Model-Based Reliability Analysis

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***Abstract*—Testing has typically been a key means of detecting anomalous performance and of providing a foundation for estimating reliability for weapon systems. The objective of model-based reliability analysis (MBRA) is to identify ways to capitalize on the insights gained from physical-response modeling both to supplement the information obtained from testing and to better-understand test results.**

Five general MBRA processes are identified which can capitalize on physical response modeling results to make both quantitative and qualitative statements about product reliability. A case study that explores 1 of these 5 processes was completed and is described in detail. It had the benefits:

- **MBRA can be used to determine a performance baseline against which current and future test results can be compared.**
- **During the design process, MBRA can provide tradeoff studies such that development time and required test assets can be reduced.**
- **MBRA can be used to evaluate the impact of production and part changes, as well as aging degradation, if they arise during the product life cycle.**
- **MBRA lays the foundation to evaluate anomalies that are observed in a test program. Typically it has been challenging to determine how anomalous behavior can manifest itself under different—but still valid—conditions. One can use modeling to inject hypothesized behaviors under different conditions and observe the consequences.**

***Index Terms*—CAD/CAE/CAM/CIM, design margin, electrical modeling, life prediction, modeling, SPICE, weapon system.**

ACRONYMS[1]

BERT	Berkeley reliability tools
C	centigrade
DMA	design margin analysis
ESD	environmental sensing devices
LHS	Latin hypercube sampling
MBRA	model-based reliability analysis
PS	product specification
SNL	Sandia National Laboratories
SPICE	simulation program with integrated circuit emphasis
STS	stockpile-to target sequence
TSSG	trajectory sensing signal generator

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[1]The singular and plural of an acronym are always spelled the same.

I. INTRODUCTION

RECENT improvements in physical-response modeling capabilities coupled with declining resources for development and qualification of new product, causes one to examine new means by which nontraditional data and knowledge obtained from modeling can be used to make inferences about reliability. The purpose of MBRA is to identify the areas where modeling can supplement the current reliability assessment methodology, which is based primarily on using product test data obtained at various levels of assembly and under various environmental conditions.

Five general areas by which modeling can assist in reliability analysis are described. Then a specific case study applying one of the elements of this framework to a weapon component is described. The insights gained, as well as the limitations and caveats of the MBRA approach, are discussed. Finally, the next steps in the MBRA project are delineated.

The initial application for MBRA has been the simulation of electrical systems using a variant of the SPICE code. There is a large body of existing literature on the use of electrical-circuit physical-response modeling in the context of reliability. Many of the tools and techniques share the following 2 characteristics:

1) Focusing on modeling at least 1 time-dependent failure mechanism at the transistor or integrated circuit level.
2) Allowing incorporation of these time-dependent effects into relatively simple circuits.

A review article [1] highlights the current state of the tools and capabilities. The most widely used of these tools is BERT [2], which offers analysis capabilities for several classes of failure mechanisms in the context of a circuit. There are many published applications and extensions of BERT [3]–[7]. There are numerous other modeling tools that examine a single time- or temperature-dependent failure mechanism [8]–[12], also in a circuit context. There are also many modeling approaches for examining time-dependent behavior of selected electrical devices, e.g., [13], [14]. To our knowledge, MBRA is unique in its approach of examining both static and time-dependent behavior in the context of system-wide variability.

II. BACKGROUND

The role of modeling in the reliability analysis process at SNL is driven by

- the nature of the product being analyzed,
- the specific way in which SNL defines reliability,
- the product test program,
- the current assessment approach.

The products are weapon systems that spend much of their multidecade lives in dormant storage. Although some of the subassemblies can be operated repeatedly, the weapon system is essentially a 1-shot device. Further complicating the reliability analysis is that, due to treaty limitations, the weapon systems cannot be fully exercised.

The customer for these systems wants to know the reliability of the weapon systems in the operational context. Thus reliability is defined as:

The probability of achieving:
- the specified explosive output ("yield"),
- at the target,
- across the STS environments,
- throughout the weapon's lifetime.

Conditions:
- The specified inputs and conditions at the interfaces are present.
- The normal environments specified by the STS have not been exceeded.
- The specified lifetime has not been exceeded.

The STS defines the various environments to which the weapon system could be exposed during its normal lifetime, and includes transportation, handling, storage, and operational use environments. The types of environments experienced range from mechanical vibration and shock, temperature, and humidity to ionizing radiation.

There are some challenging consequences of defining reliability in this fashion. The definition implies that we must assume that $\Pr\{$exposure to the worst-case set of normal STS environments$\} = 1$. A realistic lower bound on reliability is needed that applies to the entire range of conditions that the weapon system can experience. Hence the test program must span the range of environmental conditions as well as the set of weapon operational capabilities. This results in a very large state space to explore, particularly when the "throughout the lifetime" constraint is added. This is shown in Fig. 1. Each test that is performed gives information about a very limited area of this state space. Modeling can be important in leveraging these test data by allowing extrapolation of these test results to an expanded set of conditions.

Another challenge posed by the reliability definition arises in how success is defined. The desire to relate success to "yield at the target" when such a full-up test cannot be performed means that success must always be inferred. Ideally, pass/fail specifications for testing at each level of assembly are tied to this high-level definition of success, but this is difficult in practice. Here again, modeling can be important in developing test specification limits that are better related to system success.

In the context of multidecade weapon-system lifetimes, degradation due to aging is a concern. There is a major program at SNL examining age-related changes of materials and pieceparts to provide a predictive capability. One of the important challenges of this effort is relating any observed degradation at the material and piece-part level to weapon-system performance (yield at the target). These degradation mechanisms can be pervasive throughout a system, further complicating the analysis. These inferences are difficult, and modeling provides an avenue by which the impact of these changes can be evaluated in a system context to determine if they affect reliability or simply reduce design margin.

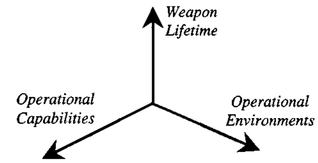

Fig. 1. Weapon system reliability state space.

The current reliability assessment approach uses data from a broad set of tests that are performed at various levels of assembly, under various environmental conditions, and with various operational objectives. This test diversity allows for defect-detection across the state space, but it also means that not every test can detect each of the defects present in the weapon systems. The reliability analyst must decide which test data are relevant when doing an assessment. This in turn requires an in-depth root-cause analysis for each defect to help determine whether or not it could be detected in each of the test programs. Modeling provides an excellent avenue to assist with the root-cause analysis. Modeling can also be used to evaluate the generalized effect of an observed anomaly; through modeling, one can vary the characteristics of an anomaly, such as its severity or where it is manifested, to examine its impact in a broader sense.

In summary, the current reliability assessment approach is based upon a diverse test program in which root-cause analysis plays a key role. The desire to capitalize on the information obtained through modeling (to aid in prediction of the impact of aging phenomena, to supplement the existing test data, and to understand better the data already acquired) is the motivation behind the MBRA effort. This is particularly important because resources for testing are becoming scarcer.

III. MBRA Framework

To develop the MBRA framework, reliability activities as a function of product life cycle were reviewed, and areas where the capabilities provided by MBRA could be applied were determined. This review identified 5 general MBRA processes:

- DMA
- Specification Limit Analysis
- Lifetime Prediction
- Anomaly Investigation
- Probability Quantification.

These are areas where physical-response modeling can be important in providing cost-effective insights into reliability.

A. DMA

DMA has, perhaps, the lowest technical risk of any of the processes with potentially a large payoff. It can be used at almost any stage of the product lifecycle when there is a desire to either quantify or to improve the performance margin of a system or subsystem. In MBRA, physical response modeling (in conjunction with validation testing) is used to explore the performance state-space of a system and to identify key contributors to performance. DMA serves as a foundation for each of the other MBRA processes.

Design margin for weapon systems has historically been determined (and improved) using an iterative process. A design is generated, and then development hardware is built and characterized. The amount of design margin is dictated by the requirements, but generally these continue to be negotiated during the design and development phase as the actual capabilities of the hardware become clearer. The process of finalizing requirements can be prolonged as the design evolves.

The key difference in the new MBRA approach is that modeling is used to explore the state space in a systematic manner rather than relying on small quantities of hardware tests for which conditions are difficult or impossible to control. The proposed process is described here for a particular example: determining the margin of an electrical subsystem using the SPICE tool. The approach is similar for other modeling disciplines and could be extended to multidisciplinary modeling when technically and computationally feasible.

Proposed Process:

1) Identify scope of analysis.

   Identify the hardware to be analyzed, as well as the interfaces (electrical sources and loads) that could influence the behavior of that hardware. The case-study approach was to emulate, to the degree possible, the production acceptance test conditions (including inputs, loads, environments, monitoring points, specific measurements, and the range of allowable values for those measurements) that are detailed in the PS document. This helped to delineate clearly the scope of the modeling effort.

2) Identify key response variables.

   Identify the key outputs of the hardware that require analysis. Existing test definitions can also provide helpful guidance in this step. For the case study in Section IV, the PS documents were used to identify the key response variables.

3) Plan variability study.

   Identify input parameters that could be contributors to the variability of the key response variables. These input parameters are generally device attributes, such as the resistance of resistors. Some semiconductor devices can have a large set of input parameters that describe their behavior. Then one must determine the phenomenologies of interest. For electrical circuits this could include temperature, ionizing radiation, and aging. These are the conditions which one wishes to vary to determine their effect upon the key response variables. In all cases, tolerances of electrical parts should be a part of the analysis unless explicit rationale is given to exclude them. These tolerances can also be coupled with the phenomenologies, e.g., tolerance bands might change with temperature. Finally, determine the range of interface conditions to be analyzed; these too can depend upon the phenomenologies, e.g., circuit loads might change with temperature.

4) Gather needed device-model data.

   Based upon both the nature of the analysis and the phenomenologies of interest, appropriate SPICE models for the devices must be obtained. For this step, one must also make any needed assumptions about parameter distributions and whether any input parameters are correlated. Both of these are important in ensuring that the output variability is based upon realistic input parameter ranges and combinations.

5) Develop model and validate.

   The device models must be combined into a subsystem model having the proper scope. The subsystem model must be exercised to ensure that it works properly and yields correct results. This is often done by comparing model results with results of testing performed under nominal conditions. Full model validation requires further study. To some extent existing test data can provide validation information, but generally it is highly advantageous to design an experimental program tailored to the validation exercise at hand.

6) Run variability study.

   One can use Design of Experiments, Monte Carlo approaches, Response Surface Methods, etc., to analyze design margins. Each has specific advantages and disadvantages. To date LHS has been used for MBRA. LHS is a type of stratified Monte Carlo sampling that helps ensure efficient coverage of the input parameter distributions. LHS is used in the case study to select values for each of the input parameters of interest (e.g., the resistance value for each of the resistors) to build the set of simulation runs. These input vectors are then embedded into SPICE netlists and executed. The output of the SPICE transient analysis tool is a set of waveforms for each of the circuit nodes describing behavior (current and voltage) as a function of time. Since generally a single attribute of the waveform (such as maximum value or rise time) is desired to characterize the response, customized post-processing software is needed to extract the attribute of interest from the waveform data.

7) Analyze results.

   One of the major outcomes of a design-margin study is a histogram of the values that the key response variables can assume. Other useful calculations include correlation coefficients that help to identify the key contributors to the output and its variability. It is very helpful and prudent to examine the scatter plots that show the relationship between each of the input parameters and each of the response variables.

These results can be used in three ways.

a) To identify meaningful specifications for the subsystem being analyzed (this is described in more detail in Section III-B).

b) To target improvements. Parameters that affect the output variability most can perhaps be screened to minimize the variability they contribute; alternatively, other parts can be selected that demonstrate more stable performance. This analysis might set the stage for a circuit optimization study once the key contributors to the outputs have been identified.

c) The modeling performed during the DMA process provides a foundation for future analyzes, such as lifetime predictions or anomaly investigations (described in Sections III-C and III-D).

There are several anticipated benefits of using the MBRA DMA process. It can provide focus for resource allocation, aiding in decisions about what parts to upgrade or screen. It can also be used to evaluate the impact of production and part changes if they do become necessary. Most importantly, the design margin will be improved. Although this might not be a quantifiable reliability improvement, it is obviously desirable and makes the subsystem more resilient to changes in external conditions and changes over time.

There are three risks in using this process:

- The model might fail to include all parameters that influence output and output-variability.
- The parameters that are included might not have their variability quantified correctly.
- Failure to identify existing s-correlations between input variables can cause misleading results.

B. Specification Limit Analysis

One of the variants of the DMA process is setting realistic test specification limits. This could result in appreciable cost savings. The cost of overly conservative specification limits can be very high due to: excess scrap and rework, unneeded inspection and screening, and selection of more expensive parts. Specifications that are not tight enough can lead to unanticipated failure; even worse, these unanticipated failures might not be easily detected in a test program.

There is an important reliability implication to setting specifications. As mentioned in Section II system success or failure must be inferred by comparing subsystem performance to the specifications, because full-up tests cannot be conducted. There have been numerous anomalies for which the focus of the investigation was understanding how realistic the specifications were and whether they really related to system success/failure. The subsystem might have failed the specification limit but would not have prevented the system from working. These investigations can be very costly and time-consuming.

Currently, specification limits for subsystems are negotiated using a combination of “knowledge gained through development hardware characterization” and the “bounds dictated by the interface requirements.” This is an evolutionary process and can lead to overly stringent requirements because of the limited data available.

The MBRA Specification Limit Analysis builds on the DMA process. The first step in establishing specifications is quantifying the design margin of the subsystem as described in Section III-A. Using the information derived from that exercise, specification limits can be defined. First, the acceptable output level must be determined. This is based on both the interface and operational requirements. Then specification limits can be placed on the parameters, focusing primarily on those that contribute most to the output and the output variability. During this process, it must be determined if variability needs to be reduced (and if it can be reduced) or if additional margin is needed. If variability can be reduced, it might be possible to return more margin to the system, allowing another subsystem to have greater variability.

C. Lifetime Prediction

Lifetime is a key decision-making and resource-allocation metric for weapon systems, and improved means of predicting the impact of age-related changes are critical. The MBRA approach allows incorporating models of material or piece-part degradation into a subassembly- or system-level context. This also provides a framework to evaluate pervasive aging throughout the system, e.g., if multiple pieceparts are changing with time.

Lifetime prediction is necessary:

1) During design development. The most obvious issue is that of the need for planned replacement for components that are known to have a limited life. A combination of testing and analysis has been done to determine if planned replacement was needed and when it would be needed.
2) During investigation of an anomaly. It is necessary to determine if the anomaly is time-dependent. If it is, the anticipated failure probability as a function of time must be estimated such that a decision regarding corrective action can be made. Again, testing and analysis have been relied upon to answer these questions. Because unanticipated retrofits are costly and difficult, credible and accurate lifetime prediction is essential.

The MBRA approach capitalizes on modeling aging behaviors that can be done at either the basic material or piece-part level. The 4 process-steps are:

1) Analyze the subsystem or system for key contributors using the MBRA DMA process. Parameters should be included that are prone to variation and/or are suspected to affect system output and variability.
2) Develop a model of behavior as a function of age. This can be physics-based and/or empirical. Although it will often be at the piece-part level, it could be at any level of assembly: piece-part, printed wiring board, subsystem, or system.
3) Incorporate the models developed in step 2) for all critical age-related variables as identified in step 1), into a subsystem or system model.
4) Exercise the model as a function of time and examine the outputs to see if specifications are not met at some time point. This will predict lifetime. This could then be extended to examine reliability as a function of time.

This process allows for more informed choices of materials and parts during design, based on the MBRA modeling results. Critical parameters can be identified for on-going monitoring. There is a much better understanding of design margin as a function of age, and cost/lifetime tradeoff studies can be performed.

D. Anomaly Investigation

Physical-response modeling is a good choice for investigating anomalies, and a variety of tools have been used for this application. Modeling is a cost-effective way to:

- perform root-cause analysis,
- examine the effect of an anomaly in a general sense,
- identify fixes.

Modeling can also help to focus on what tests need to be performed and how to perform these tests.

MBRA offers a more formalized approach to modeling in the context of anomaly investigation, as well as integrated tools to perform the analyzes. The process in this paper has three steps:

1) Develop a model with adequate detail (as for the DMA) to emulate the anomalous results.
2) Postulate root-causes and inject them into the model; compare with the observed anomaly and add to the list of possible sets of anomalous behavior if they are similar.
3) After generating a set of anomalous behaviors, it is necessary to determine their impact. Recall that specific anomalies themselves might not lead to system failure. However, they might be indicators that other units similarly afflicted could be failures due to different environments or different interface-conditions. Thus a critical role of modeling is taking each anomalous behavior and developing a generalized view of its impact. Each type of anomalous behavior should be explored *vis-a-vis* the sources of variability, the different environments that can be anticipated, and the interface conditions that might be experienced. Any time-dependence must also be examined. The relevance of this anomaly to other parts or technologies must be examined to identify any other impacts.

There are important advantages to this proposed approach. Modeling is a much less expensive way to gain insight than testing. Parameters are easily controlled, and monitoring can be done unobtrusively. The ability to inject faults without otherwise affecting performance is particularly useful. Typically it has been challenging to determine the generalized impact of an anomaly: how the observed anomalous behavior can manifest itself in other components, under different environments, and for other weapon capabilities. Use of a modeling framework allows easy injection of the behavior under these different conditions to observe the consequences. This would be prohibitively expensive to do with hardware in most cases.

E. Probability Quantification

Probability quantification is the culminating step of MBRA, but it also carries with it the highest technical risk. In order to use physical response modeling results directly to make reliability statements, it is essential to minimize uncertainty in the results and to ensure that all salient factors are included. The results must be highly credible when major allocation of resources can be at stake. It is anticipated that initially the MBRA process for probability quantification will be used sparingly or in conjunction with other methods until its credibility is validated.

Probability quantification builds on the other MBRA processes, most importantly the DMA. It is more demanding, though, in the sense that one can tolerate uncertainty in design margin analysis because the goal is typically understanding relative (rather than absolute) margin.

The probability quantification process in general is very similar to that used for the DMA. However, the final step is to compare the output distributions of the key response variables to specified success/failure criteria to determine reliability.

There are several risks to probability quantification. The need for high credibility has already been discussed. Understanding the sources and magnitude of the uncertainty is an enormous technical challenge. The cost to validate the model results could be substantial. There is always a risk that the model has not captured all of the key factors. These could lead to misleading results and improper allocation of resources.

Despite the technical challenges noted here, we strongly recommend that this process be explored thoroughly. A careful approach with thorough consideration of uncertainty is essential.

IV. MBRA Case Study

The MBRA DMA process was used to examine an electromechanical device used in a weapon system. Results to date are described in this section, along with the details of the approach.

A. Focus of the Analysis

The device being examined is a TSSG, and is a member of the general ESD class of components designed by SNL. These are very specialized devices whose purpose is to detect an actual use environment and then to cause contacts to be closed, allowing for weapon operation. In the absence of the actual use environment, these devices “reject” other environments and the contacts remain open. An ESD helps to ensure that the weapon system does not operate except when intended.

The function of the TSSG is to detect an acceleration of a certain level and duration, upon which a relay is closed. This relay then provides an electrical path for 2 coded pulse-trains that are amplified by the TSSG before being sent to an electromechanical rotary switch that causes contacts to be closed upon receipt of the proper pulse-trains. The TSSG senses acceleration using a rolamite (a mechanism consisting of rollers and a flexible band); the duration of the acceleration is measured using a simple resistor–capacitor charging circuit as a timer. The 3 general functions of the TSSG are thus measuring: acceleration, timing, and amplification.

TSSG has been fielded for almost 20 years; thus there are extensive test-data available including:

- 100% production acceptance tests,
- sample production acceptance tests at environmental extremes,
- sample testing done as part of the on-going surveillance program at SNL.

The TSSG Product Specification was used to define the scope of the modeling effort—including inputs, loads, environments, monitoring points, and specific measurements.

B. Modeling Issues

A model of the TSSG was built using a commercially available version of the SPICE electrical simulation software. The model was then converted to run using SNL’s ChileSPICE. The primary motivation for using ChileSPICE is that it offers the capability of running in a multiprocessor environment; this appreciably shortens execution time when doing variability analyzes that can require hundreds of simulation code runs.

Some of the pieceparts in the TSSG are mechanical and are thus modeled in a simplistic fashion (e.g., the rolamites are modeled as simple switches). The electrical pieceparts, however, are modeled in a relatively detailed manner using typical

SPICE constructs to describe their electrical behavior. The electrical models for these devices also include temperature dependence and tolerance information. Customized post-processing software was developed to extract the attributes of interest from the SPICE current and voltage waveform data.

C. Results to Date

The measurements relating to TSSG amplifier operation were examined first, because we felt that the amplifier model was the most mature and had the best fidelity. The PS called out 4 different measurements to verify correct amplifier operation, shown notionally in Fig. 2.

Three studies have been completed to date to determine:

- variability,
- key contributors to variability at each temperature,
- key contributors to the temperature dependent behavior.

See Sections IV-C-1–IV-C-3.

1) Variability Study: Because the PS called out tests at 3 temperatures (−55 °C, 25 °C, 75 °C), the temperature-dependent model was also run under these conditions. Also, the tolerance information was used to develop distributions for the passive devices (resistors and capacitors). The passive-device values (resistance and capacitance) were assumed to be uniformly distributed across the specified tolerance band. The actual distribution is unknown but could differ appreciably from the usual assumption of a Gaussian distribution due to the typical practice of removing and separately marketing electrical parts that meet various tolerance screens. Thus a uniform distribution was selected to ensure equal coverage of the entire tolerance range. For the semiconductor devices, high, low, and nominal models were used to represent the tolerance variability.

A SNL-developed sensitivity and uncertainty analysis tool, SUNS®, generated the variability-analysis test cases. The goal of the analysis was to use modeling to determine the range of output values that could be anticipated, given the tolerance and temperature-dependence of the various input parameters. LHS sampling was used to generate a set of simulation runs that would emulate the unit-to-unit variability and temperature-dependence that would be observed in actual hardware. The input parameter values were inserted into ChileSPICE netlists, which were then executed on a multiprocessor computer. The relevant outputs were extracted from the ChileSPICE output waveforms and processed using SUNS®.

Fig. 3 compares the production data and modeling results for the D1Q1 measurements—the measured delay time between the input and output signals. The limits on the graph are the specifications in the PS for D1Q1. The whiskers in the graph encompass the middle 80% of the data distribution, with data values outside of this range shown as individual points. The boxes encompass the middle 50% of the data range, and the line in the box is the median value of the data. One test-data point taken at 75 °C failed to meet the specification; it is shown outside of the PS limits in the graph in Fig. 3. As shown in Fig. 3, the range of the results obtained from modeling bounds the test results at −55 °C and at 25 °C. However this is not the case at 75 °C, where the distribution of test results does not match well with the distribution of model results. Model validation is still underway to determine the reason for this difference.

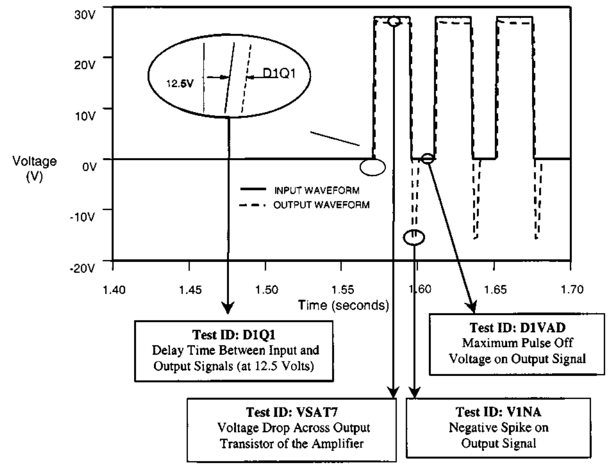

Fig. 2. TSSG model outputs (amplifier operation).

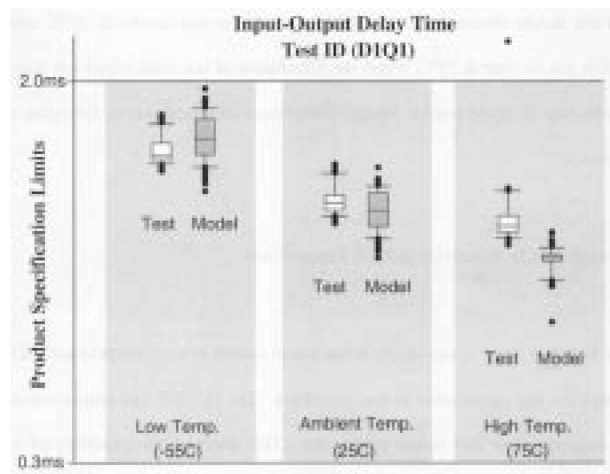

Fig. 3. Comparison of model and test-results for D1Q1.

2) Key Contributors to Variability at Each Temperature: Fig. 3 shows there is variability in the model results at each temperature. A study was done to identify the key contributors to that variability. The SUNS® tool allows one to examine s-correlations between input and output parameters. This provides the capability of identifying important contributors to the outputs of interest, as well as the nature of the contribution, i.e., if the parameters are positively correlated or negatively correlated with the outputs.

Fig. 4 shows the results of this study for the D1Q1 measurement. The results from Fig. 3 are repeated; shown beneath them are the results (at each temperature) of the s-correlation study. The simple s-correlation coefficients are plotted for several of the inputs and D1Q1.

For the −55 °C case in Fig. 4, the capacitor C102 (CBH1_C102) has a s-correlation coefficient greater than 0.9, indicating that it is a strong contributor to the variability of the D1Q1 measurement at −55 °C. The scatter plot for C102 and D1Q1 at −55 °C is shown on the right, illustrating the important relationship between the input C102 and the output D1Q1. As the capacitance value of C102 increases, the D1Q1 increases. This example shows that an increase in the

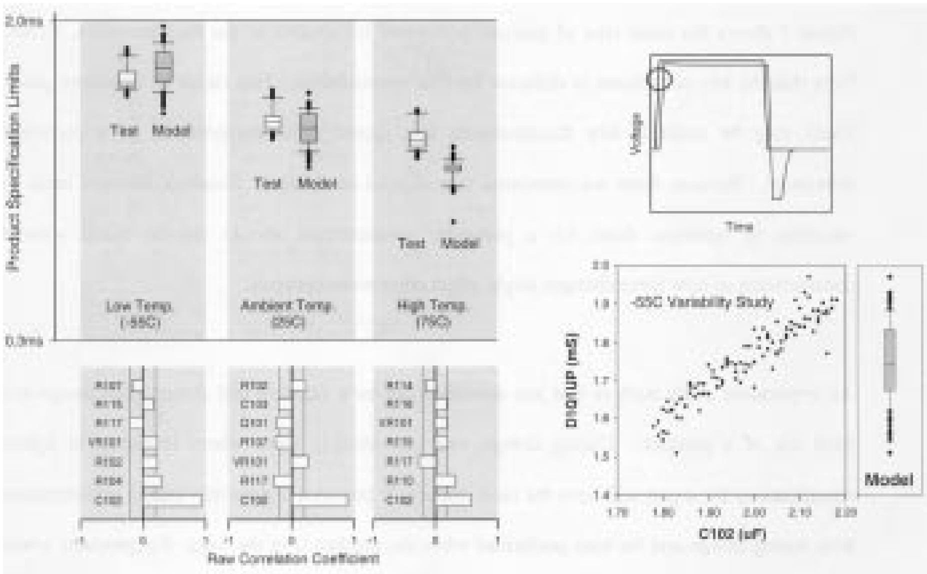

Fig. 4. Analysis of key contributors at each temperature for D1Q1.

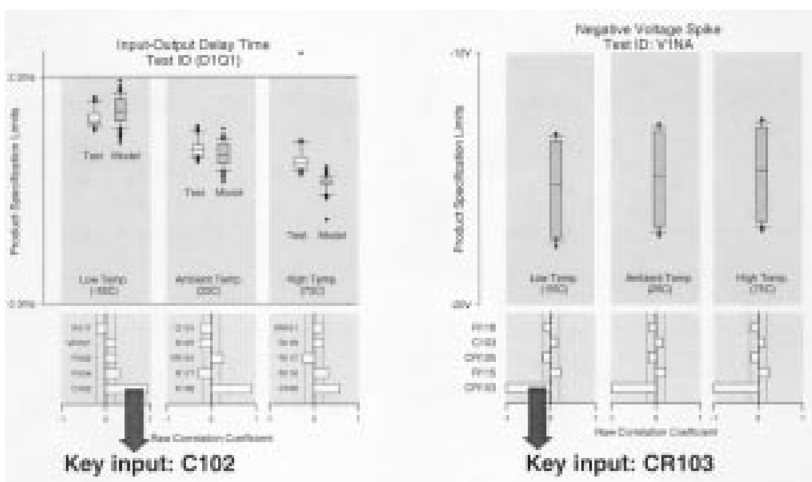

Fig. 5. Key contributors to 2 measurement.

capacitance of C102 could cause D1Q1 to exceed the PS limit at low temperatures. Similar analyzes are done for each of the measurements.

Fig. 5 shows the same type of analysis for another of the measurements, V1NA. The key contributor is different for this measurement, which raises an important point. There might be multiple key measurements that quantify the performance of a particular subsystem. Because these measurements might depend on different variables, changes made to variables to optimize them for a particular measurement should not be made without considering how these changes might affect other measurements.

An importance study, such as that just described, can be a valuable tool during both design and field life of a product. During design, one can identify areas where investing in tighter specifications for a part will have the most impact. It provides insight into testing opportunities, both during design and for field-tests. For products where aging is a concern, an importance study can help identify key investment areas for aging research.

3) Contributors to Temperature Dependence: Section IV-C-2 identified the key contributors to performance at each temperature. The next step is to determine the key contributors to the temperature dependence. Fig. 3 shows that the center value of the distribution of D1Q1, as well as its variability, appears to be a function of temperature.

This analysis was very similar to that described in Section IV-C-2. The critical difference is that the part-parameter distributions for the study were chosen to reflect values that they could assume over the entire temperature range of interest. This is slightly different from the previous study, where the parameter distributions represented values that parameters could assume due to usual variability but at a fixed temperature. In essence, for this study the temperature of each part was selected randomly; this results in input parameters that represent each part at a different temperature for a single simulation run. This does not represent a realistic scenario, and the results of the variability analysis should be used only with great caution. However, doing the importance study in this fashion can high-

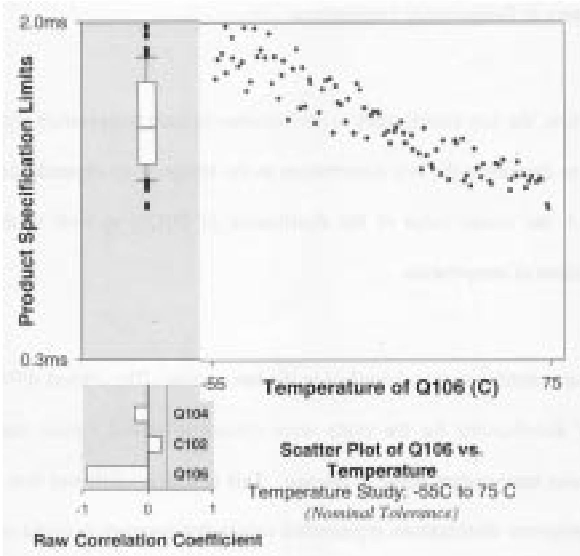

Fig. 6. Key contributors to temperature-dependence for D1Q1.

light which parts most influence the temperature dependence of the output.

Fig. 6 shows the results: the output of the variability study is displayed, along with the results of the s-correlation study. The scatter plot of D1Q1 and the main contributor, transistor Q106, is also shown. The behavior of transistor Q106 as a function of temperature is negatively s-correlated with D1Q1: as the temperature of transistor Q106 increases, D1Q1 decreases.

4) Implications and Observations: Exercise of the MBRA DMA process for the TSSG provides important insight into the anticipated performance-range of the TSSG. The results of the analysis provide a baseline to which future test results can be compared. The important contributors to the performance and variability have been identified. The SPICE model that has been developed for the DMA can serve as a foundation for lifetime studies or anomaly investigations when concerns about defects or aging arise. However, considerable effort was invested to create the SPICE model, and it is too early to know if the return-on-investment is adequate.

An important step being pursued is that of validation of the model results using the data already acquired. Once the model is validated, the MBRA Design Margin and Specification Limit Analyzes to identify key parameters and examine specifications can proceed for the TSSG. Longer-term goals include analysis of the TSSG in conjunction with its interfaces to examine synergistic effects. It is also planned eventually to incorporate other physical response modeling domains (e.g., mechanical or thermal).

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