Post-Production Tuning in Analog and RF Devices

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Abstract

In analog and RF device testing, current industry practice is to exhaustively test each device against its specifications, labeling as faulty any devices that do not meet those specifications. At this point, however, nothing is done with faulty devices—they are simply discarded. Although conservative design can improve yield, increasing variation due to process scaling renders this an insufficient solution. One promising solution is to make analog and RF devices capable of post-production tuning. In this work, we present recent groundwork for implementing post-production tuning of analog and RF devices, thereby improving yield by tuning devices that would otherwise be discarded. Specifically, we demonstrate a methodology for selecting the best set of "knobs" within a design, to convert parametrically faulty devices to working devices.

1. Introduction

Recently, there has been a great deal of research on developing test methodologies for analog devices that reduce the cost of specification test while maintaining sufficient fault coverage throughout the test process. This includes work in machine learning-based test compaction, as well as development of analog fault models. The work in this area is advancing rapidly, and the performance reported in literature by machine learning-based specification test compaction is beginning to approach industry-acceptable defects-per-million (DPM) levels [1], [2], [3], [4]. However, once we have made pass/fail decisions on devices, whether through specification test or an advanced test methodology, any devices marked as failing are discarded, and no corrective measures are taken.

Adopting the terminology of [5], we typically encounter two types of faulty analog devices. First, there are non-recoverable *catastrophic faults*, where the device has a short, open, or other failure that prevents correct operation. In this case, the device signature is typically well outside specification boundaries and is easily detectable as failing.

The more interesting devices are those that are not clearly separable from good devices, with so-called *parametric faults*. Because of process variation, the tail ends of the process distribution often fall outside specification boundaries. Thus, we are left with a set of devices that almost function correctly, but marginally do not meet specification requirements. An example of parametric faults is shown in Figure 1, where we observe the tails of the process distribution fall outside specification boundaries.

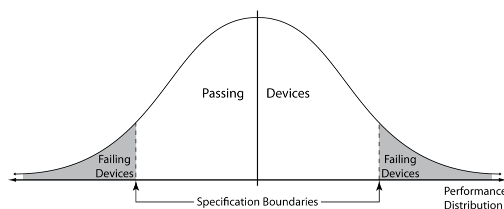

Fig. 1. Parametric Faults

If it were possible to modify the performance of these devices after production, a large percentage of them might be recoverable, as these devices are only slightly outside specification requirements. To date, however, the standard industry practice for these failing devices is to simply discard them.

To recover these devices, we propose the introduction of post-production tunable knobs within analog and RF circuits. Instead of discarding devices with parametric faults during production test, multiple test-tune iterations could be performed within a closed-loop system, as shown in Figure 2.

The first step in establishing this tuning system is implementing a process for selecting knobs. Given a arbitrary analog circuit, which tunable elements should the design have to ensure maximum post-production tunability? In this work, we present a machine learning-based technique for knob selection that maximizes tunability while minimizing the number of required circuit knob elements.

2. Related Work

In [2], the genetic algorithm NSGA-II is used in conjunction with an ontogenic neural network to achieve specification test compaction by first eliminating redundant tests, then constructing a neural network topology

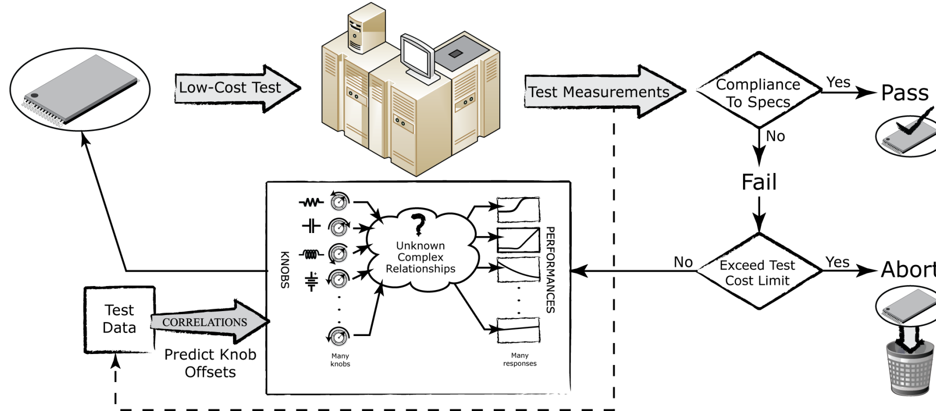

Fig. 2. Tuning System

to assign a pass/fail label to each device. Furthermore, guard bands are employed to improve performance by tagging the most difficult boundary devices for the full specification test suite.

The work in [4] parallels much of the prior work with neural nets, applying some of the concepts and lessons learned in that domain to define regression-based methods. Using multi-variate regression in lieu of a neural network sacrifices some performance in predicting pass/fail labels correctly, but has the advantage of providing the predicted values of the tests excluded during test compaction, instead of just the pass/fail label.

Biswas et. al. [6] take a different approach, employing a third machine learning technique—support vector machines (SVMs)—to partition the test hyperspace and isolate good devices.

In [5], several fault models are developed. Resistive/capacitive elements are introduced into the circuit to model the effect of catastrophic faults on the performance of the device. Parametric faults are modeled as an impulse function at a range of faulty values, testing six parametric faults per transistor and assigning the non-faulty parameters as normally distributed random variables.

3. Optimal Tunability

This work aims to provide the framework for an automated methodology for selecting a subset of knobs to insert into a design, selected from a much larger set of potential knobs in a given design. To frame the problem formally, consider an arbitrary circuit with performances P in which a set of knobs K has been implemented.

The set of performances P consists of readily-measurable characterizations of the circuit, such as gain, phase, linearity, and power. These performances may be single-ended (i.e., power usage should be minimized) or double-ended (i.e., the gain should be within a range $g_{min} \leq gain \leq g_{max}$.)

The set of knobs K consists solely of double-ended tunable parameters. For example, this may consist of tunable circuit components such as resistors, capacitors, or inductors, realized through switched-banks of those components. Additional tuning can be realized through adjustable voltages, such as an adjustable V_{DD} or biasing voltage.

We wish to implement a circuit with a set of knobs K', where $K' \subseteq K$, such that if the circuit possesses a parametric fault, K' will permit post-production tuning and recovery of the failing device. As each additional knob requires additional I/O, we note that cost is proportional to $|K'|$. Thus, we aim to minimize $|K'|$ while maximizing the tunability we can achieve in all performances P for our retained subset of knobs K'. For the purposes of this work, we define this tunability as the change in a given performance $p \in P$ for a corresponding small change in the space defined by K'. Specifically, we define the compound space of each performance with the set of retained knobs K' as $\langle p_i|K'\rangle$, such that the tunability metric can be written as:

$$\sum_i |\nabla \langle p_i|K'\rangle| \qquad (1)$$

This is the summed magnitude of the surface gradients for all p_i at some point in the space of K'.

Minimizing $|K'|$ is challenging largely due to the size of the search space. Given $|K|$ possible knobs in a design, there are $2^{|K|}$ possible knob subsets, as well as a continuous tuning space for every included knob. If all of the possible knobs introduced in a

design were independent, then knob selection would be straightforward: the best knob for a given performance p_i is the knob k_j such that $|\frac{\partial p_i}{\partial k_j}|$ is maximized.

In a real circuit, however, knobs are likely to be highly interdependent. For example, consider a situation where a given knob 1 performs poorly, i.e., $\frac{\partial p_i}{\partial k_1}$ is small for all performances i. However, with interdependent knobs, there can arise a configuration such that if knob 2 is adjusted, knob 1 will become substantially more effective, as shown in Figure 3).

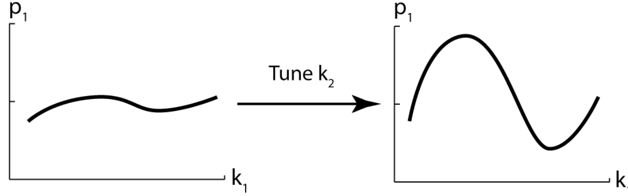

Fig. 3. Example of Knob Interdependence

Thus, an effective knob selection system must consider the knob quiescent point while reducing the combinatorial selection problem.

4. Knob Subset Heuristic

To alleviate the problem of selecting from the large number of potential subsets of K and quiescent tuning points, we propose a genetic algorithm-based search methodology to heuristically search the knob space K for the best set of knobs K', evaluating the fitness function of each knob subset as in Equation 1. Genetic algorithms are particularly suited to this type of optimization problem, as they dramatically reduce the cost of search (as compared to exhaustive search) while maintaining a high probability that an optimal solution is found.

Genetic Algorithms work by defining a set of potential solutions C, referred to as *chromosomes*. Each chromosome contains a concatenated list of variables which will be modified within boundaries specified by the user. When the algorithm is initialized, a large pool of chromosomes is generated. Depending on the specific algorithm, the chromosomes then undergo a *crossover* operation, where discrete chromosomes are mixed together to form a new chromosome, which is also subjected to *mutations*, or random perturbations of the solution which help avoid local optima. Together, crossover and mutation are referred to as a *generation*. This process continues until an optimal population of solutions is found, or at a pre-defined stopping point. At the termination of the algorithm, these solutions form a Pareto-optimal front in the fitness function space, from which solutions can be selected with different trade-offs between the fitness variables.

For this work, the NSGA-II algorithm [7] is used, due to its demonstrated efficacy [2]. For example, if we consider the case with two knobs and one performance, each chromosome point is chosen by first randomly selecting a knob tuning point $a = f(x_a, y_a)$. We then take the gradient by selecting a secondary knob tuning point $b = f(x_a, y_a)$ near a and finding:

$$\nabla f = \left\langle \frac{x_b - x_a}{x_a}, \frac{y_b - y_a}{y_a}, \frac{b - a}{a} \right\rangle \tag{2}$$

at that point, thereby uncovering the effect of interdependent knobs. Note that to ensure the performances are weighted the same, we divide each element by the original value to give a percent change. Furthermore, taking the magnitude of the gradient gives us a scalar metric which we can sum across performances, giving us a single metric m of the tunability provided by the chosen knob subset at that quiescent point: $m = |\nabla p_1| + |\nabla p_2| + \ldots |\nabla p_n|$. This is equivalent to Equation 1, and becomes the second objective function of our genetic algorithm (along with $|K'|$, the number of knobs retained).

5. Experimental Validation

A simple differential amplifier, shown in Figure 4, was employed as an example circuit for experimental validation. The amplifier consists of a differential pair, with current mirrors added to bias the circuit correctly. This circuit has the advantage of being simple to understand and analyze, while still possessing interesting specifications and performances which we can use to evaluate a tuning method. A test bench circuit, shown in Figure 5, was also implemented to enable simulation of the differential amplifier.

In this circuit, a set of five knobs was introduced:

1) R_{in}: The supply voltage for the biasing input of the differential amplifier.
2) V_{DDL}: The supply voltage for the left branch of the differential amplifier.
3) V_{DDR}: The supply voltage for the left branch of the differential amplifier.
4) V_{DDB}: The supply voltage for the biasing input of the differential amplifier.
5) V_{GS}: The voltage from the ground node to the source of the differential amplifier.

Four performance metrics were employed to evaluate knob subset tunability:

1) Gain

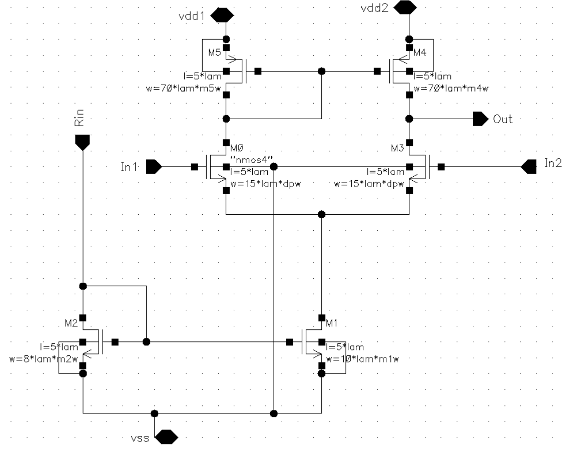

Fig. 4. Differential Amplifier

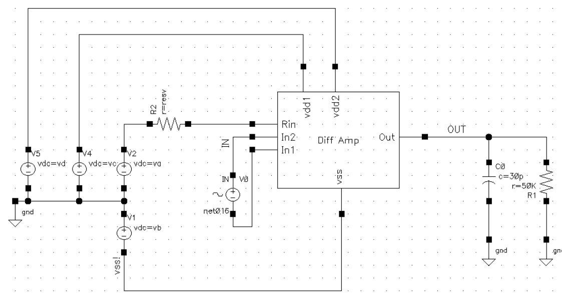

Fig. 5. Test Bench

2) Phase
3) Power
4) 1dB Compression Point

The genetic algorithm was given control over the quiescent point, direction of the gradient vector (direction to point *b*), and included knobs. Additionally, all changes in the knob space were standardized to $\pm 10\%$, thus simplifying the tunability metric (Equation 1) to include only the performance metrics. The tunability achieved by each proposed chromosome was recorded, and the algorithm was run with a population of 30 chromosomes for 20 generations. This produced the tunability vs. knobs retained tradeoff shown in Figure 6.

The results generated by the genetic algorithm indicate that for this circuit, there is a sharp threshold in the tunability, such that at least three knobs are necessary to achieve a significant change in the circuit performances.

6. Conclusions and Future Work

In this work, we have proposed a system for selecting tuning knobs in a simple analog circuit, a differential

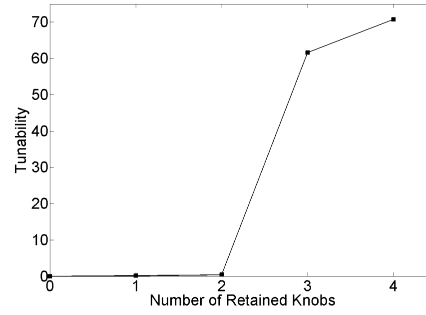

Fig. 6. Experimental Results

amplifier. Although we see a sharp threshold in the performance of knob subsets in this specific circuit, it remains to be seen whether such a threshold exists for larger and more complex circuits. The genetic-algorithm based heuristic search methodology proposed here is generally applicable and scalable to more complex circuits.

Future work will involve investigating the performance of this knob-selection technique in these more complex circuits, as well as a technique for post-production tuning, once the knob subset has been selected.

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