Robustness Metrics for Automotive Power Microelectronics

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***Abstract*—Automotive power micro-electronics complexity is driven by an ever and ever increasing demand for energy efficiency and safety. As a result of this complexity the error detection latency exceeds practical limits in standard post-silicon validation for mixed-signal power devices and often results in late detection of device failures in the final automotive application. Car manufacturers therefore push for application robustness beyond classical compliance to specification, which requires methods to assess robustness and enable quantification with an appropriate metric with respect to specific mission profiles.**

Though there is a natural understanding that robustness means to be functional under a wide range of operating environments, there is no natural metrics obvious to robustness. We therefore first want to discuss different existing measures of location and spread for use as robustness metric with respect to a device specification and or application mission profile.

The fundamental differences for the assessment of robustness in analog and mixed-signal systems are discussed and robustness metrics for an example battery management system IC with respect to a specification and with respect to a mission profile are calculated. The results show how quantifiable robustness metrics can be derived to assess real application fitness for a semiconductor device or an electronic control unit.

Keywords-component; Automotive Power Micrelectronics, Robustness, Mission Profile, Validation, Response-Surface-Model, Metamodel, Worst-Case-Distance, Process Capability

I. INTRODUCTION

With increasing complexity due to safety and energy efficiency demands automotive mixed-signal power microelectronic devices become increasingly sensitive to changes in their operating environment. They have to operate safe and robust within an increased temperature range, have to withstand an unclean power net environment and this behavior should be guaranteed over the full targeted lifetime.

There is an understanding that compliance with the device specification for such devices is a necessary condition to run in a target application, but not a sufficient condition. The set of quantitative descriptions of partly statistical information about the application is referred to as a mission profile [1]. In a typical specification upper and lower limits for operating parameters may be easily given, e.g. a supply voltage and a temperature range, but the complex timing behavior, system behavior, load behavior is only poorly specifiable. We will discuss the basic relationships between specification and mission profile with respect to performance in Chapter II. It is important to distinguish between a method to perform an assessment of robustness, see e.g. a couple of proposed methods for mixed-signal devices [7, 9, 10], and an appropriate metric for quantification. We focus this paper on robustness for operating parameters like temperature, voltage, etc., i.e. a scalar parameter and its distribution.

In Chapter II we propose qualitative characteristics of robustness measures and discuss known metrics from other fields of semiconductor development for usability as a robustness metrics. We discuss regions of performance for analog and mixed-signal devices in Chapter III and the relationship of these performance regions for assessment of robustness. An application example based on analog and mixed-signal performance for a battery management system IC follows in Chapter III, where quantitative robustness metrics are calculated and we conclude with a summary in Chapter IV.

II. ROBUSTNESS METRICS

Though there is an intuitive understanding what robustness means for the operation of semiconductor devices in a certain application, there is no commonly known metric for the definition. A formal definition is highly desirable for defining and assessing robustness with respect to specification or with respect to a certain application based on a mission profile. There are a couple of metrics in related fields, like design centering, process control and yield engineering with qualities that makes them good candidates as robustness metrics. Though quantitatively different, these metrics are often closely related and can be converted into each other.

As qualitative requirements for a robustness measure we propose:

1. Can be expressed as a single scalar value
2. Must be sensitive to both spread and distance
3. Is convertible to a probability for violation of specification or mission profile
4. Must be applicable to block, device and system level

5. Must be applicable to specification or mission profile

There are a couple of common statistical measures in semiconductor design and manufacturing, which relate the performance distribution of a design, a device or a process to a target specification. In gate-level Monte-Carlo simulations known statistical variations of the process technology are introduced in device models for simulation and the distribution of performance parameters is then observed and judged with respect to a specification. As measure of spread multiples of the standard deviation of the process variations is taken.

Another measure that includes not only spread but also distance was proposed by [3] as Worst-Case-Distance (WCD), which is the minimum distance from nominal performance to the closest specification boundary. WCD is used for design-centering and yield analysis [4] and calculated inside an acceptance region. Robustness can be also quantified and optimized by unifying the distance and spread concepts with the Response Surface Model approach [12].

In semiconductor process control the Capability Process Index C_{pk} and related quantities are an often used performance measure between the spread of a parameter and the distance to a specified border in Six Sigma [5]. These measures are mathematically closely related to WCD.

A measure based on a distance metrics from device failure to specification borders was proposed in [6] as the (normalized) distance from specification border to device failure. This measure is sensitive to distance not spread in a first place, and evaluated outside of the specification or mission profile. In a statistical extension to the base metrics the probability of correct device behavior though operating outside the specification or mission profile is calculated. The applicability of different measures will be discussed in the following Chapter.

All of the above mentioned measures have in common that a distance metric is generated on the space of operating parameters. Any of the proposed measures for robustness requires extensive knowledge of the device performance under a wide spread of conditions. Though we discuss robustness assessment on post-Si and are not limited by simulation time or accuracy, the assessment on silicon device samples is limited by missing observability, small statistics and hardware limitations.

Some of the above mentioned metrics are mathematically closely related or can be converted into each other making assumptions on the distribution. The value of the C_{pk} index for example is three times the WCD in the one-dimensional case. Based on the assumption of a normal distribution, WCD and others can be converted to yield and fallout (in terms of specification). The WCD seems intriguing because it is based on a purely statistical interpretation as a multiple of spread, and there is no need for normalization when mixing different physical quantities. The closely related C_{pk} is already used in the six sigma quality process and certain C_{pk} values relate to standard quality criteria.

III. FROM PERFORMANCE LIMITS TO ROBUSTNESS

Typical specifications for operating conditions and performance parameters span an *n*-dimensional space of upper (USL) and or lower specification limits (LSL), while a mission profile is often a distribution of operating conditions in the application. Robustness assessment must be feasible for such distributions, e.g. from histogram data. For reasons of simplicity we first start with one limit, which could be a specification limit and later extend it to a distribution, which could be part of a mission profile.

We first discuss performance regions of operation for one parameter and assume that we have one operating condition θ and one dependent performance parameter $f(\theta)$, a concept that is easily extensible to a larger dimensional space. Which methods for quantification of robustness can be applied depends on the observability of performance parameters on operating parameters. In simple analog devices a performance parameter is often directly observable on the output; see next Chapter, while in mid-to-high complexity mixed-signal devices, only certain functionality can be observed at the primary outputs.

A. Parametric Performance

Here, we assume the performance parameters to be continuous functions of the operating conditions, see Fig. 1, a behavior often well motivated in the design of individual circuit blocks with relatively few elements, like an operational amplifier or a voltage regulator. Both the operating condition θ has a specification limit θ_S and the performance $f(\theta)$ parameter has a performance parameter limit f_S.

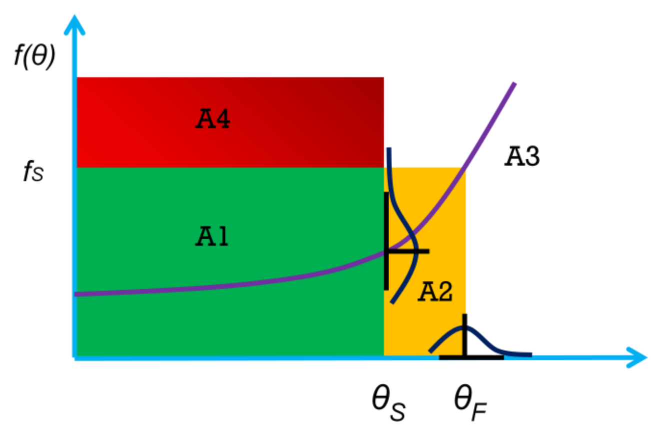

Figure 1: Performance regions one-dimensional analog case, including distribution.

In this case we can identify different regions of performance:

1. Performance is within specification limit and inside specification for operating parameters (A1)
2. Operating parameter outside specification, but performance parameter still inside specification limit (A2)
3. Both operating and performance parameter outside specification (A3)

4. Operating parameter inside specification, but performance parameter outside specification (A4)

From a statistical point of view the points where the performance parameter passes from A1 to A2, and from A2 to A3 are distributed and show the device to device spread. We will later relate robustness to the distribution at these boundaries. Crossing from A1 to A4 is not considered for any robustness assessment, because in this case the design would violate the performance specification even when being operated under valid operating conditions and thus requires a re-design.

B. *Functional Performance*

In many practical mixed-signal device cases it is not an analog parameter that is specified as performance, it is rather certain functionality, and e.g. cell balancing is working for a set of given operating parameters. This problem is even more severe for post-Si assessment of robustness, when device internal signals cannot be observed at all. In this mixed-signal case the regions of performance are:

1. Operating condition inside specification and device functional (A1)
2. Operating condition outside specification, but device still functional (A2)
3. Device fails outside specification (A3)

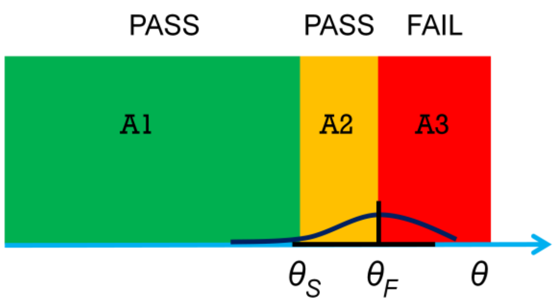

Figure 2: Performance regions for functional performance only.

In contrast to the parametric case, it is not possible to observe the distribution $f_S(\theta = \theta_S)$ and derive robustness information, only $f_S(\theta = \theta_F)$ is observable and its probability density function (PDF) can be estimated, which means that a robustness assessment needs to go beyond specification. For post-Si assessment of robustness this may mean to operate the device in a potentially destructive environment, e.g. when the operating condition θ is a temperature or a current higher than allowed.

Also the method to observe and extrapolate device behavior differs significantly from parametric to functional performance. When we assume the parametric performance to be a continuous function of the operating parameters a response surface model (meta-model) of the design performance can be extracted and subsequent robustness assessment can be based on this meta-model, this method cannot be applied to the discontinuous performance space for functional performance.

IV. APPLICATION EXAMPLE

A typical Lithium-Ion (Li-Ion) battery designed for the latest generation of Electrical and Hybrid Cars consists of several cells connected in series (to increase the overall voltage). Each single cell may be connected to further cells in parallel (to increase the overall capacity). The battery is usually divided in stacks made of 12 cells connected in series.

The energy efficiency achieved by managing the battery stack with a dedicated Battery Management System Integrated Circuit (BMS IC) is a crucial factor for the success of electrical cars.

A typical BMS consists of a micro-controller and power electronics device for cell voltage monitoring and active or passive cell balancing, see Fig. 3. The micro-controller communicates with the battery management power device using a digital interface, e.g. LIN, CAN, SPI, MSC or proprietary digital interfaces. It is of crucial importance also for safety reasons, that each block, each device, but also the full system is robust. In this application example the system robustness is evaluated first based on a VHDL-AMS system-level model and second evaluated for the physical layer communication layer in post-Si.

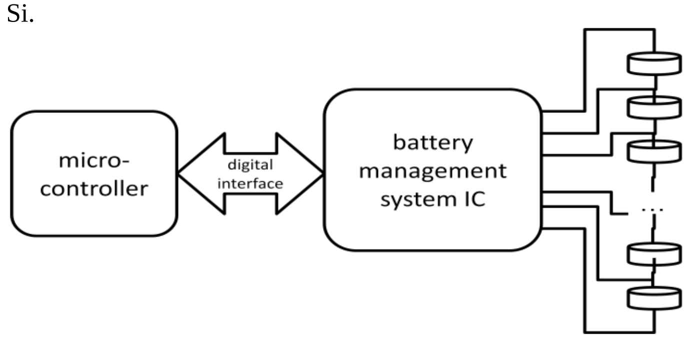

Figure 3: Schematic of a battery management system including micro-controller, battery management system IC and cell stack.

The VHDL-AMS system-level model consists of 40Ah Li-Ion automotive cell models, MOSFET models as well as a transformer model. More details will be given on the system in what follows.

A. *Parametric Performance Parameters*

First the cell balancing is briefly introduced then the relevant related parameters, as well as the investigated performance parameter, are described. Finally the pre-Silicon simulation results are presented and interpreted.

a. Cell Balancing

Li-Ion cells are very susceptible to damage outside the allowed voltage range. If the upper and lower voltage limits (e.g. 2V and 3.6V for nanophosphate types) are exceeded, the cells may be damaged irreversibly. Practically this means that if several serially connected and fully charged cells with dif-

ferent capacities C become discharged, the cell with the lowest C is the first which reaches the discharging voltage limit. Although all the cells are not all completely discharged, the discharging process must stop immediately to avoid damage on the weakest cell. This applies during the charging process as well: the first cell which reaches the upper voltage limit makes the charging process stop, thus preventing the other cells from being fully charged.
This leads to unused capacity, which in turn leads to, among others, reduced driving range, which is not acceptable.

To overcome these limitations, the cell charges within one stack must be equalized. The most efficient way is to move energy between the cells within the stack in order to keep them equally charged, meaning at some extend at the same voltage. This process is called active balancing.
The active balancing approach developed by Infineon, as described in [11], consists in transferring charge from the cell with the largest voltage to the cell with the lowest voltage using an inductor as a short-time energy storage, thus storing the energy by mean of a magnetic field. For this purpose a dedicated fly-back converter has been developed to move the energy either from one cell to the whole stack (top balancing) or from the whole stack to one cell (bottom balancing).

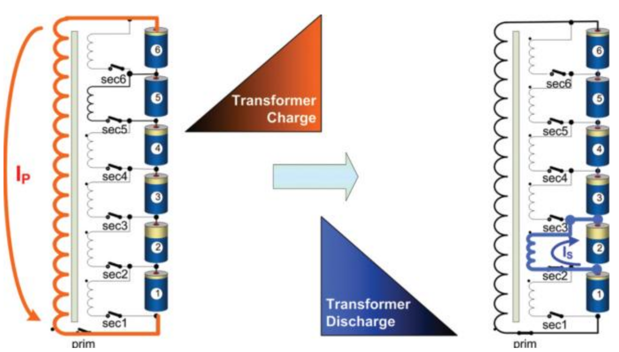

Figure 4: Bottom Balancing Principle

b. Functionality and Parameters

The Bottom Balancing scheme, as described in more detail below and illustrated in Fig. 4, is investigated in this paper. While the primary side is charged (the switch “prim” is closed), the primary current rises linearly. The charging time is determined and settled by the IC in order to reach the targeted primary current at the end of the charging phase (switch “prim” is then open). Then the secondary is discharged (switch sec2 is closed) in the weakest cell. The transformer turns-ratio determines the current flowing out of the secondary side. From this value on the current is decreasing linearly. When the secondary current reaches 0A the primary starts being charged again and the whole process restarts.

The performance parameter investigated here is energy transferred from the whole stack to the weakest cell. Many contributors degrade this performance. Practically speaking, the intended secondary current does not flow completely in the targeted cell, but some parts are diverted back to the other cells.

The most obvious degrader is the parasitic diode of the secondary switches. Indeed the switches are made from MOSFETs and their body diodes will conduct current back to the battery stack while the switches are closed, and the secondary being discharged.
Another degrader is the parasitic inductance of the cell, to which the wire inductance adds, which in a first place prevents the current from flowing into the targeted cell.

A further parameter is the $R_{DS,on}$ resistor of the Primary Side MOSFET switch, which directly impacts the currents flowing through the transformer and thus the energy efficiency
A last parameter considered here is the State of Charge of the cells in the stack, meaning the total battery stack voltage. This one impacts the currents again and thus the energy efficiency.

The varied parameters and their value ranges are listed in the following table:

Parameter	Description	Value Range
L [H]	Wire + cell inductance	150n-900nH
Rds [Ohm]	On resistor	4m-10mOhm
Vbat [V]	Stack voltage	43.6-52.4V

Table 1: Varied Parameters

The energy flowing into the transformer is proportional to the primary current integrated over time during the charging phase (designated by “energy_prim”). The energy transferred to the targeted cell is proportional to the secondary current integrated over time during the transformer discharging phase (designated by “energy_sec”). The performance parameter is the ratio of these two parameters (designated as “energy_ratio”), defined as:

$$energy\_ratio = \frac{energy\_sec}{enery\_prim}$$

c. Simulation Results

First some functional simulation results are presented to illustrate the bottom balancing energy efficiency performance. Then the Robustness-oriented statistical simulation results are presented.

The simulation results presented in Fig. 5 show two transformer charging-discharging cycles. Three Simulations are performed, one for L=1nH, another one for L=1µH and a last one for L=10µH. Moreover the theoretical secondary current (in case no current loss would have occurred) is represented by a dashed triangle for the second cycle. The 10µH value is rather unrealistic from a system implementation point of view, but illustrates pretty well the impact of L on the energy efficiency. Indeed L prevents the current from flowing through the dedicated cell and the bigger L is, the less current will flow. For L=1nH this effect is inexistent: the “missing” current is diverted through the body diodes of the 11 un-targeted switches which are opened.

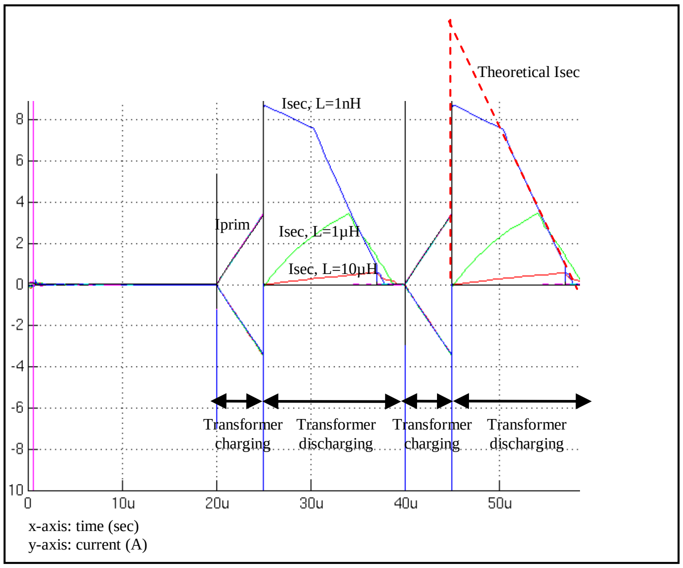

Figure 5: Bottom Balancing Functional Simulation Results

The Fig. 6 shows statistical simulation results used to perform the robustness evaluation. 100 runs have been performed.
The three input parameters presented in the Table 1 are normally distributed and the two parameters “energy_sec” and “energy_ratio” are derived from the simulation results.

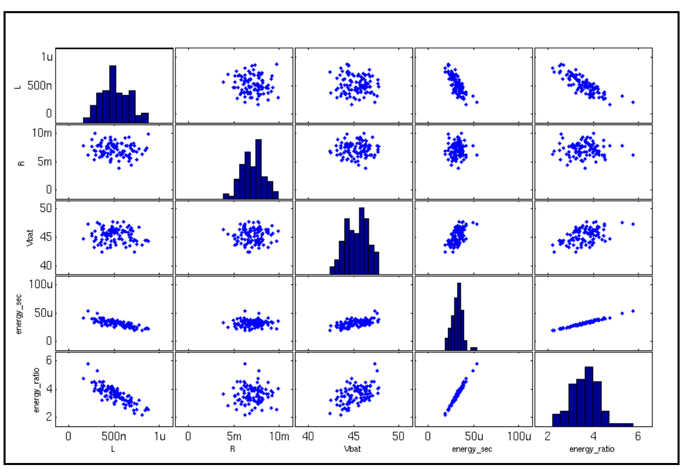

Figure 6: Bottom Balancing Statistical Simulation Results

1) Robustness with respect to specification

A second-order response surface model based on the Monte Carlo sampling for energy conversion efficiency as performance parameter is extracted first to start the robustness assessment.
A second-order polynomial model for $E = E(L, R_{DS,on}, V_{BAT})$ provides a good trade-off between mathematical complexity and model accuracy. First order models would only be capable of representing linear effects. For a linear model the worst case must be a corner point, and then a corner test would be the simplest way to find the worst case. In third order or higher order models there is no general analytical solution for local minima and maxima and numerical methods would have to be used. For second order polynomials instead extrema can be calculated from solving the Jacobian of the model equation, while an eigenvalue analysis of the Hessian matrix of the model equation is suitable to determine if the extrema are minima, maxima or saddle points.
We thus found from the Hessian matrix that a saddle point exists, no performance minimum or maximum. This means that both worst and best case performance must be a corner case, see Fig. 7.
While it is important to know the best case to estimate optimal system performance, we are rather interested in the worst case for robustness assessment with respect to specification. We take an energy efficiency of $E = 1.0$ as lower specification limit, because below 1.0 the cell loses energy. Based on mean and spread of the performance data we can now calculate

$$\mathrm{WCD} = 4.29,$$
$$C_{pk} = 1.43,$$

as a measure for robustness. Here robustness would be assessed medium high in general terms.

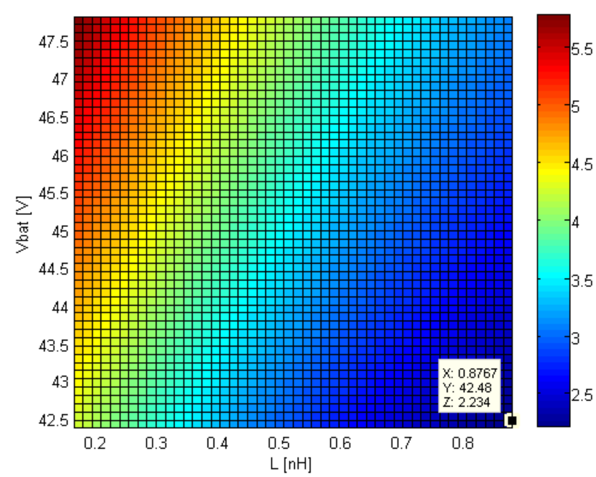

Figure 7: Visualization of the response surface model of the battery management system. Energy efficiency color coded as a function of inductance and battery voltage. In this case best and worst case performance is a corner case.

B. *Functional Performance Parameters*

As an example for the assessment of robustness for functional performance parameters we want to discuss the digital communication part of the above presented battery management system IC. The number of input parameters for the physical interface layer often exceeds 10 independent operating parameters for timing and level; robustness assessment is therefore a non-trivial task.

In the given example a microsecond-channel interface was to be tested for robustness. The robustness assessment was split into the steps: assessment – identification – robustness estimation:

1. Conduct system Monte Carlo tests on an appropriately automated test system,
2. First identification of most important failure-related parameters
3. Calculation of robustness metric with respect to specification and with respect to a mission profile

In a first step, due to the large dimensionality of the input parameter space a Monte Carlo approach has been chosen with 10.000 sample points to sample the functional performance over the input space of independent operating parameters [8]. The sample space was chosen to exceed the specification space in order to be able to assess robustness according to the observation described in Chapter II. An automated lab system was set-up and has been run for several hours to gather the conditions based on the Monte Carlo sampling. Here, functional performance was assessed as successful write and read operations to configuration registers of the device under test.

The result set of the Monte Carlo tests is a binary function of $f(\boldsymbol{\theta}) = 0$ for fail and $f(\boldsymbol{\theta}) = 1$ for pass and a function of the *n*-tuple

$$\boldsymbol{\theta} = (\theta_1, \theta_2, \ldots, \theta_n),$$

that is formed by the n independent operating parameters, where each θ_i is uniformly distributed.

While the device passes all tests under specification conditions, it has been observed that it fails with ~0.1 % overall probability in the extended range outside the specification area, which corresponds to performance region A3 in Fig. 2. Though in classical verification the device would thus be declared specification compliant, the robustness analysis now takes the width and spread of the observed failure region into account.

Therefore, in a second step, a correlation analysis, see matrix correlation plot in Fig. 8, shows, that the interface is more likely to fail for a specific combination of interface levels. The robustness assessment can be reduced to these two parameters, their correlation and their relation to the specification.

Then, different metrics for robustness have been evaluated in the context of the specification window and in the context of a distribution according to a mission profile.

1) Robustness with respect to specification

In order to apply the above mentioned metrics for robustness we propose to estimate the *n*-dimensional probability density function (PDF) inside the verification space based on the *n*-tupels, when $f(\boldsymbol{\theta}) = 0$ for fail and $f(\boldsymbol{\theta}) = 1$.

In our example the PDF for failure was estimated using an *n*-dimensional histogram method, based on the assumption that the distribution is approximately normal. We want to point out, that a significant deviation of the real performance distribution from a normal distribution can lead to a significant over- or underestimation of robustness. In this case also the type of distribution should be assessed first. In Fig. 9 the normalized specification borders and isoclines for the PDF for failure are visualized.

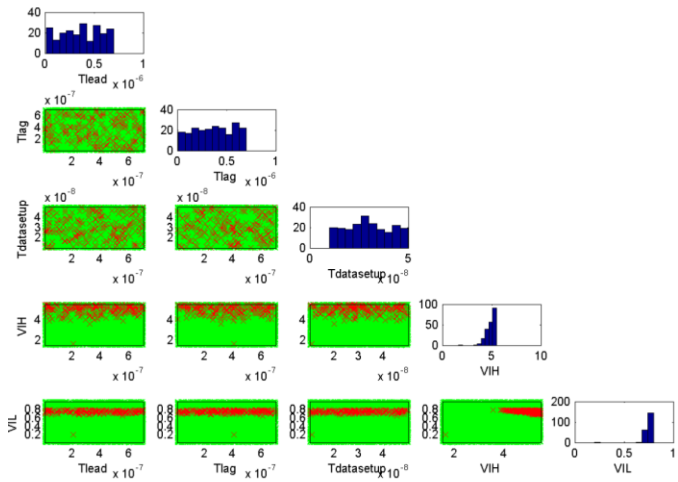

Figure 8: Matrix Plot for Monte Carlo data showing on the main axis the distribution of failures with binning on one parameter and on the lower half failure conditions (red) and pass conditions (green) for combinations of 2 parameters. Failures correlated to a set of parameters (lower plots) will show as non-uniformly distributed and are interesting for root-cause analysis of a failure related behavior, while irrelevant parameters result in a uniform distribution (upper plots). In this case failures are correlated to level parameters VIH and VIL.

With the estimated PDF and the specification borders the Worst-Case-Distance has been calculated

$$\text{WCD} = 2.6107$$
$$C_{pk} = 0.8702$$

With the given C_{pk} the estimated failure probability inside specification is 0.9%.

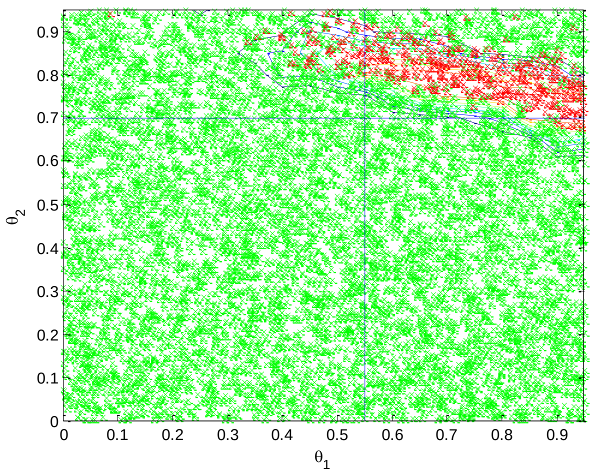

Figure 9: Estimation of PDF for failure (blue lines). Normalized specification boundaries and pass and fail *n*-tuples are shown (green and red crosses). θ_1 = input high level, θ_2= input low level.

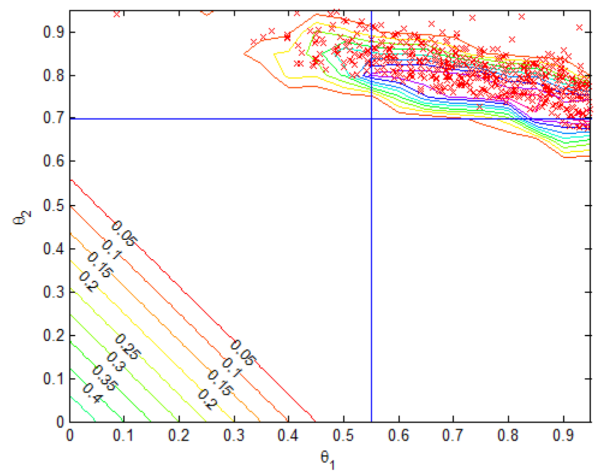

Figure 10: PDF for failure and visualization of mission profile with relative probability of system being in the lower left range. The given mission profile takes the system consideration into account, that it gets more and more unlikely that the input levels are skewed with respect to supply voltage. It is obvious already from the visualization that robustness in the application is much larger than expected from the assessment with respect to specification (Markers for passing conditions have been removed for better visibility).

Based on this WCD the final sample assessment of robustness with respect to specification was given as: Though there have been no functional failures observed inside the specification area, the robustness of the design is low with regards to the full specification area. We will see how the assessed robustness dramatically changes, when a mission profile is being added to the verification space.

2) Robustness with respect to the mission profile

The observed sensitivity of the sample device refers to input voltage levels on a digital receiver circuit. Both input levels may vary based on the spread of the driver performance of the micro-controller, but it can be excluded from an application point of view, that both the input low level and the input high level of the input signal are high with respect to the supply voltage.

Therefore a mission profile has been added and the robustness of the device under test was now assessed taking the mission profile into account, see Fig. 10. The applied mission profile in the given example is based on the assumption that a large asymmetric skew of the receiver input high and low levels is unlikely and would require a large ground shift between transmitter and receiver, while a degradation of the input level swing is more likely from a system point-of-view. A mission profile is often based on histogram data from application measurements or some other known correlation between operating parameters.

In this case the WCD with respect to the mission profile has been calculated with respect to the distance, where the mission profile predicts a negligible likelihood of occurrence for combinations of input levels, and evaluates to:

$$\text{WCD} = 16.98$$
$$C_{pk} = 5.66$$

The final quantitative robustness assessment with respect to the mission profile was: Due to the very high WCD the design is very robust with respect to the mission profile and expected failure far below 1 ppt.

V. SUMMARY

Robustness to changes in the operating environment of the automotive application is a crucial quality factor for automotive power devices, especially in the field of e-mobility. There is currently not a clear quantitative metric available for the assessment of robustness.

In this article we propose and discus several metrics for the quantitative assessment of robustness with respect to specification or mission profile. We observe fundamental differences for robustness assessment on analog devices and mixed-signal power devices.

We applied candidate metrics to a battery management system IC, both on system simulation side for analog performance of the active cell balancing and for parametric performance of the digital interface to the uC on post-Si side.

For robustness assessment on analog system level we successfully extracted a response-surface model based on Monte Carlo sampling of the input parameter space and calculated Worst-Case Distance and C_{pk} values.

For robustness assessment of functional performance on post-Si, we conducted again a Monte Carlo sampling. From the Monte Carlo data the probability density function for device failure was estimated. Then, as final assessment based on calculated Worst-Case Distance and C_{pk} values the device is considered robust with respect to the mission profile, but vulnerable with respect to the specification.

Respective	Specification	Mission Profile
WCD	2.6107	16.98
C_{pk}	0.8702	5.66
Six Sigma	Not compliant	Compliant

We see also from the Six Sigma reference, how the assessment dramatically changes, when quantifying the robustness with respect to specification or mission profile.

We propose to add quantitative robustness measures based on the proposed metrics to design automation and verification tools, in order to get quantifiable information about the design. The assessment gets more reliable if additional information in the form of mission profiles are taken into account and can avoid overdesign and estimate real application fitness.

VI. Acknowledgements

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