HIGH-PERFORMANCE MICROPROCESSOR CIRCUITS

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6.4.1 Statistical Device Models

From the perspective of circuit design, the parameters P, which characterize a process, are often the model parameters required to perform circuit simulation. Internal to a circuit simulator, the model parameters are used to express the dependence between quantities such as current, charge, and voltage. A simple example of a device model is the Spice Level-1 MOSFET model:

$$I_{ds} = 0 \quad \text{for } V_{gs} - V_{th} < 0$$

$$I_{ds} = \mu C_{ox} \frac{W}{L - \Delta L} \left[(V_{gs} - V_{th}) V_{ds} - \frac{V_{ds}^2}{2} \right] \quad \text{for } 0 < V_{ds} < V_{gs} - V_{th}$$

$$I_{ds} = \mu C_{ox} \frac{W}{L - \Delta L} (V_{gs} - V_{th})^2 \quad \text{for } 0 < V_{gs} - V_{th} < V_{ds}$$
(61)

for which $P = \{W, L, V_{th}, \mu, \Delta L, C_{ox}\}$. Many of these quantities are not directly measurable and must therefore be inferred from measurements of I_{ds} versus V_{gs} and V_{ds} . This inference process, called *model parameter extraction* is usually performed using a nonlinear least squares analysis (e.g., see [1] Chap. 6). Due to the fact that the model is only an approximation to reality, and because the minimization is performed with finite tolerances, the parameter estimate derived is subject to error.

In addition to a nominal model fit, we need to characterize variations in P. This may be done by measuring a number of devices, performing parameter extraction on each set of measurements to get a population of parameters P, and using the population to estimate the statistics of P.¹ Based on these statistics, large numbers of hypothetical cases can be simulated to study the resulting variation in performance. Numerous difficulties in this approach exist, including computational costs, data collection requirements, and potentially large errors in performance estimates due to propagation of systematic device model fitting errors.

The difficulty and high cost of getting reliable and accurate statistics for the model parameters result in a situation where (1) the parameter statistics are not updated often to reflect changes and maturation in the fabrication process; and (2) there is often a large incentive to use analysis and design methods that are less sensitive to the detailed

¹ There are a number of other approaches to solving this problem; see, for example [3], [8].

from one parameter P through to another parameter Q, by way of a known analytic or numeric function f, where Q = f(P).

In the case where f can only be evaluated numerically (e.g., in understanding the impact of some process variation such as an anneal temperature on resulting geometric structure), monte carlo or other sampling methods are often utilized [13]. In many cases, however, a simple *sensitivity analysis* approach is used through a first-order expansion of some analytical function f relating P and Q:

$$Q + \Delta Q = f(P + \Delta P)$$

$$\Delta Q \approx \left| \frac{\partial f}{\partial P} \right| \Delta P$$
(6.2)

where ΔP and ΔQ are typically considered to be the standard deviations of parameters P and Q. While many functions do not preserve normality, it is often assumed that the small deviations of ΔQ can also be approximated by a normal distribution, so that the variance propagation is approximated as $\sigma_Q^2 \approx (\partial f/\partial P)^2 \sigma_P^2$. Given approximate variance values for some set of process variations, the resulting first-order electrical impact of the variations on device or canonical circuits is often derived and compared for different circuit, layout, or other design rule options (as, for example, in Section 6.5.2).

6.4.3 Worst-Case Analysis

The various components of P are usually correlated. For example, Fig. 6.3 shows a representative distribution of four MOS transistor model parameters from a modern 0.25 μ m process. The correlation structure of P is thus required for accurate statistical analysis. Ignoring the correlation, i.e., assuming it is zero, leads to statistical performance estimates which are in reality extremely improbable and are overly pessimistic. Principal component analysis [12] is often used to transform highly correlated process parameters to a smaller set of uncorrelated parameters to simplify statistical design analysis.

The most common method for analyzing the implications of random and correlated variations is worst-case analysis [4]. Consider a circuit performance z (e.g., clock speed) that is a function of model parameters P, expressed as z = f(P). Due to variations in P, the performance z is a random variable. The goal of worst-case analysis, like all other forms of statistical design analysis [14], is to determine a measure of goodness or quality of the design. The ideal such measure is the *yield* of the design, which is defined as the proportion of circuits that meet the specifications. Since computing the function f typically involves performing a computationally expensive circuit simulation, computing the yield directly is very expensive. Worst-case analysis is the

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