Improved I_{DDQ} Testing With Empirical Linear Prediction

David I. Bergman
National Institute of Standards and Technology[1], Gaithersburg, MD 20899

Hans Engler
Georgetown University, Washington, D.C., 20057

Abstract

A new linear prediction method that improves I_{DDQ} test effectiveness is described. The method uses statistical pre-processing of exhaustive measurements on training devices to extract principal patterns in the device I_{DDQ} behavior and to generate a prediction model. Fitting the model to device measurements accommodates variations in the fabrication process. Comparison with the Delta I_{DDQ} test method using the SEMATECH S-121 data shows that for nearly equal numbers of defective parts passed, the new method fails fewer defect-free parts.

I. INTRODUCTION

An important factor in the acceptance and use of I_{DDQ} testing as a way to detect defects in digital CMOS integrated circuits is the method's ability to enhance the fault coverage of an overall test program with a small number of additional test vectors. Although an I_{DDQ} test makes no direct query of a device's ability to function as designed, it can uncover defects in a device that functional, stuck-at, and other tests miss.

With the advent of deep submicron fabrication technologies, shrinking MOSFET geometries have caused normal quiescent current to increase. Discussions of the causes of MOSFET leakage are found in [1]-[4]. Leakage current mechanisms such as subthreshold conduction, gate oxide tunneling, and short channel effects including drain induced barrier lowering (DIBL) and gate induced drain leakage (GIDL) confound a test method that seeks to discriminate good devices from bad devices with a simple comparison to a threshold.

This paper describes an I_{DDQ} test method that makes use of statistical analysis of the larger device population to extract information that can aid the test effort. The method uses linear prediction to discriminate between devices whose measurements indicate normal leakage current and those that have defect induced leakage currents. In prediction-based I_{DDQ} testing, a model is developed with which device I_{DDQ} responses may be predicted. The residuals of the predictions, the difference between actual measurements and the predictions, are used to determine if a device is defective or not. The key idea is to test exhaustively a small sample population of devices and to use information in the exhaustive sampling to enhance the test effectiveness of the small number of measurements made during on-line testing. By fitting device measurements to the model, the method can accommodate I_{DDQ} variations arising from variations in the fabrication process. Another way of describing the approach is that principal patterns in the I_{DDQ} behavior of known good devices are found. The goodness of fit between these patterns and measurements made on a device under test is used to make a pass or fail decision on the device whatever its absolute I_{DDQ} levels may be.

Section II discusses the motivation for the work and presents a brief survey of prevailing I_{DDQ} test methods. Section III discusses the rationale behind predictive I_{DDQ} and gives a qualitative description of a new empirical linear prediction method. Section IV gives an overview of the mathematics behind the new prediction method. Section V presents results using the new method with the SEMATECH Project S-121 data [5]. Section VI summarizes the main points of the paper and describes how the method might be applied to production testing.

II. BACKGROUND

The traditional I_{DDQ} test is based on two observations. One is that a digital CMOS circuit, even a large one, draws a negligibly small current from its power supply when the circuit clock is stopped (quiescent mode). The other is that the presence of a defect anywhere in the device can cause a non-negligible supply current to be drawn if the circuit nodes associated with the defect are driven to the right states. Examples of defects that can elevate supply current include resistive metal bridges, gate oxide shorts, and MOSFET floating gates.

[1]Electricity Division, Electronics and Electrical Engineering Laboratory, Technology Administration, U.S. Department of Commerce. Official contribution of the National Institute of Standards and Technology; not subject to copyright in the United States.

ITC INTERNATIONAL TEST CONFERENCE
0-7803-7542-4/02 $17.00 © 2002 IEEE

In practice, however, even a defect-free CMOS circuit does draw some current. In addition, quiescent current levels vary from device to device due to random variations in doping levels, lithographic dimensions, and other fabrication process parameters. A group of devices whose internal logic states have been set equal under static conditions will display a spread of I_{DDQ} values around some mean value. As long as quiescent current variations in defect-free devices remain small, discrimination between normal quiescent current and defect-induced current is a straightforward task. Establish a current threshold or limit, and declare as defective any device whose supply current exceeds the threshold for any of the test vectors applied.

With increased deep submicron leakage comes not just higher nominal quiescent current but increased variance too both within a single device among test vectors and among many devices. The task of discriminating good devices from bad is not as straightforward, because normal quiescent currents may be larger than defect currents. Under these conditions, a simple threshold test is no longer workable.

Researchers have refined the original I_{DDQ} test method idea with several different approaches. Gattiker et. al. [6][7] propose a current signature method that looks at the set of I_{DDQ} measurements on a device under test after sorting the measurements from smallest to largest. Discontinuities in the resulting curve are interpreted to indicate the presence of a defect. A differential current signature method is also described which compares each I_{DDQ} measurement to a reference current value and declares a device defective if any of the comparisons exceeds a threshold. Thibeault [8][9] proposes a differential I_{DDQ} method known as Delta I_{DDQ} in which the differences between successive I_{DDQ} measurements in a set are compared to a threshold. Like the current signature method, this method is insensitive to defects that elevate quiescent current at all test vectors. Since such defects are likely not caused by defects in active circuit components, ignoring these kinds of defects can reduce the number of functional devices rejected. Thibeault shows that the variance of Delta I_{DDQ} residuals ($I_{DDQk+1} - I_{DDQk}$) is less than the variance of absolute I_{DDQ} measurements since measurement variations from chip to chip or from wafer to wafer contribute to the latter but are partly eliminated by taking differences. The result is that a single threshold pass/fail criterion results in fewer misclassifications. Daasch et. al. [10] make use of spatial proximity among devices on a wafer to predict the behavior of a device under test from its neighbors' I_{DDQ} measurements. The residuals of these predictions are shown to have reduced variance. Maxwell and O'Neill [11] describe a current ratio method. The method is based on the observation that a set of devices will exhibit similar current signatures when the I_{DDQ} values for each device are plotted in the same vector order. This means that the ratio of maximum I_{DDQ} to minimum I_{DDQ} for a set of devices is nearly constant even if the absolute I_{DDQ} values among devices are very different. By applying to the device under test a test vector likely to produce a minimum (or nearly minimum) I_{DDQ} value, the maximum I_{DDQ} value for that device can be predicted. A single absolute measurement on a device under test can thus provide tailored thresholds for the device against which subsequent comparison measurements can be made. Jandhyala et. al. [12]-[14] apply clustering techniques to separate good devices from bad devices. Clustering methods attempt to classify devices into groups with similar characteristics. Clustering methods can sort devices into "good" clusters and "bad" clusters without restriction to simple, one-dimensional threshold comparisons. Variyam [15] describes an I_{DDQ} test method based on linear prediction of I_{DDQ} currents. Each I_{DDQ} value among a set of values for a given device is predicted from the remaining I_{DDQ} values in the set. The residuals of these predictions are applied to a threshold test.

Each of these methods uses to a different degree information from the overall set of test vectors and device population. All methods except the traditional single threshold I_{DDQ} test also rely on techniques to reduce the variability of I_{DDQ} test results to improve the accuracy of discrimination procedures. The traditional single threshold I_{DDQ} test makes a decision about a device based on whether any measurement exceeds a threshold. The current signature and Delta I_{DDQ} methods are based on comparisons of individual measurements with other measurements from the same device. The nearest neighbor method bases decisions on the set of measurements made over a local population of devices in the neighborhood of the device under test on the wafer. The ratio I_{DDQ} method also uses a small population of devices to determine the maximum to minimum ratio of I_{DDQ} current for the set of devices to be tested. The predictive and clustering approaches rely on statistical analysis of larger device populations to make pass/fail decisions. In doing so, these last two methods make use of additional information contained in the population where hidden correlations can offer insight into device behavior. The method proposed here uncovers the correlations among measurements at different test vectors from an analysis of a large device population and uses them to make pass/fail decisions.

III. PREDICTIVE I_{DDQ}

A predictive approach to I_{DDQ} testing recognizes that because device leakage currents among defect-free devices are correlated to one another through an underlying set of process parameters, it is possible to predict the I_{DDQ} value of one test vector from the I_{DDQ} values of one or more other test vectors. Fig. 1 illustrates how I_{DDQ} measurements correlate with fabrication process parameters. Drain/source-substrate junction areas, MOSFET gate length L_{eff}, impurity concentrations, and gate oxide thickness are a few examples of process parameters whose variations give rise to varying leakage currents. The mechanisms behind these leakage currents were mentioned in section I. The leakage mechanisms combine in state-dependent fashion to produce varying I_{DDQ} levels that are correlated with the underlying process variations.

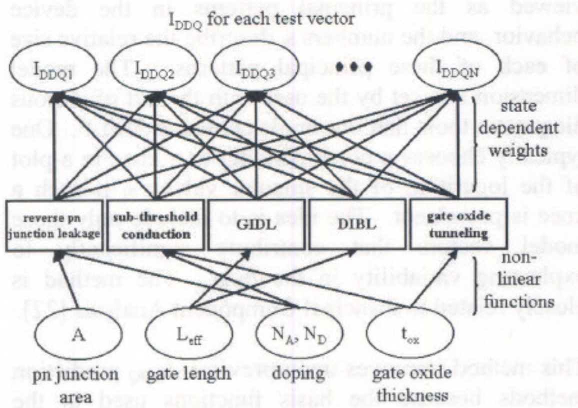


Fig. 1. Test vector to fabrication process correlation.

If one can predict these I_{DDQ} levels well, then the residuals, the differences between measured and predicted values, will be small and have less variance than the original set of I_{DDQ} measurements. A prediction method that is related in some way to process parameters and is based on the behavior of defect free devices should therefore be able to track process variations. It should reduce I_{DDQ} variability that is due to changes in process parameters alone. On the other hand, the I_{DDQ} current associated with a test vector that activates a defect will not be well predicted, and the prediction residual will be large. As a result, large prediction residuals among devices with defects will be well separated from the small prediction residuals of defect free devices.

The method of prediction described in [15] predicts a test vector's I_{DDQ} value by taking linear combinations of I_{DDQ} values from other test vectors. Appropriate linear combinations are found using regression analysis on data from a population of devices called a training set. The method described in this paper also uses information from a training set population but performs the predictions based on a mathematical model derived from the training set. I_{DDQ} values are predicted not with linear combinations of other I_{DDQ} values from the same device but with linear combinations of data vectors from an empirical model derived from device responses. Also, devices in the training set are measured for a greater number of test vectors than are measured during production testing. During production testing, the prediction method makes use of information contained in the additional test vectors measured from the training set. The method therefore allows I_{DDQ} values for a device under test to be predicted for test vectors not measured during production testing.

Empirical Models and Linear Prediction

Empirical models are learning-based models, obtained by numerically analyzing the data from exhaustive testing of representative units coming off the production line. They are based on the premise that a selected lot of devices will manifest all of the degrees of freedom or variability of the manufacturing process. At the National Institute of Standards and Technology (NIST), a user-friendly software toolbox for optimizing empirical linear model building has been developed. The toolbox, High-dimensional Empirical Linear Prediction (HELP), was developed specifically to meet the requirements of test and measurement engineers. While this paper discusses some of the methods used by the toolbox, it does not describe the software itself. Interested readers may refer to [16] and [17]. More detailed treatment of the methods used by the toolbox can be found in [18]-[21]. The toolbox incorporates a new approach for optimizing the testing of electronic devices and instruments. The approach is currently being used by mixed-signal integrated circuit manufacturers to reduce the cost of testing their products, and it is also being used at NIST to reduce customers' costs for selected calibration services. Examples of devices that can benefit from the HELP approach range from integrated circuit analog-to-digital (A/D) and digital-to-analog (D/A) converters to multi-range precision instruments.

The HELP approach is based on a simple mathematical model that relates device response over all test vectors to a set of underlying variables. Once an accurate model has been developed, algebraic operations on the model can be used to select an optimal set of test vectors and to predict the response of a device under test at all test vectors. HELP places special emphasis on empirical modeling using measurement data collected previously on devices similar to the unit under test. An efficient testing strategy tries to identify the parameters that govern the behavior of a device type and build a mathematical model for it. For a given new device, these parameters are then determined from a reduced set of measurements, and the mathematical model is used to compute the device response at all test vectors. Empirical models require no detailed knowledge of the internal device architecture to be both accurate and efficient. In addition to test optimization, the toolbox is useful for exploring the structures that underlie the behavior of the tested devices. It can reveal how many variables are actually needed to explain the behavior and what their characteristic signatures look like. It can warn production engineers when the manufacturing process has undergone hidden changes, and it may be used to help diagnose the likely causes.

IV. APPLICATION TO I_{DDQ} DATA

Although the methods described in [18]-[21] were developed for the testing and characterization of analog and mixed-signal devices, they can be applied to I_{DDQ} data analysis as well. Since I_{DDQ} measurements consist of ordered pairs of digital input codes and analog current outputs, I_{DDQ} testing may be viewed as a mixed-signal application. The data analysis methods are based on a linear coefficient matrix model **A** that relates the device's response **y** at all candidate test vectors to a set of underlying variables **x**. Once an accurate model has been developed, algebraic operations are used to:

1. Estimate the parameters of the model from measurements made at the selected test vectors.

2. Predict the response of the device at all candidate test vectors from measurements made at the selected test vectors. (The candidate test vectors are those that were used in the training set.)

The model matrix **A** is an empirical model. It requires no detailed design knowledge of the device being tested. It is obtained numerically by analyzing the data from exhaustive testing of devices similar to the device being tested.

We start with an m×p matrix of modeling (training) data $\bar{\mathbf{A}}$, where m is the number of test vectors measured in the training set, and p is the number of devices in the training set. In the situation considered here, p is larger than m. Each of the columns of $\bar{\mathbf{A}}$ contains I_{DDQ} data for a single, known good device taken over m test vectors. We want to extract a lower dimensional approximation to these response patterns, i.e. an m×n (n < p) model matrix **A** such that the columns of $\bar{\mathbf{A}}$ can be approximated in terms of the columns of **A**.

To construct an empirical model matrix from the modeling set $\bar{\mathbf{A}}$, we take the singular value decomposition [22] of $\bar{\mathbf{A}}$ so that $\bar{\mathbf{A}} = \mathbf{USV}^T$. Here, **U** is an m×m orthogonal matrix, **V** has size p×m with orthonormal columns, and **S** is a diagonal matrix whose diagonal elements ($s_1, s_2, \ldots, s_m$) are the singular values s_i that are non-negative and decreasing. One then chooses $\mathbf{A}=\mathbf{U}_1$ consisting of the n leftmost columns of **U**. It is known that no model matrix with n columns gives a better linear approximation of the modeling data $\bar{\mathbf{A}}$ with respect to a number of approximation criteria. The columns of $\mathbf{U}_1$ may be viewed as the principal patterns in the device behavior, and the numbers s_i describe the relative size of each of these principal patterns. The model dimension n is set by the user with the aid of various diagnostic tools that are implemented in HELP. One typically chooses n corresponding to a knee in a plot of the logarithm of the singular values s_i if such a knee is prominent. The idea is to include only those model vectors that contribute significantly to explaining variability in the data. The method is closely related to Principal Component Analysis [22].

This method improves upon previous I_{DDQ} prediction methods because the basis functions used in the prediction are orthogonal. And, as will be seen, through the training set, the method makes use of information in all of the available test vectors for a particular batch of devices, not just those used during on-line testing.

Modeling

We now delete all rows of **A** except those corresponding to the reduced test vector set of k test vectors (the test vectors selected for on-line measurement). Test vectors may be selected using established fault models, or they may be selected with HELP using an algorithm based on minimizing prediction variance. The result is a row reduced model matrix $\tilde{\mathbf{A}}$, with k rows and n columns (n < k < m). With a model determined and with test vectors selected, we first estimate the parameter vector **x** using least squares from a reduced number of I_{DDQ} measurements $\tilde{y}$ taken from the device under test:

$$x \approx \hat{x} = (\tilde{A}^T \tilde{A})^{-1} \tilde{A}^T \tilde{y}. \quad (1)$$

From the parameter estimate $\hat{x}$, the predicted behavior at all test vectors is given by

$$\hat{y} = A \hat{x} = A(\tilde{A}^T \tilde{A})^{-1} \tilde{A}^T \tilde{y}. \quad (2)$$

In practice, one normally needs at least twice as many test vectors as model vectors ($k > 2n$). While it is intuitive that more test vectors are likely to find more defects, from a modeling perspective, more test vectors allow better sampling of device behavior outside the space spanned by the model of good devices. With fewer test vectors, the non-model behavior of a defective device is harder to detect.

Fig. 2 illustrates with a matrix tableau how seven model vectors and measurements at ten test vectors predict the response of a device under test. The procedure computes model parameters $\hat{x}$ from device under test I_{DDQ} values measured at k test vectors (big dots) and then uses $\hat{x}$ to predict the device response at all of the device's candidate test vectors, including those measured.

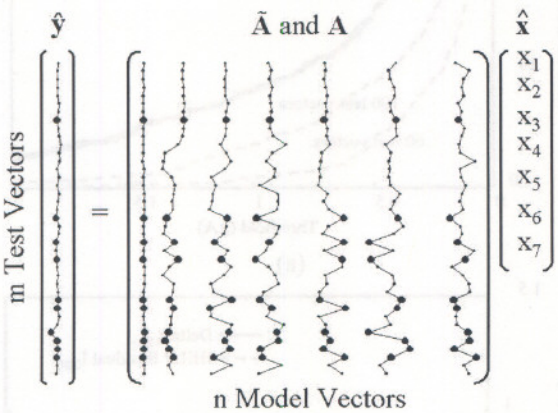


Fig. 2. Pictorial representation of equation (2).

The following statements can be made about this procedure. 1) The regression constants are determined using device under test measurements. Predictions are based upon fitting the model to the device under test, so even wildly different current levels from device to device are accommodated. 2) The method uses information from all test vectors in the training set, not just those used for the device under test. This means that I_{DDQ} values at test vectors not measured on the device under test can be predicted. 3) The model is nearly optimal for explaining the behavior of good devices. Prediction residuals are generally smaller than for any other linear model with the same dimension and the same number of test vectors.

V. RESULTS

The last statement forms the basis for improved I_{DDQ} testing methodologies. Smaller prediction residuals allow a threshold test based on residuals to discriminate better between normal quiescent and defect-induced supply currents even when absolute current levels are very different from device to device. With this thought in mind, the SEMATECH data were analyzed using a HELP-based prediction method. The results were compared with the Delta I_{DDQ} method. The two methods and their experimental definitions are as follows:

1. Delta I_{DDQ}: The maximum of the absolute value of the difference between each test vector and the next test vector is computed for each device:

$$\delta_{max} = \max |y_i - y_{i-1}|, \quad (3)$$

2. HELP Residual I_{DDQ}: The HELP prediction residuals are computed at the selected test vectors:

$$r = \tilde{y} - \tilde{A} (\tilde{A}^T \tilde{A})^{-1} \tilde{A}^T \tilde{y}, \quad (4a)$$

where $\tilde{A} (\tilde{A}^T \tilde{A})^{-1} \tilde{A}^T \tilde{y}$ are the predictions at the measured test vectors only, and the maximum of their absolute values is recorded:

$$r_{max} = \max |r_i|. \quad (4b)$$

Note: For the data analysis described in this paper, each method was preceded by a pre-screening pass to exclude from the validation set any device for which I_{DDQ} values at all test vectors were elevated (> 5 μA) but nearly equal ($\Delta I < 0.01$ μA). These devices are likely bad but would pass the Delta I_{DDQ} test as defined above.

By taking the maximum over all I_{DDQ} test vectors used, each method produces a single number that is ultimately compared to a threshold in order to make a pass or fail decision. The threshold level is set by the test engineer per an appropriate yield/quality cost function.

The mathematical model used by the HELP method to predict device response over all test vectors was derived from training data using known good devices only, i.e. devices that passed all tests at the wafer level (SEMATECH failure code $$). 500 devices were randomly selected from the SEMATECH job 1 data to comprise the training set. 1000 different good devices and 900 bad devices (failure code AF) were randomly selected for a validation set. The training set was then used with HELP to predict device I_{DDQ} values over all of the 195 SEMATECH test vectors using different combinations of model size, n, and number of test vectors, k. Model size refers to the number of principal component vectors in the model whose appropriate linear combination predicts the response of a device under test.

For each 'model size/test vector set' combination, the prediction data and the prediction residuals were computed. As an example, Fig. 3 shows measured I_{DDQ} and HELP predicted I_{DDQ} values versus test vector for an arbitrary good device in the validation set. 25 model vectors and 50 test vectors were used to predict the device response at all 195 test vectors. For clarity, only the first 60 of the 195 predictions are shown.

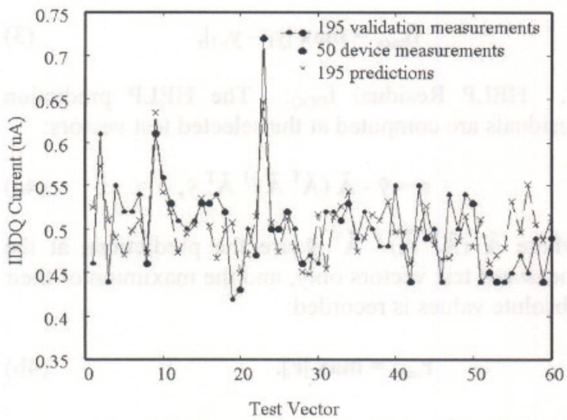


Fig. 3. Measurements predicted with 25 model vectors and 50 test vectors (only the first 60 of all 195 predictions shown).

The ability of the HELP Residual I_{DDQ} prediction method to reduce variances is illustrated in the histograms in Fig. 4. For the 1000 good devices in the validation set, the plot compares Delta I_{DDQ} values, HELP Residual I_{DDQ} values, absolute I_{DDQ} current values, and I_{DDQ} current prediction residuals using the method described in [15]. It should be recalled that maximal values over all I_{DDQ} test vectors used are employed throughout. Maximum residuals from the HELP predictions are seen to have the narrowest distribution of all the methods. It turns out that for bad devices, a proportional compression leftward of the HELP Residual I_{DDQ} distribution is not observed. As a result, the distributions for good and bad devices are separated better with the HELP Residual I_{DDQ} method than with the Delta I_{DDQ} method.

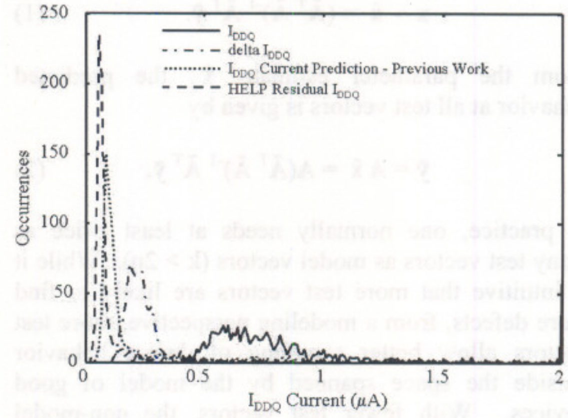


Fig. 4. Histograms of current, delta-current, and residual-current values from different test methods. 1000 fault free devices are represented. All methods used 50 test vectors. The HELP method used 25 model vectors.

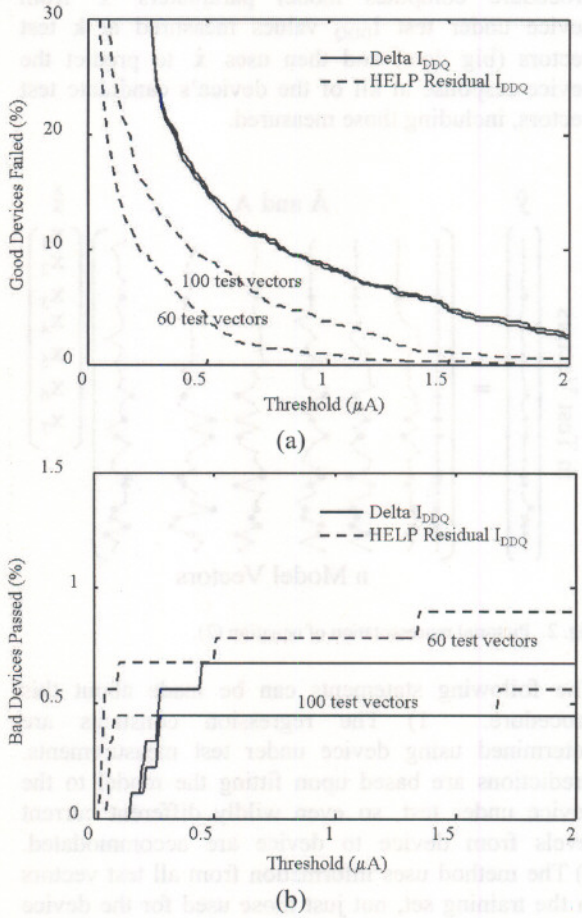


Fig. 5. Test escapes. a) Good devices failed. b) Bad devices passed. HELP model size, n = 50.

Fig. 5 supports this statement by showing the percentage of test escapes that occur with the Delta I_{DDQ} and HELP Residual I_{DDQ} test methods. Fig. 5a plots the percentage of good devices (out of 1000 in the validation set) whose test result was greater than the test threshold over a threshold range from 0 to 2 µA. The number of model vectors used by the HELP method was 50. The figure shows good devices failed versus threshold for cases when the number of test vectors used by both methods was 60 and 100. It is evident that the HELP Residual I_{DDQ} method fails fewer good devices than does the Delta I_{DDQ} method for any given threshold. The quality performance (bad devices passed) associated with the yield improvement seen in Fig. 5a is shown in Fig. 5b which plots the number of bad devices passed as a function of test threshold. The performance of the two test methods is nearly identical. While the Delta I_{DDQ} method does pass slightly fewer bad parts than the HELP method, the difference in quality is small compared to the increase in yield attainable with the HELP method.

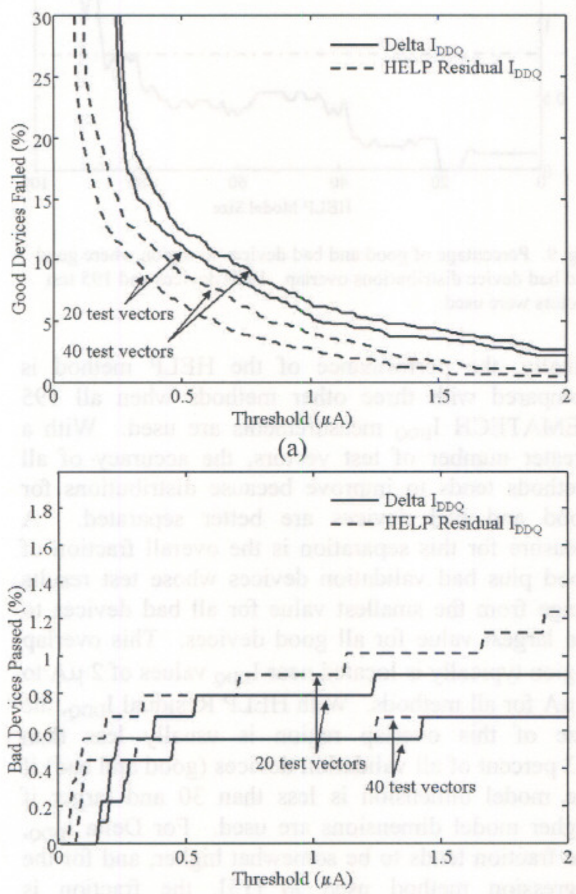


Fig. 6. Test escapes. a) Good devices failed. b) Bad devices passed. HELP model size, n = 10.

Fig. 6 shows more of the same idea but using different randomly selected devices comprising the model and validation sets and different numbers of model vectors and test vectors. In the figure, the HELP Residual I_{DDQ} curves result from using 10 model vectors with 20 and 40 test vector cases. The results are similar to those in Fig. 5.

To illustrate how model size affects performance of the HELP Residual I_{DDQ} method, Fig. 7 shows test escapes as a function of both threshold and model size when 20 test vectors are used. For a fixed threshold, the number of good devices failed decreases with increasing model size because the model does a better job at predicting device behavior. However, as the number of model vectors approaches the number of test vectors, prediction residuals for bad devices decrease as well, allowing some additional bad devices to be passed.

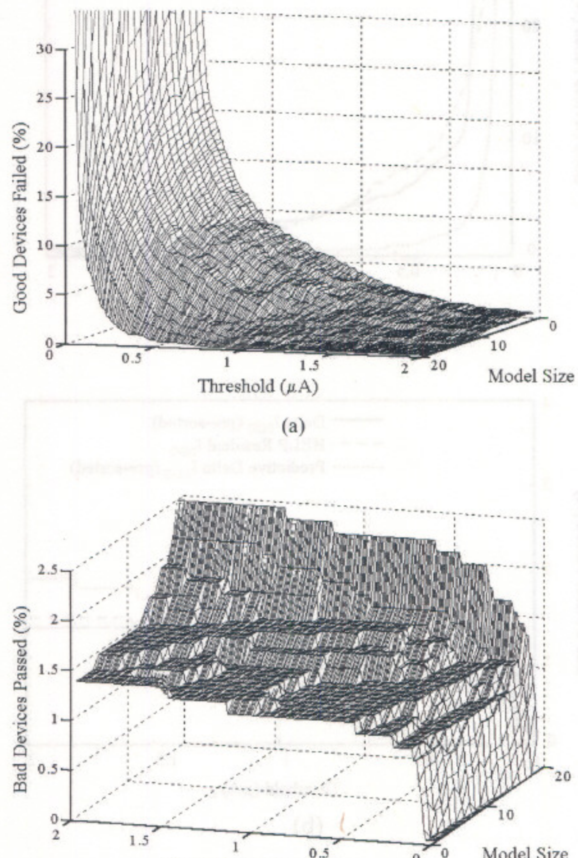
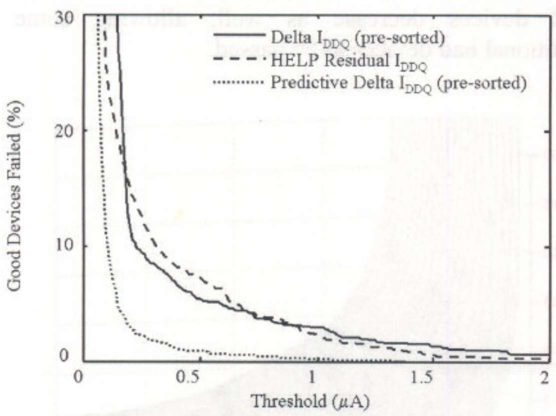


Fig. 7. Test escapes. a) Good devices failed. b) Bad devices passed. Number of test vectors was 20.

Another useful experiment considers the effect of pre-sorting I_{DDQ} data on the outcome of the Delta

I_{DDQ} test method. In [15], Variyam defines a Delta I_{DDQ} test method in which prior to the differencing operation, the data are first sorted from smallest to largest. By sorting first, the method acts as a simple prediction scheme. It is noted that the Delta I_{DDQ} method will result in smaller values with a narrower distribution if the I_{DDQ} data are indeed sorted from smallest to largest prior to the differencing operation. Fig. 8 shows the percentage of test escapes that occur with Delta I_{DDQ} (pre-sorted) and HELP Residual I_{DDQ} (sorting makes no difference to the HELP Residual I_{DDQ} method). In this case, the number of test vectors used was 20, and the number of model vectors used by the HELP method was 10. The sorted Delta I_{DDQ} method now fails fewer good devices than the unsorted Delta I_{DDQ} method (compare with Fig. 6a).



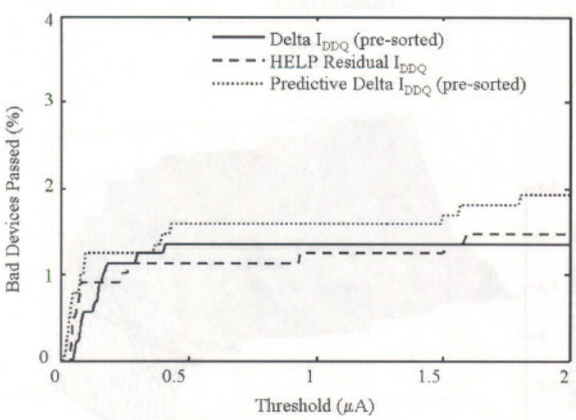


Fig. 8. Test escapes when the I_{DDQ} data are sorted from smallest to largest prior to performing Delta I_{DDQ}. a) Good devices failed. b) Bad devices passed.

Fig. 8 also shows the performance of a third possible test method. Since HELP makes available 195 predicted I_{DDQ} values, it is interesting to observe Delta I_{DDQ} performance using these predicted values. For good devices, these 195 predicted values occupy nearly the same range as the 20 measured values leading to smaller Delta I_{DDQ} values after sorting. As shown in Fig. 8a, this method fails considerably fewer good devices than the other two test methods. Again, as a sanity check, Fig. 8b shows the quality performance associated with the yield improvement. The method does pass a slightly larger number of bad devices than do the other two methods. The meaning of these results is not entirely clear at this time. It is worth noting that without pre-sorting, Delta I_{DDQ} performance using predicted values is not significantly better than standard Delta I_{DDQ} using only measured values.

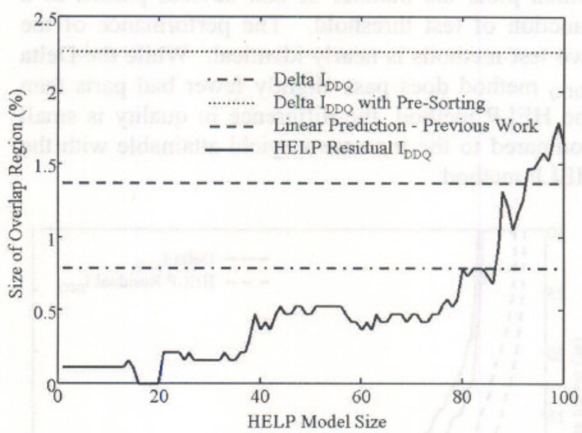


Fig. 9. Percentage of good and bad devices in region where good and bad device distributions overlap. 1900 devices and 195 test vectors were used.

Finally, the performance of the HELP method is compared with three other methods when all 195 SEMATECH I_{DDQ} measurements are used. With a greater number of test vectors, the accuracy of all methods tends to improve because distributions for good and bad devices are better separated. A measure for this separation is the overall fraction of good plus bad validation devices whose test results range from the smallest value for all bad devices to the largest value for all good devices. This overlap region typically is located near I_{DDQ} values of 2 µA to 3 µA for all methods. With HELP Residual I_{DDQ}, the size of this overlap region is usually less than 0.3 percent of all validation devices (good and bad) if the model dimension is less than 30 and larger if higher model dimensions are used. For Delta I_{DDQ}, the fraction tends to be somewhat higher, and for the regression method used in [15], the fraction is slightly higher still. With the Pre-sorted Delta I_{DDQ} method, the fraction is highest due to the consistent presence of a few bad devices with very low delta values. A typical situation is depicted in Fig. 9. Put differently, good and bad devices could be separated almost completely with HELP Residual I_{DDQ} if the threshold is chosen properly and the model dimension is not too high.

CONCLUSIONS

A new method for analyzing I_{DDQ} data is proposed. The method uses an empirical model to predict I_{DDQ} measurements for devices under test from a small set of test vectors and information obtained from a set of known good training devices. The key idea is that I_{DDQ} measurements over many test vectors are correlated since they are related to a small number of underlying process parameters. By detecting and characterizing these correlations, a better distinction can be made between variations in normal background currents and defect induced currents. The method introduces the differences between measured I_{DDQ} values and values predicted by a model of known good devices as a decision criterion. Small residuals indicate that the device is well described by the model and therefore likely to be fault free. The method is implemented in the HELP software toolbox developed at NIST. An alternative method that performs a Delta-I_{DDQ} analysis on pre-sorted predicted values is also suggested.

The methods are applied to a portion of the SEMATECH dataset, and it is shown that both methods lead to increased yields with small increases in the percentages of bad devices that are passed. As in other I_{DDQ} test methods, the increase in yield comes from a decrease in the variance of the distribution for good devices relative to the variance for bad devices. The relative decrease for the HELP Residual I_{DDQ} method is shown to be greater (better) than the corresponding decrease obtained with other methods.

Fig. 10 illustrates how a model based testing procedure might be applied to production testing. In an off-line phase of the test flow, devices are selected to comprise the training set. These devices need to be screened to ensure that the training set consists of only defect free devices. How best to perform this screening is a non-trivial problem, the treatment of which exceeds the scope of this paper. Empirical linear prediction software then builds a model from the training data. During on-line production testing, I_{DDQ} measurements are made only at the selected test vectors. These measurements are then used to predict the device response at all training set measured test points, and a pass or fail decision is made using either of the two HELP based methods described.

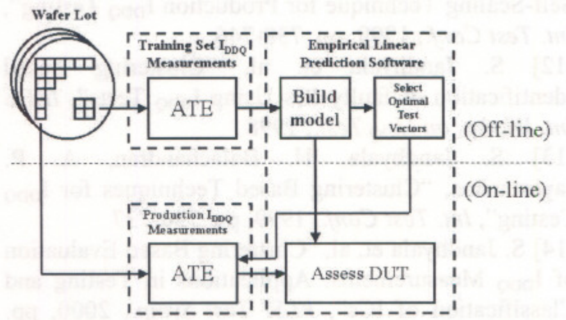


Fig. 10. Possible model based production test flow.

Acknowledgement

The authors wish to thank Phil Nigh for furnishing the SEMATECH data. The authors also wish to thank Mike Souders and Jerry Stenbakken for their advice and suggestions.

REFERENCES

[1] M. Sachdev, "Deep Sub-micron I_{DDQ} Testing: Issues and Solutions", *European Design and Test Conference*, 1997, pp. 271-278

[2] A. Ferre and J. Figueras, "I_{DDQ} Characterization in Submicron CMOS", *Int. Test Conf.*, 1997, pp. 136-145

[3] A. Keshavarzi, K. Roy, C. Hawkins, "Intrinsic Leakage in Low Power Deep Submicron CMOS ICs", *Int. Test Conf.*, 1997, pp. 146-155

[4] A. Keshavarzi, K. Roy, C. Hawkins, "Intrinsic Leakage in Low Power Deep Submicron CMOS ICs – Measurement Based Test Solutions", *IEEE Trans. VLSI Sys.*, 2000, pp. 717-723

[5] P. Nigh et. al., "An Experimental Study Comparing the Relative Effectiveness of Functional, Scan, I_{DDQ} and Delay-fault Testing", *VLSI Test Symp.*, 1997, pp. 459-464

[6] A. Gattiker and W. Maly, "Current Signatures", *14th VLSI Test Symp.*", 1996, pp. 112-117

[7] A. Gattiker, P. Nigh, D. Grosch, W. Maly, "Current Signatures for Production Testing", *IEEE Int. Wkshp. on I_{DDQ} Test.*, 1996, pp. 25-28

[8] C. Thibeault, "On the Comparison of Delta I_{DDQ} and I_{DDQ} Testing", *VLSI Test Symposium*, 1999

[9] C. Thibeault, "An Histogram Based Procedure for Current Testing of Active Defects", *Int. Test Conf.*, 1999, pp. 714-723

[10] W. R. Daasch, J. McNames, D. Bockelman, K. Cota, "Variance Reduction Using Wafer Patterns in I_{DDQ} Data", *Int. Test Conf.*, 2000, pp. 189-198

[11] P. Maxwell and P. O'Neill, "Current Ratios: A Self-Scaling Technique for Production I_{DDQ} Testing", *Int. Test Conf.*, 1999, pp. 738-746

[12] S. Jandhyala et. al, "Clustering Based Identification of faulty ICs Using I_{DDQ} Tests", *IEEE Int. Wkshp. on I_{DDQ} Test.*, 1998

[13] S. Jandhyala, H. Balachandran, A. P. Jayasumana, "Clustering Based Techniques for I_{DDQ} Testing", *Int. Test Conf.*, 1999, pp. 730-737

[14] S. Jandhyala et. al, "Clustering Based Evaluation of I_{DDQ} Measurements: Applications in Testing and Classification of ICs", *VLSI Test Symp.*, 2000, pp. 444-449

[15] P. N. Variyam, "Increasing the I_{DDQ} Test Resolution Using Current Prediction", *Int. Test Conf.*, 2000, pp. 217-224

[16] G. Stenbakken, A. Koffman, T.M. Souders, "Software to Optimize the Testing of Mixed-Signal Devices", *IEEE Int. Mixed-Sig. Testing Wkshp.*, 1999, pp. 29-33

[17] A. D. Koffman, T,M.Souders, G.N. Stenbakken, H. Engler "High-Dimensional Empirical Linear Prediction (HELP) Toolbox User's Guide", NIST Technical Note 1428, May, 1999, U.S. Government Printing Office, Washington, DC 20402

[18] T.M.Souders and G.N. Stenbakken, "A Comprehensive Approach for Modeling and Testing Analog and Mixed-Signal Devices", *Int. Test Conf.*, 1990, pp. 169-176

[19] G.N. Stenbakken and T.M. Souders, "Linear Error Modeling of Analog and Mixed-Signal Devices", *Int. Test Conf.*, 1991, pp. 573-581

[20] G.N. Stenbakken and T.M. Souders, "Developing Linear Error Models for Analog Devices", *IEEE Trans. Instr. Meas.*, 1994, pp. 157-163

[21] H. Liu, "High-Dimensional Empirical Linear Prediction", *Adv Math Tools in Metrol 3*, 1997, pp. 79-90

[22] I. T. Jolliffe, "Principal Component Analysis", Springer-Verlag, New York, 1986.