Statistical SPICE Model Characterization

PDF SOLUTIONS

333 West San Carlos Street
Suite 625
San Jose, CA 95110
408-280-7900
info@pdf.com

1.0 Executive Summary

Statistical SPICE model characterization is a critical step in understanding how manufacturing process variations impact yield. This paper describes a methodology and recommended best practices for successfully characterizing the parametric variances inherent in a process. Using this physically based methodology it is possible to realize statistical distributions of SPICE parameters that are inexpensively monitored by electrical tests. Accurate statistical distributions of SPICE model parameters are needed to allow subsequent analysis and development of worst case model sets. Cost and time constraints prohibit taking enough physical measurements to realize this goal. Instead, physically-based process and device simulation provides a viable alternative to measurement. If designers can quickly and inexpensively generate SPICE models and accurately test circuits, a great impact on first pass design success will be realized.

Fully understanding and accounting for the inherent parameter variations will afford the production engineer a better understanding of the impact of silicon processing on circuit performance. Statistical analysis of SPICE model distributions yields an understanding of several issues tying together process and design issues including: parameter correlation and the number of independent dimensions, electrical tests which can monitor the SPICE model, and generation of statistical models based on electrical test measurements. With this type of information, product engineers will be prepared to diagnose and correct problems found in manufacturing.

Using TCAD simulation tools and the methodologies outlined in this paper, it is possible to generate accurate statistical distributions of SPICE parameters for designers. However, in order to ensure that the parameters accurately represent the technology being modeled, a number of guidelines should be followed. This paper discusses the following “rules of thumb.”

- All simulation work must use physically-based tools and techniques.
- Nominal calibration must be performed using measured data.
- SPICE models should be extracted using physically-based algorithms rather than optimization.
- Process control variance should be assigned based on manufacturing equipment variation and test distributions.
- Monte Carlo and sensitivity analyses should be used to generate accurate statistics.

Because TCAD simulation can extract not only SPICE models but also a set of measurable electrical tests, it is possible to build statistically-valid mathematical expressions between these quantities. A mapping between the principal factors of the SPICE model space and the electrical tests can be made using a modified principal component analysis which includes rotations and transforms. This analysis yields equations which express SPICE parameters as a non-linear combination of electrical tests. Understanding and quantifying these equations enables a production engineer to make a great deal of analysis and take pro-active steps toward the manufacturing environment. Some possible outcomes include the ability to:

- develop SPICE models inexpensively, in large quantity, on a continual basis
- enable design verification against current manufacturing capability
- ensure proper testing, both in number of tests and specification limits on those tests
- allow monitoring and control of known critical processing steps

A physically-based worst case testing methodology can be developed once the problem of generating statistical distributions of SPICE models is eliminated. The techniques outlined above provide insight into the relationships existing between devices and electrical tests. Building on this knowledge, several avenues to worst case testing can then be explored, including basing corner models on electrical test specification limits or giving designers a database with model distributions for testing.

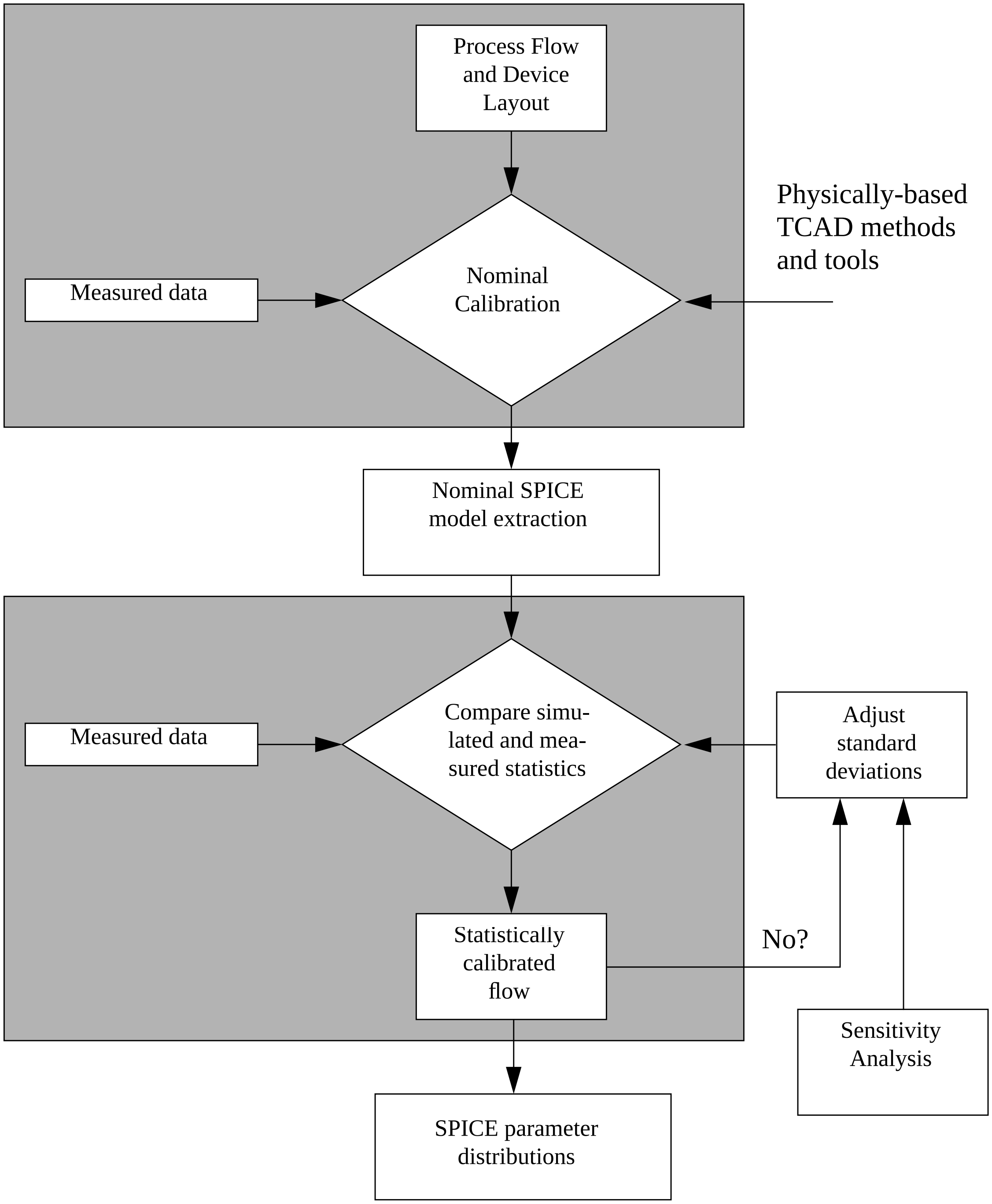
2.0 Obtaining accurate SPICE model distributions

Even if a "worst-case" model approach is used, accurate SPICE model distributions must be obtained in order to have a valid set of worst case models. To obtain these distributions, several TCAD tool usage and measured data requirement issues must be addressed. A summary of these issues is listed below.

- Use physically-based techniques for nominal simulation
- Use measured data to ensure calibration (if available)
- Extract SPICE models from simulated physical measurements and electrical tests
- Run Monte Carlo experiment to obtain correlated set of SPICE and electrical test parameters

This section outlines the procedure for taking a 0.35um standard CMOS technology through these milestones and generating statistics. Figure 1 shows a flowchart of operations that must be performed.

FIGURE 1. Flow chart for obtaining SPICE parameter distributions



2.1 Nominal process and device simulation

The generation of reasonable statistics based on TCAD simulation relies on two factors: accurate nominal simulation and assignment of correct variance to critical processing parameters. Nominal simulation is discussed here with guidelines to ensure valid results.

2.1.1 Methodology for nominal simulation

The most important goal throughout simulation is to maintain a physical basis for all work and changes to the tools. Maintaining the physics of process and device simulation is the enabling technique which will ensure proper statistics later in simulation. To this end, it is critical to represent the process technology as a single process flow. This flow should be entered directly from a technology run card, including all processing steps that manufactured wafers will see. In keeping with a singular flow for process, there should also be a single set of process (i.e. diffusion, segregation, etc.) coefficients for this flow, and these should be set only once before processing begins. Due to these needs, specific to the generation of statistics, several traditionally used TCAD techniques are not valid:

- Using unique input decks for different device types - in reality all devices in a process are fabricated simultaneously, undergoing the same physical steps. Separating them into distinct simulations will not allow inter-device correlations and dependencies to be realized during statistical analysis.
- Setting (and resetting) coefficients for individual devices - devices will see the same physical effects during processing. Separating these effects to more accurately simulate an individual device is less physical and will change correlations during statistical analysis. Coefficients should typically be set only at the beginning of simulation. If there is a theoretical justification, however, coefficients may need to be set mid-processing to more accurately represent physical behavior.
- Simulating large devices and truncating to create smaller geometries - at deep submicron geometries and more significant short channel effects, this technique will not incorporate the physical effects which must be modeled to maintain accurate device representation.
- Switching from 1-D to 2-D process simulation - care must be taken when switching process simulators. If a 2-D simulation is introduced mid-way through the process, the state of silicon must be accurately represented in the structure. This will ensure any 2-D channel effects are accounted for.

Another important aspect of maintaining a physical basis is to accurately represent device geometries. Using multiple sized device layouts (e.g., from a test chip layout) for each device type best accomplishes this goal. Furthermore, actual layers and rectangles used during statistical simulation must incorporate such physical effects as bloat/shrink and mask mis-alignment which can significantly impact the distributions of device performance and their correlations.

2.1.2 Data requirements for nominal calibration

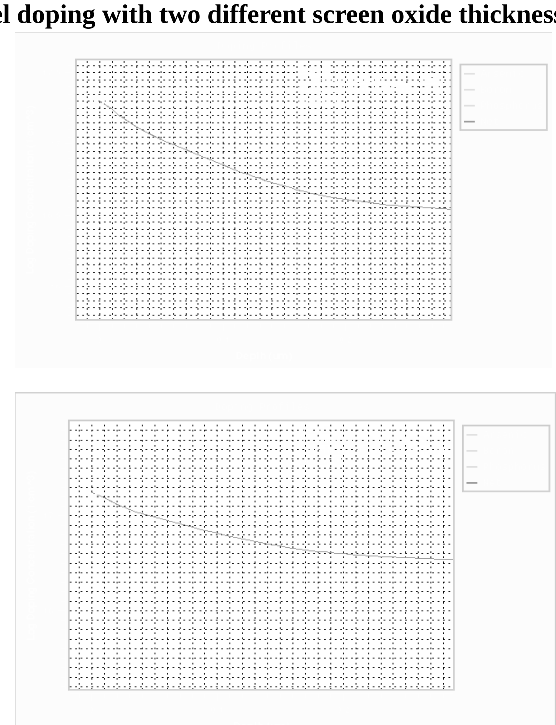
Once the technology is entered in a TCAD framework, nominal calibration is needed to ensure simulation models are predicting fabricated characteristics. Calibration will depend upon several sources of measured data including: SRP/SIMS, in-line tests (e.g., oxide thicknesses), electrical tests (e.g., sheet resistances) and device tests including Vt and drive current measures. During nominal calibration it is important to understand what parameters to check, and what nominal targets to compare them against. Typically, during new phases of a technology, a “golden wafer” will be chosen which best represents the typical wafer electrical test and device characteristics. This wafer, possibly from engineering lots before production, should be the target if the process under investigation is new. However, if a process has been in production for some time, this wafer may no longer represent typical behavior. It is important to look at process and device statistics (in the form of electrical test) to be sure that the technology has not drifted over time. If there has been no significant movement, then the “golden wafer” can still represent a nominal target. On the other hand, if significant shifting with time has occurred, new targets must be chosen. This type of analysis should also be applied to the SRP/SIMS that will be used for calibration.

It is typical to take these measurements when the process is new. However, changes can occur over time which will make them inaccurate. Care should be taken when comparing “new” electrical test data with old silicon profiles. Nominal simulation targets will significantly impact the characteristics of simulated statistics.

2.1.3 Algorithm for nominal calibration

Once nominal targets are established, calibration can be performed. Please see Appendix A for a flowchart of the steps which will be described here. The first measurements of interest to compare are oxide thicknesses. Several in-line tests, throughout processing, should exist to give a measurement of the amount of oxide being grown by diffusion recipes. While some oxide growths can be considered more important than others (gate oxide vs. well oxide thickness, for example) all must be calibrated to within reasonable accuracy. For example, Figure 2 shows the difference in doping profiles for two different screening oxide thicknesses for a channel implant in a standard MOS technology.

FIGURE 2. Channel doping with two different screen oxide thicknesses



The top graph shows the resulting channel profile with a screen oxide thickness of 430A. The bottom graph shows the resulting channel profile with a screen oxide thickness of 456A. In each case the peak net concentration has been highlighted. Table 1 shows a summary of this data along with the change in Vt for the device after device simulation.

TABLE 1. Channel behavior based on screen oxide thickness

Screen Oxide Thickness (A)	Peak Channel Concentration (atoms/ cm3)	Vt (volts)
430	1.99e17	-0.5948
456	1.77e17	-0.5438

This example shows that a *6% change in oxide thickness results in a 9.4% change in Vt for the device*. Oxide thickness must therefore be carefully calibrated to ensure proper process and device behavior. In order to achieve sufficient matching, oxide thickness targets and actual thickness measurements are needed for comparison. With this data, reasonable changes can be made to oxidation models to tune generic equations to match manufacturing specific results.

The next step is to calibrate 1-D doping profiles. Measured spreading resistance profiles (SRP's) or SIMS are needed for each unique region of interest for this task. In comparing the doping profiles of simulation to measured data, adjustments should be made to diffusion and segregation coefficients to better model regions, keeping in mind that measurements of this type can contain errors of 10% or more. Bringing simulation closer to measured data in this way ensures that the simulation is in a state which is close, although not exact, to measured silicon.

After 1-D profiles have been calibrated, electrical tests must be considered. Several tests should be performed in simulation to replicate electrical tests being measured. As further calibration of one dimensional effects, measurements for a single size device should be analyzed. Typically all SRP's, in-line, electrical and device tests will be performed on a long channel device. Concentrating 1-D calibration on a similar size device is critical. Simulation will yield poor results if, for example, SRP's are used to calibrate the minimum channel device when the profiles where actually measured on a long channel device. Problems with such cross-length calibration arise when 2-D effects start to dominate deep sub-micron channels. These process traits will not be apparent in longer devices.

One must not rely on single measurements for a clear picture of a region. For example, an SRP is most inaccurate at the surface. The surface concentration, in turn, is one of the most important physical parameters which will impact device performance. Therefore, additional data, in the form of electrical tests, is needed to calibrate the simulator further. Figure 3 shows the effects that surface concentration can have on device performance. The top graph shows the original doping profile and the bottom shows a graph that has a different boron segregation coefficient. Table 2 summarizes the data.

FIGURE 3. Surface doping profiles

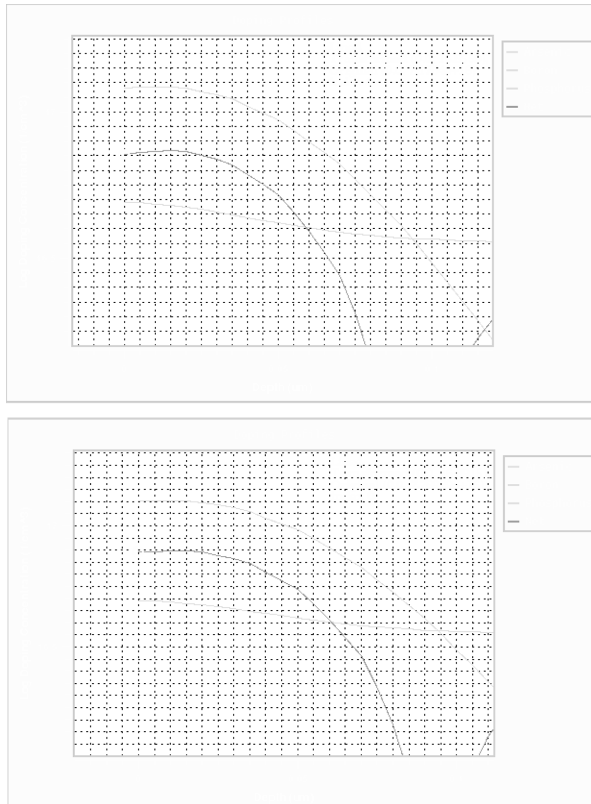


TABLE 2. Comparison of surface concentration data

Boron segregation coefficient (TMA Suprem4 2D)	Surface Boron Concentration (atoms/cm3)	Surface net concentration (atoms/cm3)	Vt (volts)
1126	1.21e17	7.176e16	-0.6248
1000	1.27e17	7.789e16	-0.6437

A small change in the diffusion model coefficient can result in large changes in doping profiles. In this example, the *net surface concentration changes by 8% while the actual boron surface concentration is only reduced by 5%*. This change in doping results in a 3% change in Vt for the device. It is not possible to read SRP's to within a sufficient accuracy (on the order of few percent) to only calibrate to these measured profiles.

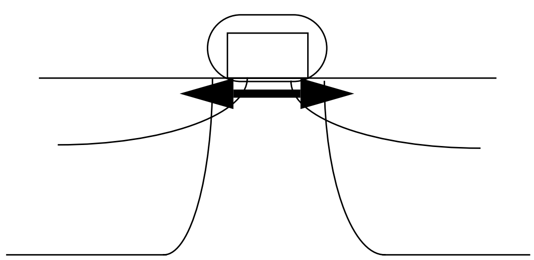
Instead, once reasonable levels of matching are achieved in a 1-D case, device performance over length must be considered. With the exception of electrical tests for different geometry devices, few physical measurements exist in quantity which describe the 2-D effects on devices. In most cases, little measured data exists for parameters such as spacer thickness and under diffusion of the LDD (and their variation.) Other short channel effects, such as boron pile-up at the LDD-channel junction, are also difficult to measure.

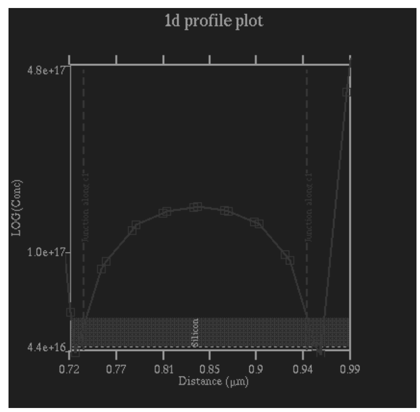
Careful consideration must be taken, therefore, when calibrating over length. Choice of 2-D models, diffusion coefficients, and small changes in processing steps such as spacer deposition should all be determined based on assimilation and comprehension of the data available. Careful consideration of the choices made is needed, as they will all impact accuracy and speed of simulation.

Figure 4 shows two profiles of net doping across a 0.35 um NMOS transistor at the surface of silicon. One simulation had TMA SUPREM-4 2D model for point defect diffusion (pd.full) turned on (top graph), the other turned off (bottom graph). Turning on point defect diffusion model creates a 3.76% change in the Vt for a minimum size transistor. Table 3 summarizes some important data from the two simulations. The magnitude of this effect is relatively small when compared among single devices. However, if as in this example, the threshold swing from minimum to long channel device is relatively small (100mV), *a 20mV change in Vt on the minimum channel device can result in a 20% change in Vt swing over device length.*

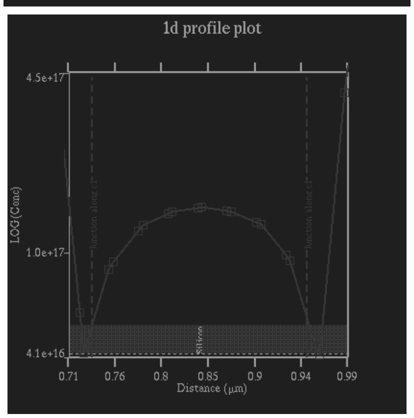
FIGURE 4. Two channel profiles with and without pd.full

Arrows across channel indicates where 1D profile is taken





with pd.full



without pd.full

TABLE 3. Data for comparison of use of 2D models

TMA Suprem4 2D model	Peak Channel Concentration (atoms/cm3)	Vt (volts)
no pd.full	1.72e17	0.6172
pd.full	1.764e17	0.5948

Due to the lack of data, 2-D calibration is the most difficult task for a technology. Nevertheless, it is perhaps the most important to ensure proper extraction of SPICE parameters (especially over length) during statistical simulation. In addition, there is little ability to apply generic algorithms to solve these problems, as each process technology, especially as smaller geometries are explored, will present its own set of unique problems and physical effects. Experience and understanding of the physical effects must be used to ensure proper calibration over length.

Device parameters may also be used to help calibration. In many cases, accurate process calibration will eliminate the need to calibrate device parameters such as velocity saturation or mobility models. However, these changes may become necessary based on comparison of I-V curves from simulation and measured devices.

2.1.4 Nominal SPICE model extraction

SPICE parameter extraction follows the successful completion of calibration over length. At this point, the methodology has striven to maintain a physical basis for all calibration techniques. The extraction of SPICE parameters can be no different. Optimization cannot be used to generate accurate statistics. Optimization will not produce unique, repeatable results which are useful in a statistical analysis. Instead, optimizing a model produces a non-physically based manipulation of model parameters solely to achieve minimal RMS error. Achieving this minimum error is not the goal of this strategy. Rather, a model with a lesser, but still reasonable, fit and a physical basis is needed. The parameter sets must be based on physical quantities and electrical tests measured in simulation. Using a combination of these and simulated I-V points will result in a physically based extraction of parameters based on silicon and geometry properties.

2.2 Statistical Process and Device Simulation

Once a nominally calibrated process flow is obtained, it is possible to generate statistics for that process. Running two statistical experiments, a Monte Carlo analysis and a sensitivity analysis, will yield a correlated set of electrical test and SPICE models and their relations to individual process controls. This section discusses the necessary techniques and data required to initially generate and calibrate the simulated statistics to represent manufactured data.

2.2.1 Methodology for statistical simulation

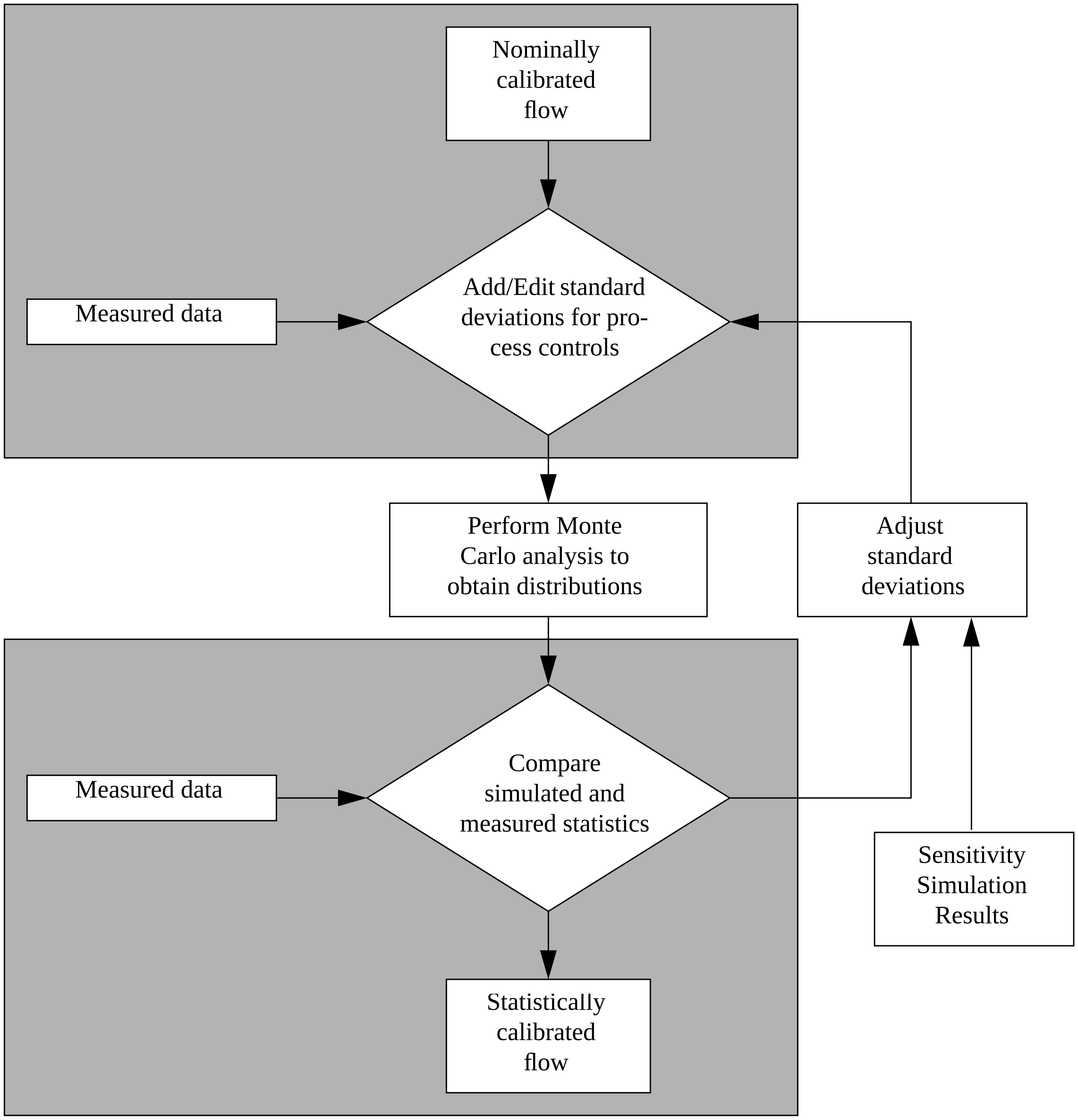
A sensitivity analysis perturbs one process control a fixed amount from its nominal setting and runs a simulation. All measurements from this simulation, including electrical test, device performances and SPICE models are extracted and kept referenced with the process control that was perturbed. This experiment is repeated for each process control with assigned variation. This analysis shows the impact of a single process control on the outputs of process and device simulation. The number of runs in a sensitivity analysis is based strictly on the number of process controls which have assigned variation.

A Monte Carlo analysis randomly perturbs every process control at once. A simulation is then run with the perturbed values and all measurements of electrical test, device performances, and SPICE extraction are made and kept in a database. The process is repeated with new perturbations each time. In this manner, a single database of statistics is constructed that mimics the random fluctuation of processing that occurs during fabrication. Some particular advantages of using Monte Carlo analysis are listed below:

- length of simulation time does not depend on the number of process controls which have variation
- the confidence interval of statistical measures such as standard deviations depend only on the number of runs performed rather than the number of controls varied
- a single process flow is used (rather than a lot split type experiment)
- large samples can be generated in a short time

Figure 5 shows a general flow for calibrating statistical simulations. It is important to note that it, like nominal simulation, is an iterative process.

FIGURE 5. Flow for calibrating statistics



2.2.2 Data requirements for statistical simulation

The initial step in generating statistics is the assignment of standard deviations to critical process controls. In this discussion, a process control is considered a manufacturing setting which determines (partly) the outcome of a particular process step, for example, the dose of an implant. A typical MOS technology may have 100 or more processing steps in a TCAD representation. Each of these steps may have 5 or more process controls. While it is possible to make variation assignments to all process controls, in reality many controls will have no effect on the overall statistics of the process. For example, if an initial cleaning oxide is grown to prepare the wafer for processing, it is highly unlikely that the variation in this oxide thickness will impact device performance. There are a set of process controls, and related processing steps, which are typically assigned variation. These include all implant doses and energies, all critical mask dimension (e.g., poly gate), all oxide growths which are known to directly impact device performance (e.g., gate oxide), all thermal cycles which impact dopant distribution (e.g., RTA), and unique process steps which impact device performance (e.g., a spacer deposit.)

One problem with assigning variation to all process controls is the lack of data to determine standard deviations. It would be desirable to use as much measured data as possible in the assignment of variation. Unfortunately, there is, in general, a lack of measured data which characterizes equipment behavior in manufacturing. While equipment manufacturers often give specifications for their machines (perhaps 1% standard deviation on implant energy) it is hard to measure actual implanter performance. All such equipment specifications can be used as initial guesses for variation on those parameters. It often becomes necessary, however, to use engineering judgement and experience to assign other standard deviations. Data can come in the form of a diffusion operator's knowledge that a furnace bank varies (e.g. by 1 degree C.) In addition, there may be no knowledge base about some processing equipment, in which case industry standards or approximations should be used. While it is necessary to make assignments to critical steps, using unsubstantiated data to make assignments to less critical steps may actually degrade simulation results.

2.2.3 Algorithm for statistical calibration

Once the process control variations are assigned, an initial Monte Carlo and sensitivity simulation is run. These two simulations will yield parameter distributions, correlations and relationships to process controls. Because many of the standard deviations assigned were not based strictly on numerical data some amount of calibration will be necessary. It is important to note, however, that SPICE extraction need not be done during calibration.

For a mature process, a database of electrical test, in-line and device performance measurements should exist. This data can be used to compare against the simulated data. Before direct comparison of measured and simulated data, an analysis of the manufacturing data is often required. Typical data sets will contain outlier lots or points, that while in reality exist, bias statistical results in an unrealistic way. For example, if the test database contains all lots that are manufactured, this may include engineering test lots. If a lot passes through test with a different well dose it could have significantly different characteristics than normal production. This lot should be screened from the measured data to ensure proper comparison to simulation results.

Once filtered, the measured and simulated data should be compared for many statistics including mean, standard deviation, distribution shape and correlations. This data should be used to understand which test parameter distributions need adjustment. Along with an understanding of the physical meaning of the tests, the sensitivity analysis relationships can be used to determine which process controls should be adjusted to correct problems in the distribution statistics. Making adjustments to process controls should be done in a physically-based, consistent manner. For example, one implant dose standard deviation should not be changed without changing all other doses unless there is some physical reason (perhaps this implant is done with a newer implanter.) Keeping standard deviations and their assignment consistent and physical is critical to generating valid SPICE parameter statistics. After adjustments have been made, the Monte Carlo and sensitivity analyses should be re-run and examined in an iterative process until adequate matching between measured and simulated distributions are obtained.

A new process, or one under development, must depend heavily on engineering judgement and experience to characterize the statistics. In addition, any previous work done to find standard deviations (perhaps in a mature process in the same manufacturing facility) should be applied to the new process. It is reasonable to assume, on a macro level, that if the newer process uses the same equipment, then standard deviations on process controls should be similar. If no data is available, then final outcomes must be based on experience, judgement, specifications of the process, and common sense.

Statistical simulation, following these guidelines, will produce a correlated set of SPICE parameters and electrical test measurements. This data set is the basis for determining the underlying relationships among SPICE parameter sets, between SPICE models and electrical tests, and how process controls can impact critical electrical test measures.

3.0 Analysis of SPICE model distributions

Once a correlated set of data is obtained there are several relationships which can be exploited to yield a better understanding of the technology. Even though the SPICE model dimensionality may be greater than 30, not all of these dimensions are independent. Typically, the set of data will have on the order of 4 to 8 independent dimensions (called principal factors.) If it is possible to characterize these factors via mathematical techniques, a great reduction in the complexity of the system is possible. Furthermore, if it is possible to map these mathematical factors to measurable quantities, the space becomes observable. And with this observation, better control strategies can be implemented.

3.1 Constructing a mapping from electrical test to SPICE parameters

The correlated set of SPICE parameters and electrical test contains information about how these two sets of data are related to each other. If a mapping between the two is possible, it opens many possibilities for better tracking of SPICE models. This mapping should be non-linear, to account for more complex relations between parameters. In addition, the mapping should be an equation that indicates which electrical tests are accountable for SPICE parameter variation. pdPCA is a data analysis tool which can provide these types of relationships given a set of correlated data.

For a particular device pdPCA is given a SPICE model set (responses) and a set of electrical test (stimuli) that could be used to track the SPICE parameters. The algorithm is as follows:

- Transform all parameters to be as Gaussian as possible - This allows a correlation to accurately represent the relationship between the parameters
- Build a correlation matrix for the SPICE parameters
- Perform an eigen-value eigen-vector decomposition of the correlation matrix - This gives the major factors of the SPICE parameter space

- Match transformed electrical tests to the factors from the correlation matrix - This tries to find which electrical tests are highly correlated with SPICE factors such that these measurable quantities can be used to span the space
- If needed, use rotations of subsets of factors to obtain matches
- all tracking stimuli found now represent a linear model between the transformed electrical tests and transformed SPICE parameters
- Apply inverse transforms to data - This produces non-linear relations between the electrical test and SPICE parameters

These non-linear equations capture the desired relationship: SPICE parameters expressed as combinations of measurable quantities, namely electrical tests. It is now possible to track SPICE model shifting based on what is currently being produced. In addition, it is fast and inexpensive to generate large numbers of SPICE models at any time from electrical test measurements already being taken.

3.2 Further analysis of relationships

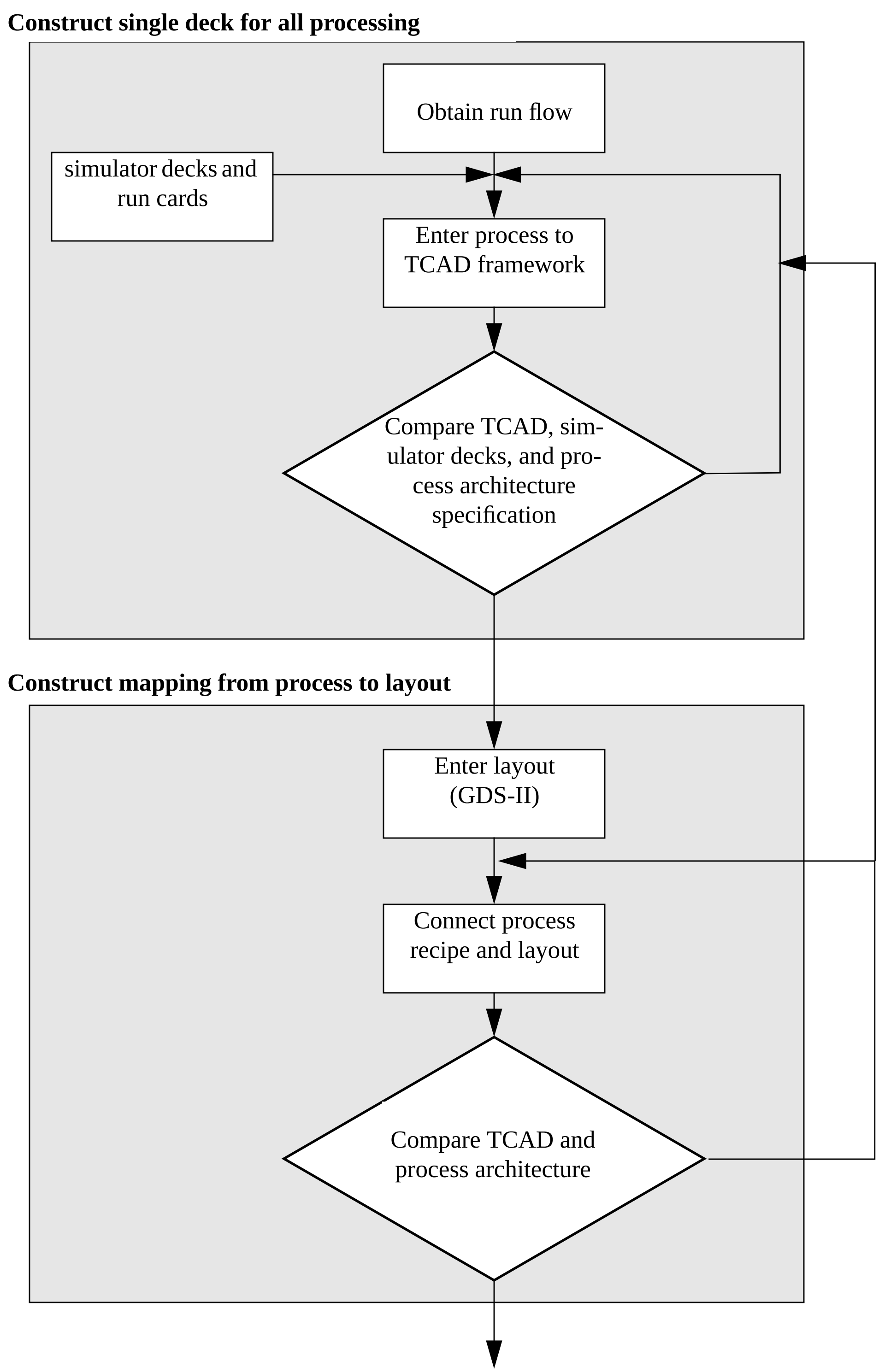
This type of factor analysis clearly indicates which electrical tests are critical to track the variations in SPICE parameters. This implies possible changes to current testing methodologies in manufacturing. Simulation is also able to provide electrical test which are currently not being taken. If one of these proves important for tracking variation it could be added to the testing suite. Conversely, based on the analysis, many tests could potentially be removed from electrical test as they do not help track SPICE parameter variation. Fewer tests result in a lower cost at test.

Because the relationship between electrical test and SPICE models (and consequently circuit performance) is known, changes to testing specification limits are also possible. Limits could be adjusted to ensure that only good product will be released from manufacturing. In addition, specification limits which are design specific could also be developed because different designs may depend on different device properties. Consider two parts with different functionality. Part A’s main function depends mainly on consistently low NMOS Vth. Part B’s main function depends mainly on the overall speed of an inverter. These two parts could have different specification limits for electrical tests because each part’s functionality depends on different physics. Finally, the sensitivity analysis can be used to assess and better control electrical test. Because this analysis shows how an individual process control impacts each test, it can point to possible processing steps which, if better controlled, will reduce overall SPICE parameter variation.

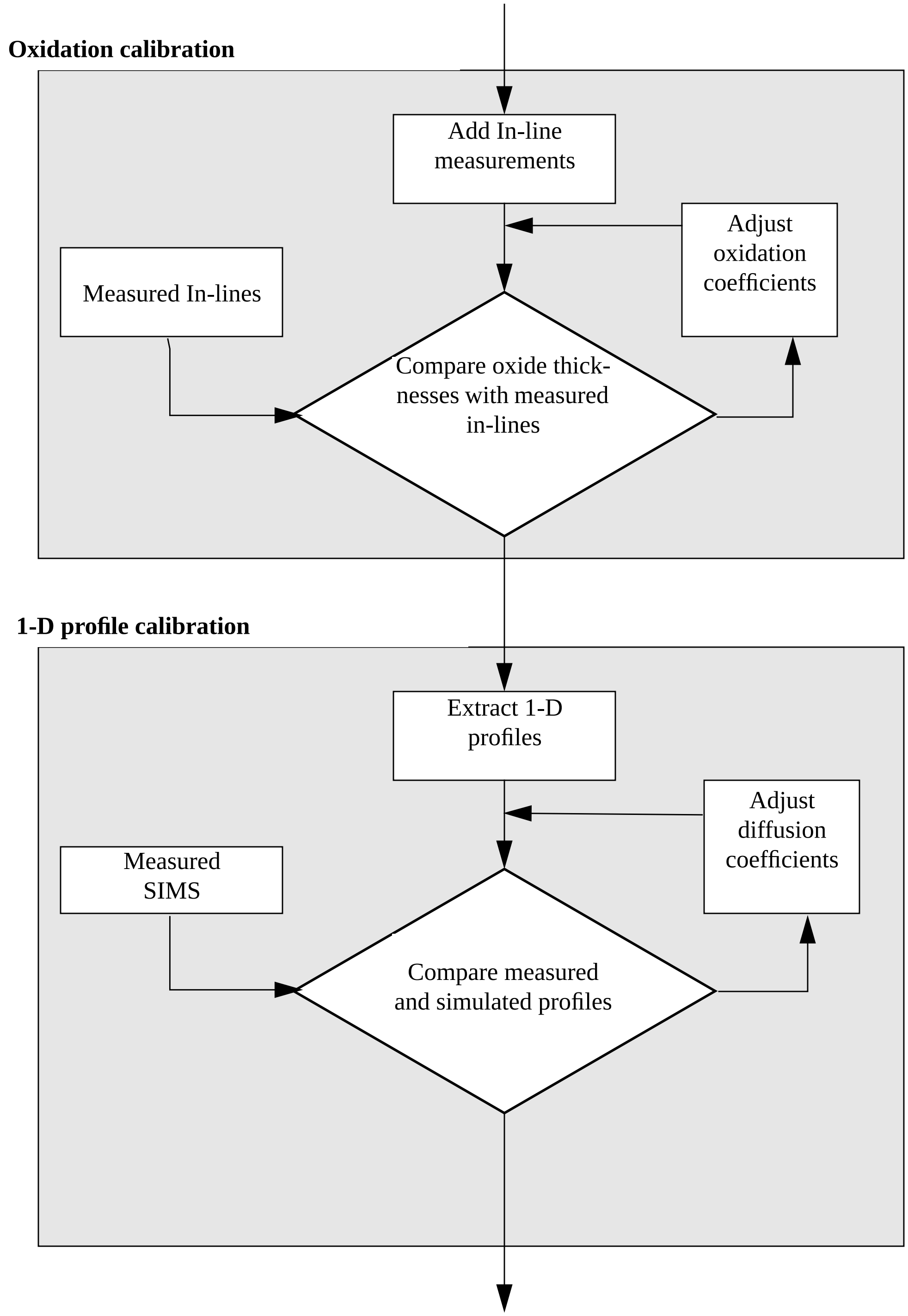
4.0 Conclusions

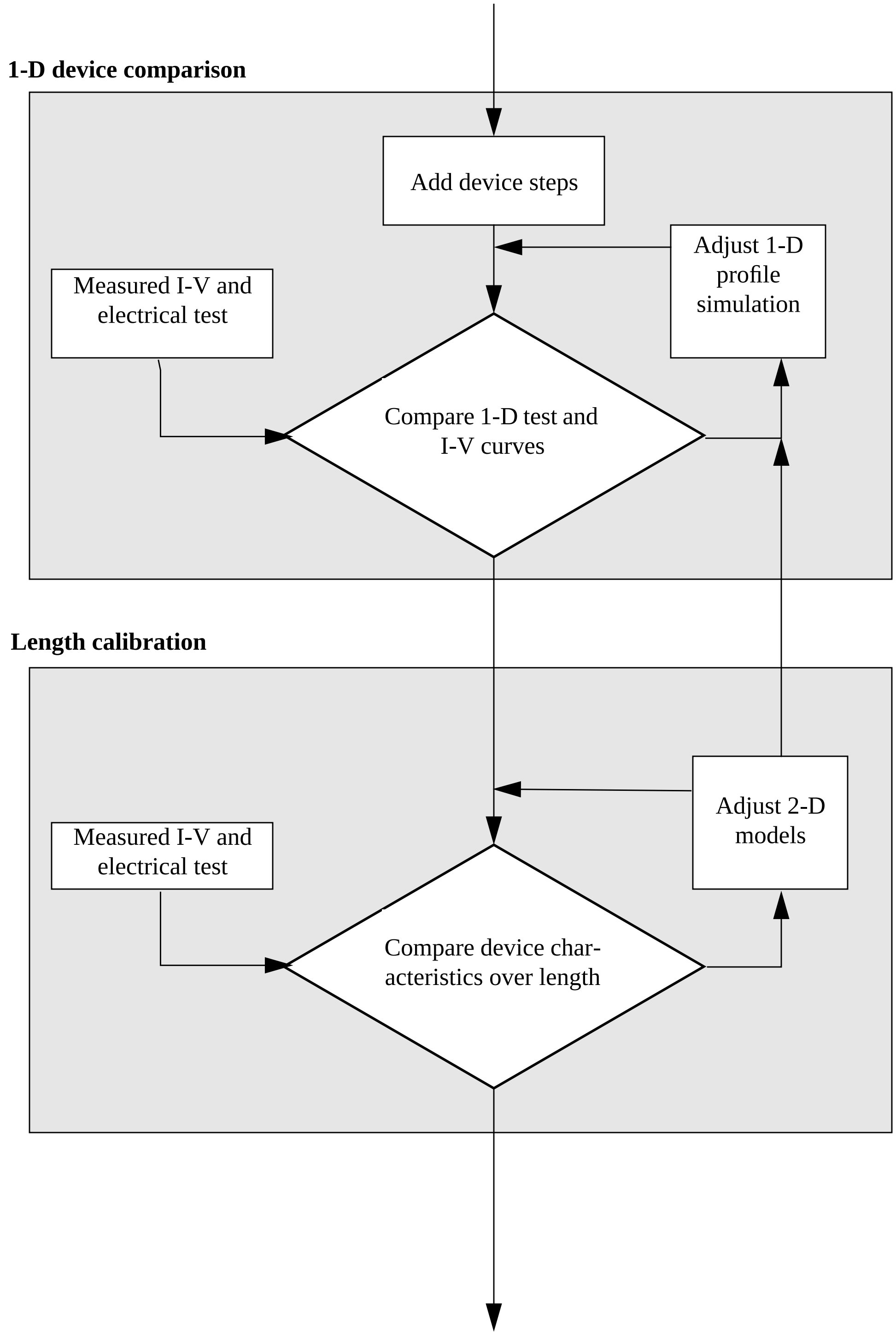
Using this physically based methodology it is possible to realize statistical distributions of SPICE parameters that are inexpensively monitored by electrical tests. Because a quickly generated database of SPICE parameters is now possible, better worst case testing methodologies can be used. Higher success rates of first pass designs result from the more accurate models available. In addition, a better understanding of what worst case truly means for individual circuits is gained because a statistically valid distribution of models is available. With frequent use of the methodology to characterize processes running in consistent manufacturing environments, development of new processes will benefit. Direct application of the knowledge gained about process interaction and variation can be applied to developing technologies to provide better and earlier prediction of device statistics and consequently faster yield ramps. Finally, the analysis discussed can have significant impacts on bottom line numbers. Testing costs can be reduced by ensuring proper tests are being taken, and those test can be customized for specific circuit analysis. Circuits can now be adequately worst case tested by a variety of methodologies which will ensure good designs based on manufacturing capability. Information gained in the study can also improve processing of wafers which will ultimately result in higher yielding final product.

Appendix A

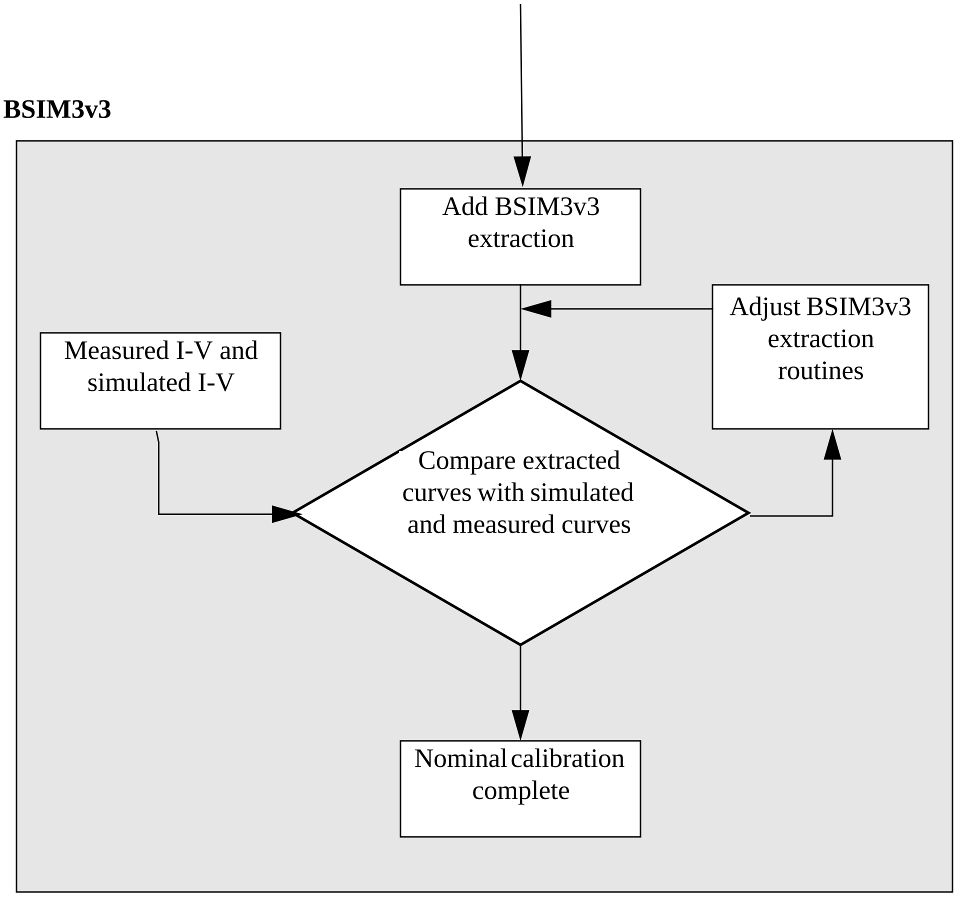


Construct single deck for all processing
Obtain run flow
simulator decks and run cards
Enter process to TCAD framework
Compare TCAD, simulator decks, and process architecture specification
Construct mapping from process to layout
Enter layout (GDS-II)
Connect process recipe and layout
Compare TCAD and process architecture


Oxidation calibration
Add In-line measurements
Adjust oxidation coefficients
Measured In-lines
Compare oxide thick-nesses with measured in-lines
1-D profile calibration
Extract 1-D profiles
Adjust diffusion coefficients
Measured SIMS
Compare measured and simulated profiles


1-D device comparison
Add device steps
Adjust 1-D profile simulation
Measured I-V and electrical test
Compare 1-D test and I-V curves
Length calibration
Adjust 2-D models
Measured I-V and electrical test
Compare device characteristics over length

BSIM3v3


Add BSIM3v3 extraction
Adjust BSIM3v3 extraction routines
Measured I-V and simulated I-V
Compare extracted curves with simulated and measured curves
Nominal calibration complete