Simulation-based Sensitivity and Worst-Case Analyses of Automotive Electronics

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***Abstract*—Simulation-based verification of electronic control units must face demands related to more functionality and less time to verify it. To ensure a reliable system, one must determine how the omnipresent, internal and external variations affect the target response, and find safe bounds for it. The main challenge is to optimally characterize a high number of sources of variation, with a reduced number of simulation runs. The paper conducts more efficient sensitivity and worst-case studies by applying concepts of Design of Experiments: screening to reduce the dimension of the verification space; sequential experiments for sensitivity analysis; gradient-based search for response bounds. The approach is evaluated on simulations of an airbag driver IC and compared with alternative methods.**[1]

I. Introduction

Growing demands on electronic control units (ECU) in terms of functionality and safety, translate into more complexity. To fulfill and control them, the points of potential system failure multiply. While requirements on ECU complexity and reliability increase, the time to cover them must decrease.

To address this issue, simulation-based verification has gained importance as a pre-silicon design phase. Much focus has been put on flexibility of specification languages and on simulation speed-up. For instance, SystemC/SystemC-AMS offers expressiveness for system-level architectural descriptions, while maintaining simulation performance high.

On the other hand, not enough effort has been put into how to perform a safe verification in the presence of many variations, within a reasonable time frame. This is necessary to validate interface requirements, given the admitted variations in functional blocks (internal/external) and in system inputs. System-level sensitivity and worst-case analyses (SA, WCA) study the impact of such variations on the overall functionality, with focus on extreme cases. Only then one can check target specifications are met, or understand why they are not met.

Airbag systems, as a major class of safety electronics, face critical requirements with respect to fault tolerance and response timing. In such systems, the squibs actuators, i.e. gas generators for the airbags, are fired by a driver unit enhanced with protection and diagnosis features [12]. Such a squib driver IC is used as case-study in the paper, to be validated against requirements.

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Starting from early phases, simulation results of the system must be validated against requirements. That means signal characteristics, i.e. responses, must be checked within admitted ranges, under any factor conditions. Factors can be operating conditions, or block parameters, internal or external to the system.

The approach applies Design of Experiments (DoE) to plan and analyze experiments (sets of simulations) on the factors, with minimum number of runs. The target is to gain maximum statistical information about how factors and their interactions impact the response, and use this information to search for extreme response values. Sequential steps towards SA and WCA are optimized in terms of number of runs:

- screening, to identify statistically significant factors.
- incremental experiments and regression, to build out of simulation results a predictive response meta-model.

This characterizes factors' effects, in nature and size, and estimates the response as an inexpensive alternative to further classical, only simulation-based way.

- search of response bounds, by optimization of the meta-model, and further iterative gradient-based search.

The approach, applied on simulation experiments of a squib driver IC, outperforms traditional trial-and-error methods (Monte Carlo, corner-cases), as quality of the SA and WCA, and as number of runs.

II. State of the art

WCA has been addressed in previous approaches, but they present some problems: methods based on Affine Arithmetic [2] lead to safe, but over-pessimistic response bounds when dealing with complex factors effects. Worst-case search is also addressed by Evolutionary algorithms [2] and Extended Monte-Carlo methods [10], but for a highly dimensional search space they require a significant amount of runs (>1M).

DoE is an approach to plan and analyze real life as well as simulated experiments, both random and deterministic [6]. It has strong statistical background. It can control simulations of parameterized systems, for various verification purposes: screening [14], sensitivity analysis [7], for robust design [1], for multi-objective optimization [13].

Simulated DoE was efficient in more areas of electronic system design: tuning microprocessors [9]; designing chip floorplanning [7]; CMOS technologic processes [11]. However, most applications are either limited to screening, or deal with relatively few factors (<10). Furthermore, such verification methodologies are not yet adopted by simulation practitioners. To the best knowledge of the authors no implementation which conducts SystemC experiments, for SA and WCA is available.

III. Concepts

The necessary concepts, as detailed in [6], are adapted to the context of the presented work. Experiments are sets of simulation runs which apply variations in the factors (e.g. operating conditions, block parameters), to identify reasons for changes in the response (e.g. signal characteristics of interest).

The target specification is a document which provides admitted variations of block parameters, typical and extreme conditions in which the device must operate normally and expected ranges for system responses. SA determines factor effects, while WCA searches for both response extremes (referred to as worst-cases (WC)) across the factor space.

The effect of a factor on the response is assumed to be composed from individual effects (i.e. main/linear effect, quadratic effect...) and interaction effects (when the factor effect depends on the levels of other factors). Interaction can occur for instance as an increase in the energy consumption when both supply voltage and current are high. 2^{nd} order effects are common e.g. with frequency in resonant systems. Results show that the assumption of simple effects is reasonable, as long as factors are varied in small ranges.

Multiple *regression* extracts the effects which best fit simulation data and approximates the response with a multivariate polynomial, i.e. a *metamodel*. Its coefficients quantify factor effects (individual and interaction).

Fractional Factorial experimental designs consist of selected corners, and are widely used to find main and interaction effects. In particular, Resolution 3 (R3FF) DoE estimates all main effects, in the assumption they are much higher than other effects. Resolution 5 (R5FF) DoE can extract main and interaction effects, assumed to be bigger than higher order effects. *Response Surface DoEs* invest more runs to also estimate 2^{nd} order effects. E.g. Central Composite (CCD) adds to Factorial DoEs the center point (i.e. with each factor set to its nominal value) and 2 axial points per factor (i.e. points with all other factors set to their nominal levels).

To evaluate fitness the of the regression model as a response estimate, residuals, i.e. differences between simulation results and meta-model values in the simulated points, are analyzed.

IV. Approach

The approach starts with the assumption of simple factor effects. Then sequential DoE can be applied to reduce the factor space, build a meta-model with respect to the remaining factor set, and evaluate its adequacy as response estimate. A final gradient-based iterative search optimizes the WCA.

A. Abstract description

Figure 1a shows the general procedure. The main cost of an experiment is the required number of runs. It shows no exponential increase with the number of factors (Figure 1b).

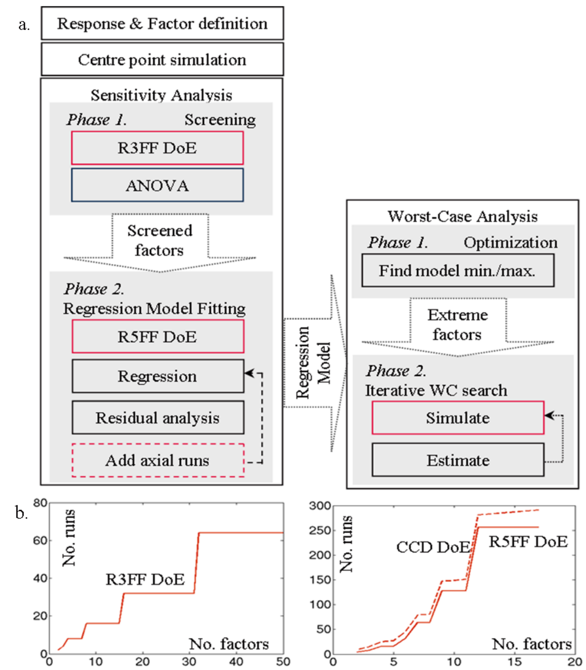

Fig. 1. a. Approach b. Number of runs

The first step is to extract from the target specification the response, and the factor set with potential impact on it, e.g. as in [8]. The specification also defines requirements on the responses and factors ranges. To reasonably assume factor effects are simple, variations of factors, relative to the center, are below 20% (as tolerances of components commonly are).

The center point is first run, to check the reference behavior.

1) Sensitivity Analysis: Phase 1. Screening

An initial screening phase is meant to remove insignificant factors and reduce the complexity. A R3FF DoE involves relatively few runs (Figure 1b), and can estimate preliminary main effects, assumed high only for significant factors.

Phase 2. Regression Model Fitting

Next, the remaining factor set is subject to a sequence of experiments, with corresponding regression, until the residual analysis is satisfactory. A R5FF DoE can be run at first, to estimate 2-factor interactions. If necessary, a CCD DoE estimates the 2^{nd} order effects.

If the residual analysis still indicates inadequacy, axial runs are iteratively added, until the regression metamodel shows a god fit on simulation data. The final estimated metamodel is: $R = c_0 + \sum_{p=1}^{Omax} \sum_{i=1}^{n} c_i^{(p)} \cdot f_i^p + \sum_{i=1}^{n-1} \sum_{k=i+1}^{n} c_{ik} \cdot f_i \cdot f_k$

These steps solve the SA problem, because each factor is characterized, in its impact on the response, individually and in interaction with others, both in nature and magnitude. Further hints to improve the metamodel, plot and interpret the results, can be found in the Results section.

2) Worst-Case Analysis: Phase 1. Optimization

This step finds the extremes of the regression model, by solving a constrained optimization problem on the 2^{nd} order polynomial (Quadratic Programming).

Phase 2. Iterative WC search

An iterative search is performed starting at the previously estimated WC point. The search algorithm sequentially estimates the response metamodel, and solves a Quadratic Programming subproblem, at each iteration. Thus, it generates an iterative sequence of points which converges to the solution.

B. Implementation

The model specification and simulation are handled with SystemC/SystemC-AMS [3], [4]. They are fit to model at the architectural level and offer high performance in simulation. The system model must enable dynamic re-configuration of factors and track of the response.

The algorithm for experiment planning, control and analysis of results was implemented in MATLAB. It also reconfigures the factors and controls the SystemC simulation.

Functions available with the Statistics and Optimization Toolboxes [5] were adapted, in order to:

- generate the set of tests for the chosen DoE, based on the specific effects to be extracted
- perform the regression and the residual analysis
- find extremes of the meta-model over the search space
- generate each factor set to simulate during the WC search.

The decision making steps, e.g. residual analysis, can be user-interactive or fully automated. The maximum number of runs or effects to be estimated can also be specified.

V. Results

A. System description

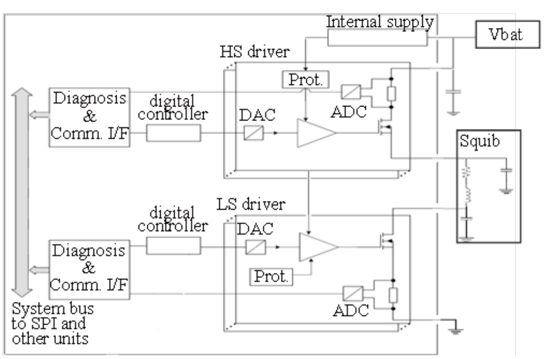

Fig. 2. System functional blocks

The system under study is the squib driver IC of an airbag ECU, as previously described. It is a smart power IC which, at the time of deployment, must send current of a predefined value through the squib, for up to a few milliseconds, heating it up and thus bringing it to the point of "explosion". The current is digitally regulated, and further protection features are available (Figure 2).

B. Results of the approach

The main signal of interest is the current sent through the squib at deployment time. Signal characteristics, both transient and of electrical nature, are chosen as responses (Table I).

TABLE I
RESPONSES

Response	*Typical value*
Response 1: Deployment delay (rising edge of SPI CSQ bit to 10% of current final value)	100us
Response 2: Deployment current slew rate	50mA/us
Response 3: Deployment current	2.9A

Table II comprises sources with potential impact on the responses, and exemplifies some factors used in the experiments. The initial factor set had **22 factors** (same for all responses). The factor ranges were extracted from the system specification.

TABLE II
FACTORS

Source of variation	*Factors*
Squib load	Lsquib, Rsquib
Supply unit	Vbat
High Side Switch regulation path	HS Vth, Ctrl. gain, ADC gain, ADC precision, DAC gain, HS Rshunt
SPI I/F	SPI Td (Transfer delay)

1) Sensitivity analysis: Phase 1. Screening

The results of the screening phase are analyzed using the analysis of variance (ANOVA) [6], i.e. a formal way to identify statistically significant factors. Table III exemplifies relevant information, for some of the factors: the sums of squares SS are measures of response variability, while p measures the probability of the hypothesis of null factor effects. Factors were filtered on the criteria: p(f_i)<0.05. Checking for a minimum variability of SS(f_i)> ϵ was also found useful.

TABLE III
ANOVA TABLE

Response	*Resp. 1*		*Resp. 2*		*Resp. 3*	
Factor	*SS*	*p*	*SS*	*p*	*SS*	*p*
Lsquib	**1604.7**	**0**	**1.693**	**0**	**4.50e-04**	**0.03**
Vbat	**338.7**	**0**	**0.108**	**0**	1.40e-04	0.17
DAC gain	**75.58**	**0**	**28.26**	**0**	4.00e-05	0.45
Ctrl. gain	0.055	0.712	0.001	0.64	**0.1051**	**0**
SPI Td	**6.604**	**0.002**	0.017	0.13	4.00e-05	0.43
ϵ	3.378		0.054		5.60e-04	

Phase 2. Regression model fitting

Figure 3 shows plots of residuals, normed to the maximum response variability, for Response 1, after the regression analysis on results of the CCD DoE.

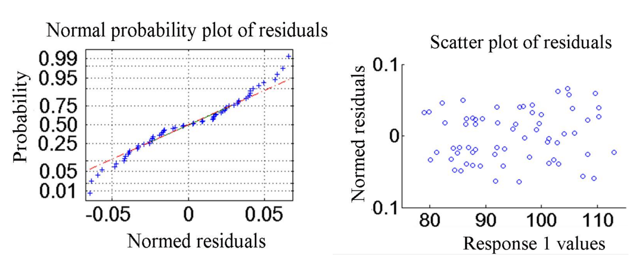

Fig. 3. Plots of the normed residuals for Response 1

The normal probability plot indicates whether they are approximately normally distributed, which is a sign of model fitness as a response estimate. Residuals of inadequate models are nonlinearly distributed or have nonzero means (center value on x-axis) [6].

The plot shows the regression meta-model is adequate. The scatter plot of residuals against response values indicates no pattern, so there are no systematic prediction errors in the regression model. The residual values are smaller than 10%.

The metamodel is plotted against each factor, at fixed values of the others, to view individual effects. Interaction plots represent the response versus a factor, at various levels of other factors. A lack of parallelism indicates interaction. Figure 4 shows individual factor effects and 2-factor interaction effects.

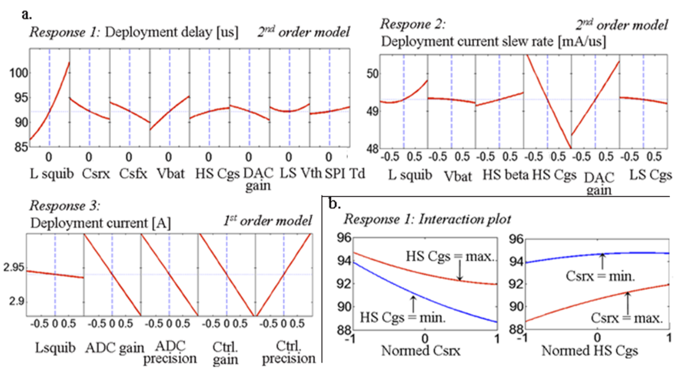

Fig. 4. a. Main effect plots b. Interaction effect plot

The study shows that regression models are reasonable approximations of responses in such systems: either a 1^{st} or a 2^{nd} order model with 2-factor interactions was satisfactory.

2) Worst-case analysis: The methods described in Section IV were applied. The iterative search was conducted in a reduced neighborhood of the previously estimated WC, for both response extremes. The search stops when one of the criteria is met: a relative change in response of less than 10^{-3} during the last iteration set, violation of constraints, or the maximum number of runs reached.

The efficiency depends on the number of factors, on the magnitude and complexity of their effects, but also on the chosen search step. E.g. when many factors present interaction, it shows lower convergence. Results after both steps are briefly compared to alternative approaches in the next section.

C. Discussion

For comparison with the proposed approach, 3 classical alternatives are implemented:

- Full Factorial DoE: all corner-cases.

The initial factor set would require too many runs (2^{22} corners), so the Full Factorial is run only for the subset of filtered factors (so it needed $2^{\#screenedfactors}$ runs).

- Monte-Carlo: 500 runs with uniformly distributed factors.
- WC direct search: Phase2 of iterative search from the WCA is directly applied on the initial factor set.

The proposed approach needed fewer runs than its alternatives: only 32 runs for the screening phase, up to 80 runs for the regression phase and up to 15 runs for the iterative WC search (depending on the response).

The approach also found better response extremes, thus a higher response variability: 22% to 56% better than the Monte-Carlo; 4% to 5% better than the WC direct search; 2% to 8% better than the Full Factorial approach.

The approach has restrictions reflected in the size of the verification space (the initial set should be kept smaller than 50 factors, while screening should reduce it to less than 20 factors). When necessary, a hierarchical approach can be applied: the initial factor set is divided in subsets with more probable interactions, which are analyzed separately.

VI. Conclusion

The approach addresses the need to handle higher dimensions of the verification space in a reduced time, i.e. using fewer simulation runs. It applies an extended DoE strategy for efficient ECU validation against value-ranged requirements. The proposed sequential experimentation flow includes factor screening (to reduce the verification space), sequential DoE to build an adequate meta-model, and iterative WC search to increase the WCA reliability. Experiments planning and analysis, applied on simulations of an airbag IC, show higher quality of SA and WCA than traditional approaches, gained with a reasonable number of simulation runs.

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