ROOT CAUSE DECONVOLUTION—THE NEXT STEP IN DIAGNOSIS RESOLUTION IMPROVEMENT

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INTRODUCTION

Scan logic diagnosis turns failing test cycles into valuable data and is an established method for digital semiconductor defect localization. The advent of layout-aware scan diagnosis represented a dramatic advance in diagnosis technology because it reduces suspect area by up to 85% and identifies physical net segments rather than entire logic nets [1-3]. The defect classifications provided by layout-aware diagnosis make diagnosis an effective tool not just for localization of defects but also for yield analysis. Diagnosis-driven yield analysis (DDYA) makes volume diagnosis results actionable by identifying the most likely causes of yield [4-7].

Layout-aware diagnosis also has its limits; a diagnosis result may point to multiple locations and one single location could be explained by multiple root causes. For instance, an open in a particular net segment could be explained by an open defect in metal 2 of that segment, an open in metal3, a single via3, or a double via3. In other words, there is a certain amount of ambiguity or noise in the diagnosis results.

Root Cause Deconvolution (RCD), a statistical enhancement technology recently made available in the Tessent Diagnosis and YieldInsight products, is the next step in diagnosis resolution enhancement. It works by analyzing multiple layout-aware diagnosis reports together to identify the underlying defect distribution (root cause distribution) that is most likely to explain this set of diagnosis results. The results are then back-annotated to the individual diagnosis suspects. Where layout-aware diagnosis points to a segment, RCD can isolate a particular root cause in that segment, as illustrated in Figure 1. This increase in the failure analysis (FA) relevance and success rate dramatically reduces the FA cycle time from months to days. RCD also enables "virtual FA", the ability to determine defect distribution for a population of failing devices before any failure analysis is performed. Later in this whitepaper, we will also review silicon results.
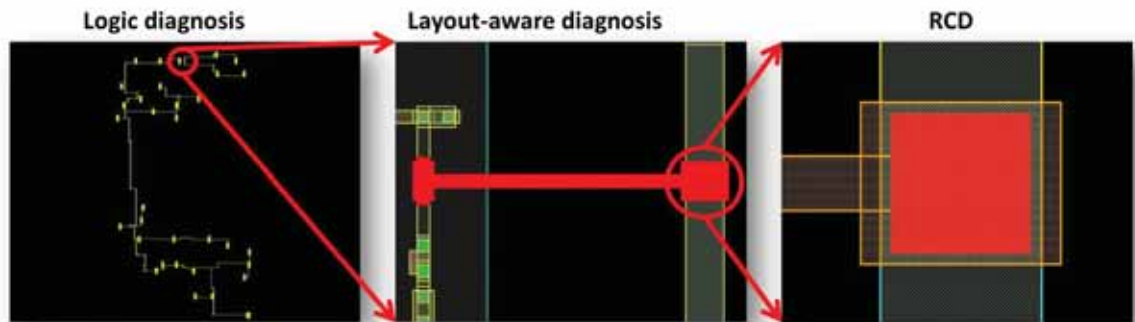

Figure 1: Layout-aware diagnosis improves scan diagnosis resolution to a net segment. Root Cause Deconvolution (RCD) leverages statistical enhancement to identify the underlying root cause, in this example, an open VIA defect.

DIAGNOSIS NOISE

The quality of diagnosis results is typically measured using two metrics; *accuracy* and *resolution*. Accuracy is a measurement of whether the diagnosis result contains the actual defect or not. It is a binary decision: is the true candidate on the list, yes or no. Resolution measures the area of the defective location captured by a suspect, that is, the bounding box of a defect and the length of the list of candidates. More candidates equals more bounding boxes and more search area. Thus, in general, a shorter list of candidates has a better resolution than a longer list. Even with advances in diagnosis technology such as layout-aware diagnosis [1-3], cell-aware diagnosis [8], compression-mode diagnosis [9], and chain diagnosis [10], there is ambiguity in the diagnosis results that limits the resolution. A diagnosis result can contain multiple suspects (potential explanations of the failure). Each suspect typically could contain multiple root causes. The example diagnosis report in Figure 2 contains just a single suspect, a bridge between two specific nets. However, these two nets are within line of sight in five different layers. That means that there are five potential root causes (a bridge in

route_1, a bridge in route_2, etc.) that could explain this report. The report can be said to contain one correct and four incorrect root causes.

Figure 2: Example diagnosis report with a single suspect and five potential root causes.

A higher ambiguity for a given device will typically result in longer physical failure analysis (PFA) cycle times and lower PFA success rate. The noise also limits how the diagnosis reports could be used to generate a picture of the defect distribution for a set of failing die.

In a simulated experiment, we injected single defects of two different types in different locations in 470 devices (310 devices with route_2 shorts, 160 devices with route_3 opens). The results are show in Figure 3, where the X axis lists all root causes identified by layout-aware diagnosis in the 470 failing die; a total of 49 different root causes. The red bars indicate how many devices had injected each type of defect. The blue bars indicate how many diagnosis reports (how many die) contain each root cause. Each diagnosis report contains one or more root cause, depending on the number and nature of the suspects.
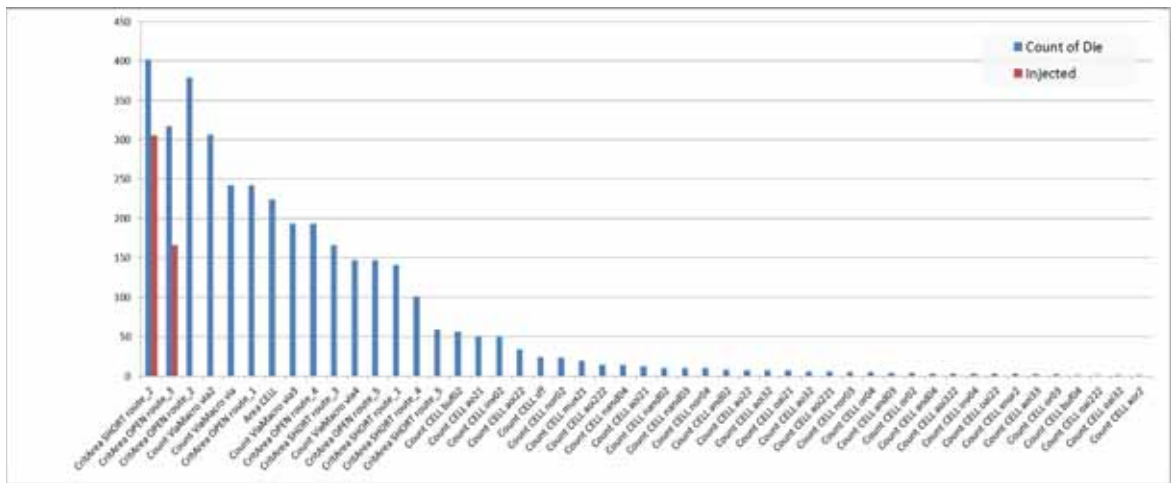

Figure 3: Results from simulated experiment. Number of die where each root cause appears in the diagnosis reports compared to the number of die with injected defects.

Although the actual root causes in this material (route_2 shorts and route_3 opens) are included in many of the diagnosis reports, the diagnosis reports also included 47 incorrect root causes. Many frequently reported root causes, such as those represented by the 2nd and 4th highest bar in the diagram do not correspond to any of the real root causes.

ELIMINATING DIAGNOSIS NOISE

Mentor Graphics developed a new technology called root cause deconvolution (RCD) to eliminate the noise from the diagnosis results and determine the underlying root causes represented in a population of failing devices. Figure 4 shows the RCD results (green) applied to the data from Figure 3. The RCD results track the injected failures with good accuracy.
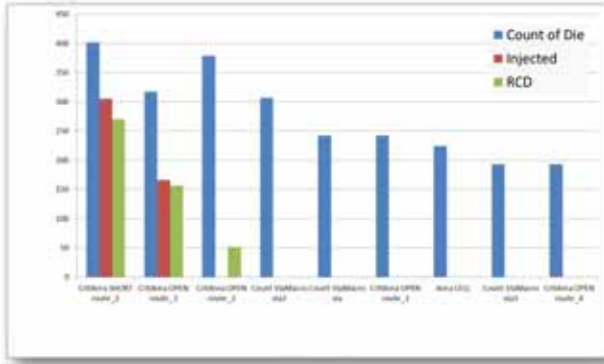

Figure 4: RCD results compared to actual defects and number of die with each root cause covered in the diagnosis report.

These results are obtained using the flow shown in Figure 5. Layout-aware diagnosis is performed on a set of die that failed manufacturing test (1). Each diagnosis result contains a set of root causes that are potential explanations for the failure (2). RCD processes the diagnosis reports, eliminates the noise, and identifies the underlying distribution of root causes that best explain the set of diagnosis reports. In this example, RCD determines that a distribution containing three root causes best explain these diagnosis reports (3). From this distribution, the user can focus on the root cause of interest. This may be the most significant root cause, or one that is deemed interesting for other reasons, for instance one that has not been seen before. For each suspect in each diagnosis report, RCD assigns a probability for the suspect being explained by each of the root causes in the RCD distribution. This means that the user can easily identify the die that has the highest probability of representing a particular root cause, and use that as way to select die for FA (4).
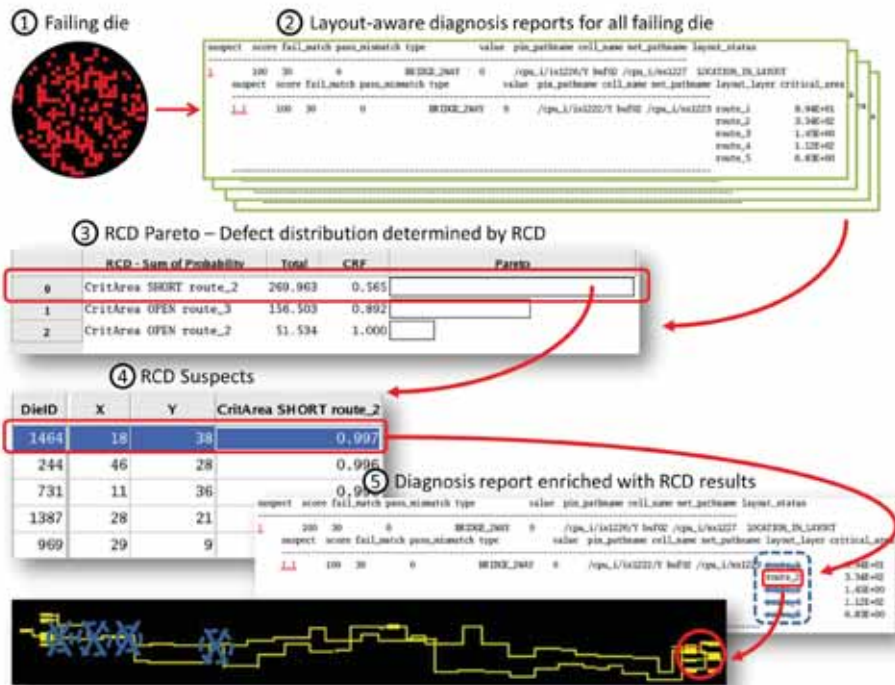

Figure 5: Typical RCD analysis process.

When comparing the original diagnosis results with the RCD results (5), we see that RCD (marked in red) has eliminated several of the original root causes (blue dotted line), thus effectively improving the diagnosis results for that individual die. In this particular example, the original report contained five possible root causes for one failing die, while RCD limited this to a single result. The layout snapshots show the defect bounding boxes before and after RCD in blue and red.

This demonstrates how RCD identifies the root cause distribution and improves the resolution of individual diagnosis results.

DIAGNOSIS NOISE AND YIELD ANALYSIS

There are several ways to deal with the noise in diagnosis reports and leverage diagnosis for yield analysis. Many of these are discussed and referenced in [11]. One such method is called zonal analysis, which manages the noise by finding relative differences in the diagnosis reports [4,5,6]. For each signature in the diagnosis reports, such as defect type layers, etc., the distribution of die containing this signature is compared to the distribution of all failing die. If the difference is statistically significant, the signature is flagged.

This method is very effective for identifying hidden systematic defects at fairly high yields, such as the last 1%-2% in high volume manufacturing. Zonal analysis is however not able to identify the actual defect distribution, which can be very beneficial for early yield ramp and excursion wafer analysis.

ROOT CAUSE DECONVOLUTION TECHNOLOGY EXPLAINED

To help explain the RCD technology, we will use an example scenario where the actual defect distribution is known. In this simple example, there are 200 die that all have metal2 open defects. The defects are located in different locations and result in different tester failures in each die. After diagnosis, most reports will likely contain metal2 opens as well as other root causes. A typical diagnosis report contains the right answer (the actual root cause or defect causing the failure) in addition to some amount of noise (additional root causes).

By leveraging certain information about the diagnosis suspects as well as information about the design itself, we can calculate the probability of seeing these particular diagnosis results for this known defect distribution. This process, illustrated in Figure 6, is a core component of RCD.
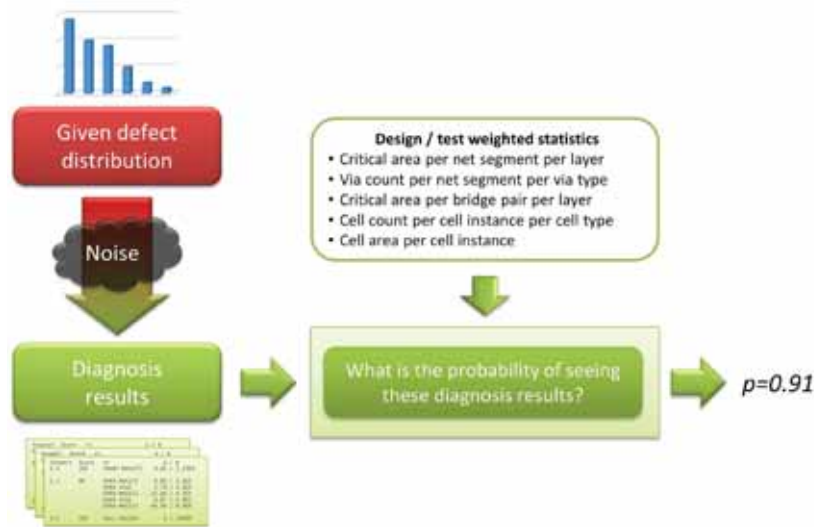

Figure 6: Based on design diagnosis suspect information, one can determine the probability of seeing a set of diagnosis results for a known (given) defect distribution.

In this example, where we know that the actual root cause is metal2 opens, the probability of seeing a diagnosis report that does not include an open suspect in a metal2 net segment is relatively low. The probability of seeing a diagnosis report that includes an open suspect in metal2 is relatively high. The higher the critical area in the metal2 segment of this suspect, the higher is the probability of seeing this diagnosis report. The critical area of a physical net segment is the area of that segment where a particle of a given size will cause a functional failure. The critical area per net segment per layer is determined as part of the layout-aware diagnosis process. For example, if the root cause under consideration is a random particle open defect on metal2, then the probability of observing a specific suspect will be equal to the suspect's critical area for open

defects on metal2, divided by the total critical area for all possible suspects. The probability of seeing all the suspects we see in the reports and can be calculated to determine an overall probability number.

This process can be repeated for a set of different defect distributions, as shown in Figure 7. Let's expand our example to a case where we again have 200 diagnosis reports, but where we consider a handful of potential defect distributions. For each defect distribution, we can establish the likelihood of seeing the set of 200 diagnosis reports. And from that, we can determine the distribution that is most likely to explain the diagnosis results.

So far, we have considered situations where the defect distribution is known. In reality, the defect distribution is, of course, what we are trying to determine. Conceptually, it would be possible to determine the actual defect distribution that best explains a set of diagnosis results by repeating the above process for all possible defect distributions. However, even when the number of root causes considered is limited to a few hundred, the number of possible distributions will approach infinity, which would be computationally impractical. RCD therefore shortcuts this process by leveraging optimization techniques based on machine learning to only test the distributions that are the most relevant. This way, RCD is able to identify the defect distribution that has the highest probability to explain a given set of diagnosis results, as shown in Figure 8. The same probability model is then used for the diagnosis reports to understand that any individual suspect is the correct suspect. This tells us which suspect is the right one, but also which root cause within each suspect is the most likely one.
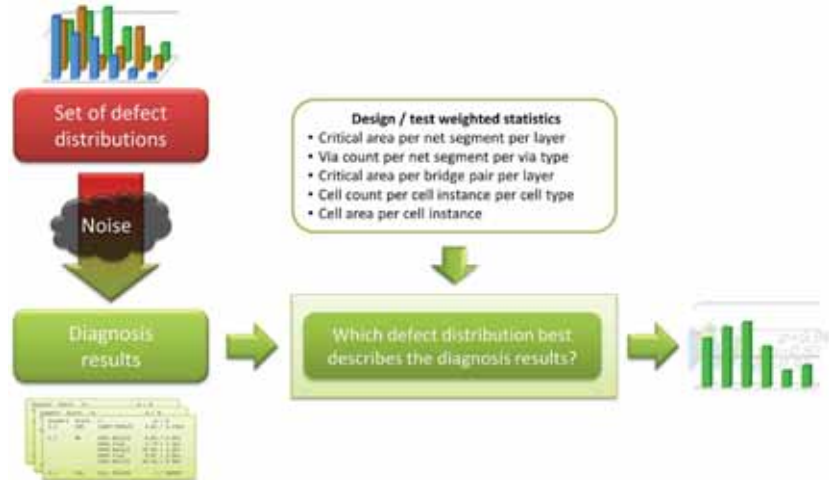

Figure 7: Based on design diagnosis suspect information, one can determine the probability of seeing a set of diagnosis results for a known (given) defect distribution.
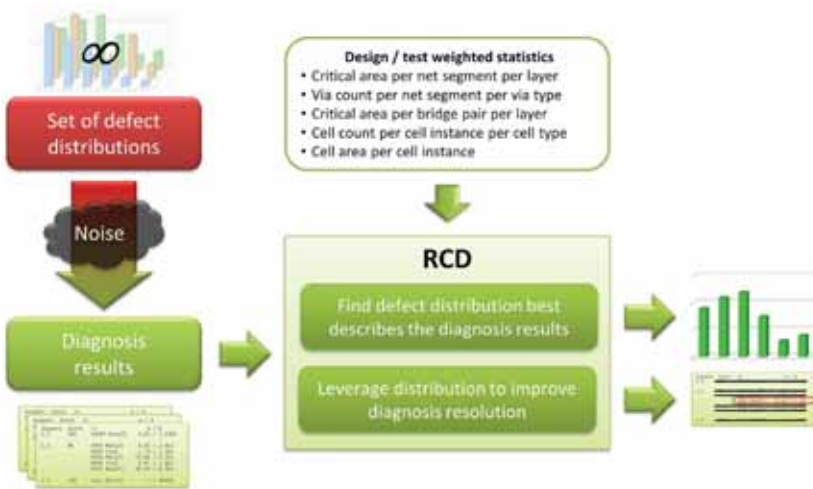

Figure 8: Based on design diagnosis suspect information, one can determine the probability of seeing a set of diagnosis results for a known (given) defect distribution.

There are two fundamental assumptions for this technology. First, RCD assumes that root cause instances are randomly distributed. If a design has 100,000 instantiations of VIA2s, and there is a VIA2 failure mechanism, any specific instance of the VIA2 is equally as likely to fail as any other instance of VIA2 in the design. In some situations, this is not the case. Some physical locations may have geometries that make them very susceptible for failures, and it's not a VIA2 problem in general, but a VIA2 problem for that specific location. A prerequisite

for RCD analysis is therefore to filter out diagnosis results with systematic locations to ensure that the RCD results are not skewed.

The other assumption RCD makes is that there is <u>one</u> underlying root cause distribution. All the failing devices should have seen similar process conditions. As an example, consider a 12-wafer lot where two wafers have much higher failure rates than the other. In this case, RCD should be run separately for those two groups of wafers. The reason is that we expect to see different defect distributions for these two groups. For a deeper understanding of some of these best practices for RCD, see [12].

RCD RESULTS AND APPLICATIONS

To illustrate the practical aspects of RCD, we will review previously published results of applying RCD to the early stages of a 28 nm yield ramp [11]. The design used for this case study is a 28 nm yield learning vehicle consisting of 24 logically identical 750K gate cores. Layout-aware diagnosis and RCD was performed on all cores for four lots manufactured on a 28 nm bulk process. Figure 9 summarizes the results. For Lot1, RCD is estimating that 46% of the defects in the population of failing devices have a root cause of short type defects at metal6. The RCD results from Lot1 and Lot2 show a 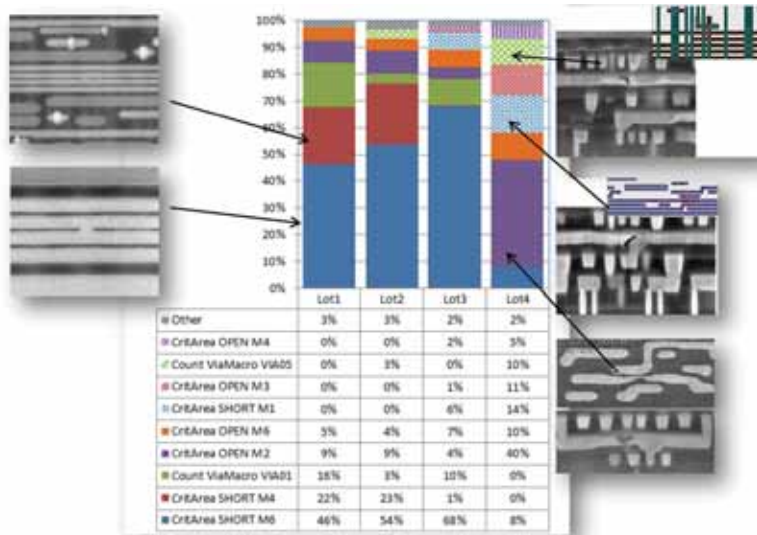similar set of yield detractors, which is consistent with the fact that these two lots saw similar process conditions. These results further suggest that the yield loss for these lots is dominated by metal4 and metal6 shorts. PFA from Lot1 and Lot2 confirms this result. This systematic defect situation arises between the inner pair of four minimum spaced metal lines when surrounded by wide metal. This specific geometry causes the inner pair of metal lines to become closer to one another and increase its susceptibility to small particle defects. Improving the wafer clean process successfully eliminated the metal4 shorts, which is accurately represented in the RCD results of Lot3 and Lot4. A change to the dielectric material used for the interconnect layers was implemented in the processing of Lot4 to produce smaller metal CDs, which significantly reduced the metal6 shorts. However, this process change had an adverse effect on the lower metal level interconnect open yields. RCD results again accurately reflected these changes with a significant decrease in metal6 shorts as well as the emergence of metal2 opens as the dominant yield detractor, and revealed that this defect mechanism was sensitive to specific layout geometries.

Figure 9: RCD results from 28nm yield ramp.

	Lot1	Lot2	Lot3	Lot4
▦ Other	3%	3%	2%	2%
▣ CritArea OPEN M4	0%	0%	2%	5%
◪ Count ViaMacro VIA05	0%	3%	0%	10%
▣ CritArea OPEN M3	0%	0%	1%	11%
▨ CritArea SHORT M1	0%	0%	6%	14%
▣ CritArea OPEN M6	5%	4%	7%	10%
▣ CritArea OPEN M2	9%	9%	4%	40%
▨ Count ViaMacro VIA01	18%	3%	10%	0%
▣ CritArea SHORT M4	22%	23%	1%	0%
▣ CritArea SHORT M6	46%	54%	68%	8%

Additional case studies are published in [12]. In one example, the root cause of static leakage on a 20 nm test chip was found by comparing RCD on two populations with low and high static leakage. In a second example, two versions of the same design were produced on the same wafers with different yields. RCD revealed that the low-yielding design had one additional fail mechanism not found in the high-yielding design. After this was confirmed in FA, a process fix was quickly applied.

RCD APPLICATIONS

From a flow and usage perspective, RCD is different than other diagnosis improvements in the sense that it relies on statistical enhancement of a set of diagnosis results in order to improve the resolution of the individual reports. The number of reports required to generate meaningful results depends on the yield scenario. As a general rule of thumb, for a yield excursion, which typically has one dominant root cause, 100-200 diagnosis reports (100-200 failing die) is required. In a relative mature yield situation with lots of small contributors to yield loss, 1,000-2,000 diagnosis reports are required.

However, RCD does not require any additional data beyond what is required for layout-aware diagnosis. This means that RCD fits well into existing diagnosis flows. Many fabless semiconductor companies enable their foundries to address yield issues by performing diagnosis on low-yielding wafers and providing the diagnosis results to the foundry. The foundry will then use the diagnosis results along with other data to analyze the problem and perform FA on select die. These diagnosis reports are often encoded, which means that all design information such as instance and net names are removed from the report. The foundry (the user of the reports) uses the physical locations of the suspects for the investigation and FA. RCD is fully compatible with this flow. By adding the RCD analysis step and enriching the diagnosis report with the RCD probability score, as shown in Figure 10, the fabless company can provide higher resolution results to the foundry and enable the foundry to resolve yield issues faster without any changes to the analysis process on the foundry side, and without providing any sensitive design information.
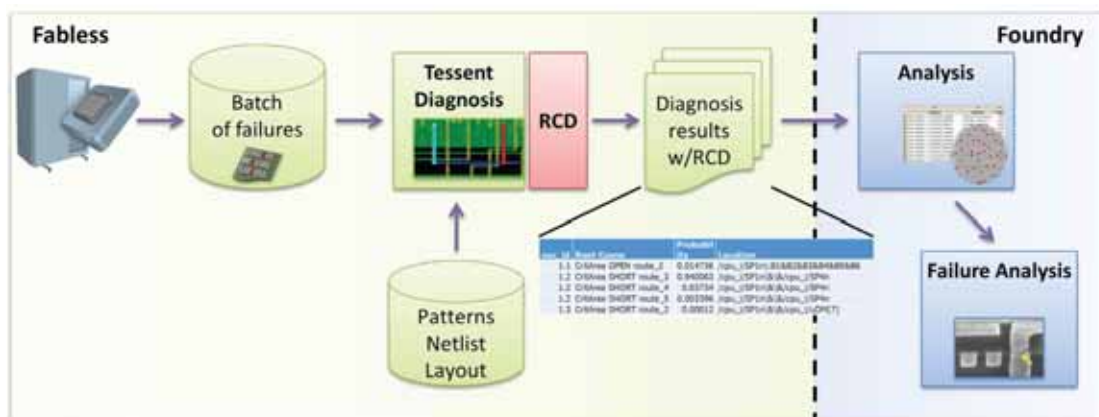

Figure 10: Common diagnosis flow modified to add RCD analysis to enrich the diagnosis results.

With the ability to identify root cause of yield loss from fail data alone, RCD is a very cost effective way of establishing a clear picture of the defect distribution before any FA is done. This is something that in the past has been virtually impossible for fabless companies, with little access to manufacturing data, to do.

RCD also provides a rich data set for yield monitoring. RCD simplifies and reduces the cost of comparing failure mechanisms across multiple designs, IPs, and manufacturing processes. RCD results can easily be added to existing yield monitoring flows and systems.

CONCLUSION

Diagnosis-driven yield analysis with RCD is a quick and cost effective way to determine the underlying root causes represented in a population of failing devices from test data alone. RCD enables the concept of "virtual FA": determining the defect distribution for a population of failing devices before any failure analysis is performed. RCD provides a dramatic reduction in FA cycle time by increasing FA relevance and success rate. To

learn more about how the RCD technology works, see [11]. For additional case studies and applications of RCD, see [13].

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