# Efficiently Performing Yield Enhancements by Identifying Dominant Physical Root Cause from Test Fail Data


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## Abstract

*Yield enhancements in the manufacturing process today require an expensive, long and tedious physical failure analysis process to identify the root cause. In this paper we present Axiom, a new technique geared towards efficiently identifying a single dominant defect mechanism (for example in an excursion wafer) by analyzing fail data collected from the production test environment. Axiom utilizes statistical hypothesis testing in a novel way to analyze logic diagnosis data along with information on physical features in the design layout and reliably identify the dominant cause for yield loss. This new methodology was validated by applying it to a single excursion wafer produced on a 90nm process, in which the dominant failing physical feature was correctly identified.*


## 1. Introduction

The semiconductor manufacturing process has become more sophisticated and expensive with each new technology node. Hence, in order to amortize the cost of fabricated chips, a very high production volume per design is usually required over an extended period of time. During this time of high volume manufacturing there is a need to perform continuous yield enhancement. In certain situations there is a single dominant defect mechanism, and yield can be enhanced by tuning the fabrication process to reduce this defect type. In this paper we focus on opportunities to perform yield enhancement in a single dominant defect mechanism situation. One good example of such a situation is an *excursion wafer* which refers to a wafer whose yield is lower than normal baseline level. Throughout the paper we base our discussion on excursion wafers as an example.

Excursion wafers may happen due to various unavoidable reasons like changes in fabrication equipment, changes in process parameters etc. When this happens, it is critical to quickly identify the source that is causing the yield to drop below normal and fix it. Sometimes the cause of an excursion wafer can be identified based on wafer histories, analysis of process history etc. [1][2][3]. However, with increasing manufacturing process complexity these methods are becoming less effective. In such cases, the method that is then most often used today is, to select a small number of die from an excursion wafer and determine the defect in the die using physical failure analysis (PFA). However, this is an expensive and time consuming process. Moreover, it can only be done for a small number of failing die which implies that the results may still not be conclusive.

Recently there has been an increasing trend to analyze results of logic diagnosis on production test fails for identifying yield issues. It would be attractive to do the same for identifying the cause for an excursion wafer because this would result in an overall cheaper and faster process. The use of diagnosis results to identify and rank systematic yield limiters for a particular design/process has been described in several previous studies [4]-[11]. However, these studies are geared towards analyzing large populations typically consisting of thousands of failing die over several manufacturing lots. On the other hand, the cause for excursion wafer must be determined from a relatively small number of die, typically a few hundred die from a single wafer. Moreover, unlike the scenario in previous studies, excursion wafers are most commonly caused by a single factor and the goal is to identify this dominant failing mechanism rather than identify and rank various systematic yield limiters. Due to these reasons the previously presented analysis techniques may not be suitable for dealing with excursion wafers.

Motivated by the reasons presented above, we present **Axiom**, a novel analysis technique that allows the use of logic diagnosis results from failing die on the excursion wafer along with physical features from the design layout to identify the cause of the excursion wafer. This new method is cheaper, quicker and more accurate than the current state of art of relying on PFA techniques alone. Axiom is specifically designed to draw conclu-



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sions from a small number of failing die and take full advantage of the fact that there is a single dominant mechanism. Axiom utilizes statistical hypothesis testing in a novel way to reliably identify this dominant defect mechanism.

The new methodology in this paper is presented through the discussion of an industrial case study. The target design of this case study was a graphics processor chip, which we will refer to as GP500 (not real name). The study focuses on an excursion wafer with 209 defective die on it. All these dies had failed structural logic testing and failure data in terms of failing test channel and test cycle had been collected for all the failing dies. Note that a preliminary study using the same data as this paper is a workshop presentation at the 2008 European Test Symposium. Even though this paper uses the same case study as the ETS workshop presentation, Axiom, the new analysis technique presented here in this paper, has not been discussed in any previous work.

The following sections detail the new methodology to identify the excursion root cause and present the results and conclusions.

## 2. Overall Yield Enhancement Analysis Flow

In this paper we limit the discussion to yield enhancements for open defect mechanisms even though the presented techniques are generally applicable to all defect types like bridges, cell internal etc. There are two main reasons for this. First there has been no published work on yield analysis from diagnosis results that talks specifically about open defects. Second, just focusing on the opens simplifies the discussion in the paper at the same time keeping it general enough to aptly highlight all the issues associated with such a methodology.

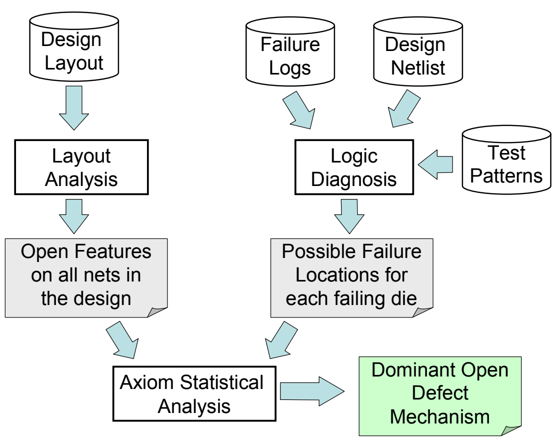


**Figure 1: Flow for determining dominant open defects from manufacturing test data**

The Figure 1 illustrates the flow used for doing root cause analysis of excursion wafer from manufacturing test data. The inputs to the flow are the design netlist, the physical layout information and the fail logs of die from an excursion wafer that failed logic test during production test. The output is analysis results indicating dominant open mechanism causing the excursion wafer. The main steps in the process are as follows: High volume logic diagnosis of the fail logs is performed to determine logical failing locations for all the failing dies. The design layout information is used to extract layout features that are likely to lead to interconnect opens when defective. These layout features are discussed in detail in Section 3. Note that layout feature extraction is a preprocessing step after which the features are stored in a database and the extraction is not repeated for the same design.

The two sets of information, diagnosis results and layout features, are then analyzed together using Axiom to determine the dominant open defect mechanism within the set of failing die. This information can then be fed back to the manufacturing process and can lead to the identification of particular process steps for yield improvement. Section 4 discusses specific challenges to overcome in the above data analysis. Section 5 discusses the Axiom data analysis method. Finally, the results of applying Axiom data analysis to the excursion wafer in the target case study of this paper are presented in Section 6.

## 3. Open Feature Extraction

In order to determine the dominant open defect mechanism from the failing nets determined by logic diagnosis, the first requirement is to extract *open features* on these nets from the design layout. Open features are layout features on nets that are prone to being mal-formed during chip fabrication, such that it most likely leads to an interconnect open. In this study, along with some common open features like vias (Figure 2), critical area of a net etc., the following additional features are extracted for each net from the design layout.

**Stacked Vias:** In some cases when a net jogs multiple layers (e.g. from metal layer 2 to metal layer 4), a stacked via structure may be used to go directly from the lower metal layer to the upper metal layer (Figure 2). Such structures are prone to failure in particular because of the tighter tolerance on the alignment of such vias

**Stress Vias:** In copper based technologies if a single via is close to or connected to a large piece of metal then such a via is prone to copper stress migration which can lead to voiding (Figure 3) and hence resistive or complete opens. In this study such vias were termed as stress vias and were distinguished from other single vias.

**Long run minimum width wires with wires at minimum space on both sides (SWS):** It has been shown that if there is minimum width metal line then it is prone to being open due to resist collapse [12] (Figure 4). To account for this defect mechanism, minimum width wires flanked by wires on both sides at minimum spacing for long run lengths are identified and this open feature is extracted as total run length for a net under the above condition.

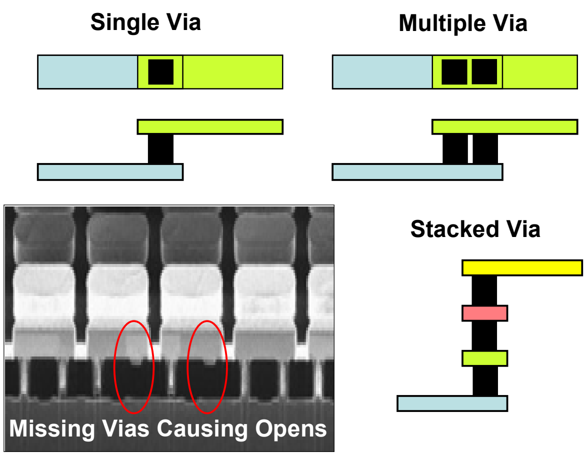


**Figure 2: Open features related to vias**

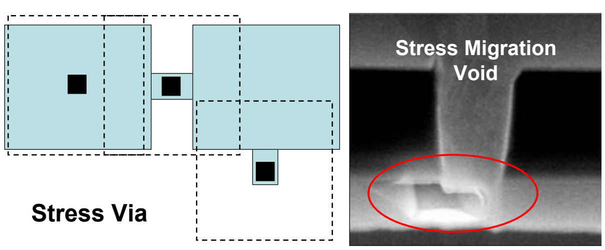


**Figure 3: Example of stress via open feature**

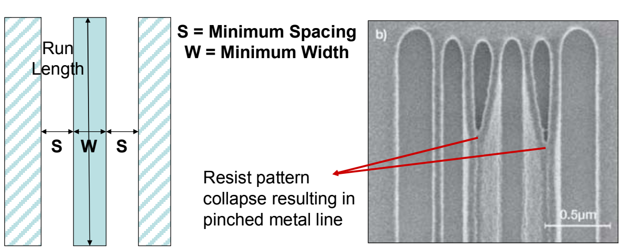


**Figure 4: Example of SWS open feature**

## *Open feature extraction results*

All the above open features were extracted for the target design GP500 in this study. The outcome of the extraction is a list of open feature type, feature value pairs for each net in the design. The following terminology will be used in this paper to denote the various feature types:

| | |
|---|---|
| **m*i*_open** | Critical open area on metal layer *i* |
| **m*i*_sws** | SWS open feature on metal layer *i* |
| **single_v*i*** | Single Via from metal layer *i* to *i+1* |
| **multi_v*i*** | Multiple Via from metal layer *i* to *i+1* |
| **m*i*_v*j*_stress** | Stress via on layer *i* due to metal layer *j* |
| **stacked_v*i*…*i*+*x*** | Stacked via going from metal layer *i* to layer *i+x+1* |

Since this design had 7 metal layers, there are a total of 53 open feature types = (6 x 4 Via open features) + (15 stacked via types) + (7 critical open areas) + (7 SWS opens).

As discussed above the feature value for via related open features was a count of such features on the net. Feature value for critical open area was the actual critical area determined as described before, and finally, that for SWS open was the associated run length. The feature value was assumed to be directly proportional to the probability of the net failing due to that feature being defective. The charts in Figure 5, Figure 6, and Figure 7 below show some basic statistics of the extracted features.

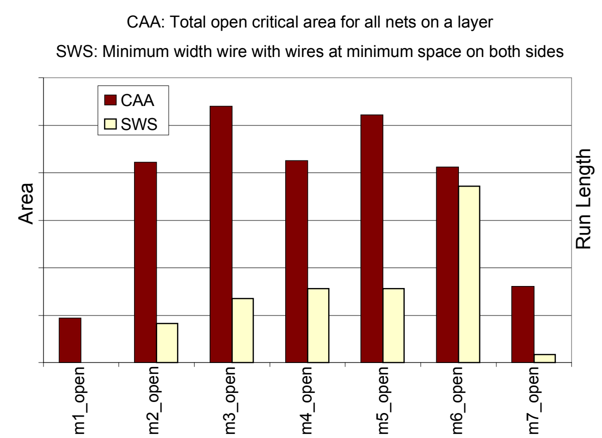


**Figure 5: Total critical area per metal layer**

Figure 5 shows the distribution of critical open area with metal layer and the run length associated with SWS open feature. The chart in Figure 6 plots the distribution of total counts for various via types in the design with layer. In the chart the TopMetalStress and BottomMetalStress denote stress vias where the large piece of metal causing stress migration is in the layer above or below the via respectively. Finally Figure 7 shows the counts of stacked vias between various layers in the design. It can be seen that the most common stacked vias in the design were those that connect metal layer *i* to *i+2*, e.g. stacked_v12 connecting metal layers 1 and 3. Other stacked vias are much less common.

Since, analyses of features that occur rarely in the design produce statistically unreliable results, all such features, e.g. stacked vias with very low instance counts, were not considered during yield learning data analysis.

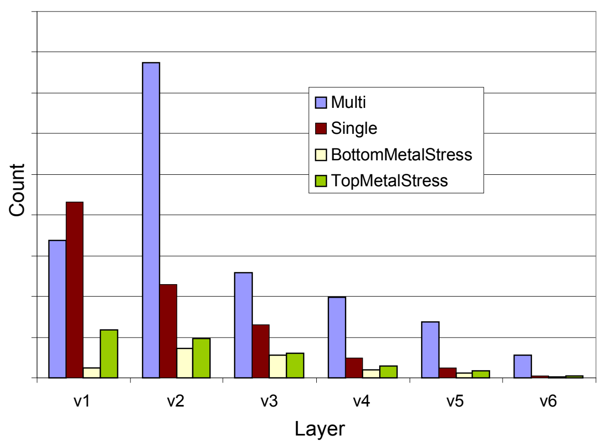


**Figure 6: Total counts of via types per layer**

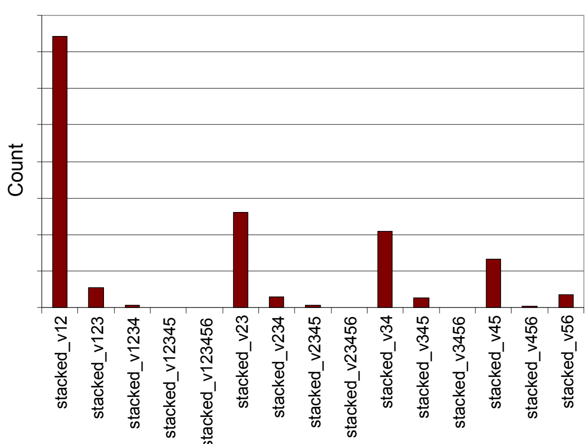


**Figure 7: Total counts of stacked vias betwen various metal layers**

## 4. Logic Diagnosis Related Issues

Statistical yield learning from logic diagnosis results presents some unique challenges. This is because logic diagnosis typically produces a list of candidate failing nets, whereas the end goal is the defective open feature. This section addresses some of the main challenges in this process.

### *Ambiguity in diagnosis results*

Typically logic diagnosis of a fail log from a failing die produces a list of logical nets as candidates failing locations. This means that the actual defect may lie on any of these candidate failing nets. In other words there is inherent ambiguity in the diagnosis results which can throw off a statistical analysis if not properly addressed. This is one of the main factors why naïve analysis methods, for example just adding up all the features occurring in diagnosis results, will not yield any meaningful conclusions. The next section explains how our new analysis technique Axiom handles ambiguous diagnosis results.

### *Correlation among open features*

Logic diagnosis typically produces net level failure location information even though the end goal is open feature level failure information. Hence this information must be obtained through statistical population based analysis of open features on failing nets. However, typical nets in a design contain multiple open features and if two feature types are such that they tend to occur together on the same nets a lot then it becomes difficult to differentiate among them. As an example in the target design of this study, features like single via layer1 and metal layer 1 critical open area tend to naturally occur together on the same nets. Therefore if statistical data analysis shows more defects in single via layer1, the actual problem may also be due to metal layer1 random particles. So, realizing these natural correlations among open features is important. In this study most of these correlations were found among open features which are within one metal layer of each other.

## 5. Axiom: New Method for Analyzing Logic Diagnosis Results

Previous sections described the various open features extracted for the target design, GP500, as well as the main challenges in analyzing the failing location data obtained from logic diagnosis. This section describes Axiom, the new analysis technique that identifies the dominant failure mechanism in the given set of failing die from an excursion wafer by analyzing their logic diagnosis results along with the extracted physical features.

### *Background of statistical hypothesis testing*

As mentioned before Axiom is based on statistical hypothesis testing, so we start with a brief description of the same. Statistical hypothesis testing is a method to draw conclusions from a given set of data. First we create a *null hypothesis*, which is basically something that we would want to **disprove** using the given data set. As an example, for our application, using the diagnosis data, we would like to disprove all those features as the dominant defect mechanism which are not so in reality. Following the creation of a null hypothesis, a statistical test is performed on the data set based on this hypothesis. A variety of statistical tests are known; in this paper we use the chi-square test since it is the least restrictive. The chi-square test returns a probability value, commonly referred to as the *p*-value. If this *p*-value is less than a constant $\alpha$ (where $0 \le \alpha \le 1$ and the actual value of $\alpha$ is one minus the desired confidence level from the test) then the null hypothesis can be rejected (or disproved) with a probability equal to $1-\alpha$. On the other hand if the *p*-value is greater than $\alpha$, then we say that there is not enough statistical evidence to disprove the null hypothesis with the desired confidence level.

### Axiom Analysis Technique: High Level Overview

Based on the above discussion we can now begin to describe the main analysis steps in Axiom at a high level as follows:

1. Given logic diagnosis results of a set of failing die and a list of open physical features along with their values on each net in the design (Recall from Section 3 that the value of a feature on a net for vias is the count, for critical area is the area and for SWS open is the run length). The goal is to identify the dominant defect mechanism from among these features.
2. Analyze each open feature one at a time. When analyzing an open feature form the null hypothesis that this feature is *the* sole defect mechanism.
3. Perform the chi-square statistical test to determine the *p*-value for the above null hypothesis. This is done by matching the expectations generated by the null hypothesis against the actual diagnosis data.
4. If the p-value calculated in the above step is small then the null hypothesis can be rejected with high confidence, which would mean that the current feature is **not** a dominant defect mechanism. The feature that passes the chi-square test with the highest *p*-value will be the most dominant defect mechanism.

While the overall methodology above seems like any standard statistical hypothesis testing the main novelty in Axiom comes from step 3, where a procedure is needed to match the expected data against actual data. The details of how this is done are explained next.

### Procedure to match expected data with actual data

This procedure should be such that it can handle the ambiguity in diagnosis results as discussed in Section 4. The procedure that can be used to accomplish this and is one of the key contributions of this paper is as below:

3.1 Let $ft_i$ denote the open feature that is currently being analyzed. Let ***NETS*** denote the set of all the nets in the design.

3.2 Sort the nets in the design in descending order of the value of feature $ft_i$ on the net.

3.3 Divide ***NETS*** into *N* equal groups (where *N* is some fixed constant): $Gp_1, Gp_2, \ldots, Gp_N$, such that the top $|\boldsymbol{NETS}|/N$ nets as ordered in the previous step go into group $Gp_1$, the next $|\boldsymbol{NETS}|/N$ nets according to the ordering above go into $Gp_2$ and so on. Therefore by construction, the value of the feature $ft_i$ summed over all the nets in $Gp_1$ will be the highest among all the groups and it will continuously decrease as we go from $Gp_1$ to $Gp_N$.

3.4 Based on the hypothesis that $ft_i$ is the sole failure mechanism; calculate an **expected** diagnosed count for each of the *N* net groups. The *diagnosed count* for a net group is defined as the total number of times a net in the group is included as one of the candidate failing nets in a diagnosis report.

3.5 Calculate the **actual** diagnosed count for each of the *N* net groups from the diagnosis reports. This is simply done by going through each candidate failing net in all the diagnosis reports and increment the diagnosed count of the group to which the net belongs.

3.6 Regarding the diagnosed counts for the net groups as independent measurements perform hypothesis testing by doing a chi-square analysis on the expected and actual values.

The main novelty in the above procedure is the idea of dividing the nets into several groups distinguished by the feature values on the nets. This allows for the computation of expected and actual values which in turn enables statistical testing. The basic idea behind this approach can also be understood as follows: let us assume that some excursion wafer is caused by the presence of excessive impurity particles during a metal layer 4 fabrication step. This would mean that dominant failing feature is m4_open (critical area on metal layer 4). Therefore, in this case nets with high value of m4_open would tend to fail and show up in the diagnosis reports more often. In other words the actual diagnosed count for net groups should better track the total value of the feature m4_open as opposed to the total value of any other feature. This basic idea is systematically exploited in the procedure described above.

Using net groups as described above also best mitigates the effect of correlation between features (Section 4). This is because grouping the nets such that higher feature valued nets are together will result in amplifying the small differences among correlated features, eventually resulting in differentiation between them.

### *Computing the expected diagnosed count*

In order to complete the description of Axiom, we still need to describe how to calculate the expected diagnosed count for net groups in step 3.4. We will denote the expected diagnosed count for a group by $\mathrm{Exp}_{diagn}(Gp_i)$. As mentioned before the expected diagnosed count for a net group, $Gp_i$, is the number of times we would expect to see nets from $Gp_i$ in the diagnosis reports given that the null hypothesis is true.
Now, since the null hypothesis states that the sole failing mechanism is the feature, $ft_i$, being currently processed, we can determine the rate at which this feature must fail given the hypothesis as below:

$$p_{fail}(ft_i) \approx \frac{\text{Number of failing die}}{DIE_{total} \times \sum_{\text{All Nets}} v(ft_i)}$$

In the above equation $p_{fail}(ft_i)$ denotes the fail rate of feature $ft_i$, $v(ft_i)$ denotes the value of that feature on a net and $DIE_{total}$ denotes the total number of manufactured die (total number of die on the excursion wafer). Hence, this equation basically states that the fail rate of the feature can be estimated as the ratio of number of times it fails to the total number of times it is fabricated. Note that here we assume (for the sake of simplicity) one defect per failing die. From the feature fail rate as determined above we can now determine number of times some net in a group is expected to fail:

$$\mathrm{Exp}_{fail}(Gp_i) = \left[ DIE_{total} \times \sum_{\text{Nets in } Gp_i} v(ft_i) \right] \times p_{fail}(ft_i)$$

$$\mathrm{Exp}_{fail}(Gp_i) = \left[ \frac{\sum_{\text{Nets in } Gp_i} v(ft_i)}{\sum_{\text{All Nets}} v(ft_i)} \right] \times \text{Number of failing die}$$

In the above expression $\mathrm{Exp}_{fail}(Gp_i)$ is the expected fail count of the net group $Gp_i$. Finally, we need to account for noise due to ambiguity in diagnosis results (Section 4) to determine the expected diagnosed count for a group $Gp_i$. The diagnosis noise is estimated by assuming that the diagnosis report always includes the real failing net, and that the remaining candidates belong to random groups. In other words it is assumed that all the candidate nets in the diagnosis reports besides the real failing nets (i.e. diagnosis noise) are spread evenly over all the groups. This is a valid assumption because the main source of diagnosis noise is logical equivalency between various locations in the design, while the net groups are constructed based on feature values. Since there is no correlation between the two factors, there is no reason for the diagnosis noise not to be randomly distributed over the net groups. Now, all the net groups are of equal size by construction, therefore the diagnosis noise for a group is estimated by:

$$Diag_n = \frac{\left( \begin{array}{c} \text{Total candidate net count in diagnosis reports -} \\ \text{Number of failing die} \end{array} \right)}{N}$$

In the above expression $Diag_n$ denotes diagnosis noise. With the estimation of diagnosis noise, the expected diagnosed count for a group can be determined as below:

$$\mathrm{Exp}_{diagn}(Gp_i) = \mathrm{Exp}_{fail}(Gp_i) + Diag_n$$

With the above process of determining the expected diagnosed count for a net group, the description of Axiom is complete. The next section presents the results of application of the new technique to the target case study in this paper.

## 6. Experimental Results

To recall the target of this study was an excursion wafer whose yield was much below normally yielding wafers of the same design. The target excursion wafer had 209 failing die on it.

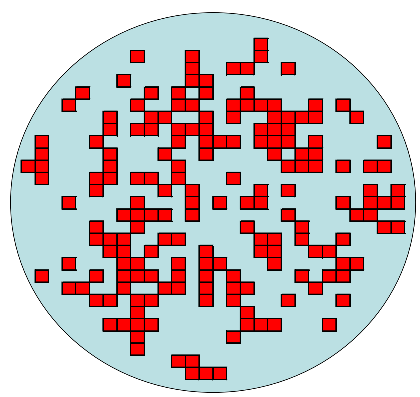

**Figure 8: Wafer Map of Failing Die on the Excursion Wafer**

A wafer map of failing die on this wafer (Figure 8) does not reveal any particular spatial pattern in the failures. This makes it harder to choose target die, which will most likely reveal the dominant defect mechanism, for PFA. Fail logs from these failing die were input into a logic diagnosis tool to determine the most likely failing locations or nets for each failing die. This failing nets data along with the open features extracted for each net were then analyzed together using the Axiom analysis technique described in the previous section. In these experiments we focused on the main open features, i.e. the single vias on each layer and critical open area for all metal layers. Furthermore we used *N*=20 net groups for these experiments. The choice of the number of groups is determined by a trade off between number of data points on which the Chi-square test is run and the size of each group. A higher value of *N* is desirable since it means a larger number of data points per feature, since each net group represents one measurement for a feature. Therefore a higher *N* means that there is more chance for the Chi-square test to reject the non-dominant failing features. On the other hand a higher value of *N* implies smaller size of each group and at some point each group will cease to be a statistically significant measurement value. Hence the value of *N* will need to be chosen based on design size, number of failing die available, total number of features etc. The number also depends on the fail rate of the dominant failing feature. However, since this is an unknown, the actual choice of *N* has to be done by trying different values and choosing one which gives the most statistically significant results.

The results of the analysis are plotted in the chart in Figure 9. This chart plots the *p*-values for each feature type in the design as calculated by step 3 of the Axiom analysis.

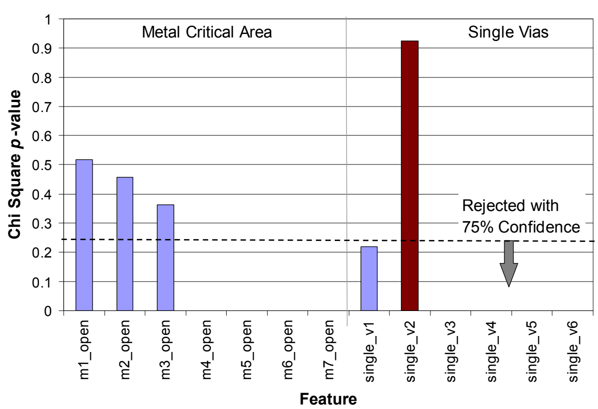


**Figure 9: Analysis Results for Basic Feature Types**

Recall from Section 5 that the (1-p-value) gives the confidence level with which a feature can be rejected as the dominant failure mechanism. For example if the *p*-value corresponding to a feature is 0.25 then it can be claimed with 75% confidence that it is not a dominant failure mechanism. Based on this, the first observation to be made from the chart is the following features have very low *p*-values, and hence can be removed from the list of possible suspects with a high confidence: critical open area on metal layers 4 and above and single vias on layer 1 and layer 3 and above. This leaves us with the m1_open, m2_open, m3_open, and single_v2 as the possible culprits. Among these single_v2 stands out with the highest *p*-value. This indicates single vias on layer 2 could be the dominant fail mechanism. However, if that is the case why do we get high *p*-values for the other four features? This can be attributed to the issue of correlation among open features as discussed in Section 4. It is very likely that nets that contain single_v2 also contain the features m1_open, m2_open and m3_open. This is the likely reason behind getting high *p*-values for these features. Notwithstanding these correlation effects it is clear from the chart in Figure 9 that the Axiom analysis technique is able to make a clear distinction between single_v2 and the other high *p*-value features indicating that this feature is most dominant failure mechanism.
To further support the argument above, the Axiom analysis was re-run this time only on a randomly chosen subset of the failing die. The goal of this experiment was to show the effect of sample size on the results of the analysis. Basically, the idea is that as more and more failing dies are included in the analysis we should be able to more confidently differentiate the dominant failing mechanism from the others which show up due to correlation. This means that the difference between the *p*-value of the dominating feature and the others should increase going from the analysis on a subset of die to the entire population. The results of this experiment are in Figure 10 below:

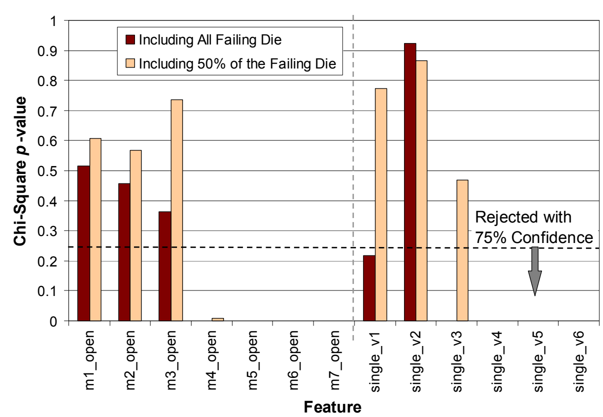


**Figure 10: Analysis Results on a Sample of Failing Die**

It can be seen from this chart that the while the *p*-values of features m1_open, m2_open, m3_open, single_v1 and single_v3 reduce as we go from 50% of the failing die to the full population, while the *p*-value of single_v2 does not reduce (in fact it increase slightly). This further supports the theory that single_v2 is the dominant failing mechanism while the other features with high *p*-values are an artifact of correlation among features. As more data is included these other features are filtered out with more confidence. In the next section we present independent validation of this result through the traditional PFA based methodology.

At this point it should be noted that without the statistical analysis described in this section, it would not be possible to determine single_v2 vias as the highest failing features. For example if we simply count the total number of failing features in diagnosis reports, we would get single_v1 as the highest failing feature. Moreover, it can be seen from Figure 6 that the number of single_v2's in the design is much lower that multi_v1, multi_v2, single_v1 etc.

Hence, from the diagnosis results we can conclude that the cause of the excursion wafer is most likely an abnormality in a process step related to the fabrication of single vias layer 2. This information can be used to identify and subsequently correct the deviant process step and hence restore the yield back to normal levels.

## 7. Validating Conclusions Drawn from Analysis of Diagnosis Results

In order to validate that single vias on layer 2 are indeed the dominant failing feature in the defective die on the excursion wafer, eight failing die were selected for performing detailing physical failure analysis (PFA) of the defects. These die were selected based on the ease of isolating the defect based on the diagnosis results and data from probing equipment etc. The PFA process on **all** eight selected dies isolated the defect to a mal-formed layer 2 via which was leading to an open net in the device. The PFA picture of one such defective via is show in Figure 11. Hence, these PFA results provide independent validation of the analysis techniques presented in the previous sections.

Further analysis determined that all these defective via had a thin oxide layer on the bottom which was leading to the net open. Once this information was fed back to the manufacturing process, it was determined that one of the metal deposition steps was unclean leading to higher failures. Having a tighter particle control on this step resulted in yields getting back to normal.

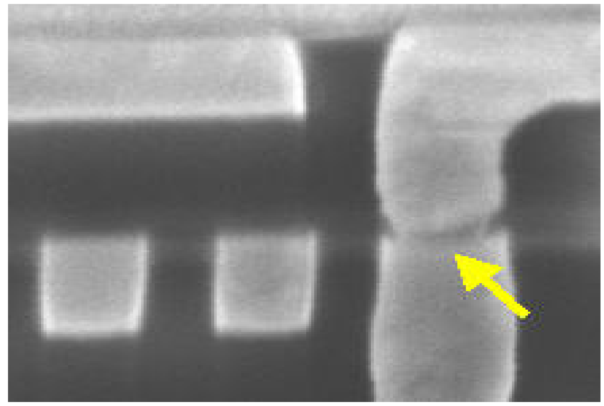

**Figure 11: Defective layer 2 Via**

## 8. Conclusions

During chip manufacturing there are certain oppurtunities of yield enhancement where there is a single dominant defect mechanism that can be targeted. One such example is an excursion wafer where a wafer would suddenly have a lot of failing die. The results presented in this paper highlight the advantages of using diagnosis results to identify the dominant defect mechanism in such situations. This information can be used for achieving overall yield enhancement. Traditionally this has been done through a PFA based process which is expensive and time consuming and hence can only be performed on a small number of failing die. In the end the results from such a small number of failing die may not be conclusive. So even after this process some trial and error may be required to zero in on the process step causing which can be tuned for better yield, increasing the overall time and cost for yield enhancement.

On the other hand using diagnosis results to identify the dominant defect mechanism among failing die, for example on an excursion wafer as described in this paper, is a much cheaper and faster process. It also has the advantage of being able to analyze **all** the failing dies, which means that statistically significant conclusions can be drawn from the data. An excursion wafer for products with low volumes can especially benefit from using diagnosis results since low volumes imply insufficient lot, process and yield history data to analyze. With today's fabrication processes becoming very complex and expensive, combined with very high volume manufacturing, it is important to enhance yield as quickly and efficiently as possible. This paper presented the novel Axiom analysis techniques to do so, based on the analysis of logic diagnosis results for failing die. With this new capability the dependence on PFA can be reduced or possibly eliminated completely. Axiom is specifically designed to perform analysis for situations where there is a single dominant defect mechanism and is able to handle inherent ambiguity in logic diagnosis and the problem of correlation among features in a design. Experimental results validate these claims about Axiom. In the future we would like to apply this methodology more widely on different products and technology nodes, as well as perform controlled experiments for further validation.

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