Measurement Ratio Testing for Improved Quality and Outlier Detection

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Abstract

Measurement Ratio tests of analog test values are used to improve product quality using existing ATE test data. The use of measurement ratio tests is shown to have no impact on overall lot test time, while improving product quality through the detection of fabrication and test outliers. The definition of a data driven method to select test pairs for Measurement Ratio testing based on production test data improves fabrication outlier elimination in production.

1. Introduction

Statistical test methods, such as the Part Average Testing (PAT) standard developed by the Automotive Electronics Council (AEC), have repeatedly been shown to improve product quality by detecting and removing outliers from samples of production material [1,2]. Industry data is quite widely available on the benefits of outlier reduction in reducing infant mortality and improving IC quality [3,4,5,15]. Measurement Ratio testing is a form of statistical based testing that uses existing ATE test results to detect and fail outlier ICs.

In this paper, results from several RF and Analog ICs that are used in cellular telephone applications will be discussed. The use of ratio tests as part of the standard production ATE test flow on these products is used to illustrate the quality and cost benefit of Measurement Ratio (MR) testing. The MR test technique has been applied with success on production RF, Analog-M/S, and Digital ICs.

2. The scope of the problem

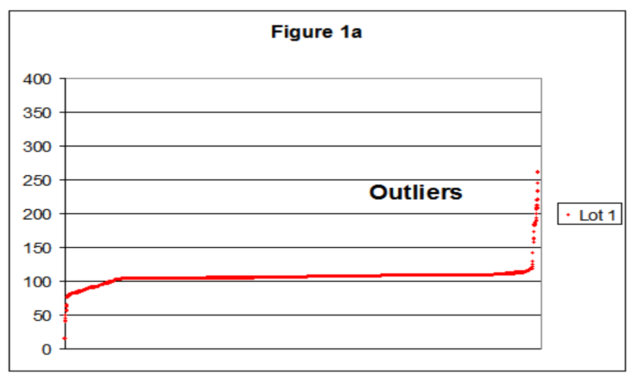
2.1 Production Outliers

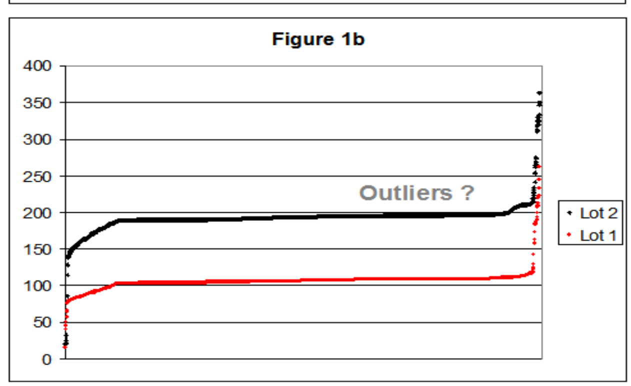
Whenever test data on any large sample of parts is examined, production test outliers will be found, and there are a variety of methods to detect and control these outlier products [1,3,6,7,8,9]. MR testing is unique among these methods because it uses data from different tests to expand outlier signatures into two-dimensions, giving better visibility and control.

As has been described elsewhere [6], traditional pass/fail test limits are too wide to detect many production outliers, because they can not be adjusted to accommodate lot-to-lot and part-to-part variation. As a result, these pass/fail test limits (or datasheet limits) end up being set too wide to be able to detect many production outliers.

Measurement Ratio testing is particularly insensitive to lot-to-lot and part-to-part variation since the test data being examined is only for a single part at a time. MR testing is very sensitive to intra-die processing variations, but if these variations are extreme enough, the die should properly be classified as an outlier.

Figure 1a shows a typical example of a large data set of values for a single test parameter (static current), and there are obvious outliers in this data set. However data sheet test limits may not detect these outliers because (as shown in figure 1b), the data sheet limits have to be set wide enough so that normal lot-to-lot processing variations do not cause excessive yield loss. If the test limits were adjusted to detect the Lot-1 outliers in figure 1a, then many of the parts from Lot-2 in figure 1b would be failures.





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Statistical techniques, such as PAT, were developed in order to isolate and fail outliers such as those in figures 1a and 1b from production lots. Using a dynamic PAT methodology, certain parametric values, such as supply current, would be post-processed at the conclusion of a wafer test to reject any die that exceed the lot-based production control limits.

In the specific case of the two wafers in figure 1b, the application of dynamic PAT testing would be a very effective technique for outlier control. However dynamic PAT analysis can be expensive as it must be run at the conclusion of a lot, after all of the test data for the lot is available. This requires an additional processing step for data manipulation, as well as off-line adjustment of wafer maps to eliminate the PAT reject die. Therefore there is a significant investment in time and cost for good units (Bin1) that end up being reclassified and failed as PAT outlier rejects. A technique that can identify these outlier parts during production would be much more cost efficient.

Measurement Ratio (MR) is proposed as a test technique that can be as effective as dynamic PAT in eliminating outliers, but since it performs this function in-line as each part is being tested, it does not require off-line data processing, and by eliminating reject die earlier it has no net impact on overall lot test time.

Measurement Ratio testing can be performed at both wafer and package test, while PAT testing can be difficult (or impossible) to perform at the packaged part level.

2.1.1 Definition of Terms

Moving, or Adaptive, test limits are general descriptions for a production test philosophy that reacts and adapts to test information to change the testing conditions experienced by production ICs. Typically these changes in testing result in a modification of existing test limits to adjust for changes that are being seen in production. In other applications, additional tests may be added (or tests deleted) to provide different testing when lot yield information indicates that some material may be 'suspect' [10], or at risk of containing defects. Neighborhood yield data [9,12], the feed-forward concept [13], and intra-die measurements can all be sources of the information used to modify, adapt, or change the testing of an IC in production.

Measurement Ratio is a specific kind of adaptive or moving test limit, in which the relationship between two test measurement values is further processed to extract more information about the quality and/or perceived reliability of an IC being tested.

Measurement Ratio testing is different from other types of moving or adaptive test, because the MR test itself is a unique test that neither moves tests, nor adapts the limits of the existing tests. The MR test is included in the standard production flow for all ICs that are being tested, and the limits of the MR test are determined by a predefined relationship between two test values.

In the most general case, two series of data can be related to each other using the simple slope formula $Y = mX + b$, and how well the two series fit the equation is the degree of correlation between the two data sets. In reality, there will be divergences from the ideal line, and the measure of correlation indicates how closely the two sets of data actually match the approximation.

In a simplest case, where the slope (m) is unity, and the offset (b) is zero, then the two sets of data are indistinguishable. Testing of 2-channel specifications such as gain matching in a stereo component utilize this simplification, and define gain matching as being the absolute difference between the X and the Y values (left and right channel). In this type of testing, the UL and LL of the test can be defined as $LL < (X-Y) < UL$.

The concept of MR testing is that it allows for a similar comparison of data sets when the match of the slopes is not unity ($m \neq 1$) and when the offset is non zero ($b \neq 0$).

In the general case of MR testing, the UL and LL of the new test are defined by two different equations with different slopes and different offsets :
$UL = m1*X + b1$ and $LL = m2*X + b2$

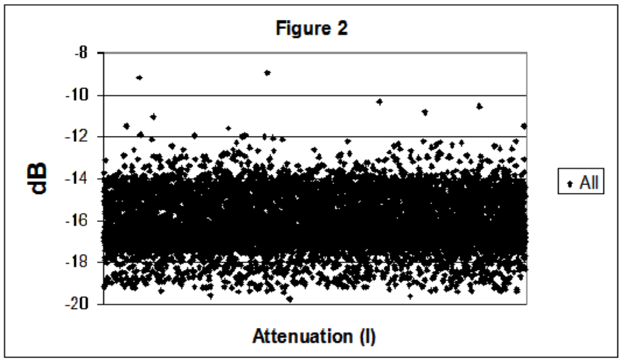
The challenge is to identify two tests that have a relationship that can be exploited for MR testing, and then to determine the m1, m2, b1, and b2 values. Since the X value will be different for every die tested, the Y (or UL and LL) for that die in the MR test will also change for every die tested.

2.2 Test Data Case

As an example of how MR is used in production, for a production package test run of approx 9K devices the attenuation factors on the "I" and "Q" channel outputs on an RF IC were collected. The measured values of the "I" channel were then plotted using two different rules :

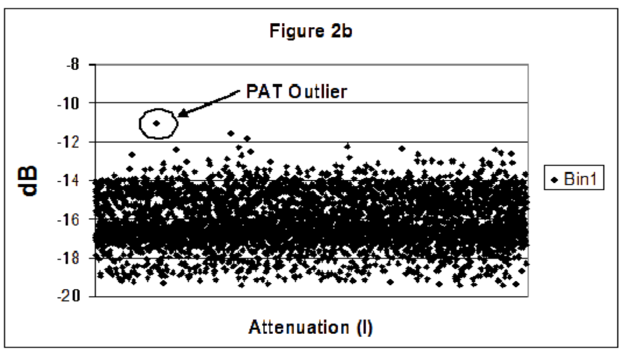
1) Plot the data on all the parts that pass the attenuation test
2) Plot the data only on Bin1 parts

Figure 2 shows the distribution of "I" channel attenuation values for all of the devices that passed this test, with test limits of -8 dB and -20 dB.



Between -12 dB and -8 dB there appear to be a small number of outliers, but very few of these devices will continue to pass all tests and end up as Bin1 parts.

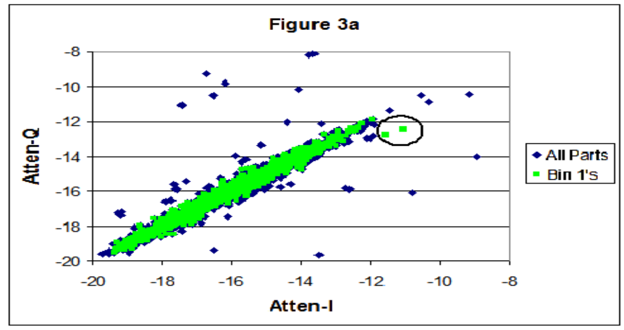
Figure 2b examines the same group of parts, but now only the final Bin1 devices are plotted.



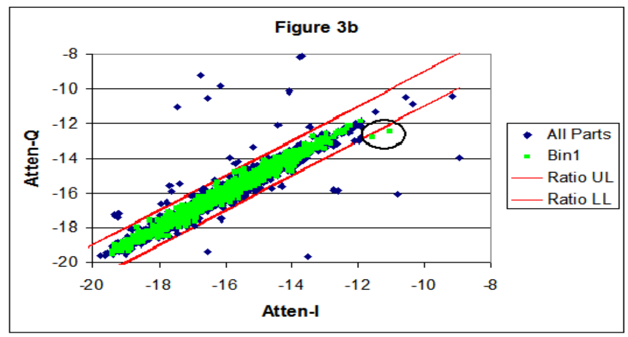
In the data presented in Figure 2b, there is one outlier die at -11.1 dB in the Bin1 population that failed PAT. This is a reject rate of 1/8467, or an outlier failure rate of 0.01%

When the test data for the "Q" channel on the same packages is plotted, a similar chart is obtained, but there are no outliers, and no rejects from PAT.

However, when test values for the "I" and "Q" channels are plotted against each other on the X and Y axis, there is an obvious test signature that can be used to identify and fail outliers, as shown in Figure 3a.



Most of the Bin1 ICs lie in a tight distribution where the "I" and "Q" attenuation factors are similar. When MR tests limits are applied, the results in figure 3b show that the MR production test is able to fail the PAT reject IC, as well as a nearby neighbor, and it predicts 45 future failing ICs (0.5% of lot), by using the attenuation test data.



The application of the MR technique to a set of parameters (like I and Q channel attenuation) that are expected to be correlated is routinely performed in production on many types of analog products. A typical example would be a requirement for gain matching or phase matching in stereo components, or as in this case, on the I and Q outputs of a communications IC.

Where the MR technique gains it's novelty and true benefit is in the establishment and correlation of test results from significant pairs of tests; tests that actually detect production outliers, even if they might not have been expected to have a close relationship.

2.3 Data reduction and analysis

The initial difficulty in implementing MR tests in production is in the amount of data that must be analyzed, and the large number of potentially correlating tests that need to be examined.

If a typical analog IC has 150 test values that are measured in production, then there are 150x150, or 22,500 possible test pair correlations to examine. With a typical production sample of 10K Bin1 parts being examined to determine correlation for each test, the computational requirements can quickly become extreme. Note that for the correlation to be meaningful, the correlations must be run only on Bin1 parts. If the MR test is going to be effective, it should detect reject parts that are outliers. If rejected parts are included in the correlation analysis, their test values may be outliers, and that can skew the correlation results.

The data analysis task can be reduced by just over 50% by the use of two simplifications in the data set. The first simplification that can be made is that no test can be correlated to itself. And the second simplification is that the correlation of test “A” to test “B” will be the same as test “B” to test “A”.

For a test program of 150 tests, the full set size would be 150x150 = 22,500 potential test pairs. Using the first two simplifications reduces the set down to 11,175 test pairs. But this is still an unworkable number of candidate pairs for MR test selection. A method for the selection of a smaller number of possible MR test pairs is needed in order to implement the MR method.

The first step in this simplification process is to identify from the Bin1 correlation data those tests that are the most (and least) well correlated to other tests within the Bin1 population. In the example of the production test containing 150 tests and 11,175 possible test pairs, with ~10K Bin1 devices to be analyzed, it required an overnight run on a Sun-Blade100 to extract and record all 11,175 test pair correlation values. Other sets of production data that were analyzed required similar amounts of CPU time, making this step time consuming, but not unrealistic as a one-time activity for each IC design in production.

Once extracted, all correlation values are converted to positive numbers, as a correlation of “-1” is as valid as “+1” when sorting correlation coefficients. After the correlation table is converted to positive correlations, the entire table is then sorted by descending correlation values, and all the correlation test pair values below the absolute midpoint (0.5 on a 0.0 to 1.0 scale) are eliminated.

This greatly reduces the size of the data set of test pairs for analysis (reductions of over 95% are typical), and preserves only the tests with the highest relative correlation values for further processing.

The first 8 entries of a reduced data set, reduced to 503 test pairs out of a possible set 25,921 pairs, for a sample of 20K Bin1 parts, is presented in Table 1.

Table 1: Maximum test correlations

Test	Name	Test	Name	Corr
156	Tx850_freq	157	TxPCS_freq	1.00
34	VLDO2_2.9v	37	VLDO2_5.5v	1.00
226	DCS_IGR	227	DCS_QGR	1.00
224	GSM900_IGR	225	GSM900_QGR	1.00
222	GSM850_IGR	223	GSM850_QGR	1.00
194	GSM900_Igain	195	GSM900_Qgain	1.00
228	PCS_IGR	229	PCS_QGR	1.00
200	PCS_IGain	201	PCS_Qgain	1.00

Caution must be used when considering these correlation values, because this is the correlation only for Bin1 parts. It is likely, and probable, that for a full production set these tests will not be this well correlated. If (however) a full set of production test data with Bin1 and reject parts still identify a test pair as having perfect correlation, then it is probable that the second test is redundant, and it can be eliminated from the production test list.

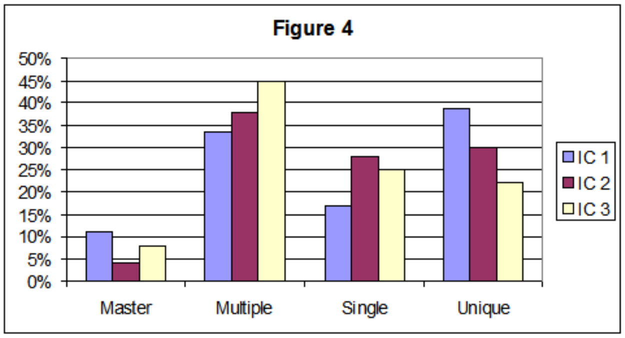
The list of correlating tests is then re-sorted, and for each test in the list, an entry is added to the table indicating how many times that test shows up as being correlated to a later test. A small sample of this type of sorted data for the same product, with 161 production tests, is provided in Table 2.

Table 2: Maximum correlation hits

Test #	Name	Hits/161
194	GSM900_Igain	16
195	GSM900_Qgain	15
38	VLDO3_5.5v	14
182	GSM850_Igain	14
14	Itotal_Wait	13
35	VLDO3_2.9v	13
188	GSM850_Qgain	13
234	IP_1dB_DCS	12
15	Itotal_Alert	11
17	Itotal_Rx900	11
34	VLDO2_2.9v	11
18	Itotal_Rx850	10
19	Itotal_Rx_DCS	10
235	QP_1dB_DCS	10

When the list of tests with correlation hits is completed, the list can be broken down into 4 categories of tests to continue the process of MR test pair selection.

The diagram in figure 4 illustrates the breakdown of all tests on three IC products into one of the 4 categories of “Master”, “Multiple”, “Single”, and “Unique”.



The categories of “Master”, “Multiple”, “Single”, and “Unique are explained below.

2.3.1 Unique tests

A large number of production tests will have no entry in the maximum correlation “hit” list, indicating that they lack a strong correlation (> 0.5) to any other test. This means that they are unique tests. The unique tests are of special interest to product and test engineers, because if these tests have any production failures, they are very likely to be IC failures that no other tests can find. This reinforces results that have previously been published, discussing how the best overall test strategy for any product relies on orthogonal test techniques, where using many different ways of testing for defects is a far more effective test method than using any one method exhaustively [14]. But the unique tests are not useful for MR testing, and they can be dropped from further consideration.

2.3.2 Single correlation tests

A second group of tests show a correlation to only one other test in the data set. These are called single pair tests, and they can be dropped from further consideration since the potential number of outliers that they are sensitive to is rather small. But a thorough engineering and data analysis of the second test in these single test pairings may result in the uncovering of a test that can be eliminated from production without a reduction in quality.

2.3.3 Master correlation tests

At the other extreme from the unique tests, as shown in Table 2, there will be a relatively small number of tests that will show correlation to a large number of other tests. In some products, as many as 15% of all the tests of the IC can be correlated back to a single test. These super-tests, that show strong correlation to 10 or more other tests, are called the master tests. They are the most useful tests to pursue for MR analysis, and most often they are supply, current, power, or gain measurements.

Logically this makes sense, as defects within the IC that can be observed on the supply lines, or as a loss of power and/or gain, are likely to effect many different sections of an IC, or to have quality and reliability implications. An excellent example of this is a published comparison of IDD (Istandby) and frequency (Fmax) on a microprocessor. When the outliers were compared to the other Bin1 parts, the outliers (MR test rejects) were found to have a 7.5x increase in early life failure rate [15].

2.3.4 Multiple correlation tests (Slave tests)

Often the largest category is for tests that have multiple correlations, to any number from 2-9 of other tests. Typically these tests are closely linked to the master tests, and when an MR test pair is implemented in production, it is the tests in this group that are most often paired with the master test as a Master/Slave pair. In order to identify the best candidate tests in this group for use in an MR test pair, data on test variance and/or PAT outliers for the slave tests is required. Most yield analysis tools can provide statistical data such as Standard Deviation, Variance, and Cp or Cpk data on production test data. The more variance (or Std Dev), lower repeatability (Cp), or more production test outliers (PAT) that these slave tests have make them stronger candidates for an MR test pairing. Because Cp and Cpk data are commonly available and used test metrics in production, ascending Cp/Cpk data is used to sort the slave test list, to see which ones are the most likely to be useful as the slaves in an MR test pair. A sample of this data for the slave tests with Cpk’s below 2.0 is in Table 3.

Table 3: Cpk sorting of Slave tests

Test #	Name	Hits/161	Cpk
201	PCS_Qgain	7	1.430
24	Itotal_Tx_PCS	2	1.460
200	PCS_Igain	8	1.520
59	2.985GHz_fcal	4	1.530
220	I_IP3_PCS	7	1.530
232	IP_1dB_900	4	1.530
233	QP_1dB_900	3	1.530
221	Q_IP3_PCS	4	1.560
237	QP_1dB_PCS	9	1.560
23	Itotal_Tx_DCS	3	1.570
211	Q_IP3_850	4	1.590
60	3.000GHz_fcal	4	1.670
63	2.751GHz_fcal	2	1.690
175	Q_res_850	7	1.700

By concentrating the selection of MR tests to be used in production on the master tests, and pairing the master test with a slave test that has a history of high variance (low Cpk) in measured test values, the maximum benefit and efficiency for the MR test technique will be achieved.

2.4 MR test pair selections

Working from the list of master tests (Table 2), and from the list of slave tests (Table 3) with Cpk > 2.0, the next step is to find Master/Slave pairs within these 2 lists that have correlations of greater than 0.5. The results (for this IC) were that master tests 14-15-17-18-19 should/could be paired with slave tests 23 or 24, and that masters 182-188-194-195 should/could be paired with slave tests 200-201-220-221-232-233. Adjacent tests in these lists are also prime candidates for MR pairings, so test pairs 14-15, 17-18, 18-19, 23-24, 194-195, 200-201, 220-221, and 232-233 need to be considered.

This gives 42 possible test pairs that could be plotted and examined as MR test candidates. Starting from a matrix of 161x161 tests (25,921 potential pairs), the reduced set of only 42 candidate test pairs is now a manageable number

Because of the degree to which master tests correlate to so many other tests, there is no need to duplicate MR test set pairs using the same slave tests twice. Therefore the set of 42 tests can be further decreased, leaving only 16 MR test pairs for detailed review and consideration:

14 :: 23, 15 :: 24, 14 :: 15,
17 :: 18, 18 :: 19, 23 :: 24
182 :: 200, 182 :: 201, 188 :: 220, 188 :: 221
194 :: 232, 195 :: 233, 194 :: 195
200 :: 201, 220 :: 221, 232 :: 233

Plots of the first 6 of these possible MR test pairs are included in Appendix "A", as examples of how a small subset of tests can be easily plotted and visually examined for valid MR test candidates. For the first 6 test pairs, all 6 are capable of detecting some early-failure ICs, and 4 of the 6 test pairs also detect some Bin1 outlier parts. Out of these 6 pairs, test pair 14::23 detects the most Bin1 outliers in the population (6/19409 = 0.03%), as well as a reasonable number of early-failure ICs.

From all 16 test pairs listed above, three MR test pairs (14::23, 188::220, 232::233) were found to be significant and valid for future work. Looking at X-Y data plots of all 16 potential test pairs required less than 1 hour of work, and a visual examination of each plot was able to quickly refine the 16 test pairs down to the 3 MR test pairs that would proceed to limit setting and validation.

Previous work on establishing MR test pairs based on multiple-parameter correlation [5] has relied exclusively on knowledge of the IC architecture and test conditions to select appropriate test pairings. That method has a built-in bias in that test pairs are only considered if there is a reason to expect that they will correlate. By using a test data driven process, the design bias is eliminated, and improved outlier detection of random and unpredictable defects is achieved by the use of unexpected test pairings.

Using test data also permits the process to be better automated, with less manual intervention. Design driven information on possible MR test pairs can be valid, and for certain data sheet driven test limits such as I-Q gain/phase matching, design and datasheet information is critically important. But in large volume production, the benefit of this new selection process is that it finds MR test pairs independent of designer bias or expectations.

2.5 Review of the MR pair selection process

Collect data on 10K Bin1 parts from multiple lots
Determine correlation values for all test pairs
    Replace negative values with positive ones
Sort tests by descending correlation values
    Eliminate correlations below 0.5 (mid range)
Sort tests by descending # of correlation hits
    Eliminate Unique and Single tests
Extract Master test list (10 or more correlations > 0.5)
Extract Slave test list (2 to 9 correlations > 0.5)
Append Cpk data to Slave test list, and sort
    Eliminate Slave tests with Cpk's above 2.0
Match Master and Slave test lists for test pairings
Examine proposed test pairs for usefulness

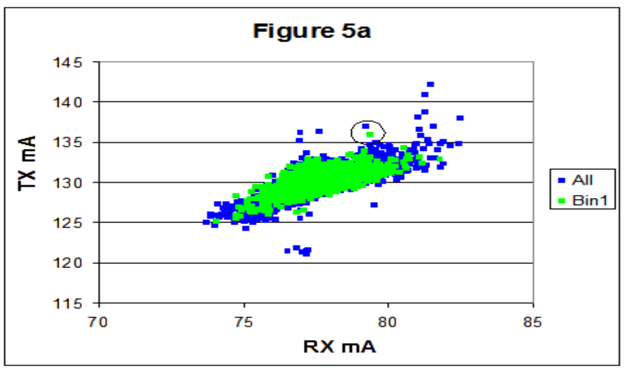
2.6 Setting Ratio limits

The initial data analysis that is used to establish correlation can suffer from an inherent source of error, which is false correlation due to random effects. Although the data set used for the correlation study should include a variety of tested parts from different wafers and wafer lots, false correlations can still occur. To eliminate these errors, a second test data set, containing no overlaps with the original set, needs to be run in order to verify that the tests that are being identified as high correlation events are real.

Assuming that the list of correlated tests has been validated, the next step in the process is to analyze the test data for the correlated pairs to determine where the MR limits should be placed. During the limit setting process, it is important to have all the test data available, as well as the data for only the Bin1 parts. It is by exploiting the differences between the Bin1 parts and the remainder of the population that MR is able to fail defective devices more quickly. And earlier detection and removal from the production test lot will save total production test time.

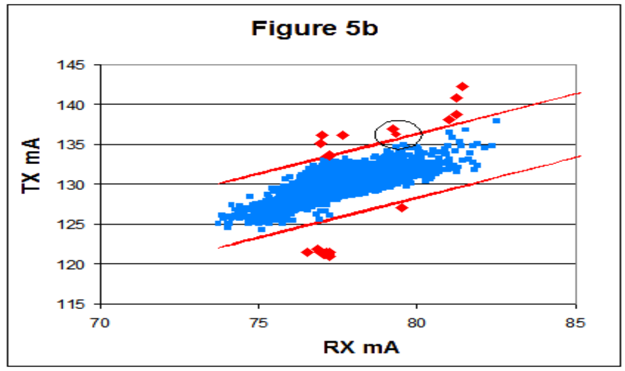
Figure 5a shows two sets of data from another product, combining data on all tested parts with the data from only the Bin1 ICs. The Bin1 parts are tightly grouped, and there are obvious outliers above and below the grouping that can be eliminated from the production lot by the use of an MR limit.

Note that the two tests that are being compared are tests that might not have been anticipated (in advance) as being tests that would show a tight correlation. One test is the supply current for the Rx path at 1.9 GHz, while the other axis is the supply current used by the Tx path at 800 MHz. This demonstrates the benefit of the data driven approach to the MR test pair selection process.



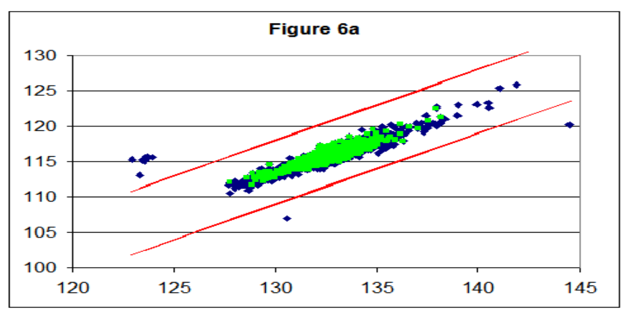
Test limits for this MR pair were established so that the maximum number of defective die would be eliminated, along with the single Bin1 outlier. These limits were set using a manual method, using EXCEL to calculate the slope and offset that best fit the Bin1 data, and then adjusting the slopes and offsets of the upper and lower limits (m1, m2, b1, and b2) to isolate the majority Bin1 population from the outliers and known failure parts.

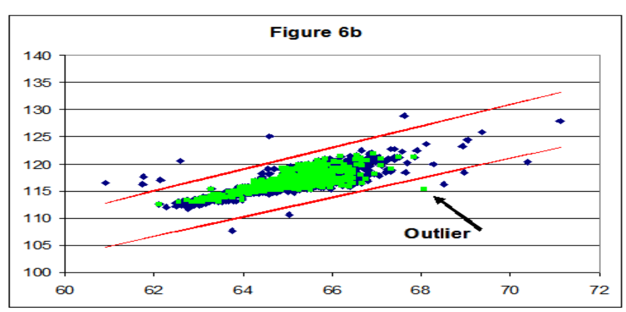
The plot of the production data of Bin1 parts and rejects, with the MR test limits included, is shown in Figure 5b.

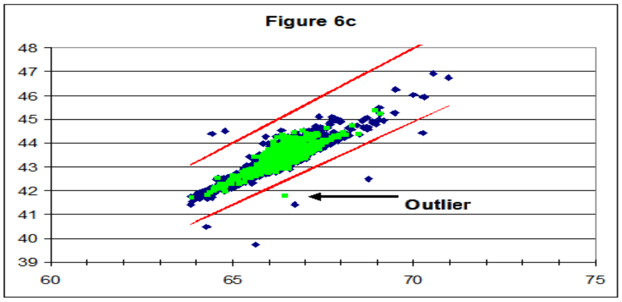


For this test pair, with 5285 ICs recorded, the MR test detected 19 failing ICs, of which 18 were early detection failures (not Bin1), and one IC was a Bin1 part. For the one Bin1 device failed by this MR test, the IC was not detectable as a PAT outlier reject. The overall yield impact of this MR test was 1/5285 (0.02%), while 18 parts were rejected early.

Additional sets of MR test pairs with limits are plotted in figures 6a-b-c, illustrating how the Bin1 population in a well correlated MR test pair can provide a clear signature for the establishment of MR limits. Because this proposed method for MR test pair selection is data driven, and does not rely on any knowledge or assumptions about which tests may correlate, test names and units have been omitted from the X and Y axis in figures 6a-b-c to illustrate that the type of test does not matter in MR test pair selection. What is important is that the selected MR test pairs and limits do detect production outliers, and also result in the early failure of defective ICs.







When tests are properly paired, data outliers that would otherwise be buried inside of single-dimension distributions, like PAT, can be expanded out of the data.

MR test limits are used to eliminate these outliers from the population, and also provide a method for the earlier detection (and failing) of some defective ICs.

2.7 Proving Validity

After initial development of the MR test limits on the training set (or sets) of parts, additional independent sets of production test data are examined against the proposed MR test limits before releasing the new tests into production. This is a critical step in order to verify that the limits have been set properly to accommodate lot-to-lot variation, as well as variations in testers, hardware, and assembly. It is a vital part of the process to ensure that independent sets of test data are used to validate the proposed tests and limits.
Once the new software has been released to production, and approved by the quality monitors, the data and yields of the new tests need to be closely monitored initially. As was noted in other work [5], monitoring of new tests for a few weeks after initial release is critically important, as not all variations (tester, HIB, site, and lots) that are going to be seen in production can ever be captured by any limited number of training sets and validation lots.

3. Test Time Impact

The total test time and cost benefit offered by the MR technique occurs by failing defective ICs earlier in the test flow, and by covering many of the same outlier ICs that would be detected by PAT, without the cost of PAT test data analysis. These savings are offset by the additional test time required to perform the MR test itself, using the test data that has already been measured by the ATE.

The test time required for each MR test was measured on several Teradyne Catalyst ATE platforms, and the time required for each MR test varied from 15 uSec up to 25 uSec. An average figure of 20 uSec is used as an approximation of typical MR test time impact for each MR test added to a Catalyst production program.

The benefit of early failure detection will vary significantly depending upon where in the test flow the MR test (or tests) are added, and where in the test program the early failure ICs would have failed if the MR test had not been included. For simplification, it is assumed that a Bin1 device requires 1 second of test time, that a reject device will (on average) fail after 500 mSec of test time, and that an early failure detection will save 250 mSec of test time.

Our experience with MR tests has shown that (on average) each MR test will result in 0.2% of the ICs in a production lot being failed early, and a Bin1 yield loss of 0.02%. Using a typical production volume of 1,000,000 parts with a 90% test yield, the effect of MR testing on total test time (excluding indexing and setup) is virtually unchanged, with a net reduction of only 42 seconds in test time for 1,000,000 parts and 6 MR tests, as summarized in Table 4.

Table 4: Test Time impact for different #'s of MRs

# of MR	Tested	Pass	Fail	Test Time (sec)
0	1000000	900000	100000	950,000
2	1000000	899600	100400	949,786
4	1000000	899200	100800	949,772
6	1000000	898800	101200	949,958

Since this does not include the cost savings from the elimination of the PAT data analysis, the net benefit from the use of MR tests can be quite significant, if PAT post-processing and data analysis can be eliminated.

4. Issues in Production

The primary issue in production testing using MR limits is that the limit(s) for each part being tested are not absolute because the MR limits for each part will be different from every other part due to the correlation effect. Therefore traditional methods such as 6-sigma for ensuring test robustness and test escape rates, will not work for MR tests. This can be a very difficult problem for Quality Assurance, whose tools and methods may be based on comparing test data against data sheet limits to ensure sufficient guardbanding and test repeatability. When the test limits are themselves variable, the standard tools will not work.

This is particularly noticeable when using third-party data and yield analysis tools, as their systems for data analysis can not accept variable test limits.

Whenever possible, the ratio limit between two tests should be expressed as a specific offset, as it would be in a gain or phase-matching test. By setting up the MR test in that fashion, this will ease the burden on Quality Assurance software which expects to see test results in that format.

5. Conclusion

The application of MR tests to a production product allows for quality and cost improvements to be obtained by the elimination of outliers, some of which may not be detectable by any other test method.

The proposed method for the selection of MR test pairs provides significant additional outlier detection capability, without the need for detailed IC design and/or layout information.

The MR technique does require a significant initial investment in test data collection, in the evaluation of potential test correlation pairs, and in proving the validity of the test in production to the satisfaction of relevant Quality organizations.

Traditional Quality Assurance methods for test guardbanding and repeatability may require modification to normal practices to account for the variability of the MR test limits.

6. Future work

Improvements in the tools and the algorithms used to analyze correlating test pairs, and especially to automatically generate MR test limits without manual intervention, will assist in making this technique easier to implement on a larger number of production parts.

7. Acknowledgements

I would like to thank Susan Hickey and Ming-Chen Lee of Analog Devices for their efforts in writing the test code needed to implement these tests into production, for their critical reviews of this paper, and the feedback they provided on the quality and test time implications.

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9. Appendix A

Plots of candidate MR test pairs