Fab Fingerprint for Proactive Yield Management

YE: Yield Enhancement/Learning

David Gross & Katherine Gramling
SkyWater Technology
David.Gross@skywatertechnology.com,
Katherine.Gramling@skywatertechnology.com

Prasad L. Bachiraju
Onto Innovation
Prasad.Bachiraju@ontoinnovation.com

The following paper presents a case study describing how to improve yield and fab productivity by implementing a frequent pattern database that utilizes Artificial Intelligence based Spatial Pattern Recognition (SPR) and wafer process history. This is important because associating spatial yield issues with process and tools is often performed as a reactive analysis, resulting in increased wafer scrap or die loss that could be prevented. The implementation of fab fingerprint technology proactively generates a pareto of high impacting process steps and tools based on a pattern score, enabling the production team to concentrate more efficiently on yield limiting events.

Keywords: Spatial Pattern Recognition, Pattern Mine, Defect Analysis

Motivation

Upon analyzing yield loss from both defect and wafer probe data, it has become very clear that solving systemic Spatial Pattern challenges in production is the missing link between inline tool control and yield improvement.

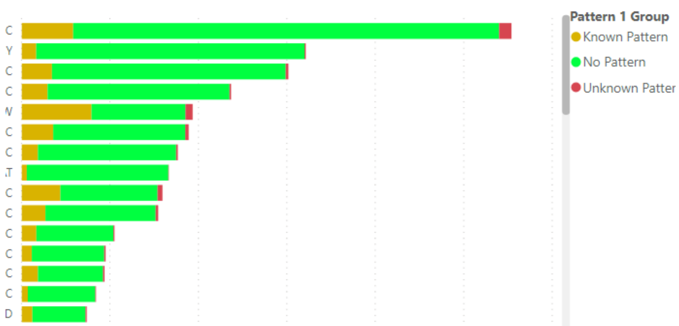

Figure 1: Wafer AOI results showing spatial challenges by product

Approximately 21% of wafer starts are seen to have some form of spatial pattern. Further investigation highlighted that 4% of those wafers exhibit a previously unidentified grouping, or an UNKNOWN Spatial Pattern. This prompted implementation of an inline spatial signature monitoring solution. The semiconductor industry is not new to adopting SPR, however, efficient use of SPR results to quicken determination of root causes and corrective actions is still a challenge. In this paper we discuss the methodology and techniques that were adopted to address the issues described above.

Introduction/Approach

To get a complete picture, we started with three months of production data focusing on Automatic Optical Inspection (AOI) defect and Wafer Probe data (Fig. 2). We then performed the following seven steps with iterations as needed:

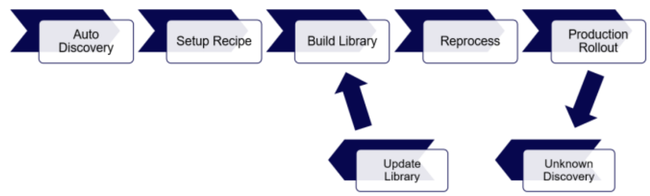

Figure 2: Overview of methodology

Auto Discovery is the process of discovering spatial yield limiting issues from production data. At this step engineers are less involved and the ML-based SPR Engine presents the most common patterns found from the production database. An engineer reviews the system discoveries and recommended pattern samples and adds them to the production pattern library. A recipe is setup to allow the software to process production data by selecting SPR Engine settings and a library of interest. Different combinations of library and recipe settings can be used to improve pattern recognition across multiple products and layers, but for this study, we chose to normalize the recipe. Only one library was used for all production data, simplifying the SPR database. Auto Discovery, Library Building, and Recipe Setup are a one-time task until SPR is rolled into production.

Reprocessing is a step where we select historical production data and run the SPR Engine against it after rolling out the recipe and library into production. By performing this operation, the engineer gets an understanding of past and present spatial challenges in the fab.

The next step is monitoring the production SPR results and understanding what new patterns are happening in production, or if any fine tuning of the recipe is required. As additional patterns are uncovered, results are confirmed by the engineer. Defect images are compared against processing steps and spatial signatures to determine the validity of the positive result. As this process is repeated, the library matures, and false positives dwindle. This procedure is the basis behind learning from the UNKNOWN. Knowledge gained from this practice is incorporated into the Library so both reprocessed and future runtime production data takes advantage of new learning.

As a last step, Dashboard and Reporting templates are built to review the trend of score by time and compare the result with wafer scrap.

Figure 3 below shows a high-level data flow diagram of how SPR Engine works in production. As wafer inspection, metrology, and probe data are fed real time into the Yield system, the SPR Engine detects and classifies wafers with spatial signatures/patterns. Based on an engineer's monitoring criteria, appropriate automatic actions are taken. These include feed forwarding of pattern summary results to internal SPC systems, email alert notifications, and automatic reports.

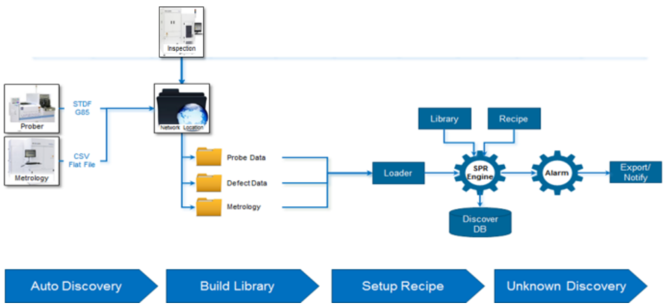

Figure 3: SPR Engine Operational Workflow

Learning from the "UNKNOWN"

One of the key challenges we faced was to learn from "UNKNOWN" patterns. An UNKNOWN pattern is an identified spatial signature that does not match an existing pattern in the production database.

We started by adopting Machine Learning techniques to perform auto-discovery on these UNKNOWN patterns. This auto-discovery process generates a Pattern Pareto report by grouping wafers with similar patterns based of hundreds of feature vectors generated by the SPR Engine. As a result, we end up with top-n high-impacting auto-discovered patterns to help us understand patterns that are new, starting to emerge, or going unnoticed. This process helped us to efficiently maintain a comprehensive Pattern Library that enables proactive response to production issues.

SPR Engine finds UNKNOWN patterns for the two reasons below:

1. When the Library and Recipe are not sufficiently catching known patterns. This is not common and mostly happens in the initial weeks of SPR rollout into production. This could also mean that the Similarity Threshold set for pattern classification may need to be fine-tuned. Pattern robustness is also improved through the inclusion of diverse pattern samples.

2. When there are genuinely new spatial issues happening in production that are not part of the library. The frequency of this type of UNKNOWN patterns also will reduce as the library matures over several months.

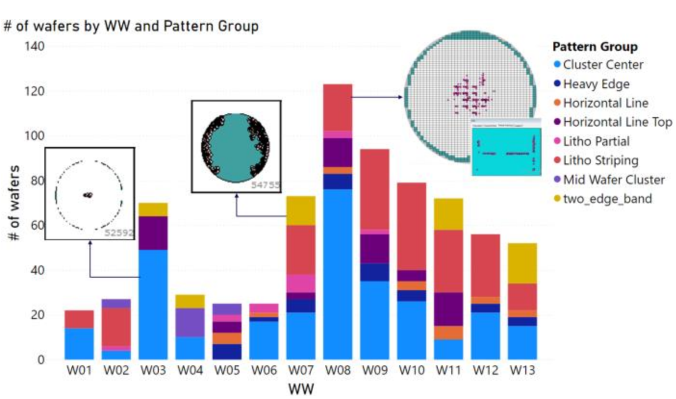

Figure 4: Results of Learning from UNKNOWN Pattern over 3 months

Figure 4 highlights the multitude of patterns that arose from previously unidentified signatures. Three months of data were processed and binned into unique patterns. These were tracked on a weekly basis to show the frequency and impact to production. Three key patterns were discovered: Litho Striping, Two Edge Band and Center Cluster. This analysis shows the potential for hundreds of wafers to be classified and correlated to yield limiting spatial issues.

During this process, we learned that two completely different production challenges may lead to the same macroscopic pattern. For example, Litho Striping could be due to reticle contamination or an Inspection Recipe sensitivity issue. However, performing a drilldown analysis such as Repeater and Event Reports isolated the root cause quickly.

Even if a spatial pattern is linked to multiple physical attributes, the analysis is still value-added. In the case of Litho Striping, highlighting an inspection recipe issue prompts corrective action from the engineering team, thereby reducing false defects and increasing the robustness of the recipe. If the root cause were reticle contamination, maintenance can be performed and product risk is effectively mitigated.

Scratch Improvement

As Scratch patterns are unique and critical to detect accurately, we realized that we needed to go beyond standard scratch detection algorithms provided by SPR Engine. Therefore, we built an additional post processing algorithm dedicated to run image-based scratch detection instead of defect-based detection using dynamic threshold determination (based on density and distribution) to eliminate or reduce false positives. As a result, we were able to separate two scratches that cross over or are close to each other, outlined in Figure 5 below.

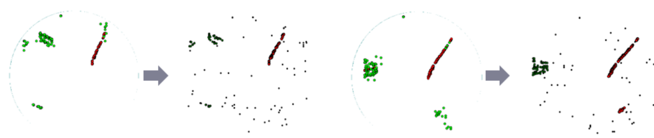

Figure 5: Examples of Scratch Improvement

Proactive Deep Analysis

To avoid repetitive lot holds at multiple steps for wafers with spatial pattern issues, the software was enhanced to track if a wafer pattern is a new or a carryover pattern from previous steps. This helped production to efficiently move along reworked lots and avoid unnecessary Out of Control Action Plans (OCAP) as shown in Figure 6.

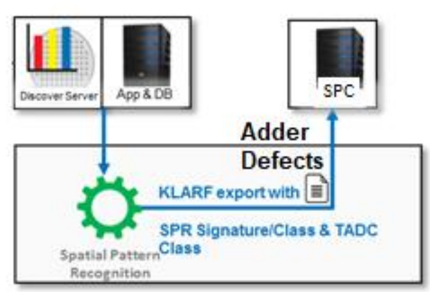

Figure 6: New vs. Carryover Pattern info export to SPC/Fab Host

It must be noted that a yield limiting pattern on a wafer is a sign of a systematic issue due to process or tool marginalities. Recognizing this signal early on is key for a Frequent Pattern Database; it proactively utilizes and associates Automatic Optical Inspection, Metrology, Electrical Test, and wafer probe data with wafer history without any offline analysis.

The SPR System stores pattern statistics such as size, area, number of dies impacted, and wafer scrap equivalence along with pattern feature vectors. The Frequent Pattern Database uses this information to score high impacting patterns, process steps and tools as shown in Figure 7 below:

Rank	Failure Type	Wafer Map	# of Wafers	Failure Rate	Route/Stage : Step	Process Tool
1	Edge Arc		410	0.32	C-MET1ET : CE51B	CELRC01X
2	SP2		350	0.28	C-BCAPCLN : CA085	CAFSI02X
3	Center Core		100	0.10	C-YWDEP2 : CY311	CY310

Figure 7: Automatic high impacting Route Step and Tool/Chamber

Pattern Search is another technique that contributes to proactive analysis and build the Frequent Pattern Database. As shown in Figure 8 below, the SPR Engine can pull wafer probe data that exhibits a similar signature to inline defect patterns. For example, a defect edge band pattern was used as reference to pull top 50 similar wafer probe patterns.

Notice that the Center Large pattern from wafer probe data is a new pattern found during the Learn from UNKNOWN process. The SPR Engine finds and classifies similar yield limiting data regardless of if it has been previously classified. This powerful tool explicitly defines inline to EOL pattern commonalities and can be used to obtain accurate kill ratios.

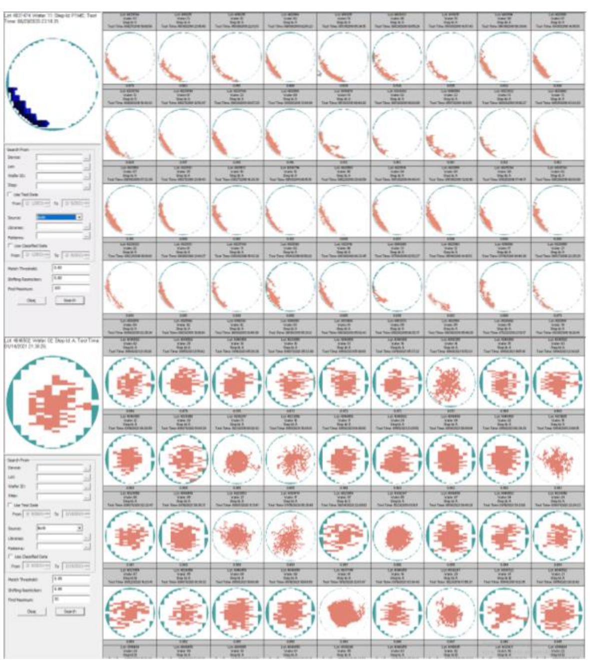

Figure 8: Pattern Search pulls similar patterns across data types for edge band (top) and center heavy (bottom) signatures

Amplify Pattern Signal

To support detecting very hard to find/faint patterns, such as certain type of scratches and wafer bonding related edge patterns, we adopted a technique that will amplify the pattern signal.

Stacked virtual maps were processed using the SPR Engine to detect faint patterns of interest. This approach amplifies the pattern signal and provides a clearer picture of process marginalities. However, this technique is subject to noise and must be used with discretion on known patterns.

Case Study #1:

In the case of a defect excursion, SPR finds all inspected wafers that are impacted by a spatial pattern without the need for manual classification, which can be time consuming and subjective. This enables an expedient picture of event scope & quickens mitigation efforts.

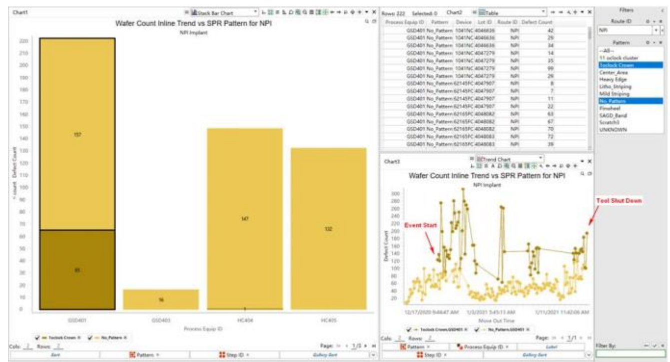

Figure 9: SPR Identifies Root Cause Tool in Particle Excursion

Figure 9 above corresponds to a particle excursion linked to a recurring wafer handler issue. Due to the intermittent nature, the tool was not shut down for several days. Characteristic of this event is a 1 o'clock crown spatial pattern. Integration of this signature into the Frequent Pattern Database quickly highlights the root cause tool and event timeline.

Case Study #2:

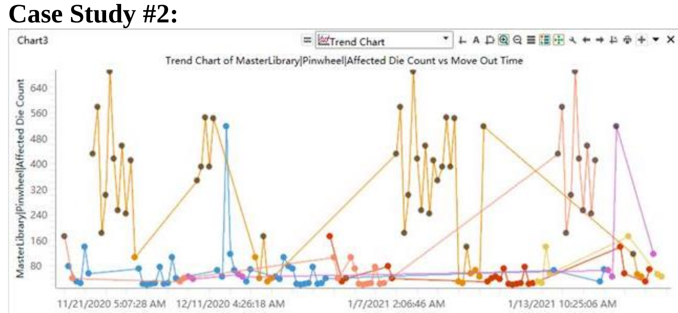

Figure 10: Killer Pattern Excursions by Process Tool & Date

In a second case study, die-killing etch flakes fall upon the wafer in a pinwheel pattern. This known failure mode requires part replacement each time it occurs. Application of real-time alarm monitoring will notify the engineer and maintenance staff of this yield-impacting defect pattern, allowing for quick reaction times and minimal product risk. See Figure 10 above.

Monitoring

Many Dashboards have been rolled out to monitor yield limiting patterns in production. Below is an example of a Dashboard that improves engineering productivity by ~25% by combining Equipment Study with AOI defect images as shown in Figure 11.

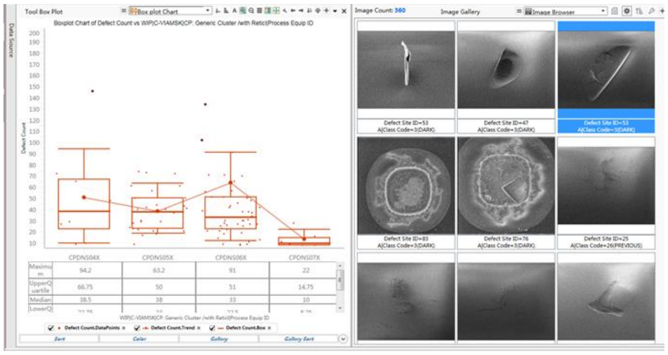

Figure 11: Dashboard using Step & Equipment against defect images

Process Event Report

As a daily pass down report, as seen in Figure 12, the production team is provided with a dashboard highlighting process tools that contribute to yield limiting alarm conditions. While one of the purposes is to improve production efficiency to react faster and recover from yield impacting events, we are exploring another use case to utilize the quality score of tools for job scheduling and smart sampling purposes.

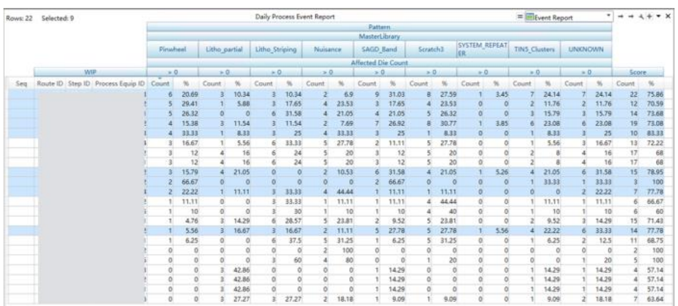

Figure 12: Daily Process Event Report

Analysis Performed

In addition to novel use of SPR, the Discover platform also provides additional analytics which can aid and inform engineering staff for efficient Process Control and Yield Enhancement. These include lot commonality and WIP impact analyses, plus equipment studies and yield mining.

Conclusions & Future Work

Implementation of an Artificial Intelligence based Frequent Pattern Database allows for the expedient association of spatial signatures to yield loss, thereby creating an avenue for proactive process control & yield enhancement. This paper shows the many uses of SPR to shutdown faulty tools, outline excursion scope, and correlate inline signatures to yield-limiting defects.

Further work includes SPR on metrology data, full wafer image-based classification, and an application study to quantify the effectiveness of defect image sampling.

REFERENCES

1. Use of wafer backside inspection and SPR to address systemic tool and process issues https://spie.org/Publications/Proceedings/Paper/10.1117/12.846688?SSO=1

ACKNOWLEDGEMENTS

Authors would like to thank Jeff Zia from Onto Innovations Inc for his contributions towards Reprocessing and Auto Discovery tasks

Authors would like to thank Daniel Alan Arellano Tavara, Staff Manager, from the semiconductor industry & Dr. Alan Fan, Engineer Staff, Seagate for inspiring discussions on Discover Patterns and its application in fabs.