature swing, a and n are parameters which are determined experimentally.

Estimating of the Lifetime Distribution. When small amounts of reliability data are available, the lifetime distribution is estimated. The work [PPGP12] presents a method for estimation of the lifetime distribution of CMOS power devices based on a mixture of two normal distributions, as two dominant failure mechanisms were observed. Instead of computing point estimates, the posterior lifetime distribution was considered, by using a Bayesian framework. This approach is continued in [PBP13], by introducing new parameters which reflect interactions between different geometric designs or material properties of the semiconductor devices. In both works the failure criterion considered is the total destruction of devices. Furthermore, the methods can not be applied on small data available when using testing setup with discrete loads.

Degradation Modeling – Based Models. The methods based on degradation modeling are also used for lifetime estimation. In [LCR+16] the damage accumulation determined by the solder fatigue is modeled by the changing in time of the thermal resistance (R_{th}) of IGBT modules. The increase of R_{th} over a threshold was considered the criterion for device failure. The method has some limitations in terms of maximum ambient and junction temperatures. The work [HDNA17] proposes a linear model for estimation of the remaining useful life, where the on-state resistance is considered the fault signature. The model was validated on a limited number of operating conditions.

Physical Modeling – Based Models. Another approach used for lifetime estimation is based on physical modeling, for instance, describing the solder behaviour. A thermo-mechanical model is presented in [Cia05, Cia08], describing the creep mechanics in materials under cyclic loads (i.e. the time-dependent plasticity). The work [KDK10] takes into account not only the time-dependent deformations, but also the time-independent elastic and plastic deformations of the solder. The calibration and utilisation of such physical models require some skills, as the knowledge of the mechanical behaviour of materials submitted to thermal cycles is essential.

2.2 Estimation of the Lifetime Variation

Considering the Initial Information of a Performance Parameter. In the literature, to the best of our knowledge, there are very few references based on the idea of estimating of the lifetime variation from the initial values of EP. The method presented in [LLY+16] shows some similarities with the proposed approach, but only from some points of view. An apriori known parameter was used to predict the lifetime of electromagnetic relays, considering that information of the initial parameter (the initial contact resistance) may contain potential defects of devices. In order to measure the initial parameter information, the operation of the relays for a set time was necessary. Only one parameter was considered and it was known from the beginning, while, in case of semiconductor power devices most often this is not apriori known.

Global Sensitivity Analysis. An important part of the this thesis is the specially developed global SA method. Concerning the Sensitivity Analysis, the work [KoB+16] presents a comprehensive comparison of the most used SA methods for systems with a high number of factors. The research describes and compares, from the factor ranking point of view and the execution cost implied (number of runs), six SA methods. Four of them are based on the variance decomposition: Fourier Amplitude Sensitivity Test (FAST), Extended Fourier Amplitude Sensitivity Test (EFAST), Sobol indices and the Jansen method. Another method presented is the One-Factor-at-a-Time (OAT) Morris method and the last one is the metamodeling technique (based on regression analysis). The statistical approach ANOVA (Analysis of Variance) [SC89] is not included in this study because, for systems with high number of factors, it has higher computational complexity. The work [KIo+16] introduces two new SA methods based on entropy, that overcome the limitation of above presented methods, which impose a specific DoE and a high computational cost (number of simulations/experiments required). The main issue with all presented methods is that they require a significant number of runs/measurement points (at least 10 times higher) compared with the number of factors. For this reason, the existing SA methods are not proper to be used when a small amount of measurement data is available.

Chapter 3

Theoretical Fundamentals

3.1 Regression Fitting

Statistical learning [GDTR13] consists of a set of tools used for understanding data. These tools are classified in: supervised and unsupervised. In supervised learning, a statistical model is built, in order to predict an output from some inputs.

The linear regression is a very simple approach for supervised learning. In particular, it is useful for predicting a quantitative response. As an example, a simple linear regression is a simple approach for predicting a response Y based on a single predictor (input) variable X. In this case, an approximately linear relationship between X and Y is assumed, that, mathematically, can be written as (3.1):

$$Y \approx \beta_0 + \beta_1 \cdot X \tag{3.1}$$

where: β_0 and β_1 are two unknown constants, that represent the model coefficients or parameters, which are estimated from data with the least squares method.

3.2 Electro-Thermal Simulation

The electro-thermal simulation [PJS08, BIMR18] is a powerful tool used for analyzing the heat dissipation within the power devices structures, especially for reliability assessment. For instance, the self-heating of DMOS devices within a fast thermal cycle corresponding to the active cycling can be simulated and peak temperatures of hundreds $^\circ C$, as well as very fast temperature transients can be detected.

An electro-thermal simulator estimates the temperature propagation in time and space, from the heat source region into the rest volume of the simulated structure (the DMOS device). To take into consideration nonuniform temperatures and different power densities, the simulated structure is usually divided in several parts.

The works [PJS08, PBLS13] present a comprehensive strategy for electro-thermal simulation of self-heating in DMOS up to very high temperatures (thermal runaway), including an approach for calibration of the device electro-thermal model and a 3-D numerical temperature simulator optimized for a reduced simulation time. The two works will be considered the main references for the electro-thermal simulation topic.

Chapter 4

Proposed Methodology for ΔT Estimation

This chapter presents the author's contributions to the methodology for ΔT estimation and modeling in the space of the operating conditions corresponding to active cycling applications.

The electro-thermal simulation method [PBLS13] is the most suitable solution in case of active cycling (repetitive clamping) of power devices, as presented in section 3.2. Therefore, the proposed strategy for ΔT estimation is based on electro-thermal simulation (introduced in [PBD$^+$19]), with a suplimentary calibration approach at the package level and in the space of the application operating conditions. Furthermore, the thesis introduces a methodology for ΔT modeling in the space of application operating conditions, based on data from a grid of electro-thermal simulations (introduced in [PBD$^+$20]). The proposed methodology will also be applied for the estimation of the mold compound mean temperature within a fast thermal cycle ($T_{avg-Mold}$), which is used for the application-aware lifetime model.

4.1 ΔT Estimation based on Electro-Thermal Simulation

The methodology consists of running electro-thermal simulations for all available operating conditions profiles, in order to determine the maximum junction temperature swings, based on the simulated time-and-spatial propagation of the temperature in the chip within a thermal cycle. The operating conditions power profiles of the active cycling scenarios have to be converted into power pulses that will represent inputs, in Piecewise Linear (PWL) format, for electro-thermal simulations.

The Operating Conditions in Active Cycling Applications

The operating conditions considered in this thesis for the active cycling experiments performed and for the developed models are the ambient temperature (T_{amb}) at which the power device operates and the electrical measures: load current (I_L) and repetitive energy (E_R). It is considered that the frequency and duty cycle of the command pulse are ensured by the application, in order to avoid the temperature accumulation.

4.2 ΔT Modeling

For the estimation of the main stress-factor of the lifetime, i.e. the junction temperature swing, in the space of application operating conditions, the following ΔT modeling methodology is proposed. The idea is to fit the ΔT model from data corresponding to a grid of electro-thermal simulations performed in the space of the operating conditions. First, in order to run electro-thermal simulations in points of operating conditions where no power pulse parameters are available from experimental measurements, the PWL parameters required for the electro-thermal simulations must be modeled in the space of operating conditions. Then, based on the grid electro-thermal simulations, the data-driven model of ΔT is built and validated. With this model, the dependencies of ΔT with the operating parameters can be observed and predictions of ΔT on different application operating conditions can be done. The methodology flow for ΔT modeling is presented in Figure 4.1.

4.3 ΔT Model Validation

The ΔT model is validated on two data-sets. First, the validation is performed on the training set (grid data), by means of the leave-k-out and bootstrapping methods. Then, the ΔT model is evaluated on the experimental scenarios - based electro-thermal simulation data.

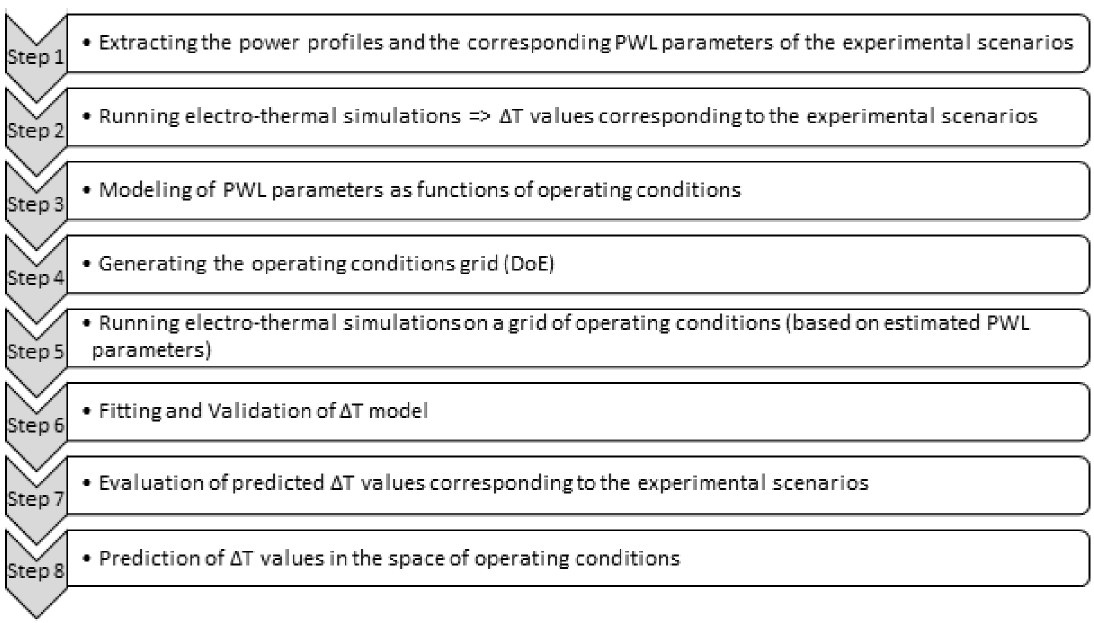

Figure 4.1: The methodology flow for ΔT modeling.

Chapter 5

Proposed Methodology for Application-Aware Lifetime Estimation

5.1 The Methodology Flow

Figure 5.1 presents the methodology flow for application-aware lifetime estimation.

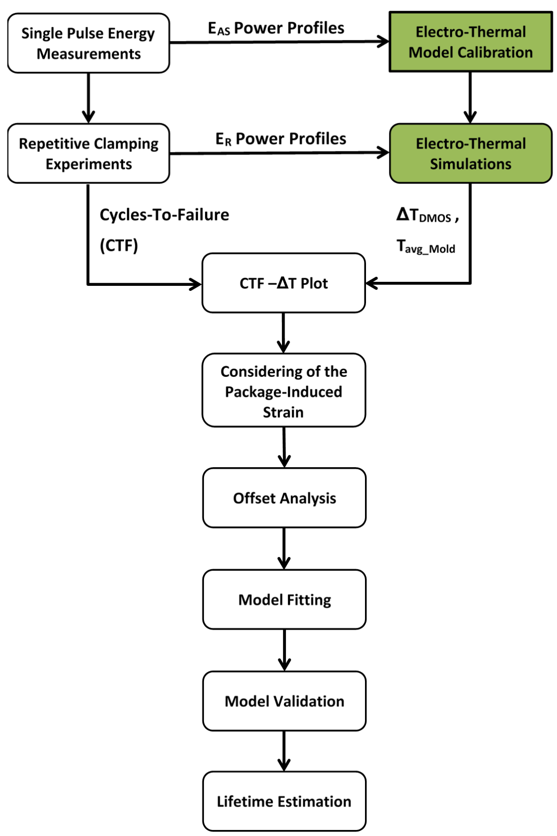

Figure 5.1: The methodology flow for application-aware lifetime modeling.

Starting from the classical Coffin-Manson approach, an extended model of the mean lifetime is developed (introduced in [PBD+19]), which can be applied on different application operating conditions and for a predefined failure criterion (instead of total destruction of devices). According to JEP122H Standard [JED16], the thermal cycling mechanism is known to fit to Coffin-Manson law (5.1). In log-log scale, this relation shows a linear dependence between lifetime and ΔT, with a negative slope.

$$N_f \sim [\Delta T\,]^{-q} \tag{5.1}$$

where: N_f is the lifetime, expressed in Cycles-To-Failure (total destruction of the devices); ΔT represents the maximum junction temperature swing; q is a constant.

The single pulse energy (E_{AS}) is determined experimentally for all (I_L, T_{amb}) pairs of operating conditions scenarios and the lifetimes, expressed in Cycles-To-Failure (CTF), are measured based on active cycling (repetitive clamping) experiments on different operating conditions. In parallel, electro-thermal simulations are running for all operating conditions profiles in order to determine the corresponding ΔT values.

5.2 The Development of the Application-Aware Lifetime Model

5.2.1 The Assessment of Coffin-Manson Law

Based on the measured lifetimes and the corresponding maximum junction temperature swings for all experimental scenarios from different operating conditions, the CTF-ΔT plot (in log scale) is drawn. From this plot it was observed that the expected linear dependence of the lifetime with ΔT is not achieved for all operating conditions scenarios. The linear dependence is valid only locally, for scenarios on fixed (I_L, T_{amb}) operating conditions, when only the repetitive energy varies. It seems that, for different (I_L, T_{amb}) pairs of operating conditions, ΔT is not the only stress-factor. There are also other sources of stress, which depend on the load current and the ambient temperature of the active cycling experiment.

5.2.2 Considering of the Package-Induced Strain

The work [NSK+03] presents a similar conclusion. It shows that the log-log plot of the lifetime versus ΔT do not follow the same line for different test conditions. The authors explain here that the root cause of the failure mechanism is the shear stress from the packaging, generated due to the different thermal expansion coefficients of the silicon chip, moulding compound used in assembly and the package substrate. The mold compound which is injected in the assembly process at high temperature (about $175°C$) generates an additional strain upon the die, when it is cooled-down to the ambient temperature. This mechanical stress from plastic packages has different amplitude when devices are operated at different ambient temperature. It is reduced to zero when the ambient temperature is equal to the injection temperature of the mold compound. Consequently, in order to take into account also this effect, in the Coffin-Manson model the term ΔT_{Mold}, defined as in (5.2), is subtracted from ΔT.

$$\Delta T_{Mold} = T_{avg\_Mold} - T_{molding} \tag{5.2}$$

where: T_{avg_Mold} is the mean temperature in mold compound during a Fast Thermal Cycle (FTC), $T_{molding}$ represents the mold compound injection temperature.

By considering this effect, the disposal on the log-log plot of the scenarios from different (I_L, T_{amb}) pairs of operating conditions changes. As expected, a different disposal can be observed for scenarios on low ambient temperature. However, it is still not enough for obtaining a global linear dependence of the lifetime with this combined stress-factor, for all operating conditions scenarios.

5.2.3 Extending of the Lifetime Model in the Space of Operating Conditions

There is still a non-constant term (offset), for different (I_L, T_{amb}) pairs of scenarios. The log-log plot of the lifetime versus the combined stress-factor reveals that the offset of each (I_L, T_{amb}) pair is proportional with the stress-level of the operating conditions. Furthermore, it will be shown that this offset can be linearly modeled with just one feature (factor), namely the product of the load current with the ambient temperature. Consequently, the proposed mean lifetime model is presented in (5.3):

$$\log_{10}(CTF) = \alpha_0 + \alpha_1 \cdot I_L \ \cdot T_{amb} \ + \beta \cdot \log_{10}(\Delta T_{DMOS} - \Delta T_{Mold}) \tag{5.3}$$

where: the coefficients α_1 and β are negative.

The resulting lifetime model is simple, with only three coefficients to be fitted and also robust, as the leave-one-out and bootstrapping validation methods will show.

5.3 The Validation of the Application-Aware Lifetime Model

The validation of the lifetime model is done with **leave-one-out method**. For each scenario data, the model is fitted using data of the rest available observations (scenarios) and, then, the prediction relative error is computed, by evaluating the model on the current observation. This process is repeated for all available scenarios. At the end, the maximum unsigned relative error obtained is considered. The confidence interval is estimated with **the bootstrapping technique**. From all available measurements (N), a bootstrapp sample is generated by randomly picking $(1 \div 3)$ x N observations. Next, a model is fitted based on this sample and the left-out observations (that are not part of the bootstrapp sample) are estimated with this model, resulting the prediction relative errors. These steps are repeated for 10 000 times. Eventually, the confidence limits (corresponding to the desired confidence level - typically 95%) are computed from the histogram of prediction relative errors.

Chapter 6

Proposed Methodology for Lifetime Variation Estimation

This chapter introduces the methodology for estimation of the lifetime spread (caused by the manufacturing process variation) and of the minimum lifetime. The methodology was already presented in [PBP+19]. In order to overcome the problem of the limited amount of reliability data that is available, data from different stages of product development and tests are considered together. The link between the lifetime measurements and the back-end stage measurements is done by means of the developed global SA method (introduced in [PBP+18]), which is capable to perform even when a small amount of data is available. This is used to find, in an automatic way, the most relevant EP which correlate with the lifetime spread. The lifetime spread model is fitted from experimental data, considering as factors the most relevant EP. The prediction of the lifetime distribution is performed by evaluating the lifetime spread model on BE distributions of the most relevant EP, measured on thousands of devices. The minimum lifetime is estimated out of the predicted lifetime distribution.

6.1 The Methodology Flow

The proposed methodology flow is shown in Figure 6.1. First, initial EP measurements are performed for all DUTs, in the same fashion as in BE stage of the product development. Also, the DUTs are numbered (serialized) for future data tracking. Then, the lifetime stress-tests (active cycling experiments) are made.

6.2 Finding the Top Most Relevant Electrical Parameters (EP)

Finding the most relevant EP that are correlated with the lifetime spread is performed with the developed global SA method. It consists of the following steps: data preparation (clustering and normalization), computing of correlations (sensitivity analysis), ranking of the relevant factors and validation of the top most relevant EP.

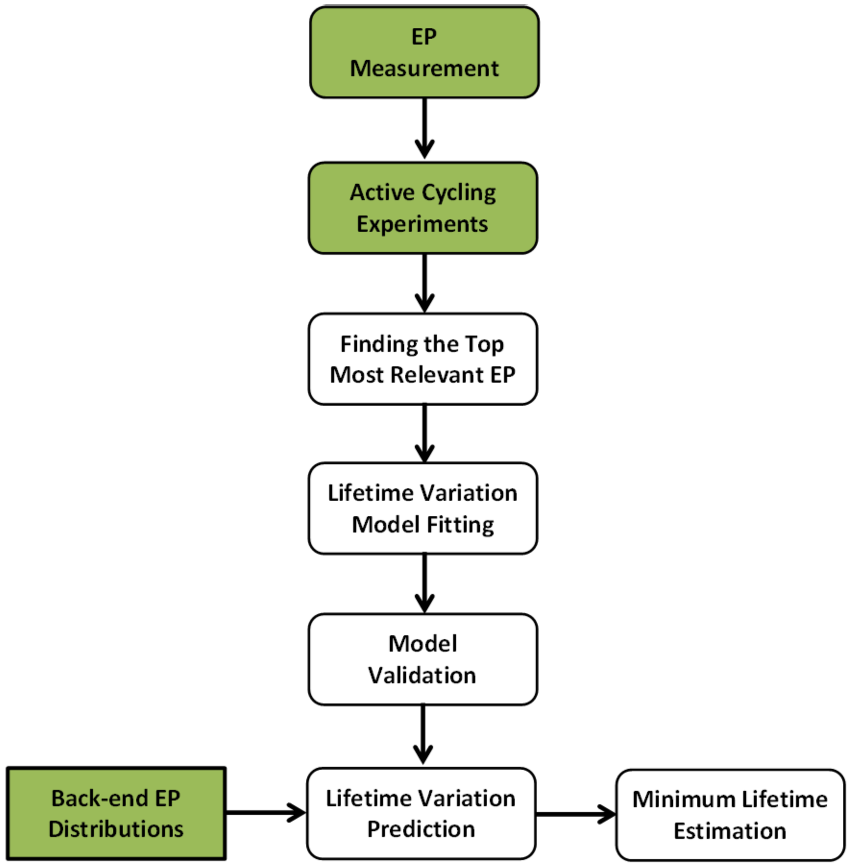

Figure 6.1: The methodology flow for lifetime spread modeling.

Sensitivity Analysis. After the clustering stage, only independent EP are further considered (from each cluster only the representative one is kept). The next step consists in computing the correlations of the initial EP with the lifetime variations. The idea is to assess each effect at a time. For that, the correlations are computed on three orders, which cover not only the linear effect, but also the quadratic and interaction dependencies. The first order correlation represents the 1-to-1 dependency of the lifetime variation with each electrical parameter. The second order correlation consists in the dependency of the lifetime variation with new factors obtained from the product of each EP pair. In the pairs are also included the pair of each electrical parameter with itself. The third order correlation represents the dependency of the lifetime variation with new factors obtained from the product of each triplet of EP.

The global SA continues with **the ranking of the factors (EP)**. With the correlations computed before, three Top 10 relevant EP (for each order) are performed and the Top Most Relevant Factors is done, by computing the normed-weighted scores with (6.1), based on the numbers of EP occurrences in those three Top 10 lists:

$$score_{EP_i} = 0.45 \cdot \overline{occ_{ord1}} + 0.35 \cdot \overline{occ_{ord2}} + 0.20 \cdot \overline{occ_{ord3}} \tag{6.1}$$

where: $\overline{occ_{ord1}}$, $\overline{occ_{ord2}}$, $\overline{occ_{ord3}}$ are occurrence numbers of EP_i on those three lists.

6.3 Lifetime Variation Model Fitting

In previous section the most relevant EP that explain the lifetime variation are found in an automatic way, by a black-box approach. It does not mean that they represent the root causes of lifetime spread. However, their correlation to CTF provides an important hint to what the lifetime spread could be for a given set of EP values.

With the resulted most relevant EP which are considered factors, a lifetime variation model is fitted in the next step. Having only a few lifetime data available, complex or high order polynomial models can not be fitted or, if they can be fitted, they are prone to overfitting. Consequently, the linear model (6.2) is considered. The logarithm of the lifetime is taken as output of the model, so that the dependency to the EP (input factors) can be modeled with a low order polynomial (linear).

$$\overline{\log_{10}(CTF)} = c_0 + \Sigma_{i=1}^{N} c_i \cdot \overline{EP_i} \tag{6.2}$$

where: CTF is the lifetime (expressed in cycles-to-failure), EP_i are the most relevant EP (considered as factors), N is the number of factors taken into account and c_i are the model coefficients, that are extracted from the experimental data.

6.4 Validation of the Lifetime Variation Model

The validation of the lifetime spread model is performed with the leave-one-out method. At a time, each sample is excluded and the model is fitted using data of the rest available samples. Then, for the current left-out sample, the prediction relative error is computed. The process is repeated for all available samples. The maximum unsigned relative error obtained is eventually considered.

The prediction confidence interval is determined by means of the bootstrapping technique. From all available measurements (N observations) a bootstrapp sample is generated by randomly picking (1÷3) x N observations. Based on this sample data, a model is fitted. Then, the left out observations (that are not part of the bootstrapp sample) are predicted with this model, resulting the prediction relative errors. These steps are repeated for 10 000 times. From the histogram of prediction relative errors the confidence limits are computed, corresponding to the desired confidence level.

6.5 Prediction of the Lifetime Distribution and of the Minimum Lifetime

The lifetime distribution corresponding to each scenario of operating conditions is predicted by evaluating the lifetime spread model on the distributions of the factors (most relevant EP), taken from back-end stage of development where thousands of devices are measured. The BE stage represents the EP testing (voltages, currents, delays, etc.) of the assembled devices. Based on the predicted lifetime distribution, the minimum lifetime is estimated by computing the required ppm quantile. For instance, in automotive, the 1ppm quantile is usually considered.

Chapter 7

Experimental Results

7.1 Lifetime Measurement Setup

After the measurement of devices electrical parameters and numbering (serializing) of the DUTs, the lifetime tests are performed. Active cycling of power devices consists in applying repetitive voltage pulse commands to power switches that drive inductive loads. The stress-test setup consists of the following components: PC, with custom software for configuration, control, visualization and data saving; dedicated test board, containing the devices under test; discrete inductive loads (with series resistances); custom board for DUTs control and shut-off and the measuring interface; measurement instruments; thermal chamber, where the dedicated test board containing the DUTs is placed. The repetitive clamping experiments are performed on 12 different operating conditions scenarios, consisting of 5 (I_L, T_{amb}) pairs, each on 2-3 values of E_R (repetitive energy). Figure 7.1 illustrates the measured lifetimes in the space of operating conditions where the active cycling experiments are performed.

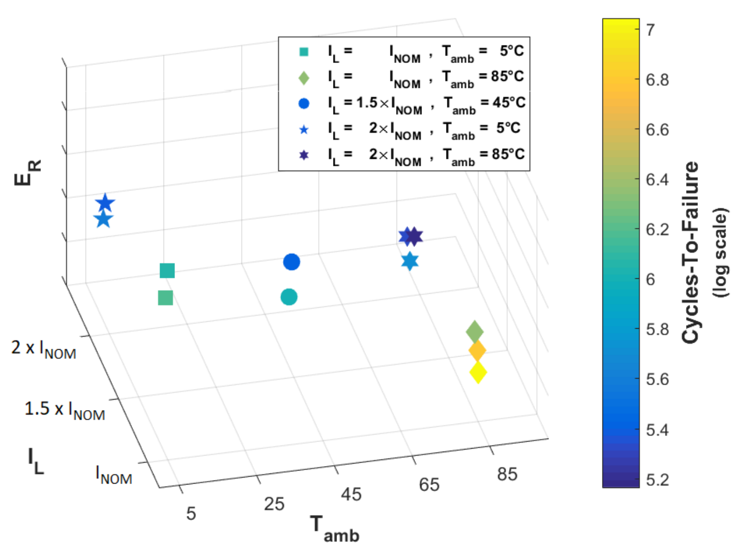

Figure 7.1: The lifetime measurements.

7.2 The Application of ΔT Modeling Methodology

In the first step, the power profile and the corresponding PWL parameters are extracted for all scenarios of active cycling experiments. Based on the PWL parameters of the experimental scenarios, data-driven models or formulas for PWL parameters are built, in order to make predictions in the space of the operating conditions.

The simulation DoE on the grid of operating conditions consists in 125 data-points (5 values for each factor). Figure 7.2 presents the simulated values of ΔT_{DMOS} corresponding to the grid of power profiles scenarios (with circles), together with the values resulted from the simulations on the active cycling measurements power profiles (with dots). All ΔT_{DMOS} values are coded by the color of the markers.

The ΔT values resulted from the grid simulations are used to fit the ΔT model (3rd order polynomial with interactions), that has as factors the operating conditions.

The validation of ΔT model is done with leave-k-out method. For that, from all observations (data-points), a number of $k = 3$ are left-out and the ΔT model is fitted based on the rest available observations. Then, the fitted model is evaluated on the k left-out data-points. The process is repeated for 317 750 times (combinations of 125 chosen by 3). The maximum unsigned relative error out of all prediction errors computed is 1.34%. The bootstrapping technique is used to estimate the confidence interval of ΔT model prediction. A bootstrapp sample set is used, that is generated from the original set of observations by randomly picking (with replacement) a number of observations equal to the size of the original data set. The number of left-out observations for each iteration is randomly chosen. In total, 10 000 iterations (consisting of model fitting + evaluation on left-out data-points) are performed. According to the errors distribution, the 95% confidence level interval spreads over relative errors within the lower limit of -0.65% and the upper limit of 0.64%.

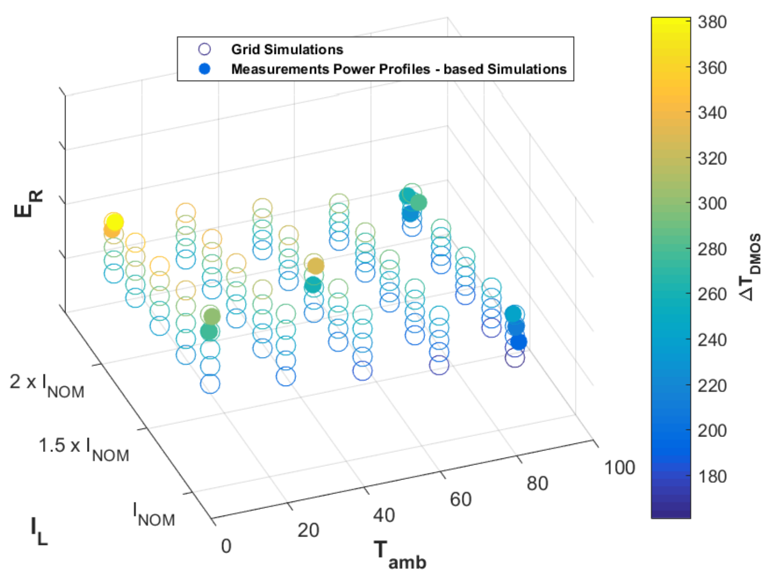

Figure 7.2: The resulted ΔT values for the grid of power profiles scenarios.

7.3 The Application of the Methodology for Application-Aware Lifetime Estimation

7.3.1 Development of the Application-Aware Lifetime Model

As presented in Chapter 5, the first step is the assessment of the Coffin Manson law, in the space of active cycling experiments. Having the lifetimes from experiments and the ΔT values from simulations, the CTF-ΔT log-log plot is drawn and analysed. Contrary to theory, the expected linear dependence of the lifetime with ΔT is not achieved for all scenarios of operating conditions. The Coffin-Manson law looks like is valid only locally, for fixed (T_L, T_{amb}) operating conditions, while the ΔT feature seems not to be the unique stress-factor in all the space of operating conditions.

Taking into consideration also the package-induced strain, there can be observed some changes in the disposal of the scenarios from different (T_L, T_{amb}) pair of operating conditions on the log-log plot. As expected, a different disposal can be observed for scenarios on low ambient temperature. However, the expected global linear dependence of the lifetime with the combined stress-factor, in all the space of operating conditions can not be seen. Figure 7.3 presents the log-log plot. For different (T_L, T_{amb}) pairs of scenarios, there is still a non-constant term (offset).

Moreover, the Figure 7.3 shows that the offset of each (T_L, T_{amb}) pair is proportional with the stress-level of the operating conditions. The offset dependence with the operating conditions has been further studied and eventually, it was linearly modeled with just $I_L \cdot T_{amb}$ feature. Consequently, the final lifetime model (presented in 5.3) is obtained. A possible explanation for this simple dependence, from physical point of view, is the fact that, in terms of energy (and junction temperature swing, respectively), there is a limitation given by the (T_L, T_{amb}) operating conditions. For a given (T_L, T_{amb}) pair of operating conditions, the repetitive energy applied can not take any value. E_R is limited by the corresponding E_{AS} value for that scenario, while the single pulse energy is inverse-proportional with the product $I_L \cdot T_{amb}$.

Furthermore, by fitting the coefficients of the lifetime model (5.3) and rewriting the model equation in the form (7.1), it results a global linear dependence of the lifetime (in log scale) with the resulted unique stress-factor, in all operation conditions space.

The resulted plot is presented in Figure 7.4. It clearly shows that, with the proposed application-aware lifetime model re-written in form (7.1), the disposition of the lifetime values (in log scale), corresponding to all test conditions, with regard to the resulted combined stress-factor follow a single line. This means that the resulted combined factor (F) is the unique stress-factor for all operating conditions scenarios.

$$\log_{10}(CTF) = \alpha_0 + \beta \cdot F \tag{7.1}$$

where: $F = \frac{\alpha_1}{\beta} \cdot I_L \cdot T_{amb} + \log_{10}(\Delta T_{DMOS} - \Delta T_{Mold})$

Table 7.1 shows the three coefficients (α_0, α_1 and β) of the lifetime model (5.3), computed with the least squares method from the experimental and simulation data.

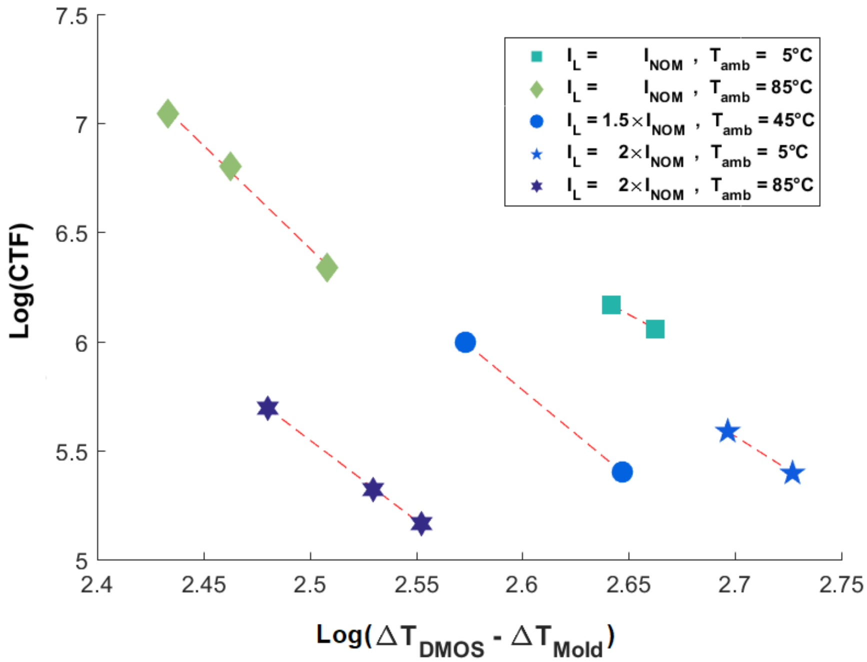

Figure 7.3: The log-log plot of the lifetime versus the combined stress-factor.

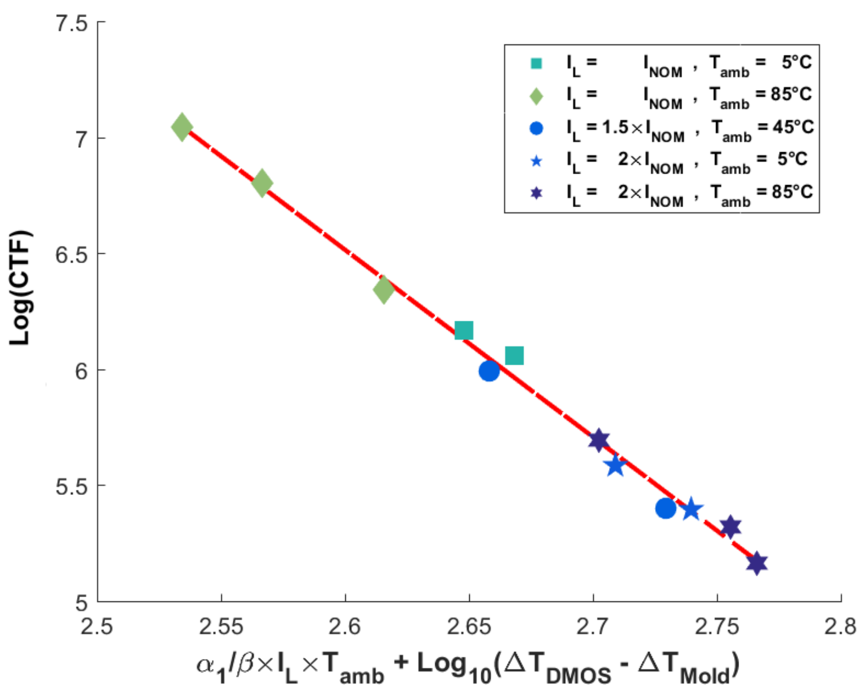

Figure 7.4: The linear dependence of lifetime vs. the unique stress-factor.

Table 7.1: The coefficients of the lifetime model (5.3)

α_0	α_1	β
27.5041	-0.0019	-8.0728

7.3.2 Validation of the Application-Aware Lifetime Model

The validation of the lifetime model is done with **leave-one-out method**. For that, each scenario data (out of 12 measurements) is left-out at a time and the model is fitted using the rest 11 observations. Then, the relative error is computed based on the model prediction of the left-out observation. The maximum unsigned relative error obtained is 24%. The confidence interval is estimated with **the bootstrapping method**. The bootstrapp sample is generated from all available measurements, by randomly picking (with replacement) 2 x 12 observations. Based on the bootstrapp sample a model is fitted and then evaluated on the observations that are left out (not part of this sample). This process is repeated for 10 000 iterations, 16 597 errors being computed in total. Figure 7.5 presents the histogram of the relative errors. The 95% confidence level interval spreads over relative errors between the lower limit of -25% and the upper limit of 25%. The figure also displays the relative errors obtained with the leave-one-out method (with green color), the counts being scaled by 20.

The validation methods show that the resulting model for application-aware estimation of the mean lifetime is robust, despite the fact that it is not a complex model (having only three coefficients to be fitted).

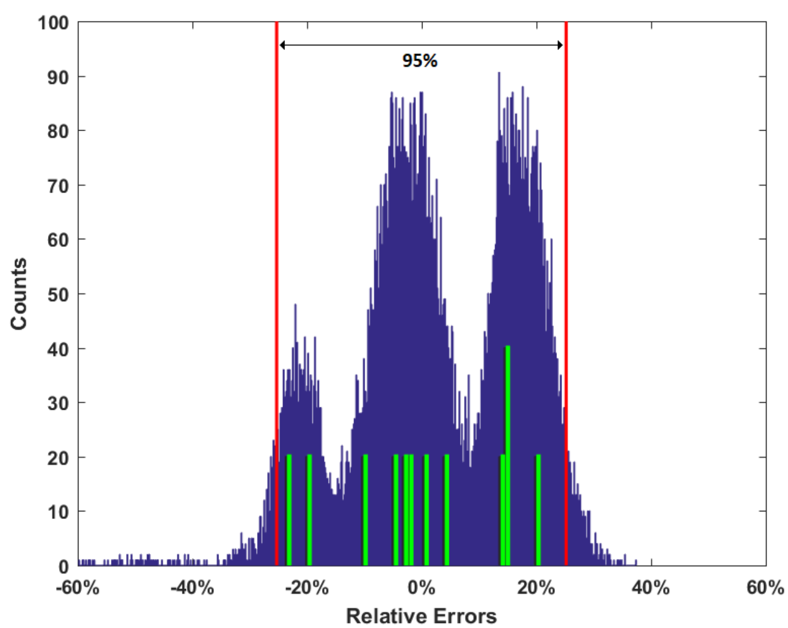

Figure 7.5: The prediction relative errors (model 5.3), with bootstrapping validation. The leave-one-out errors are drawn with green (counts scaled by 20).

7.4 The Application of the Methodology for Lifetime Variation Estimation

7.4.1 Development of the Lifetime Variation Model

Before running the lifetime tests, the EP of all DUTs are measured (in the same fashion as in BE) and the devices are numbered (serialized). There are 45 parameters taken into consideration for the analysis.

In the next step, data are prepared for the analysis. The clustering of the EP is performed, in order to reduce the problem complexity. For that, the method based on inter-correlations is used. As condition for EP to be part of a cluster, a minimum inter-correlation threshold of 0.9 is considered. For each cluster, the electrical parameter which has the biggest minimum correlation coefficient with the other EP from the cluster is designated the representative one. There are also EP which are considered independent, as they do not belong to a cluster (their correlation coefficients with the others EP are smaller than the considered threshold). In total, 11 clusters are found, while 9 EP are considered independent. As, from each cluster, only the representative parameter is kept, 20 EP are considered for the following analysis.

The active cycling experiments are done in two scenarios of operating conditions. The resulted lifetime values and the EP values are normalized in [0,1] interval. This is required because the values are on different ranges and magnitude orders.

Based on lifetime data and EP values, the Sensitivity Analysis is performed next. It consists of computing the correlations of the lifetime data with EP, on three orders, by using the Pearson's coefficients method (*corrcoef* function - MATLAB). The 1-to-1 correlation of the lifetime with each electrical parameter is the first order correlation. The second and third order correlations are the correlations of the lifetime with new factors obtained from the product of each pair, respectively, each triplet of EP.

Based on the correlations coefficients of the Top 10 factors, Top 10 pairs of factors and Top 10 triplets of factors, the ranking of the factors comes next. The final Top Most Relevant Factors is performed, by computing the normed-weighted scores of EP with (6.1), based on the numbers of occurrences of the EP in these three Top 10 lists.

The final list of the most relevant 5 EP that explain the lifetime spread is: 12, 9 13, 10, 7. The resulted EP represent features that reflect the power devices capability to dissipate the internal heat. This conclusion is relevant, knowing that, in case of repetitive clamping (active cycling), the thermo-mechanical failure mechanisms are caused by high temperature swings at which the devices are exposed to.

The validation of the Top Most Relevant EP is done by fitting successive linear regressions of the lifetime with step-by-step increasing the number of factors (EP). For each new factor added in the model, the standard deviation of the residuals (estimation errors) decreases. This means that the new electrical parameter considered is relevant and that it explains a part of the lifetime variance. Table 7.2 presents the evolution of the standard deviation of the estimation errors for metamodels with 1 to 5 factors. The decreasing percentage of residuals standard deviation of the 5-factors metamodel represents the lifetime variance explanation level (71%).

Table 7.2: The reduction of the residuals standard deviation (lifetime spread model)

	Standard Deviation	**STD Reduction**
Lifetime	0,1581	
Residuals Model (EP_{12})	0,1193	**-25%**
Residuals Model (EP_{12}, EP_9)	0,0754	**-52%**
Residuals Model (EP_{12}, EP_9, EP_{13})	0,0660	**-58%**
Residuals Model ($EP_{12}, EP_9, EP_{13}, EP_{10}$)	0,0600	**-62%**
Residuals Model ($EP_{12}, EP_9, EP_{13}, EP_{10}, EP_7$)	0,0455	**-71%**

In the next stage, **the lifetime variation model is fitted**, where, as factors (inputs) are considered the resulted most relevant EP. The linear model (6.2) is used.

7.4.2 Validation of the Lifetime Variation Model

The validation of the lifetime spread model is done with **leave-one-out method**. For that, the lifetime spread model is fitted 11 times, based on different data-sets. For each observation (out of 11), the model is fitted with the rest 10 data-points and the prediction relative error of the current left-out observation is computed. The maximum unsigned relative error obtained is 25%. The confidence interval is estimated with **the bootstrapping method**. A bootstrapp sample is generated from all available measurements, by randomly picking 2 x 11 observations. Based on this sample, a model is fitted and, then, evaluated on the data-points that are not part of the bootstrapp sample (left out observations). These steps are repeated for 10 000 times. In total, 15 179 errors are computed. The 95% confidence level interval spreads over relative errors between -26% (the lower limit) and 30% (the upper limit).

One can consider that the accuracy is not big enough, but, without this methodology, the estimation of the minimum lifetime based only on the lifetime data of a few DUTs can be done very conservatively, with very large safety margins taken.

7.4.3 Prediction of the Lifetime Distribution and of the Minimum Lifetime

Eventually, the lifetime spread model is evaluated on the distributions of the most relevant EP (factors), taken from back-end stage of development, where thousands of devices were measured. In Figure 7.6 is presented **the predicted lifetime distribution** for a scenario of operating conditions. With green are illustrated the measured numbers of cycles-to-failure of 6 DUTs over the estimated lifetime distribution for that scenario. One can observe here that the lifetime measurements do not cover the predicted distribution and the average of the real data differs from that of the predicted lifetime. This is because a small number of devices (only 6) are measured and the selection of the DUTs so that the entire manufacturing process variation to be covered is very difficult to be done.

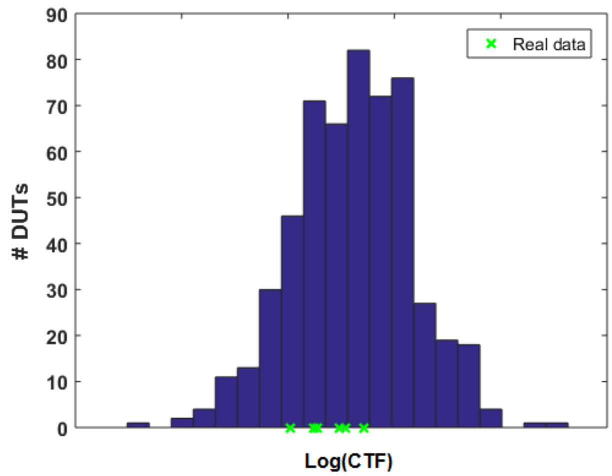

Figure 7.6: The predicted lifetime distribution.

The minimum lifetime for each scenario is estimated out of the corresponding predicted lifetime distribution. For that, the ppm quantile is computed. Figure 7.7 illustrates the probability distribution function of the predicted lifetime, on a normal probability plot. On this plot, the y-axis is modified so that a normal distribution to appear as a straight line. There are also drawn (with green) the lifetime measurements of 6 DUTs from the considered operating conditions scenario. One can observe that the estimation of the minimum lifetime from 6 measurements can lead to a different conclusion than that from the predicted lifetime distribution. Moreover, depending on the selection of DUTs for lifetime measurements, the estimation based on the small set of real data can be either optimistic, or pessimistic. Instead, based on the proposed methodology, the resulting lifetime distribution is predicted by indirectly taking into account the manufacturing process tolerance through variations of EP.

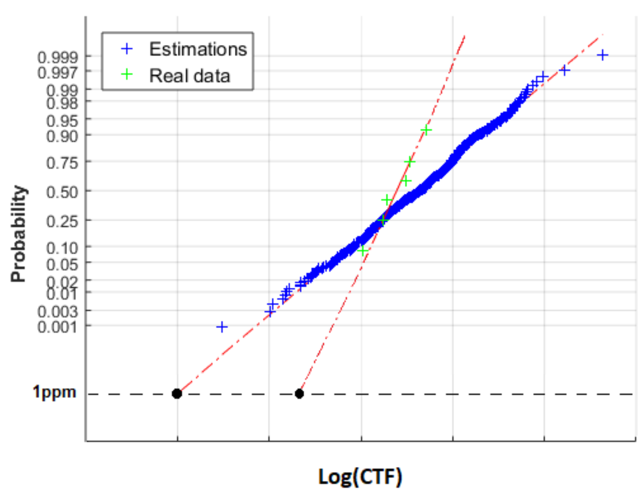

Figure 7.7: The predicted lifetime distribution on a normal probability plot.

Chapter 8

Conclusion

This research was dedicated to the non-functional characterization of the smart DMOS power devices. Because the active cycling (repetitive switching of inductive loads) is a time consuming process and testing setups are very complex and expensive, a limited amount of reliability data is available. The general scope of this thesis was to develop methodologies in order to characterize the power devices more, in terms of diversity (lifetime estimation at different operating conditions) and accuracy (a more accurate estimation of the lifetime spread), based on the available reliability data.

8.1 Objectives and Results

I. Lifetime Estimation on Different Operating Conditions

The first objective of the research was to estimate the lifetime at different application operating conditions. In order to accomplish that, the thesis has proposed a two-step approach for application-aware estimation of the mean lifetime.

First, the thesis has introduced a methodology for modeling of the main stress-factor, i.e. the junction temperature swing within a thermal cycle (ΔT), on different operating conditions, based on electro-thermal simulation. The proposed concept involves the following stages: estimation of ΔT values corresponding to power profiles of active cycling experiments; modeling of time parameters of the power pulse in the space of operating conditions; generating a grid in the space of operating conditions, for running electro-thermal simulations; fitting the ΔT model based on electro-thermal simulation grid data. The validation of ΔT model with leave-k-out and bootstrapping methods showed a maximum relative prediction error of 1.34%. The same methodology was applied for modeling of the mean temperature in mold compound within a fast thermal cycle (T_{avg_Mold}), necessary for the application-aware lifetime model.

The second step was the development of the model for application-aware estimation of the mean lifetime, based on electro-thermal simulation. The model considers ΔT as the main stress-factor, but it was also extended in order to be applied over a wide range of application operating conditions and with a predefined failure criterion (instead of total destruction of devices). The resulting lifetime model is robust and simple, with only three coefficients, which are fitted from experimental data. The validation of the mean lifetime model was performed with leave-one-out and bootstrapping methods, resulting a maximum relative prediction error of 25%.

The thesis has also introduced a direct data-driven methodology for estimation of the mean lifetime in the space of application operating conditions (not presented in this summary). This approach is a fast and efficient alternative for application-aware lifetime estimation, but it is intended only for interpolation of lifetime estimation within a targeted space of operating conditions, based on which the lifetime model is fitted and when only one failure mechanism is observed at the failure analysis.

II. A More Accurate Estimation of the Lifetime Spread

The second objective of the research was to improve the accuracy of the estimation of the lifetime spread (caused by the manufacturing process variation). This requirement was even more challenging, in the context of a limited reliability data available.

The proposed solution was the development of a methodology for modeling of the lifetime spread, which uses data from different stages of product development and tests. It is mainly based on the variations of the most relevant electrical parameters (EP), measured before the stress-test, which correlate with the lifetime spread. The most relevant EP were automatically determined by means of the global Sensitivity Analysis method (also introduced in this thesis), which is capable to perform even with small amounts of data. The lifetime spread model was fitted from experimental data, considering the resulted most relevant EP as factors. The model was validated with leave-one-out and bootstrapping methods, resulting a maximum relative error of 25%. Eventually, by evaluating the lifetime spread model on the distributions of the factors (EP) from back-end stage (where thousands of devices are measured), the lifetime distribution and the corresponding minimum lifetime could be predicted. By using the initial EP in the estimation of the lifetime spread, the variation of the manufacturing process is indirectly taken into account.

8.2 Author's Main Contributions

The main contributions of the author are presented in chapters 4, 5, 6 and 7. The developed methodologies are fitted for use-cases with small amounts of data available, as it is the case of the reliability assessment of power devices under active cycling. This section summarizes the methodologies and concepts introduced in this thesis:

- methodology for application-aware estimation of the mean lifetime, based on the estimation of the main stress-factor for lifetime, i.e. the maximum junction temperature swing within a fast thermal cycle (ΔT), with electro-thermal simulation; the resulting lifetime model is robust and simple, with only three coefficients to be fitted;

- methodology for estimation of ΔT at different operating conditions, based on electro-thermal simulation, including the approach for calibration of the device electro-thermal model on the package level (not presented here);

- methodology for modeling of ΔT in the space of application operating conditions, also including:
  - application-aware model for prediction of the maximum allowed repetitive energy (E_{R-max}) in active cycling experiments (not presented here),
  - application-aware data-driven models for estimation of time parameters of the power pulse (not presented here);
- methodology for application-aware estimation of the mean lifetime, based on direct data-driven models; the approach is a fast and efficient solution for interpolation estimations when only one failure mechanism takes place in the targeted space of application operating conditions (not presented here);
- methodology for estimation of the lifetime spread/distribution and of the minimum lifetime, based on the introduced concept of using data from different stages of product development and tests (e.g. EP measurements from back-end stage), linked together by means of a small group of electrical parameters (EP) correlated with the lifetime spread, that are automatically determined; the general scope of the methodology is to estimate the degradation spread of a targeted parameter under a stress-test (accelerated or not);
- global Sensitivity Analysis, developed to perform even when it is applied on small amounts of data; apart from the use-case introduced here, the method was successfully applied on other such cases, e.g. to find correlations between EP and Process Control Monitor (PCM) parameters (not presented here);
- methodology for indirectly improving the degradation performance of a targeted parameter under an accelerated stress-test (e.g. HTOL - High Temperature Operating Life), by improving the robustness of other EP, that are automatically determined with the introduced global SA method (not presented here).

8.3 Future Work

Further work can address the following topics:

- extending the use of the application-aware lifetime methodology for characterizing of power devices from other technologies;
- applying the degradation spread estimation methodology in Product Monitoring, for pass/fail prediction or early warning of critical drifts in production;
- in Product Qualification/Characterization: estimation of EP maximum drifts under stress-tests, based on the degradation spread estimation methodology;
- in Product Development: finding influencing factors of EP degradation, based on the global SA method, in order to indirectly improve their performances.

8.4 Author's Publications

1. [PBBP17] - **Ciprian V. Pop**, Corneliu Burileanu, Andi Buzo and Georg Pelz. Application-Aware Lifetime Estimation of Power Devices. In *2017 22nd IEEE European Test Symposium (ETS)*, pages 1–2, May 2017.

2. [PBP+18] - **Ciprian V. Pop**, A. Buzo, G. Pelz, H. Cucu and C. Burileanu. Methodology for Determining the Influencing Factors of Lifetime Variation for Power Devices. In *2018 IEEE 23rd European Test Symposium (ETS)*, pages 1–2, May 2018.

3. [PBD+19] - **Ciprian V. Pop**, A. Buzo, C. V. Diaconu, G. Pelz, H. Cucu and C. Burileanu. Application-Aware Lifetime Model for Power Devices based on Electro-Thermal Simulation. In *2019 IEEE 42th International Semiconductor Conference (CAS)*, pages 177–180, Oct. 2019.

4. [PBP+19] - **Ciprian V. Pop**, A. Buzo, G. Pelz, H. Cucu and C. Burileanu. The Estimation of the Lifetime Variation for Power Devices. ***IEEE Transactions on Device and Materials Reliability***, 19(4):654–663, Dec. 2019.

5. [PBD+20] - **Ciprian V. Pop**, A. Buzo, C. V. Diaconu, G. Pelz, H. Cucu and C. Burileanu. Application-Aware Estimation of the Junction Temperature Swing under Active Cycling. *University POLITEHNICA of Bucharest Scientific Bulletin, Series C: Electrical Engineering and Computer Science*, 2020.

6. [Pop16a] - Ciprian V. Pop. Application-Aware Lifetime Estimation of Power Devices - State-of-the-Art. Technical report, University POLITEHNICA of Bucharest, PhD Report no. 1, June 2016.

7. [Pop16b] - Ciprian V. Pop. Application-Aware Lifetime Estimation of Power Devices - The Methodology. Technical report, University POLITEHNICA of Bucharest, PhD Report no. 2, Dec. 2016.

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9. [Pop17b] - Ciprian V. Pop. The Estimation of the Lifetime Variation for Power Devices. Technical report, University POLITEHNICA of Bucharest, PhD Report no. 4, Dec. 2017.

10. [Pop18] - Ciprian V. Pop. Application-Aware Lifetime Model for Power Devices based on Electro-Thermal Simulation. Technical report, University POLITEHNICA of Bucharest, PhD Report no. 5, June 2018.

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