

An Experiment Analysis System for Fixed and Random Effects in Overdispersed Binomial Responses in Semiconductor Manufacturing

José G. Ramírez, Ph.D. and Randall S. Collica
Digital Semiconductor
Division of Digital Equipment Corporation
75 Reed Road
Hudson, MA. 01749

Abstract

In order to manufacture the worlds fastest commercial microprocessor chips (Alpha™ products) extreme process control and improvement methodologies are required to obtain desired performance and cost. At Digital Equipment Corp. we use SAS GUI interfaces for process experiment analysis of chip probe data. This paper presents how one can model the binomial chip responses from wafers which have received special process treatments in order to characterize and improve the process. Often, process experimenters will repeat an experiment on different lots (batches of wafers grouped together) and thus the effects of lot-to-lot variability is needed in the experiment analysis methodology. We show in this paper how to start with a very simple simplistic view of the data in a designed experiment and progressively add complexities which mimic reality much closer. We show that if one ignores these complexities, the results of an analysis can be rather misleading or even completely reversed. We also show that from experience in teaching process specialists and analysts; the easiest way to standardize the analysis is to minimize the amount of computer logistics; i.e. we provided SAS/AF Frame™ entry programs which are very easy to use for extracting data, comments on experiments, and logistic analysis of the binomial response data. We use %GLIMMIX macro developed by SAS Institute [1] to accomplish the pseudo-likelihood analysis of a mixed-effects overdispersed binomial model.

Introduction

In today's semiconductor market the need for fast microprocessors with high reliability and relatively low cost is in demand. How process engineers user their data to uncover differences in experiment treatments is the topic of this paper. Also, how to deliver those results to the engineering and management community is also the topic of this paper. The first problem in relating integrated circuit yields to process treatments is how to effectively analyze chip yields. Many yield analysts in the past have used the Negative Binomial, Seeds, or the Murphy's model for yield when using mean defect density or failure density estimates [2] - [6]. In this paper we describe the yield data from a very simplistic view all the way to using a binomial model [7] which will take into account lot-to-lot variation (when multiple lots have repeating experiments), wafer-to-wafer variability within treatment groups, and chip-to-chip correlation's within a wafer which received a particular treatment combination.

We also show that when these special analysis reports are generated, the resulting information needs to be brought to the engineering and management community in a simple fashion otherwise the analysis will be a waste, and the information will not

get delivered in a timely manner. We use a combination of SAS/AF™ and SAS/EIS™ objects to deliver a complete analysis and reporting package to our engineering community. Productivity gains by using these techniques has been outstanding, typically greater than 10 to 1 improvements in time reduction, report standardization, and improve accuracy have resulted in the EIS's wide spread use in manufacturing.

The Problem

The main problem in semiconductor manufacturing is that almost everything can and usually does effect the yield of the integrated circuits, however, it is not always predictable as to which factors are in effect for a particular lot in question. This makes it somewhat difficult to analyze process experiments to determine if the experiment factor settings are giving the expected yield and other desired electrical responses. This problem gets even worse when multiple lots are used to increase the sample sizes; lot-to-lot variability is now also introduced as a source of potential variation. The Negative Binomial model used to predict chip yields has been very successful, however, this model is not tractable to obtaining odds ratios from the parameter estimates and also hypothesis testing of experimental factor settings. The ability of an analyst to determine if an equipment chamber, tool setting, process recipe, etc. caused an increase or decrease in the wafer chip yield adds great value in the experimental learning curve. Odds ratios from experiments with combined lots of identical experiment factors and levels can be used to give an extended population analyses and thus estimate the expected production line yield improvement from such process changes.

Analysis

Section 3.1 starts with a simple analysis in which the wafer yields are treated as continuous data using analysis of variance, and disregarding the lot-to-lot variation component. Then we proceed to perform a logistic regression analysis taking into account the binary nature of yield. In section 3.2 the logistic regression analysis is performed for each lot. Section 3.3 includes lot in the analysis as a fixed effect, while in section 3.4 we used %GLIMMIX to include lot as a random effect.

3-1) Simple Analyses

a) Proportions

A very simple analysis for this data is to consider the proportion of good die per wafer as a continuous response, and not take into account the lot information, and the binary nature of the response. An analysis of variance is performed to determine if there is a statistically significant difference between the levels of the experimental factor CMP.

Table 1-a below shows the results of PROC GLM. They indicate

a statistically significant difference between the three levels of the factor CMP. These results, however, should be interpreted carefully because two of the basic assumptions are not met; i.e., the errors are not normally distributed because the response is binary, and the variance is not constant. The violation of these assumptions could invalidate the results of the analysis.

**Table 1a Two Lots Combined - Proportions
General Linear Models Procedure**

Dependent Variable: P_ZZ % Pass - ZZ

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model (CMP)	2	0.09511073	0.04755536	6.32	0.0041
Error	40	0.30100257	0.00752506		
CT	42	0.39611330			

b) Logistic Regression

A more appropriate analysis accounts for the binary nature of the response, and uses logistic regression. The two assumptions that were not met in 3.1 are now taken care of by assuming a binomial distribution for the data, and by using maximum likelihood to estimate the parameters of the model.

The results of PROC GENMOD are shown in Table 1-b. As before we find that there is a statistically significant difference between the levels of the factor CMP. Note however, that the CMP behavior can change from lot to lot.

**Table 1b Two Lots Combined - Logistic
The GENMOD Procedure
LR Statistics For Type 3 Analysis**

Source	NDF	DDF	F	Pr>F	χ^2	Pr>Chi
CMP	2	40	6.27	0.0043	12.54	0.0019

3-2) Analysis by Lot

One way to consider the lot effect, although not the best one, is to do a separate analysis per lot, and see if the results differ. This would be an indication that the behavior of CMP varies with lot.

Table 2 below shows the results of a logistic regression analysis perform on each of the lots. We now clearly see that the difference between the levels of factor CMP is present in lot B52497 and not in lot B52495. This is an indication of an interaction effect between the lots and the experimental factor CMP.

The major drawback of this analysis is that the factor CMP is tested independently of lot; i.e., the test is performed separately for each lot. We would like to be able to test CMP across the different lots. In this analysis the LOT component is not estimated, nor tested for significance.

**Table 2
The GENMOD Procedure**

LOT=B52495

LR Statistics For Type 3 Analysis

Source	NDF	DDF	F	Pr>F	χ^2	Pr>Chi
CMP	2	17	1.39	0.2771	2.77	0.2503

LOT=B52497

LR Statistics For Type 3 Analysis

Source	NDF	DDF	F	Pr>F	χ^2	Pr>Chi
CMP	2	20	8.10	0.0026	16.20	0.0003

3-3) Analysis Including Lot as a Fixed Effect

Rather than performing an analysis by lot, we use all the data by including Lot in the model. The first thing we can do is to consider Lot as another experimental factor, and test for differences between the two lots as well as an interaction effect between Lot and CMP.

As before we perform a logistic regression analysis using PROC GENMOD. The results indicate that there is a statistically significant difference between the levels of CMP after adjusting for LOT, and that the interaction between LOT and CMP is not statistically significant.

**Table 3 Lot as a Fixed Effect
The GENMOD Procedure
LR Statistics For Type 3 Analysis**

Source	NDF	DDF	F	Pr>F	χ^2	Pr>Chi
LOT	1	37	3.54	0.0677	3.54	0.0598
CMP	2	37	6.01	0.0055	12.02	0.0025
LOT*CMP	2	37	2.39	0.1060	4.77	0.0920

3-4) Analysis Including Lot as a Random Effect

The final and more appropriate analysis is to consider LOT not as an experimental factor, but as a source of variability that needs to be estimated and accounted for in the analysis. [8] Here we run into a problem because in order to estimate variance components we need a procedure like PROC MIXED, and this procedure assumes that the data is normally distributed or a least continuous. In our case however, we are dealing with a binary response.

We can use the macro %GLIMMIX to perform this type of analysis. This macro works like a combination of PROC GENMOD and PROC MIXED, allowing the user to fit mixed models to discrete data.

In our situation %GLIMMIX allows to estimate the variance components due to LOT and the interaction between LOT and CMP, and to test the effect of the experimental factor CMP.

Table 4 below shows some output from %GLIMMIX. The covariance parameter estimates table shows the variance

components for LOT and the interaction LOT*CMP. Note that the LOT*CMP component is about 2.75 times larger than the LOT component. The test for fixed effects table shows that there is not a statistically significant difference between the levels of the experimental factor CMP. This conclusion is opposite to the one obtained in the analyses of sections 1, 2, and 3. In those analyses CMP was tested using the within LOT variability rather than the appropriate LOT-to-LOT variability.

GLIMMIX Model Statistics

Description	Value
Deviance	58.7022
Scaled Deviance	43.7936
Pearson χ^2	51.0257
Scaled Pearson χ^2	38.0667
Extra-Dispersion Scale	1.3404

Table 4 GLIMMIX Analysis
Covariance Parameter Estimates

Cov Parm	Estimate
LOT	0.01932940
LOT*CMP	0.05316643

Tests of Fixed Effects

Source	NDF	DDF	Type III F	Pr>F
CMP	2	2	2.69	0.2709

GUI Interface

In order to increase our time productivity of analyses we developed a SAS/AF and SAS/EIS environment to perform the analyses and also deliver the final reports and graphs to manufacturing. An experiment analysis EIS page which is pointed to from a more general EIS is shown in Figure (1).



Figure 1

The EIS page in Figure (1) allows the analyst to choose from the Probe analysis, which we have been presenting, to using SAS/Insight™ for ad hoc analyses and investigations, to Lot-Wafer-Box tool which is a custom AF Frame interface to pull electrical test data about the transistor and special test structure data , to extracting remarks from remarks Rdb database. The Probe Analysis menu is the one we will center on and the reports delivered from the analyst in the reports menu.

The analyst will typically pull any pertinent information recorded

about the experimental lot by using the Yield Remarks application from the Experiment Analysis Menu. This application pulls all notes, comments, remarks, tool settings, etc. which were noted during manufacturing and formats these in a detailed 132 column report or an 80 column reduced report. Next, the analyst will select the Probe Analysis icon to start gathering the probe data along with the experimental factors which are recorded in another relational database. The Probe Analysis page is given in Figure (2).



Figure 2

From the menu in Figure (2) the analyst can gather data combined with the experiment factor setting for each wafer using the 'Get Probe Data' icon. Then the data is prepared so that an automated Logistic regression analysis with a report of p-values, experiment factor settings, and percentages for each response for the treatment combinations and selected model is

automatically generated for each available failure mode response including the chip yield. Use of SAS/Insight™ allows the analyst to produce ad hoc boxplots and how good the data fit against the requested model. The Frames which allows the analyst to get the data and analyze the data are shown in Figure (3).

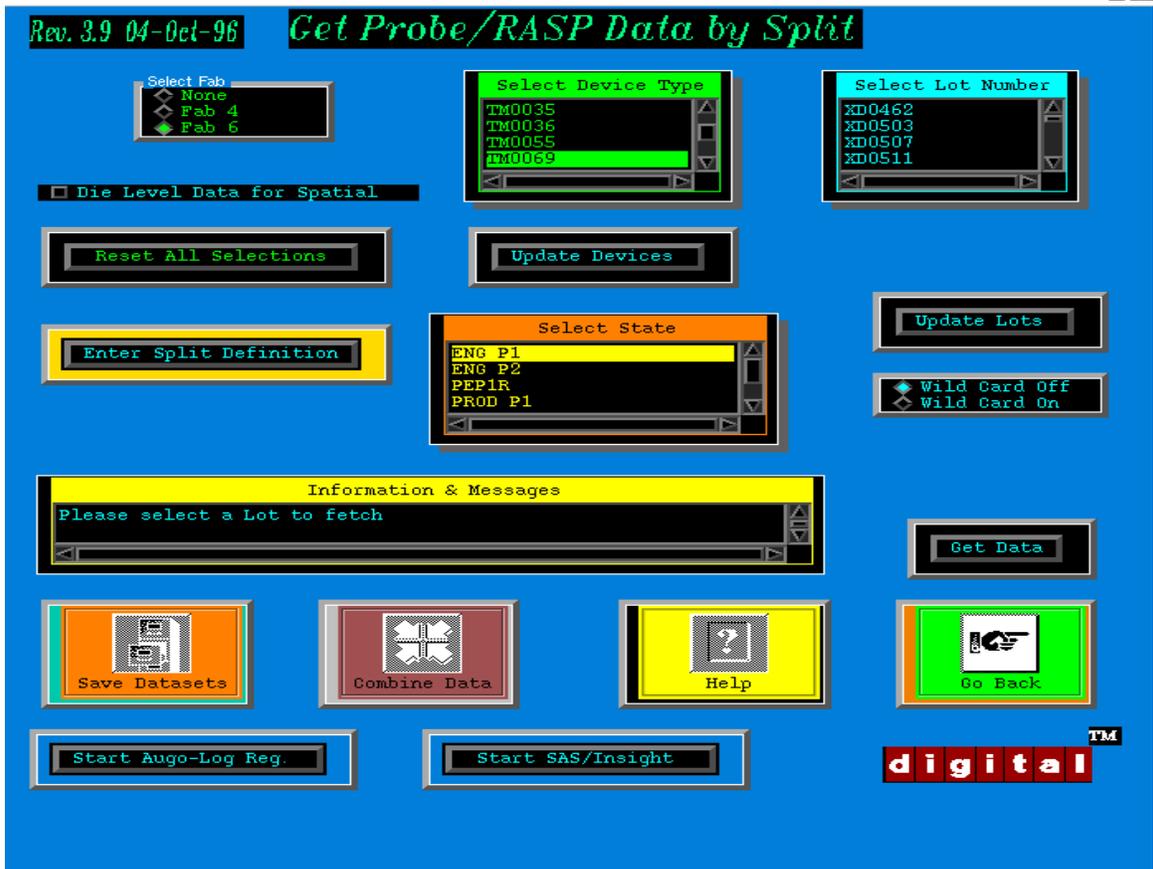


Figure 3

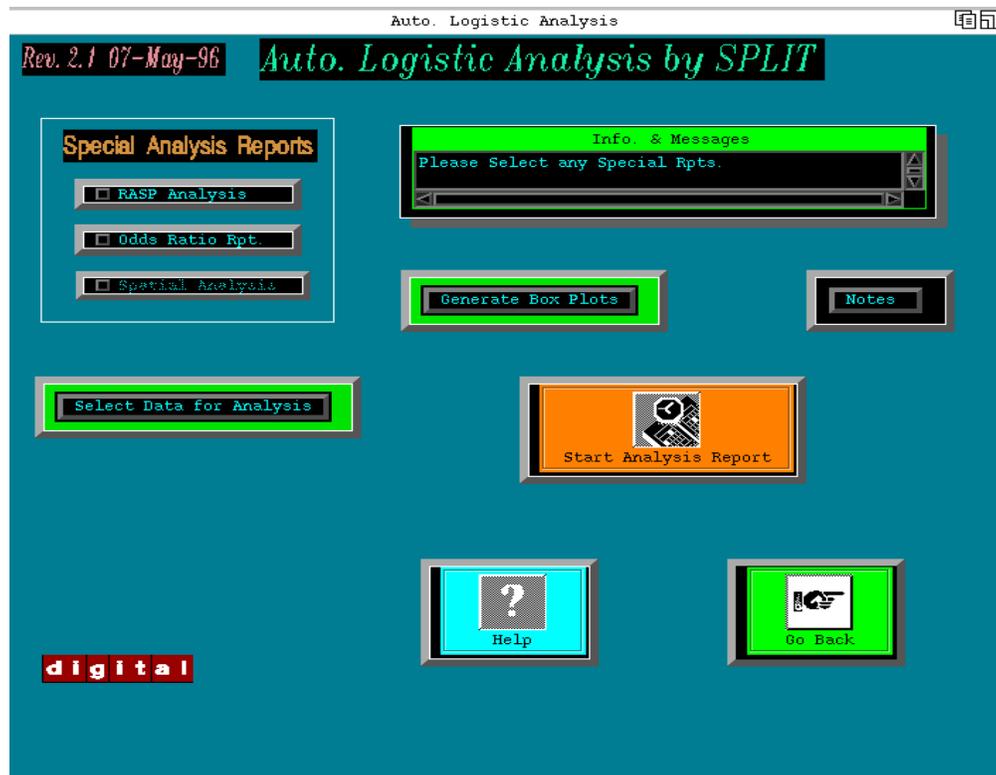


Figure 4

Use of these easy-to-use SAS/AF Frame™ entries allows users of somewhat limited computer skills to still extract the experiment settings for each wafer treatments, yield and failure codes for each wafer, remarks and notes of the experimental lot during manufacturing and the logistic analysis of factor combinations.

After the user selects the dataset, the user is asked to select the factor and model to use for the analysis. Custom boxplots of various proportions and treatment combinations are useful tools along with the logistic analysis and odds ratios reports.

Conclusions

In summary, we show how to analyze the semiconductor wafer yields with respect to experimental process settings and going from a very simple view of the analysis all the way to incorporating multiple experimental lots and treating lot as a random mixed-effect using an overdispersed binomial model. An easy-to-use GUI interface allows analysts and process experimenters to evaluate the effectiveness of process recipe treatments on the semiconductor wafer yields. The use of SCL programming language behind the SAS/AF™ frames allows custom reports of the process factors and tabulation of the yields and p-values from the resulting fitted logistic models. Boxplots of treatment combinations aid the analyst in determining the effect of the treatment on wafer yields and failure modes when yields are not as expected. Productivity is greatly enhanced when using these tools whereas a completely ad hoc approach used to take greater than 48 hours to complete the analysis and report. Now the complete report can be done within 2 hours and the actual logistic analysis takes typically less than 1 to 2 minutes.

Acknowledgments

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