Deterministic Process Control Using a Multivariate Model

D. Miller

M/A-COM, Inc. Microwave Solutions Business Unit
5310 Valley Park Drive, Roanoke, VA 24019
Phone: 540 563-8600, E-mail: millerd@tycoelectronics.com

Abstract

Circuit performance characteristics (Z's) are dependant on keeping physical device and process variables (X's) in control, as reflected in DC and RF PCM characteristics (Y's), but the precise relationships between X's, Y's, and Z's are not usually known. We have determined these relationships for one of our processes precisely by fitting the data (X, Y, Z) obtained from a full-factorial variational experiment to a simple linear additive multivariate model. Using this model, we can map the allowable variation in amplifier performance (Z's) back on to the critical device physical parameters (X: Implant dose, Lg, etc.) and determine what level of control is required to achieve high yields.

INTRODUCTION

To make the manufacturing of low cost high performance MMICs possible, consistent transistor characteristics are required. This allows useful design iteration to optimize circuit characteristics to fit specifications so that high yield and thus low cost can be achieved. Variation of in-process parameters (gate length, channel dose, etc.) ultimately leads to variation in circuit performance (frequency response, output power, power-added efficiency, etc.), but precise relationships are not usually known. DC and small-signal RF characteristics of standard process control monitor (PCM) structures are used as a compromise between the worlds of process control and circuit performance—if their values are within pre-determined specs, the wafer is deemed "PCM good" and sent on for circuit evaluation; if not, the wafer is scrapped. However, "PCM good" is not always a sufficient condition for good circuit yield, since the device characteristics required are not all measured—specifically, the output power and efficiency.

Another problem is the lack of correlation between process variables (X's) and either PCM parameters (Y's) or circuit performance characteristics (Z's). Figure 1 shows an example where we are looking for a relationship between gate length and breakdown voltage—from this plot, we would conclude that there is not any simple relationship.

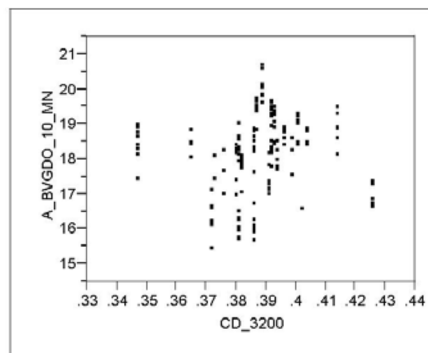

Figure 1. Breakdown voltage (wafer mean) vs. gate length (lot mean) for production wafers, showing no clear relationship.

One reason for the apparent lack of correlation is the fact that any given Y or Z depends on many different X's, but, when "line data" as in Figure 1 is used, the other factors are not necessarily the same for all samples. Which other factors are significant may not even be known.

EXPERIMENT

In order to determine which parameters are important for one of our power MESFET processes, we performed an experiment where we intentionally varied all the critical parameters we know of at the same time. Factors of interest included process parameters such as ion implant dose and energy and several of the FET geometrical factors, including gate length and drain-gate spacing. Parameter values were varied independently above and below their standard values. Where possible, die-level measurements were made to determine the actual values achieved for each parameter as it was varied in the experiment. Depending on the parameter, variation was either achieved across the same wafer via variation in mask dimensions or wafer-to-wafer within a lot by varying a process setting during fabrication of each wafer. After preliminary evaluations we focused on three different critical dimensions in the FET layout, including gate length and drain-gate spacing, and the process factor channel-implant dose, giving a total of four X factors that were evaluated in detail.

One unique characteristic of the MSAG process is the two part T-shaped gate [1]. The stem is formed from

refractory metal (TiWN) which has high resistivity, and then later in the process, a conductive (Au) T-top is added. This means that we can measure the stem and T-top lengths electrically at different points in the process. Figure 2 shows the stem gate lengths for 3 wafers from this lot—the highlighted wafer is centered on the nominal target, while the other wafers are long and short. As shown, across-wafer variation leads to a continuous range of gate lengths.

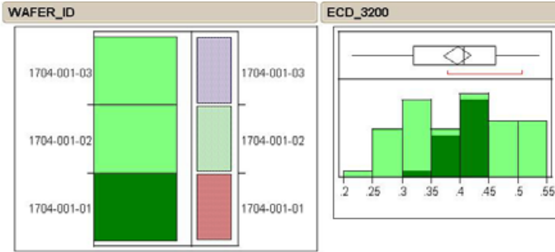

Figure 2. Gate Length (stem) distribution from 3 wafers. The highlighted wafer was targeted to the standard dimension and the other two were targeted long and short. As shown, the total gate length distribution is continuous across a wide range.

Another characteristic of the MSAG power GaAs FET is the asymmetric placement of the gate with respect to source and drain: the n+ doping is spaced close to the gate on the source side (to give low source resistance) but spaced further away on the drain side to give higher breakdown voltage. A unique test structure [2] allows us to monitor the value of this spacing electrically. Since the FET uses interdigitated fingers, we measure a "left hand" and "right hand" finger and determine both size and misalignment. Figure 3 shows the distribution of size and alignment for the nominal FET, which varies unintentionally by wafer. We have also varied this dimension intentionally on each wafer by changing the device layout.

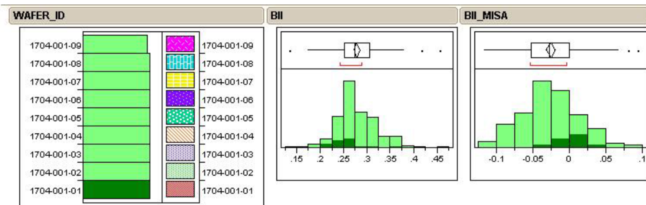

Figure 3. Gate-drain spacing PCM data distribution. Highlighted wafer shows expected value (0.25, misalignment = 0). Other wafers are not as nominal.

RESULTS

DC PCM measurements were made on a series of small FETs which have intentional variations in the critical X-factors for this experiment. Figure 4 shows the distributions of parameters Ipeak, Vt, and Bvgdo_10 as measured.

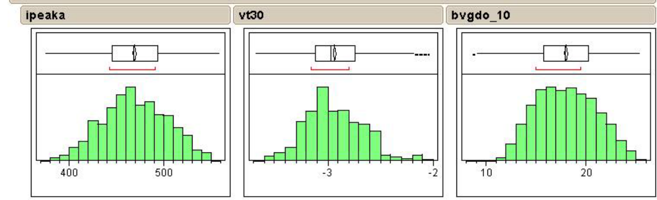

Figure 4. DC PCM data distributions measured across the entire experiment.

RF PCM measurements (s-parameters at a fixed bias point which are fit to an equivalent circuit) are made on a similar series of RF-probe-able FETs. Figure 5 shows the distributions observed for parameters Gm, Cgs, Rds, and Ft.

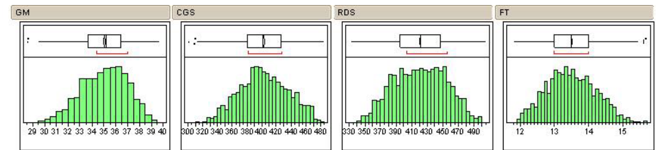

Figure 5. RF PCM (small signal equivalent circuit) data distributions measured across the entire experiment.

To provide circuit data, a small single-stage amplifier is measured on-wafer. Copies of this fixed amplifier design with the same series of FET variations are also measured. Figure 6 shows the distributions measured—Z1 varies from 23 to 26, Z2 from 0.25 to 0.5, and Z3 from 0.2 to 0.4.

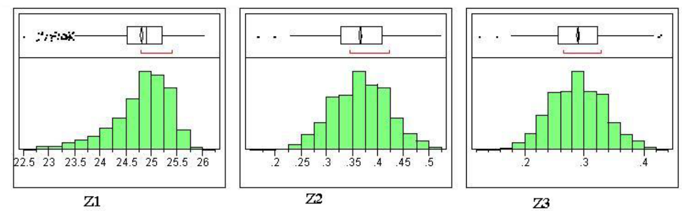

Figure 6. On-wafer amplifier MMIC data distributions measured across the entire experiment.

As stated earlier, we processed a lot which gives us the full set of X's (X1, X2, X3, X4). Measurements were performed to obtain Y's (Ipeak, Vt, Bvgdo_10), and Z's for the full factorial set of intentional variations in each X, centered around the standard values. Two multivariate least-squares fits are now performed on this set of data. The first maps Y back to X, defining each Y as the sum of the product of each X and a sensitivity (as well as an intercept). The values of sensitivities and intercepts are varied to get the smallest total squared deviation between measurement and prediction across the entire set of data. The set of data is very large: 3 X1's * 3 X2's * 4 X3's * 3 X4's * 15 reticles = 1620 data points! Figure 7 shows an example of the fit to breakdown voltage—as shown, the fit is quite good (Rsquared = 0.91).

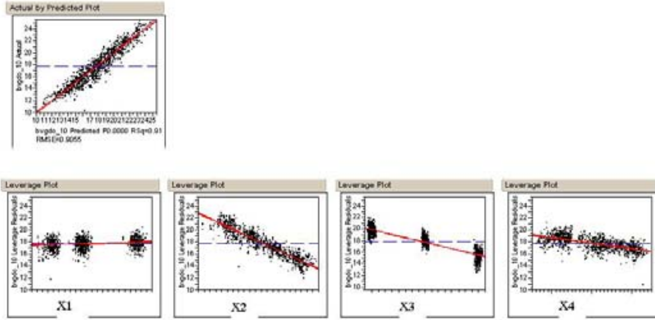

Figure 7. Example of multivariate least-square fit. Here Y (breakdown voltage) is fit to 4 X's. As shown, the fit is very good (Rsquared = 0.9).

The leverage plots in Figure 7 show the influence of each X on breakdown voltage. Similar fits were performed for the other Y's; the coefficients and Rsquared values are shown in Figure 8.

	Critical Process Parameters			Multivariate Fits						
	Factor	t/m	std. Dev	Ipeaka	Vt	Bvgdo_10	Gm	Cgs	Rds	Ft
	(intercept)			-507.1	5.98	92.69	38.6	669.3	716.9	7.33
	X1			140.9	-1.47	-10.67	-2.39	-73.2	-50.6	1.319
	X2			108.6	1.12	-9.48	17.9	234.97	78.5	-0.879
	X3			1.56	0.187	1.19	3.39	154.4	61.14	-3.53
	X4			131.6	-0.0486	-17.4	8.27	-58.27	-235.4	3.53
			rsquared	0.84	0.78	0.9	0.82	0.88	0.86	0.89
	Target			460	-2.75	19	35	390	400	14.25
	low spec			410	-3.45	15	30	320	320	12.5
	high spec			510	-2.05	99	40	460	999	16
predicted	mean			472.478	-2.85424	17.1328	35.1472	400.828	411.383	13.5226
predicted	stddev			14.576	0.124	1.443	0.856	12.810	16.077	0.297
predicted	Cp			1.14	1.88	9.70	1.95	1.82	7.04	1.96
predicted	Cpk			0.86	1.60	0.49	1.89	1.54	1.89	1.15
actual	mean			454.6	-2.77	18.63	35.4	397.7	409.3	13.95
actual	stddev			18.6	0.145	1.5	1.33	16.1	16.6	0.375
actual	Cp			0.90	1.61	9.33	1.25	1.45	6.82	1.56
actual	Cpk			0.80	1.56	0.81	1.15	1.29	1.79	1.29

Figure 8. Table of multivariate model coefficients (yellow) with Rsquared values for each Y. Also shown are pass/fail limits (orange), predicted and actual means and standard deviations for each Y, and predicted and actual Cpk values (pink).

The same information is shown graphically in Figure 10, where the X variables map to the Y variables according to the slope of the lines on each graph.

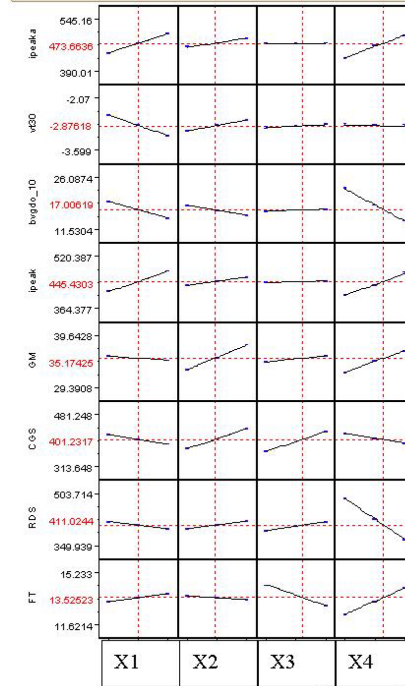

Figure 9. Multivariate model information in graphical form. Sensitivity of each Y to each X is shown by the slopes of the lines.

A similar procedure can be used to map Z back to X. In this case, we use some second order terms ($Z = A + B*x + B*x^2$) to get a better fit to the data. The result is shown in Figure 10, which shows graphically the relationship between each X and Z.

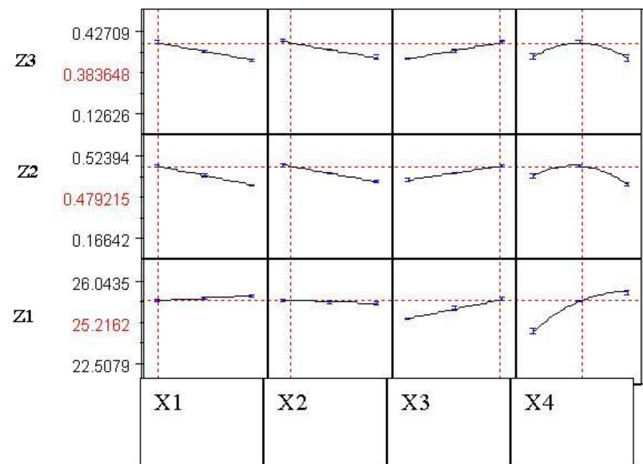

Figure 10. Multivariate model connecting in-process variables (X's) to circuit performance (Z's). X3 was included as a second order term to obtain a better fit to the data. Rsquared values for the multivariate fits were 0.69, 0.74, and 0.62 for Z1, Z2, and Z3, respectively.

As shown in Figure 8, the sensitivities determined from this experiment can be used to predict the variation in Y's if the

variation in X's is known. "Predicted Mean" values for each Y are calculated by multiplying the target value for each X by the appropriate sensitivity and then adding the contributions along with the intercept value. Assuming that each X is independent and has a normal distribution, we can calculate "Predicted Standard Deviation" values by multiplying the standard deviation of each X by the appropriate model sensitivity. The standard deviation of each Y is the square root of the sum of the squares of these components. Figure 11 shows the squared deviation components for each X and Y; as shown, the main contributors to variation of each Y are easy to determine.

	squared deviations:						
	Ipeaka	Vt	Bvgdo_10	Gm	Cgs	Rds	Ft
X1	127.058	0.014	0.729	0.037	34.293	16.386	0.011
X2	14.448	0.002	0.110	0.393	67.633	7.549	0.001
X3	0.005	0.000	0.003	0.023	48.275	7.570	0.025
X4	70.937	0.000	1.240	0.280	13.908	226.972	0.051
sqrt(sum)	14.576	0.124	1.443	0.856	12.810	16.077	0.297

Figure 11. Calculation of predicted standard deviations of each Y. Standard deviations of each X are multiplied by the sensitivity given in Figure 8 and then squared. The predicted standard deviation for each Y is the square root of the sum of these squared deviations. Major contributors to the variation of each Y are shaded.

Figure 8 also shows the PCM spec ranges for each parameter—using them, we can calculate a predicted Cpk for each Y—as shown, the lowest Cpk is for breakdown voltage. Referencing Figure 11, the biggest contributor to breakdown voltage variation is X3, followed by X2. To improve PCM yield, we must tighten the distribution of X2 and/or X3, or we can adjust their target values to move the "predicted mean" value of breakdown voltage further above the minimum spec. The known sensitivities immediately give us new predicted means and standard deviations for each PCM parameter—in this way, we can determine which parameters to adjust or tighten to achieve the best PCM yield.

Figure 8 also shows the observed mean and standard deviations for actual production wafers over a period of time. It is useful to compare the actual and predicted means and standard deviations—as shown, the "predicted to actual standard deviation ratio" is fairly close to 1 for all the Y's—this implies that we are explaining most of the actual variation in Y's with our model (assuming the variations in X's are accurate). If this ratio is too small, we should look for other factors which contribute to the variation besides those included in our model.

As stated earlier, achieving good PCM yield is not the only goal—we would like to have good circuit yield which requires consistent high performance. Figure 10 implies that we can achieve better performance (higher FOM) by changing the target values of our X's. Figure 12 shows what happens if we try to optimize Z3; by changing each X so its contribution to Z3 is maximized, we can see that the average Z3 increases from 0.29 to 0.38.

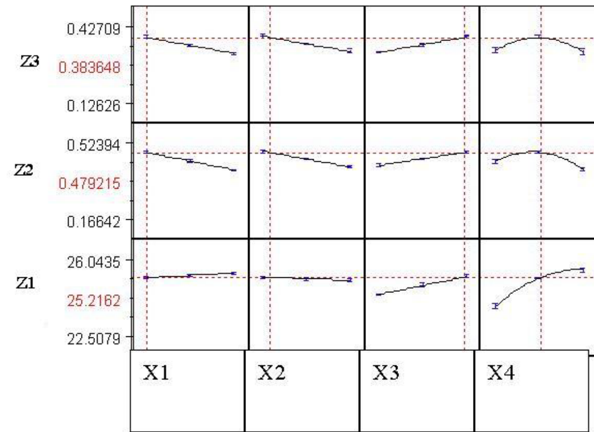

Figure 12. Predicted value for Z's when X's are adjusted to maximize Z3. As shown, the predicted mean of Z3 has increased to 0.38 from the value shown in Figure 11 (0.29).

We can plug the same shift in X's back into Figure 9 to see what the effect would be on the average Y's (used to pass/fail wafers). Further testing to confirm the Z data is in progress, but we anticipate a large increase in average performance when we decide to go ahead and shift the target values of X as suggested.

CONCLUSIONS

Exhaustive data from a full-factorial variational experiment has revealed the "built-in" process-to-RF correlations in a GaAs MESFET process. Analysis of this data allows us to determine what targets and what level of control is required to achieve a given level of RF performance.

ACKNOWLEDGEMENTS

Thanks to M/A-COM ADBU Roanoke for doing the variation experiment mask layout and to the M/A-COM MSBU Roanoke wafer fab personnel for excellent wafer processing.

REFERENCES

[1] Bahl, I.J. et. al., *IEEE Transactions on Microwave Theory and Techniques*, 38:9 pp. 1175-82 (Sept. 1990).

[2] Balzan, M., private communication.