An Effective Data Analysis Approach to Identify Source of Parametric Performance Variations for GaAs Manufacturing

M.W. Tsai, H.T. Li, H.F. Tsai, J.W. Chen, W.H. Wang

WIN Semiconductors Corporation
No.35, Technology 7th Rd, Hwaya Technology Park,
Kuei Shan Hsiang, Tao Yuan Shien, Taiwan 333
e-mail: mwtsai@winfoundry.com Phone: +886-3-3975999 ext.1352

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Abstract

Manufacturing data sets collected in WIN Semiconductors are massive and ever-growing in time because of capacity expansion, new products, new processes, new test items, etc. It is a challenge for engineers to analyze maverick events in such a big and complex database with traditional software tools. In order to save time and cost and reduce risk, we have been developing an in-house computer program to analyze these valuable data by means of systematical and statistical techniques. In this paper, we will present the data and information of two examples using ANOVA (Analysis Of Variance) to help us identify and resolve problems. If the maverick event was caused by a problematic tool in a process step, the program can help us to identify or narrow down the possible source(s) in a short time for further analysis and eventually finding the root cause

INTRODUCTION

In semiconductor manufacturing, a large volume of process control data is generated at every one of the hundreds of processing steps. Engineering data analysis (EDA) for problem solving is very important for process control and quality assurance; however, it is very time and resource consuming for the analysis with such large amount of inline process, PCM, and DC/RF probe data for each processing technology. Therefore, an effective and efficient way of performing EDA is highly desirable for a wafer fab, especially for a foundry such as WIN Semiconductors with a wide range of process technologies to serve its broad customer base. In this paper, an in-house EDA computer program is introduced. It helps us to identify root cause and solve problems more effectively and efficiently while analyzing large amounts of raw processing data. Two maverick events are shown as examples on how an abnormal process tool was quickly identified in each case by our EDA system and the different aspects of its usage will also be shown.

As shown in Fig. 1, each semiconductor process step usually has multiple production tools, each having a slightly different performance. In the initial phase of the EDA program development, one-way ANOVA test [1] was used for analysis. Basically, it tests the mean value equality of all the process tools in a given process step. We use p-value, which is the tail-end probability of the F-statistics distribution, to determine null hypothesis (the process tools are without different mean values) is true or not. The smaller the p-value, the larger the performance variation is for that particular process step. In other words, we employ an ANOVA test to analyze the performance difference among the different tools in a process step, then the same ANOVA test is automatically applied to all process steps with a computer program. These process steps are ranked using statistical criteria to find out potential problematic process step and identify the tool(s) with the largest variations.

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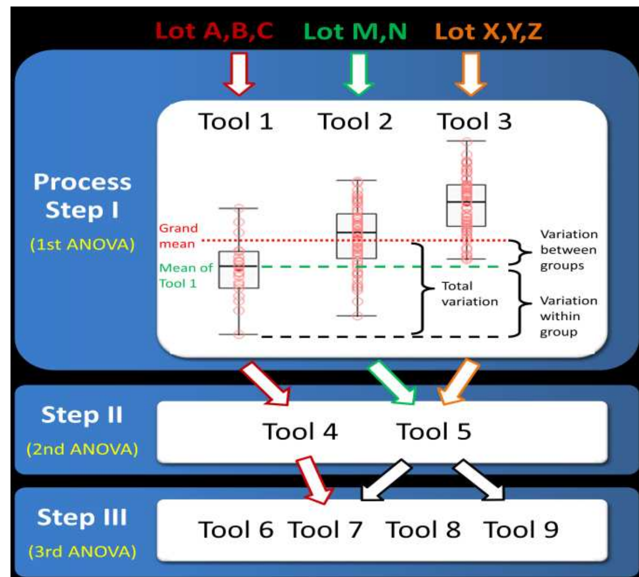


Figure 1: An illustration of 8 random wafer lots routing through different process tools at each process step. Each tool would have different performance as shown in Process Step 1.

A friendly user interface was also designed for user to select options such as: Lot-Mean, Lot-Max, Lot-Min for data sensitivity setting and Process Tool, Recipe, etc. for selecting item to be compared. Besides process tool and process recipe analysis, process route, material batch or any data related to man, machine, material, or method in the

database can also be analyzed by the EDA program. Relevant data of manufacturing process steps are automatically extracted from database based on an initial wafer lot list imported by users and an ANOVA test is performed according to the selected options. Results include a p-value ranking of all the process steps, with the lowest p-value indicting the process step with the largest variation. Further investigation or analysis can then be focused on the lowest p-value ranking steps to identify any problematic tool, recipe or route. The initial wafer lot list for the EDA is usually from the observation of any abnormal variations of in-line process parameters, PCM, wafer probe data or even visual inspection results. Other statistically tests or approaches are also under development to be applied to the dataset for different circumstances. For example, non-parametric Kruskal-Wallis H Test can be used to analyze dataset with non-normal distribution.

ANALYSIS/RESULT

The results of using the EDA program to identify potential problematic process step and tool for a maverick event are shown here. Two examples are provided as following:

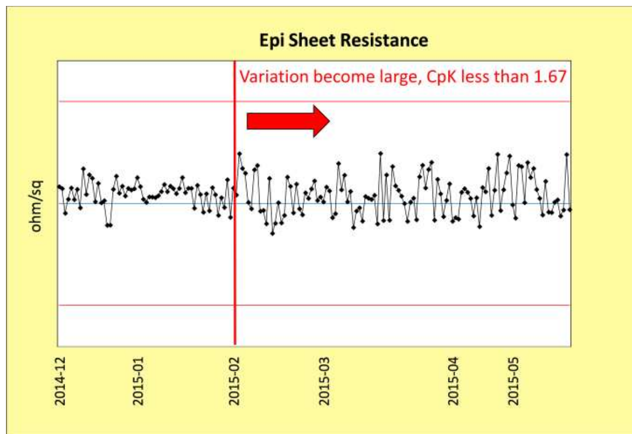
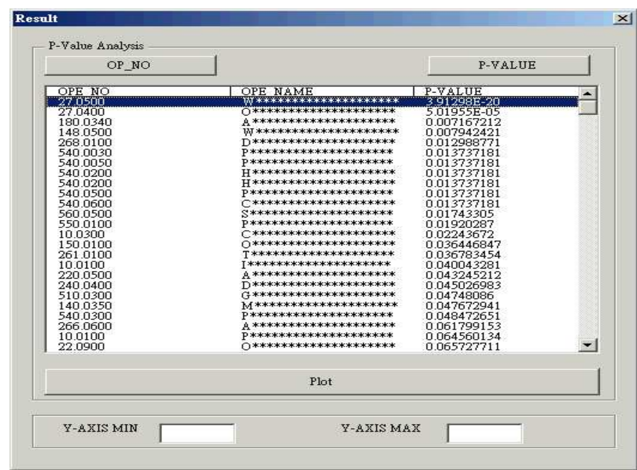


Figure 2: PCM Epi sheet resistance trend chart of a WIN Semiconductor process.

In the first example, PCM epi sheet resistance trend chart was observed to have larger variation and C_{pk} value had fallen below 1.67 (Fig. 2). An analysis was done by one-way ANOVA auto-comparison tool. The analysis was completed within five minutes on 170 wafer lots which were fabricated in about half a year period. The performance differences among all the tools in each process step were analyzed by the ANOVA tool and a total of more than 400 process steps were examined. The process steps were ranked using p-values (Fig. 3) of the ANOVA analysis with the lowest p-value indicating the process step with the largest performance differences among its tools. The process step with the lowest p-value was identified to be a post-metal surface cleaning step. A trend chart was plotted for individual tools for this cleaning step and EQ1 was quickly identified to have different performance (an up-trending mean value) than the rest of the process tools (Fig. 4). The root cause was eventually identified to be a dilution of the cleaning solution by residual D.I. water from wafers of another process technology sharing the same cleaning tool. A higher volume of such wafers had started to go through EQ1 and the dilution began to affect the cleaning effect on the epi surface. After the root cause was found and the appropriate action was taken to resolve the issue, the process variation came back to normal.


Result

P-Value Analysis

OP_NO   P-VALUE

OPE_NO	OPE_NAME	P-VALUE
27.0500	W********************	3.91298E-20
27.0400	O********************	5.01955E-05
180.0340	A********************	0.007167212
148.0500	W********************	0.007942421
268.0100	D********************	0.012988771
540.0030	P********************	0.013737181
540.0050	P********************	0.013737181
540.0200	H********************	0.013737181
540.0200	H********************	0.013737181
540.0500	P********************	0.013737181
540.0600	C********************	0.013737181
560.0500	S********************	0.01743305
550.0100	P********************	0.01920287
10.0300	C********************	0.02243672
150.0100	O********************	0.036446847
261.0100	T********************	0.036783454
10.0100	I********************	0.040043281
220.0500	A********************	0.043245212
240.0400	D********************	0.045026983
510.0300	G********************	0.04748086
140.0350	M********************	0.047672941
540.0300	P********************	0.048472651
266.0600	A********************	0.061799153
10.0100	P********************	0.064560134
22.0900	O********************	0.065727711

Plot

Y-AXIS MIN   Y-AXIS MAX

Figure 3: ANOVA result of the 1st example in sequence of p-values.

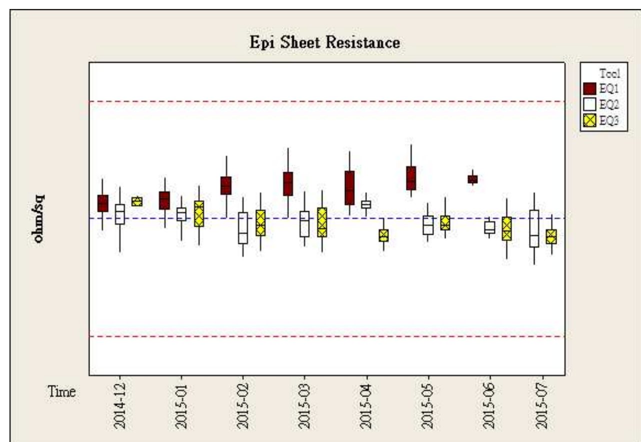


Figure 4: Example trend chart showing different mean value for EQ1.

In the second example, we noticed DC yield variation of a customer product became worse since the middle of Feb. in year 2015 (Fig. 5). ANOVA auto-comparison program was employed again to check the most discriminating process tool possibly led to the yield variation from others in each of the process step. P-value ranking (Fig. 6) for all the process steps indicated tens of step were regarded as with different yield mean value (p-value < 0.05). We started looking into detailed information of these problematic steps

one by one. The ranking at the first place was a visual inspection step which should not correlate to the yield drop and the second place was a TFR (Thin Film Resistor) photo exposure step. A trend chart was plotted for individual tools for this exposure step and EQ5 was immediately found to have lower yield performance than the rest of the tools (Fig. 7). The root cause was finally confirmed that EQ5, which had been transferred from another production line in Feb., had different chuck configuration than other tools and caused different TFR CD uniformity at wafer edge only for some specific mask sets. This phenomenon was not observed when we collected DC yield data for the qualification of different chuck configuration. A proper action was then taken to correct the chuck issue and the DC yield came back to normal.

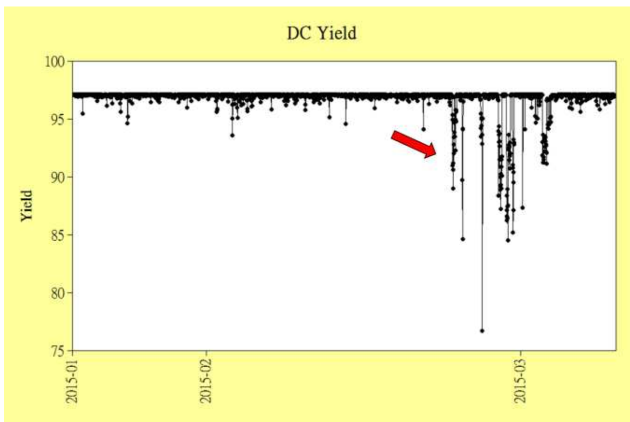
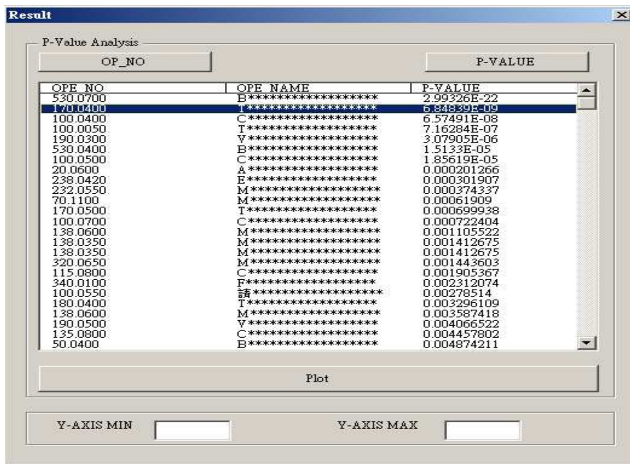


Figure 5: DC yield trend chart of a mask in WIN Semiconductor.


Result

P-Value Analysis

OP_NO | P-VALUE

OPE_NO	OPE_NAME	P-VALUE
530.0700	B******************	2.99326E-22
170.0400	T******************	6.84839E-09
100.0400	C******************	6.57491E-08
100.0050	T******************	7.16284E-07
190.0300	V******************	3.07905E-06
530.0400	B******************	1.5133E-05
100.0500	C******************	1.85619E-05
20.0600	A******************	0.000201266
238.0420	E******************	0.000301907
232.0550	M******************	0.000374337
70.1100	M******************	0.00061909
170.0500	T******************	0.000699938
100.0700	C******************	0.000722404
138.0600	M******************	0.001105522
138.0350	M******************	0.001412675
138.0350	M******************	0.001412675
320.0650	M******************	0.001443603
115.0800	C******************	0.001905367
340.0100	F******************	0.002312074
100.0550	請******************	0.00278514
180.0400	T******************	0.003296109
138.0600	M******************	0.003587418
190.0500	V******************	0.004066522
135.0800	C******************	0.004457802
50.0400	B******************	0.004874211

Plot

Y-AXIS MIN | Y-AXIS MAX

Figure 6: ANOVA result of the 2nd example in sequence of p-values.

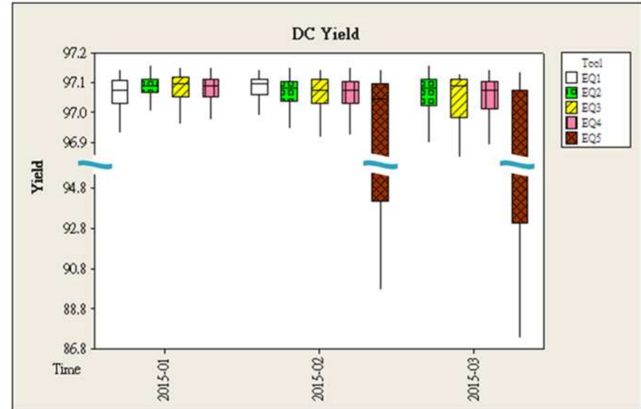


Figure 7: Example trend chart showing different yield mean value for EQ5.

CONCLUSION

A rapid and efficient analysis program has been developed to identify source of parametric performance variation. Engineers can easily verify all the processing steps instead of manually checking a few steps based mainly on their own experience. Sometimes the maverick event is beyond prior experience and the EDA program can be even more helpful in identifying the root cause in such cases and obtaining a new lesson learnt.

In the first example shown above, engineers may not be willing to put resource on analyzing the data since the variation was subtle without the help of the EDA program. However, we were able to identify the problematic tool within only a couple of minutes after the program was called into action. Its ease of use and quick results would facilitate and motivate engineer to identify process variations earlier or reduce more subtle variation from their processes. The quick, efficient and objective analysis process makes problem solving easier, less tedious and less experience-dependent. It would also help engineers not just by saving time but by increasing the successful rate of finding the correct root cause.

It goes without saying that the EDA program has its limitations and the users have to understand such limitations to fully utilize the program. For example, sufficient data must be collected from the different machine tools after the cause of the abnormal process variation has been (inadvertently) introduced into the process before the EDA program can generate a statistically meaningful result for the p-value ranking. Otherwise, the p-value ranking might not be too useful. Furthermore, the selection of the initial lot list and other factors might also affect the p-value ranking results. Therefore, the user must not just investigate the process step with the lowest p-value but might also need to spend more time to investigate the process layers down in the ranking list. We are still optimizing and adding more analytical capability to our EDA program.

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REFERENCES

[1] Wackerly Dennis, William Mendenhall, and Richard Scheaffer. "Mathematical statistics with applications. " Cengage Learning, pp.667-677, 2008.

ACRONYMS

ANOVA: Analysis of variance
CD: Critical dimension
Cpk: Process capability metric
DC: Direct current
EDA: Engineering data analysis
FAB: Fabrication plant
PCM: Process control monitor
RF: Radio frequency
TFR: Thin film resistor