

A Rapid Yield Learning Flow Based on Production Integrated Layout-Aware Diagnosis

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Abstract

This paper presents a flow for using logic diagnosis to turn production material into vehicles for yield learning. High throughput logic diagnosis is combined with the newly emerging field of design for manufacturing to enable layout aware diagnosis. The ability of the flow to calculate feature failure rates and the application of the failure rates for yield learning is demonstrated through volume data analysis on a production ASIC.

1 Introduction

At the inception of each new technology node there is a yield ramp that must be surmounted before a company can begin generating positive revenue. Each new technology brings with it new challenges that must be addressed and new solutions that must be found for dealing with these challenges [1][3]. Traditional methods for yield learning such as test chips and physical failure analysis (PFA) are highly effective but cumbersome, expensive, and only feasible to perform on a small sample of defective parts. Memory based analysis has proven to be an effective technique for identifying defects in the front end, however memories don't represent all layout scenarios and they will not allude to issues in the upper metal layers. Inline inspection data can aid in identifying the suspect process step, however this data isn't always readily available and the size of killer defect is ever-decreasing [1]-[4]. During yield ramp the nature of the yield limiters is changing as well. At present, the industry has recognized the importance of the interaction between design and manufacturing which has spawned a slew of design for manufacturing (DFM) techniques and rules [4]-[10]. When problems in yield learning are coupled with the problems in yield ramping we can clearly see the challenges that lay ahead for the next technology node. What remains is to develop a robust engineering solution to address these challenges.

One of the yield learning techniques that has begun to gain a lot of traction is in using the logic diagnostic results for large samples of data taken off production material. This kind of approach is less costly than building dedicated test chips which don't provide the company any direct revenue.

Diagnosis of the random logic ensures that all process layers are represented. In the case of systematic defect mechanisms diagnosis can serve as a method for defect identification as well as a way to estimate a defect's impact thus focusing the efforts of physical failure analysis. There is an added opportunity to craft additional test patterns that maximize coverage on defect prone features. By analyzing silicon failures through diagnosis one is able to determine the features that are actually causing yield loss, as well as their relative impact [4]-[6], [8]-[16].

This paper introduces a yield learning flow based on high volume production integrated logic diagnosis. It starts off by extracting layout features which are determined to be defect prone. This is done through process simulation, lithographic simulation, or DFM (Design-for-Manufacturing) rule application. The flow combines the results from volume diagnosis with layout extraction to enable computation of failure rates and identification of the yield limiters. The proposed method can be used to continuously monitor the fallout contribution of each layout feature. By closing the loop between DFM techniques and the actual defect behavior there is the potential to not only improve yield but also provide validation and calibration of DFM rules.

The paper is structured as follows: First is an overview of the proposed flow including by a detailed discussion of its components. Section 3 is a discussion of potential applications of the flow. Section 4 provides experimental data for a controlled experiment that was run to validate key components of the flow. Results from silicon fail data from a customer industrial design are presented in Section 5. Finally, the paper is summarized and conclusions are drawn.

2 Rapid Yield Learning Flow

The introduction already explained that in today's technology, the design and the manufacturing interact. Therefore, in order to determine the design's yield limiting factors, the design itself must become its own test chip. Features of the layout that are prone to fail (such as adjacent signals lines, single vias, or certain library cells) can point to potential defect locations. The failure rates of these layout features can then be used further in

applications such as ranking the defectivity of features, monitoring the yields, or as the predictive test set that is required when applying adaptive test [17].

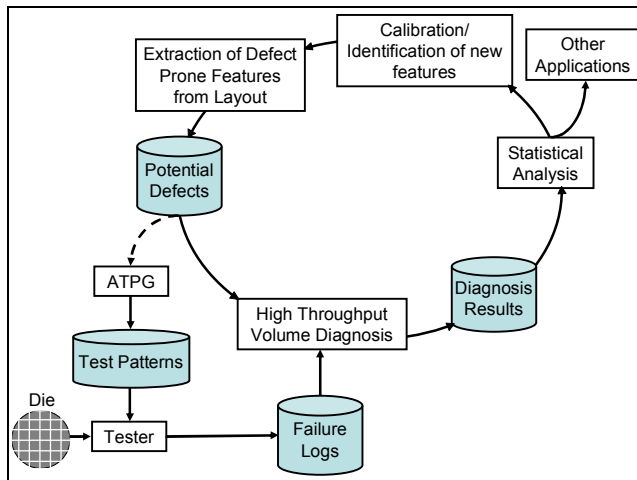


Figure 1: Proposed rapid yield learning flow

The proposed flow presented in Figure 1 consists of the following key components:

- Extraction of defect prone features from layout
- High quality test pattern set
- High throughput volume diagnosis
- Statistical analysis of all diagnosis results
- Determining yield limiting factors based on the statistical results
- Quantifying and qualifying extracted features

In the following, the flow is briefly described. Later sections discuss key components of the flow in more detail.

The flow starts off with a given set of defect prone features. One example feature is two pointing corners of polygons in the same layer of the layout. Each feature implies one or more potential defects; in the case of the pointing corner the defect is a bridge. Optionally, these defects are fed into an ATPG tool, which may compute additional top-off patterns to cover the defects implied by the features. But this step is not imperative, as the flow works well also with traditional test patterns. The test pattern set is transferred to an ATE and the test is executed. Here, it is important that the test does not stop-on-first-fail, rather the failing data has to be collected for an adequate number of failing cycles.

After diagnosis has been run on all fail logs, statistical analysis is started. The goal of statistical analysis is to compute the failure rates of all previously extracted features. Statistics can organize the data in many different ways, some of which don't directly relate to extracted features. For example, the overall defectivity of a metal layer or a particular library cell can be computed. For purposes of analysis, the statistical data can also be visualized, e.g. in the form of Pareto charts. It is possible

that diagnosis cannot determine the reason for a failing die, thus these candidates will show up as undetermined. Further investigation is required in order to determine the root causes if the number of these cases becomes too large.

Based on the computed failure rate, the yield limiting factors of the design can be determined. Depending on the type of the yield limiting factor, physical failure analysis may or may not be necessary to validate the finding. With this data a number of different applications are possible, which all base on the statistical results.

2.1 Feature Extraction

As mentioned earlier, many unique layout features exist and the defect scenarios that may lead to failure can be even more. For example, the lithography process may be out-of-line, or a DFM rule may not be calibrated properly. In general, the failure rate of features in the design varies with the unpredictability of the manufacturing, and some features are more susceptible to certain process variations than others.

To be able to form a flow which determines the design-process interaction and to determine the yield limiting factors, candidate features must be identified in the layout of the design. Different tools can be used to do this, for example the lithography process can be simulated to find potential shorts and opens in standard cells. Other tools may try to identify particular layout structures in order to find potential locations of failure. For improving the diagnosis and the statistical analysis, not only the feature type needs to be identified, it would also be very helpful to determine the exact coordinates (layer/X/Y) of the feature in the layout. In the implementation presented in this work the flow used a commercially available tool for Design Rule Checking (DRC), which inspects the layout and flags violations against a given set of rules. The DRC rules are written in such a way that they identify the layout features of interest and determine relevant physical parameters, like the size of the potential defective area and its location. Subsequently, all identified layout features and data are written into a file. Using a DRC tool is only one way to extract layout features. The suggested flow does not imply or depend on any particular extraction method.

Currently there are two broad categories of defects the industry is concerned about: bridges and opens. As a representative of open defects all instances of single vias are identified and extracted. Further, five types of bridging scenarios are analyzed. These types are derived from DRC and DFM rules and known bridge causing layout features:

- Type 1: Side-to-side
- Type 2: Corner-to-corner
- Type 3: End-of-line
- Type 4: Via-to-via
- Type 5: Side-to-side over wide metal

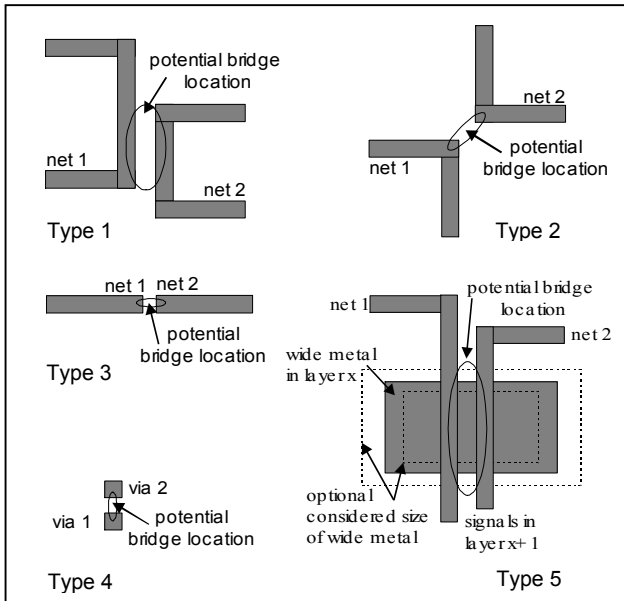


Figure 2: Extracted bridge features

Sketches of each of the five types are shown in Figure 2.

The defect extraction itself is parameterized: For bridge Types 1 and 5 the minimum parallel run length and the maximum distance between the signal lines must be defined. In addition for Type 5, the minimum size of the wide metal can be parameterized as well. Types 2 and 4 use only a distance parameter, and Type 3 considers distance, parallel length, and the minimum length of the signal arm.

The first type, side-to-side, resembles the “classical” type of bridge where two signal lines run in parallel for some distance. Capacitance coupling based bridge extraction such as that used in [18] falls into the category of side-to-side bridges. Random particle defects are typically covered by side-to-side signal lines because of the high critical area associated with this type of bridge. Limiting the extraction to bridge locations with a high critical area may be sufficient to generate particle induced failure but it is not sufficient to identify systematic yield limiting defects (such as Types 2 and 5).

The five bridge types and one open feature shall by no means imply a complete set of layout scenarios that cover all observed (systematic) defects of current designs. A practical flow must be open to allow the inclusion of additional layout features. In the suggested flow, all that is needed is a method of identifying the feature of interest in the layout and extracting its properties.

2.2 Test

By combining traditional production patterns with layout extraction information it is possible to identify suspicious behavior in any design already in production. With the proposed methodology no change of the test flow is

necessary, since traditional test patterns usually have fairly high defect coverage. However, if the statistical analysis determines a high failure rate of a particular feature, it can be advantageous generating additional patterns based on extracted features in order to improve test quality. Note that an extracted feature based test pattern set can only be computed *after* the layout is finalized.

2.3 Production Integrated Diagnosis

In order to perform successful production integrated diagnosis several capabilities may ease the implementation. One of these capabilities is being able to diagnose the test response for die having on-chip compression. This can be accomplished either by putting the chip into bypass mode and collecting the data or by performing diagnosis directly on the compressed pattern [19][20]. Another issue that must be addressed is diagnosis on parts that fail scan continuity testing. This so called chain diagnosis may be performed by logging many more cycles than are normally collected, whether compressed or in bypass mode [21]. Often this data is ignored because of the cost of extraction; however it may need to be addressed if the fallout becomes unexpectedly high.

Another improvement of diagnosis tools is the inclusion of physical data, for example the layer(s) of a net, or it’s X/Y-coordinates [13][14][22]. Reporting of physical data can improve the turn-around time of PFA by considerably reducing the area on the chip to be inspected. The inclusion of physical data into the diagnosis algorithms can also improve the quality of the diagnosis results [23].

The diagnosis tool that is elaborated here enables high volume diagnosis combined with a low demand of resources (number of workstations) due to its speed. It also integrates the physical data which comes with each defect implied by the layout features. In contrast to other tools this methodology points directly to the potential defect locations in the layout, thereby further reducing the ambiguity.

2.4 Volume Data Analysis

Diagnosis results from production failing die contain a large volume of data. The goal of statistical processing is to draw actionable information from this data and to provide visualization of results. More specifically, statistical processing has two main objectives:

- To approximate the failure rates of known yield limiting factors.

$$Failure\ rate = \frac{\# \text{ failing_features}}{\# \text{ features_manufactured}}$$

- Identifying outliers among the failing die which represent discrepancies from the known yield limit factors. These die are good candidates for going through the PFA flow so that new unknown yield limiting factors can be determined.

Both of these tasks are complicated by the fact that diagnosis does not always exactly pin-point the defect location or failing feature in a defective die. Many times diagnosis produces a list of possible suspect defect locations (suspects), one of which will be the actual defect in the die. It is also possible that multiple extracted features are associated with each suspect. Sometimes diagnosis may not identify the correct defect location at all. So, in order to accomplish the above two goals, special statistical techniques have been developed that can tolerate the ambiguities and errors in the diagnosis results. These techniques can be divided into two main categories: (1) iterative fail rate estimation and (2) correlation with an a priori prediction mode.

Iterative Fail Rate Estimation

The techniques of the first category use a probability model in which each yield limiting factor acts independently of the other yield limiting factors and only cause a single defect. It starts with an initial estimate of the fail rate of each known yield limiting factor. This estimate is then used in conjunction with the diagnosis results to compute an improved estimate of the failure rates. Hence starting from some initial guess, the actual failure rate of each yield limiting factor can be estimated by iteratively improving upon the guess and converging towards a solution.

As a simple example, consider a case in which there are two yield limiting factors reported by diagnosis for the same die (1) single via, and (2) two parallel metal lines. In addition let the bridge share one net with the reported potential open. At this point diagnosis cannot tell which of the layout features is likely to cause the failure of the die.

The iterative method starts with an initial guess in which both features fail with some equal probability. Next this initial guess is used to estimate the expected number of failures of each type from all diagnosis results in the population being analyzed. This expected number of failures, along with the total number of instances of each of the two features in the design, result in an improved estimate of the fail rate. The process is repeated until it converges and the final failure rate is reported. Based on this methodology it may turn out that the one of the features is more likely to explain the failure than the other.

Correlation with an A priori Prediction Mode

The technique of the second category starts with parameterized failure prediction models where the parameters are the failure rates of each yield limiting factor. These models are used to predict the likelihood of observing certain diagnosis results. This predicted likelihood is then matched with the actual diagnosis results and this correlation leads to a regression model for which failure rates can be estimated. This method can also point to new (thus far unknown) systematic yield limiters because such cases will result in a mismatch between the predictive model and the observed behavior. Die that fall

into this category are good candidates for detailed root cause analysis in order to uncover new failure modes.

It should be observed that both of the above described techniques rely on the underlying assumption of *diversity* in design from the point of view of yield limiting features. In other words if two yield limiting features happen to be tightly correlated in a design, then it will be impossible to estimate their failure rates independently of each other. However, it is still possible to estimate the failure rate of these two features considered together as one class. As an example if a design is such that all the nets contain an (about) equal number of vias on metal layer 2 and layer 3. It will not be possible to independently determine the failure rates of vias on layer 2 and layer 3, but the failure rate of the class comprising of vias on layers 2 and 3 can be determined.

In the subsequent experiments the first technique to estimate the failure rates of the yield limiting factors will be used.

3 Applications

This section presents a number of applications of the results of the statistical analysis.

3.1 Yield Learning

A first application of the statistical analysis results is to identify yield limiting factors. This is especially important during yield ramp up. The faster the ramp up, i.e. the faster yield limiting factors can be identified and resolved, the faster a mature yield is established. Consequently, the faster a product is commercially sound, the higher the overall return on investment is. Using the statistical analysis data the yield limiting factors of a design can be identified. Since the statistics also allows ranking of failing features, the most important yield limiters can be categorized in order of importance.

In this context and stage of the product life cycle, the yield limiting factors can be very broad. It could be that the design is susceptible to opens or shorts, that a certain layer shows problems, or that a particular standard cell has a significantly higher failure rate than expected. Also DFM rules might not be calibrated precisely enough to give a good yield. The results of the statistical volume data analysis in the proposed flow may provide help in identifying some of the most important yield limiting factors.

With additional data, like the type of the defect and its location in the layout, physical failure analysis efforts are more directed in two aspects: (1) the selection of a *typical* die for the defect of interest is much more guided, and (2) the failure analysis itself is more focused since the types of

the potential defects of a die are given together with their locations in the layout.

Of course, one must take care not to blindly trust the diagnosis answer with or without using extracted features. Diagnosis tools operate on the logical level of a design and therefore also the diagnosis answer is based of this logical view. Using extracted defect locations improves the diagnosis answer but the quality of the answer relies on the quality of the defect extraction. If a diagnosis tool determines that an observed behavior can best be explained by a defect which is not in the list, there are two reasons for it: (1) the extraction parameters don't meet the actual defect, or (2) this is a new type of defect, for which no extraction was executed. Thus, diagnosis only determines a potential explanation and the use of ranking and statistical analysis of thousands of die can only attempt to improve the confidence level. In the end the failing die has to be examined physically to confirm or reject the logic level diagnosis answer.

The statistically analyzed factors which explain the yield loss don't necessarily have to be exactly the extracted features. The statistical analysis can summarize results and may conclude that a certain layer has unexpectedly high failure rate across all extracted features. Another example may be that a certain wafer shows statistically more defects of a certain type than other wafers of the same lot. These kinds of yield limiting factors may not correspond to a particular layout feature, but to a problem in the production line. Yield engineers should be able to use the statistical data to quickly determine the root cause of the observed failures. Performing PFA may not be required for such kind of yield limiting factors.

3.2 Continual Yield Monitoring

The failure rate of features can also be monitored over time. If the failure rate of bridges in general increases, this may point to a drifting litho process. Another example may be a sudden increased failure rate of bridges over wide metal, which may indicate issues with one of the chemical mechanical polishing (CMP) steps.

Performing a relative analysis of the failure rate of features over time, between lots grouped by processing, or between design respins, can give a direct measurement of yield impacts based on feature. As production design learning improves over time, design styles may trend towards more robust designs with respect to manufacturing variability and yield.

3.3 Validation and Calibration of Features

Having computed the failure rate of all defects implied by the extracted layout features, the failure rates can be back annotated to the respective layout feature. The relative yield impact of each feature rule is now directly

observable. In case the feature is parameterized, the yield impact of a change in the parameters can be concluded as well. For example, a DFM rule might state that nets should not run in parallel for more than a certain length. Having the parallel run length as a parameter, the relative yield impact of increasing or decreasing a net pair's parallel run length can become part of the DFM rule's data. The DFM rule is now quantified, not only qualified.

Since the yield impact of each feature is now available, the features themselves can be ranked against each other. This guides the designer in which DFM rule to adhere to more strictly than others, making educated trade-offs between different features, or to chose a different library cell.

3.4 Other Applications of Volume Data Analysis

The most important applications of the statistical analysis of the volume diagnosis results have already been discussed. Here, a few additional applications are presented, but this is not intended to be a complete list.

Without a calibration of the statistically computed failure rate to the actual failure rate, only a relative yield improvement measure can be presented to a user. If a calibration can be accomplished, a true yield prediction can be given. Since a change of one feature of a design will have implications to other features or parts of the design, the overall net yield gain can then be computed before the actual modification is carried out.

Visualization is a powerful tool as well. In many cases a human just has to see a wafer map of the failures of a feature to know what to change. Since each extracted feature comes with its locations in the layout, this principle can be extended to a visualization of failing features in the layout. One example might be signal noise caused by a poorly shielded PLL, causing neighboring nets to fail with a higher rate than comparable nets elsewhere in the design. Overlaying the diagnosed failing features with data from inline inspection, temperature simulation, or power grid simulation could lead to a better understanding of the cause of the observed failing behavior. A second type of visualization is summing up the raw statistical data graphically, e.g. in the form of a Pareto or any other type of graph a user might find useful or appropriate.

Using the actual failure rate of features, the escape rate of defects associated with the features can be better estimated. This may lead to adaptive test sets for which the test pattern generation was lead by a ranked set of important non-covered defects.

The computed failure rate of all features can be used in the tools which identify the defect prone layout features in the first place. The data can help improving the predictions of the tools. Similarly, DFM rules can be improved and new

rules can be created covering previously unknown yield limiting factors.

4 Controlled Experiments

In order to validate the high volume diagnosis algorithm and statistical yield learning method, controlled experiments are performed on an industrial design as follows:

1. Bridge features are extracted from layout.
2. A certain number of these bridges are randomly selected to be injected as “real defects”.
3. In order to make the experiments more realistic, a SPICE model based simulator is used to simulate the injected bridge defects and derive the fail logs [24].
4. The high volume diagnosis algorithm is used to diagnose these fail logs.
5. Feature failure rates are computed by applying the statistical volume data analysis.
6. Compare the computed failure rates with the rates based on the actually injected bridges.

Since the statistical analysis needs a reasonably large number of samples to compute statistically meaningful results, more than ten thousand fail logs are created using extracted bridges. The volume diagnosis algorithm is then used to diagnose these fail logs. In order to satisfy the high throughput requirement of production integrated diagnosis, the volume diagnosis algorithm is designed to allow sacrificing a small amount of diagnosis resolution for very high throughput compared to traditional simulation based diagnosis. The small amount of diagnosis resolution loss of the volume diagnosis algorithm has been verified to have little impact on the final statistical results of the yield learning based on a large number of failed dies.

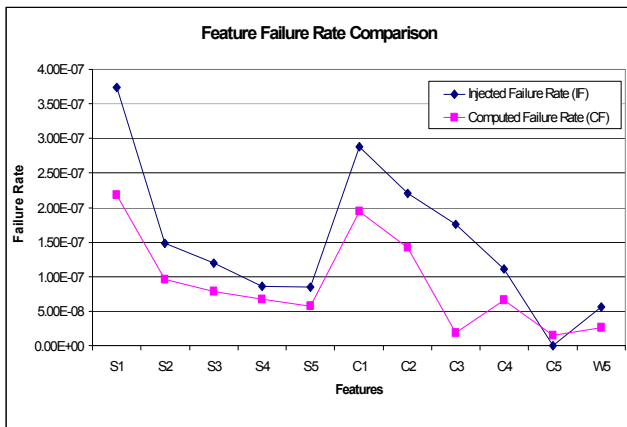


Figure 3: Controlled experiment, failure rate of different features

The design for the controlled experiment has a total of five metal layers excluding the metal layers dedicated to power and ground. All five types of bridge features shown in Section 2.1 are extracted for each metal layer, so the total

number of features is twenty-five. Some features have little or no representative instances because of the small size of the design. After excluding such features, only eleven features are considered in this study: side-to-side metal 1 through 5 (S1 to S5), corner-to-corner metal 1 through 5 (C1 to C5), and side-to-side over wide metal on metal 5 (W5), see Figure 3.

Based on the golden answer of the injected and SPICE simulated bridges, the actual failure rate for each feature is computed. The comparison between the injected and computed failure rate is shown in Figure 3. The rate of each feature based on the injected bridge defects is represented in the curve *IF* (Injected Failure rate). Since the injected bridges are randomly sampled from the extracted bridges, these failure rates have nothing to do with the real defect mechanism, and should not be linked with reality. The second curve, called *CF* (Computed Failure rate), shows the failure rate for every feature derived from the statistical volume data analysis.

It can be seen from the figure that these two curves, *IF* and *CF*, are quite similar. For nearly all features the actual failure rate is a multiplicative factor of 1.6 larger than the computed failure rate. More importantly, notice that the relative order, i.e. the ranking from the most important yield limiting feature down to the least important yield limiting feature, is the same between the injected and the computed features. Only for C3 is the ranking lower, which requires further investigation.

Based on this controlled experiment, it can be seen that the defect mechanism information can be effectively recovered from a large number of failing die using a volume diagnosis algorithm and statistical methods. Assuming the absolute yield is unknown, only a relative accuracy of the failure rate can be achieved with this flow. This relative failure rate can still be used to correctly prioritize the yield limiting factors. With additional calibration the absolute accuracy of failure rate for each feature may also be computed and a precise yield prediction may become feasible.

5 Industrial Design

The volume diagnosis algorithm and statistical yield learning have been carried out on real fail data from an industrial customer design with more than two million gates, manufactured in 110nm technology node. A total of 23,197 actual production fail logs from 1,640 wafers of 86 lots spanning over several month are used in this study. Fail data logs have been collected on the ATE for a pattern set of 1000 vectors. The diagnosis results of the 23,197 fail logs identify a total 580,870 suspects, involving 113,395 distinct nets of the design. All five types of bridges and all single via locations are used as defect prone features. The diagnosis results, the extracted features, the feature physical data, and the die and lot information are fed into

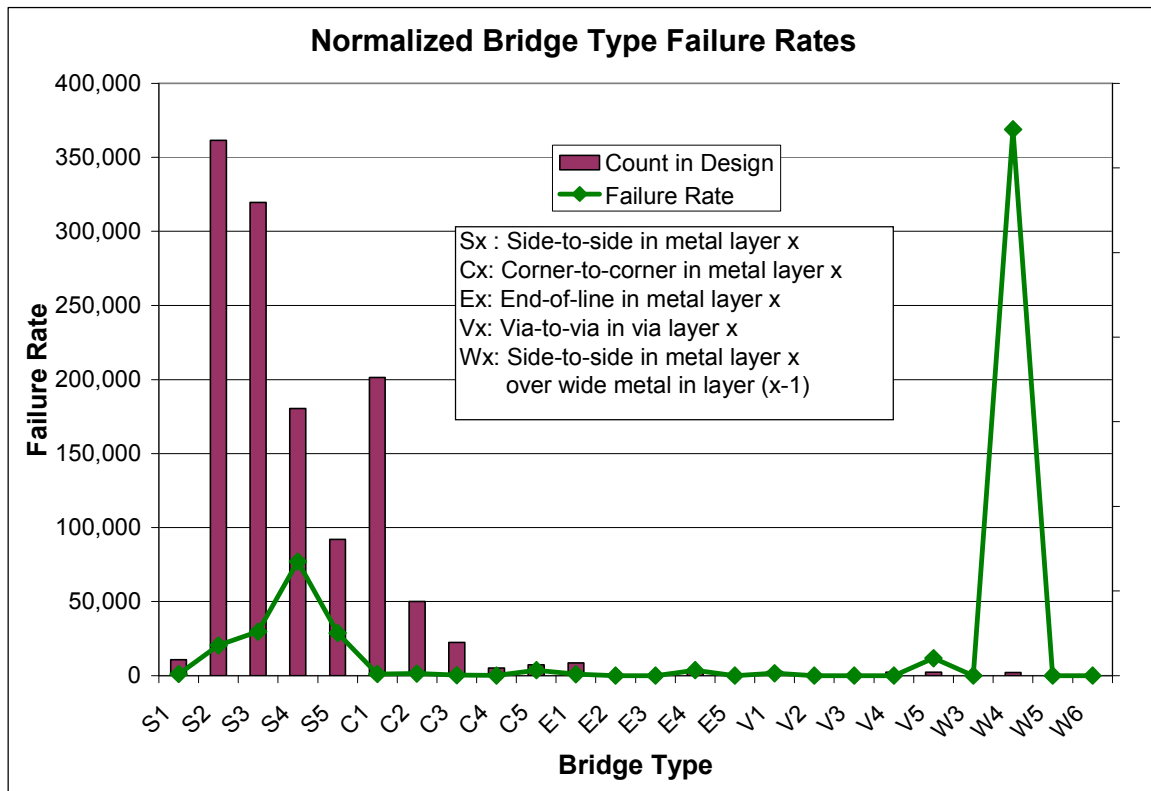


Figure 4: Normalized failure rate of all bridge types over all metal layers

the statistical algorithms. The algorithm then estimates the failure rates of various features and outputs the results for visualization.

The following subsections discuss results for three example statistical analyses. First the relative failure rates of extracted features are analyzed, followed a by discussion on how to calibrate yield limiting layout features, and finally a lot based feature analysis is presented.

Note that in all charts the actual feature count and the actual failure rate of features of the customer design have not been included. Instead the failure rates have been normalized: The smallest failure rate not equal to zero of each chart is set to 1.00. All other failure rates are in proportional relation to this value as computed by the statistical analysis. This does not change the relative order of the features or the reported relative magnitude of the failure rate of the features in the chart.

5.1 Feature Failure Rates

In the first analysis run the failure rates of various features are estimated. The results of this run are presented in Figure 4 though Figure 7.

Figure 4 plots the failure rate versus various types of layout features which are prone to bridging. As a reference the total number of each type of bridge in the design is also included in the chart. The X-axis shows all the bridge types and the Y-axis plots the (normalized) failure rates. The total number of bridge types in the design is given in a

linear scale. As before, the bridge types are abbreviated as S: side-to-side, C: corner-to-corner, E: end-of-line and V: via-to-via and W: side-to-side over wide metal. The digit next to the letter denotes the metal (via) layer the bridge is on.

Figure 5 and Figure 6 magnify the failure rates of two particular types of bridges: side-to-side and corner-to-corner, respectively. Each figure contains the failure rate of the bridges of the respective type for all metal layers.

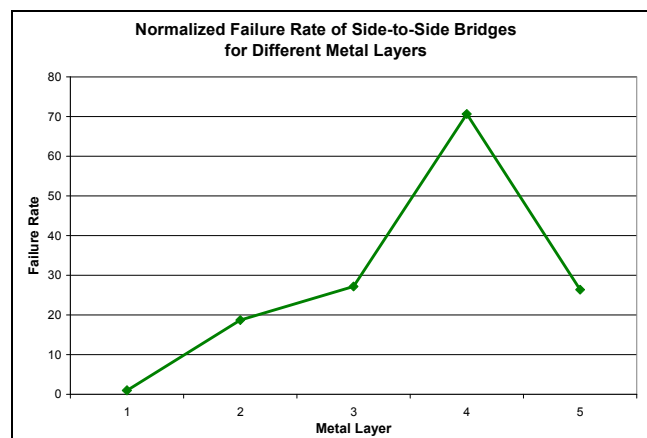


Figure 5: Normalized failure rate for side-to-side bridge feature over all metal layers

Such an analysis can be used for ranking the various features in the design in terms of impact to yield. For

example from these results (Figure 4) it can be concluded that the side-to-side bridges over wide metal in metal layer 4 has a significantly higher failure rate than other kinds of bridges. For future design re-spins or future new designs, special consideration of avoiding such scenarios should be prioritized. In addition, ATPG should target this type of bridges more thoroughly than any other type of bridge. Furthermore, the fabrication process itself can be analyzed to determine what might be causing these types of bridges. This may eventually lead to modification of process steps to alleviate the issue.

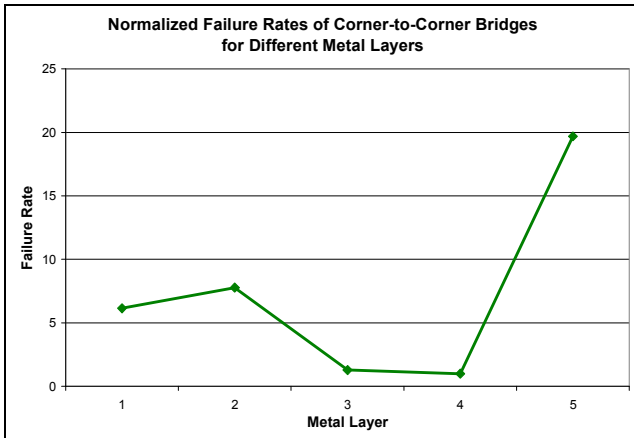


Figure 6: Normalized failure rate for corner-to-corner bridge feature over all metal layers

Figure 7 plots the failure rates of single via opens for various metal layers. Similar to Figure 4 the bars in this chart denote the total count of single via for each layer in the design. On the X-axis the single via metal layer are given, the primary Y-axis shows the failure rate and the secondary Y-axis denotes the total number of single via in the design.

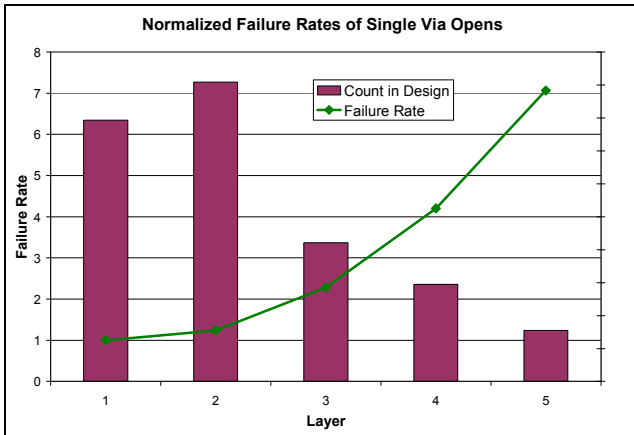


Figure 7: Normalized failure rate for single via open over all via layers, compared to the raw count of single vias

The failure rates of single via opens (Figure 7) indicate that the failure rate increases with the via layer. Such

information can indicate process anomalies in certain process steps and thus provide clues as to where to look for fixing the problem.

5.2 Calibration of Features

This section demonstrates the calibration of the layout feature “two signal lines running in parallel.” Such a feature is prone to bridging due to random particles etc. and hence is a yield limiting factor. The feature has three dimensions: The layer in which the signals run, the parallel run length, and the distance of the signal lines.

In this analysis the bridges extracted from the design based on this layout feature are classified into different buckets based on their parameters. The failure rates for each of these bridge buckets can be determined and plotted against the bridge bucket number to visualize results.

The chart in Figure 8 compares side-to-side bridges classified by their parallel run lengths and layer (metal 2 though metal 5). The actual minimum spacing for all the extracted bridges is virtually identical, and is thus ignored for this analysis. The higher the bucket numbers the longer the parallel run length of bridges in the bucket. Again, the computed failure rates are normalized.

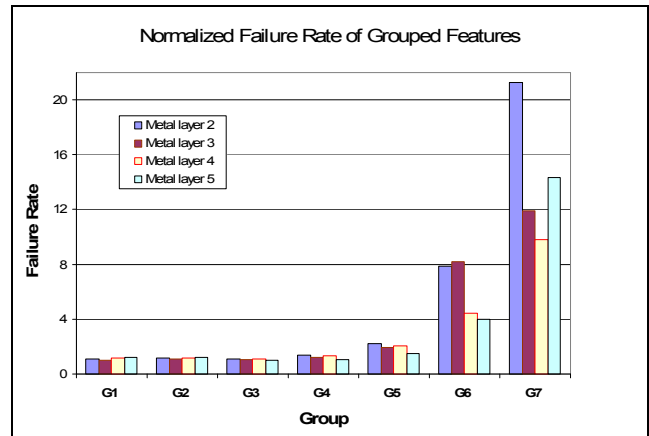


Figure 8: Normalized failure rate for side-to-side bridges grouped by parallel run length and metal layer

The bars in the chart correspond to the four different metal layers. It is expected that longer bridges fail more often than shorter bridges because they have more critical area and hence are more likely to be rendered defective by a contamination particle. This is confirmed by the results in the charts shown in Figure 8. This provides another validation of the statistical processing algorithms.

Based on the statistical data the respective layout feature can be calibrated as follows: from the data it becomes obvious that the failure rates of groups 1 to 4 are virtually identical. Moving to a parallel run length according to group 5, increases the failure rate by about 1.5X. Group 6 and 7 increases the failure rate by 4x to 8x, and 10x to 22x,

respectively, depending on the layer. Having the feature calibrated in this way offers many opportunities. For example it enables the designer to estimate yield implications of design changes based on the parallel run length and may take appropriate counter measures. Another application is to feed back this information to synthesis tools in order to improve place and route. Also, yield analyzing tools may be able to improve their predictions.

5.3 Lot Based Analysis

As a third type of analysis, the failure rates of various types of bridges are estimated for failing die in two different lot groups. The lots are grouped according to the manufacturing date. Such an analysis is useful for tracking yield excursions from one lot to another or drifting parameters over time, and can also be useful in root cause analysis. The chart in Figure 9 shows the results of this analysis.

Two observations can be made from this chart. First, most of the bridges have similar failure rates in both the lots. This serves as yet another indirect validation of the statistical failure rate estimation techniques. The second observation is that failure rates of side-to-side over wide metal bridges have a lot of variation between the two lot groups. This may indicate systematic process related issues that change over time and can provide further clues on how to fix the problem when correlated with process information.

6 Conclusions

This paper presented a comprehensive flow for rapid learning of yield limiting factors caused by design-process interactions. The flow starts off with known defect prone features and extracts these features from layout. By integrating test, high volume production diagnosis, and statistical analysis of the diagnosis results, failure rates for each extracted feature were computed.

The experimental data underlining this proposed flow covers more than 23,000 die from an industrial design failing production test. The data demonstrates the applicability of the flow and the benefit it provides for improving PFA related efforts, yield monitoring, and faster yield learning. It also has been demonstrated how to validate and calibrate defect prone layout features, which may be fed back into DFM tools.

7 References

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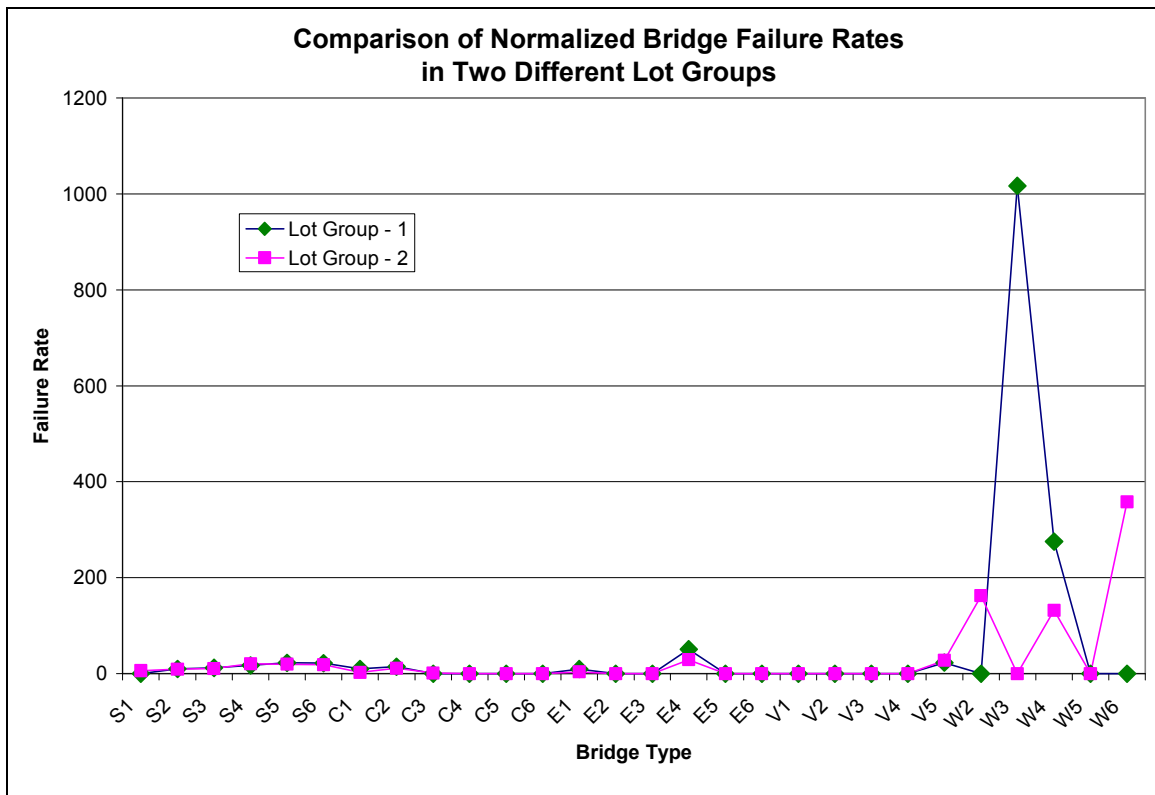


Figure 9: Comparison of failure rate of various types of bridges in two lot groups

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