Manufacturing Excellence using Multi-Platform Ellipsometry Thickness Measurement Fleet on Advanced Nodes

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Abstract— **In this paper we will demonstrate a systematic approach to significantly improve and sustain a large fleet of thickness metrology tools being used for several advanced nodes and products including 10/7nm at GLOBALFOUNDRIES Fab8 site. This challenge is compounded due to having multiple platforms of tools in the same fleet (heterogeneous tool matching) – Aleris 8350, Aleris 8510 & LD10 Ellipsometry tools. In order to assess the health of this combined fleet, a set of critical inline parameters were identified and patterned wafers were designated for metrology monitoring purposes. The chosen matching parameters covered a range of thickness values, single layer and multi-layer stacks, and measurements that utilized different tool subsystems. These subsystems include BBSE (Broad-Band Spectroscopic Ellipsometry), UVSE (Ultraviolet Spectroscopic Ellipsometry), and SWE (Single Wavelength Ellipsometry). These critical parameter measurements incorporate our most challenging measurements (down to a total measurement matching budget of 0.2 A) and are a representative subset of the thousands of recipes that we run on these tool sets.**

This methodology provides us with data to help identify the problem tools in our fleet and breaks down the contributions from four key failure modes. This data is rolled up into a weekly summary from which we can schedule work to investigate and improve tool health. Through tracking the improvements in measurement performance from week to week, we are able to demonstrate the effectiveness of this methodology. Additionally we have been able to link these failure modes to specific hardware configurations in order to improve our ability to maintain our fleet.

Keywords—Ellipsometry; Fleet Matching; FMP; Thin Films

I. INTRODUCTION AND MOTIVATION

Ellipsometry based thickness measurements have played a large role in the development and monitoring of transistor technologies for many years. However, as we transition into highly advanced 1X and beyond technology nodes, optical metrology techniques are being pushed to their fundamental limits.

The trend driven by Moore's Law pushes for the number of transistors to increase with each new technology node. Creating more transistors in the same area however, requires that the design dimensions of these transistors decreases and with this, the process control requirements tighten. The previous rule of thumb for a metrology budget of 10% of process tolerance is sometimes no longer valid. These new requirements are driving the need for sub-angstrom measurement repeatability and reproducibility. In addition to smaller structures and thinner films, in our quest to continue Moore's law, the industry has been introducing more complex integration schemes and novel process/materials. Process flows requiring multiple sacrificial layers are causing measurement structures to contain many, often highly correlated films. With each new layer we are also adding more measurement steps to routes. Because of these complex flows, the sheer number of measurements makes maintaining recipe runpaths a burdensome task. Additionally, these measurement structures can contain multiple implants as we try to mimic the films present in the actual device areas. The use of advanced materials such as SiGe, SiP, and HKMG stacks creates the need for composition monitoring (more floating parameters) in addition to thickness measurements. Often times, these advanced process techniques require very short Q-times or are even deposited in a single tool removing the ability to make a measurement after each layer deposition.

All of these factors contribute to the need for more complex metrology solutions. Models with increasing degrees of freedom are often needed to find solutions for multi-layer stacks, composition measurements and advanced materials. However there is also a general trend of trading model robustness for precision gains in order to meet ultra-tight metrology repeatability and matching budgets. In light of all of these challenges, maintaining a large fleet of tools capable of meeting process control needs with shortest mean time to detect (MTTD) and at a low cost of ownership is critical to the success of a foundry. Matching the fleet to these challenging requirements is quickly becoming one of the top challenges in the semiconductor fab. Due to the smaller metrology budget and more sensitive measurements, there is less room for measurement tool hardware mismatches.

II. FLEET MATCHING METHODOLOGY

When assessing the health of a large fleet of measurement tools, this analysis can typically be broken down into two main components, the measurement precision of each individual tool and the matching performance between the various tools that make up the fleet.

Traditionally, Gauge R&R has been the main analysis technique used to quantify the precision of a measurement system. This technique evaluates the amount of expected variation or uncertainty from a measurement based on two components, repeatability and reproducibility. Gauge R&R studies calculate the overall system variance as a sum total of these components. This technique is very powerful at identifying measurement irregularities, but as we apply Gauge R&R to thinner films, and as we expand our tool fleet to include more tools, the gaps in Gauge R&R are revealed. The main problem arises when the measurement delta between two tools is larger than the variance from either of those tools. In this situation, the variance of the population is much greater than that from a single tool. Another major drawback of Gauge R&R is that it lacks information that would help to identify problems. It is simply a pass/fail test. When the number of tools included in a Gauge R&R is large, determining where the largest sources of variability exist can be difficult.

Tool to tool matching is the other main component of measurement fleet management. A large fleet of measurement tools is a dynamic system. Measurement outputs from individual tools are constantly shifting due to the regular tool deterioration like lamp aging and stage navigation drift. Regular maintenance and optical re-alignment can correct for these issues but also can cause shifts in tool output. The easiest solution is to manage runpaths to only use the healthiest tools, but this is not always feasible in capacity limited high volume manufacturing and can have a negative impact on lot cycletime due to variability in the availability.. The other common option is to consider mismatches as fixed or linear deltas and compensating these deltas by applying offsets to the data outputs. This technique typically masks underlying issues with tool health and can be very manually intensive to maintain. When coupled with automated process control, measurements using tool specific offsets can place product at risk if not properly maintained.

Fleet measurement precision (FMP), is an improved gauge study metric aimed at capturing the overall health of a fleet of measurement tools and Tool Matching Precision (TMP) provides a method to diagnose fleet health, by looking at individual tool precision and repeatability as well as site level matching between multiple tools [1]. FMP gives a readout on the overall cumulative health of a fleet as a percentage of the nominal value for a given measurement parameter. Because of this, FMP remains valid for all applications irrespective of their dimensions (such as ultra-thin applications). The FMP value is calculated from individual tool based TMP values, and each TMP is calculated from each tool's precision, offset, slope induced shift offset (SISoffset) and non-linearity. FMP allows us to evaluate a fleet of tools based on a single number to compare against requirements and at the same time gives us the ability to drill down to see which tool(s) are raising the fleet FMP, and which parameter is causing the raised TMP of that tool. An example FMP and TMP readout can be seen in Fig. 1.

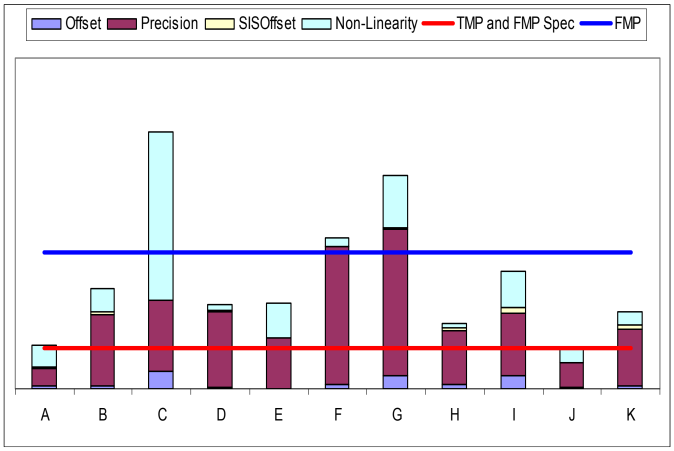


Fig. 1: FMP readout of a fleet compromised of tools A-K. In this example tool C has the highest TMP value, due mainly to a non-linearity in the data as compared to the other tools in the fleet.

A. *Components of FMP*

In FMP analysis we still want to quantify the measurement repeatability and reproducibility. The overall precision of each individual tool, is calculated from the average of the variances of all measurement sites *x*, for a given number of measurement repetitions *n*.

$$s^2 = \frac{\sum_{j=1}^{n}(x_j - \bar{x})^2}{n-1} \tag{1}$$

Calculate the variance for each site x:

$$(s_1^2, s_2^2, s_3^2 \dots s_x^2) \quad (2)$$

Average the variances to get the total Precision for Tool *i*:

$$\sigma_i^2 = \frac{(s_1^2+s_2^2+s_3^2 \dots s_x^2)}{n} \quad (3)$$

When looking at measurement tool matching, we must first define our benchmark (BMS) to which we will compare individual tools. We use the fleet average as our reference. A single golden metrology tool reference is the other common benchmark. However, in our testing we have found that in a metrology fleet, it can be difficult to maintain a single golden tool free of drifting over time or shifting baseline after regular maintenance.

FMP breaks down tool to tool matching and considers three main contributors- Offset, Non-Linearity, and SISoffset. The first contributor, offset, is simply the fixed delta between the mean of each tool and our fleet average.

$$offset_i = \overline{x}_{BMS} - \overline{x}_i \quad (4)$$

Non-Linearity describes the uncertainty associated with the Mandel Net Residual Error about the best fit line between the tool and our fleet average. Randomness in data from a tool set will result in higher non-linearity.

$$\sigma_{nonlinearity,i}^2 = \sigma_{MNRE}^2 - \sigma_i^2 - \sigma_{BMS}^2 \quad (5)$$

Slope induced shift offset or SISoffset is the final matching component of FMP. SISoffset describes the amount of deviation of the slope (β_i) of the line plotted between our Reference (BMS) and Tool *i* from unity.

$$SISoffset_i = \upsilon \times ProcessWindow \times (1 - \beta_i) \quad (6)$$

where υ is the fraction of linewidth variation expected in production for this artifact and $ProcessWindow$ describes the overall range of measurement values expected across a wafer.

Using these four components we can then calculate the 3 sigma TMP measurement uncertainty associated with each tool. Taking the average resultant of all TMP values, we calculate the total FMP of our system.

$$TMP_i = 3\sqrt{\beta_i^2\sigma_i^2 + offset_i^2 + SISoffset_i^2 + \sigma_{nonlinearity,i}^2} \quad (7)$$

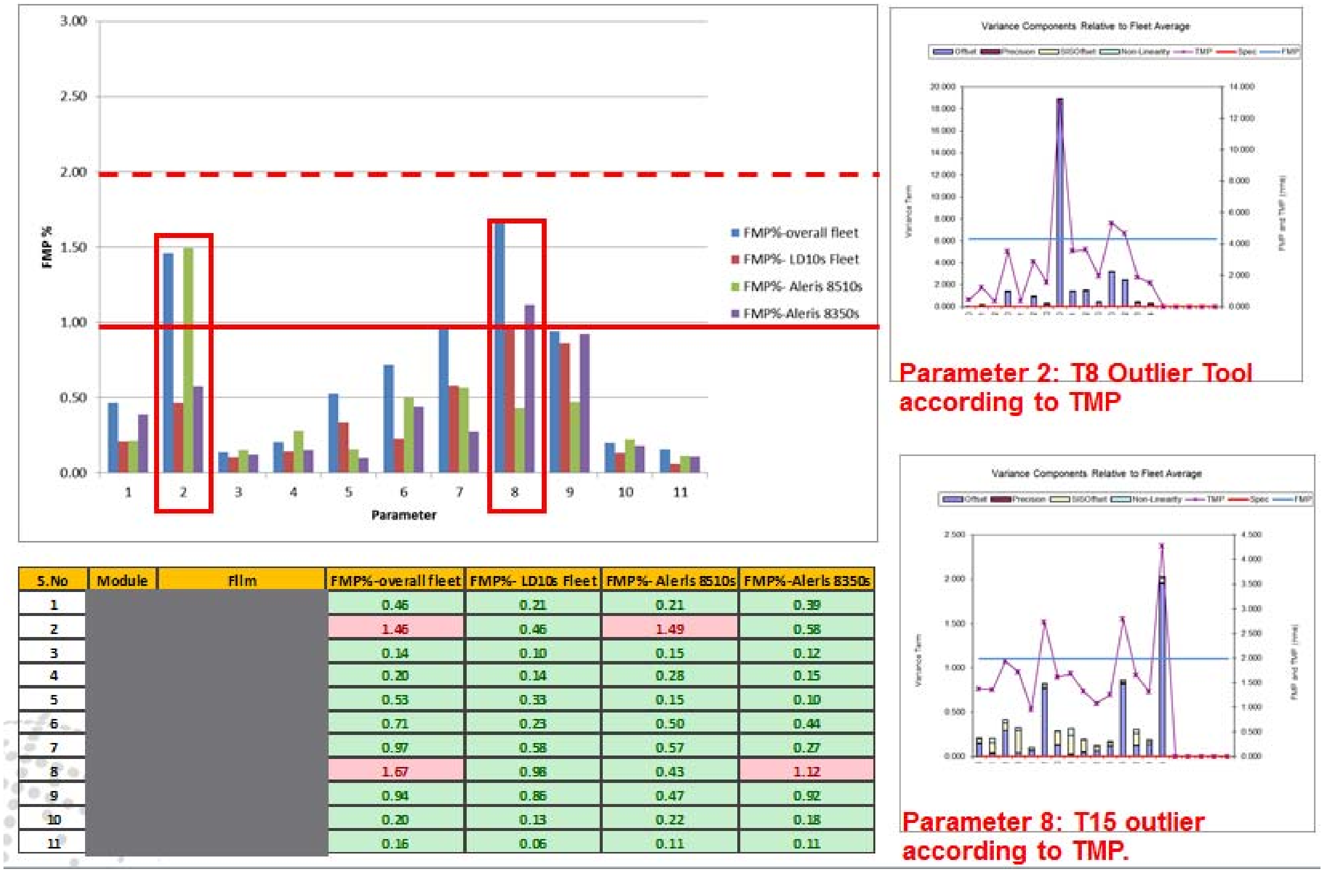
$$FMP = \sqrt{\sum_{i=1}^{N} \frac{TMP_i^2}{N}} \quad (8)$$

B. Using FMP System to Drive Continuous Improvement

In order to maximize the effectiveness of the FMP methodology as a tool to drive improved fleet health, we first identified and acquired wafers for the most challenging applications running on our fleet of ellipsometers. The chosen matching parameters covered a range of thickness values, single layer and multi-layer stacks, and measurements that utilized different on tool subsystems available to us. These critical parameter measurements are a representative subset of the thousands of recipes that we run on these tool sets. Using FMP on this set of wafers provides a comprehensive view of matching and tool capability.

For our initial testing, we measured this set of wafers across a subset of tools at various frequencies, with different numbers of measurement sites and with varying numbers of repeats. Based on this testing we decided that by running them 3x times across all tools using a five site cross pattern on a weekly basis, gives us a strong data set of FMP and TMP values of all parameters with minimal use of tool time. The measurement patterns and numbers of repeats are enough to give us visibility to wafer loading or stage navigation problems, but do not waste time.

Once we had collected a large data set consisting of measurement data from all tools, the next step was to compile this data into an easy to follow report. In this report we listed the different applications and FMP values for each tool type as well as the FMP for the entire heterogeneous fleet for each parameter. Using this format, we are able to identify measurement applications failing to meet our FMP specifications and drill down to the TMP plots to highlight potential problem areas. In each TMP plot we can see which tools are contributing the most to the failing FMP of the given application and a graphical representation of the contributions of each of the four TMP components. We often see strong signals from tools needing maintenance work across multiple parameters. This weekly report helps us to plan activities to investigate and improve the tools' health. Figure 2 shows a FMP report as well as two TMP drill downs.



S.No	Module	Film	FMP%-overall fleet	FMP%- LD10s Fleet	FMP%- Aleris 8510s	FMP%-Aleris 8350s
1	[redacted]	[redacted]	0.46	0.21	0.21	0.39
2	[redacted]	[redacted]	1.46	0.46	1.49	0.58
3	[redacted]	[redacted]	0.14	0.10	0.15	0.12
4	[redacted]	[redacted]	0.20	0.14	0.28	0.15
5	[redacted]	[redacted]	0.53	0.33	0.15	0.10
6	[redacted]	[redacted]	0.71	0.23	0.50	0.44
7	[redacted]	[redacted]	0.97	0.58	0.57	0.27
8	[redacted]	[redacted]	1.67	0.98	0.43	1.12
9	[redacted]	[redacted]	0.94	0.86	0.47	0.92
10	[redacted]	[redacted]	0.20	0.13	0.22	0.18
11	[redacted]	[redacted]	0.16	0.06	0.11	0.11

Parameter 2: T8 Outlier Tool according to TMP

Parameter 8: T15 outlier according to TMP.

Fig. 2: Multi-application cross platform analysis. 11 different measurement parameters from multiple wafers evaluated. Two applications highlighted for failing 1% spec, problem tools identified using TMP. From the TMP plots we can see the failing tools, as well as the fact that these high TMP's are being driving mainly by offset.

III. FMP DRIVEN HARDWARE MAINTENANCE

Driving hardware maintenance and improvement based on measurement performance is not always a straightforward task. Measurement data is the output of many moving parts and changing an alignment or calibration may improve one application while worsening others. It is key to try and understand what "hardware knobs" we have available to us, and what effects turning these "knobs" will have. Figure 3 shows the theoretical concept of using FMP to fine tune hardware settings. By adjusting our hardware configurations and monitoring our measurement outputs, we are able to find an optimum setting. Using the tools highlighted by our FMP report, we were able to modulate multiple parameters to develop a subset of hardware knobs which we use to maintain our tools. Once we had found our optimum values, health check procedures were created to standardize these settings across all tools.

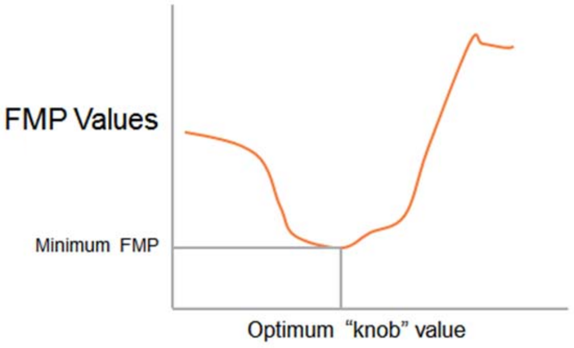


Fig. 3: A Theoretical display of FMP performance as we vary a hardware "knob". Finding a minimum FMP value can help to determine the optimum tool settings. Once these values are identified, they can be applied across the measurement tool fleet.

The tight matching distribution realized through our efforts is achieved by a combination of hardware installation control within fine tolerances and an advanced calibration process. A unique calibration methodology was developed that minimizes the spectral errors between tools. This is a system-level calibration process, thus ensuring accurate and consistent matching performance for all film stacks, requiring no additional fine-tuning. By maintaining strict hardware performance, spectral based matching provides a means to improved fleet matching without the constant need for offsets.

FMP allows us to focus our efforts and highlights areas in need of improvement. By tracking FMP values over time and acting on individual tool TMP signals to resolve hardware issues, we are able to get a visual confirmation of our continuous improvement (Fig. 4 & Fig. 5). Significant improvement of almost a 3x tightening was observed on Aleris 8510 fleet and even larger gains were realized across platform decreasing our overall matching budget within a five month period.

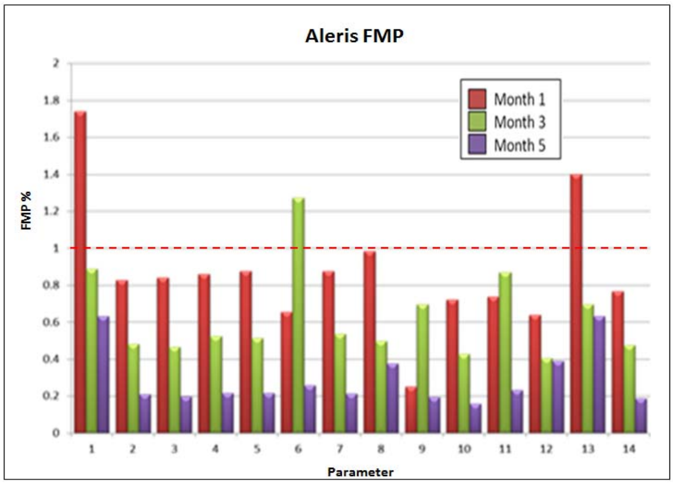


Fig. 4: FMP tracking by Month across critical parameters across the Aleris tool fleet. Fleet health improvement results in downward FMP trend over a five month period.

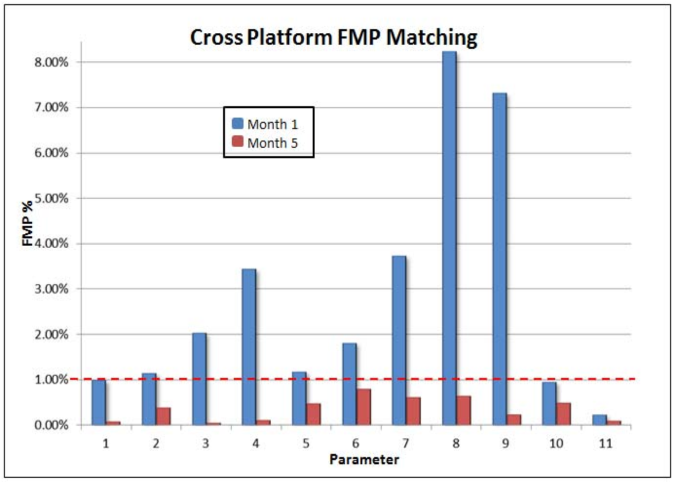


Fig. 5: FMP tracking in a heterogeneous tool fleet over a five month period across critical parameters. Significant matching improvements are realized across platform in this time period.

IV. FMP BASED CONTROL METHODS

Traditional control theory (SPC) is a tool used heavily in the semiconductor industry for maintaining an established baseline through identifying outlier processes or drifting tools. This is typically done by comparison of the mean and sigma of an individual measurement to the statistical distribution of an entire population over a stable time period. SPC control effectively maintains a process to continue to run as it has been running, but does not drive any continuous improvement. Traditional control lacks the drill down capability provided by FMP.

Of the 4 main components of FMP, control theory is only able to highlight offset in the form of repeated OOC/OOS violations. Identifying trends or drawing correlations from control charts can be challenging when systems have high non-linearity or SISoffet. Another drawback of creating control limits from an existing population of data is that those limits are built to allow to current system noise to continue, this could lead to false positives when the current system performance is not meeting the needed specifications. Figure 6 demonstrates an example where the current 3 Sigma limits correspond to a FMP of 6%, however using limits based off on 1% or 2% will result in too many failures. In this situation, FMP methodology can be used to drive tighter measurement performance across the tools. 4% limits can be set temporarily until tighter limits can be realized.

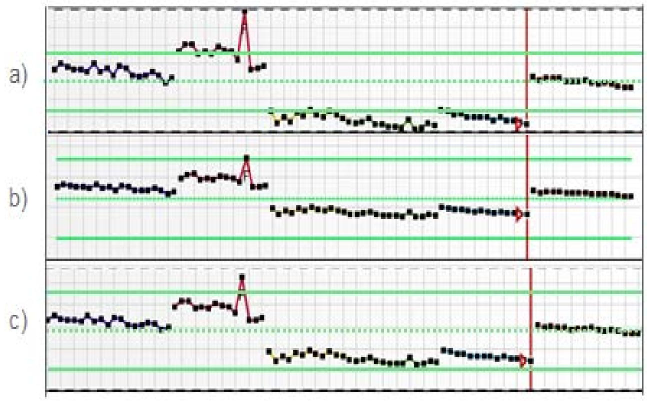
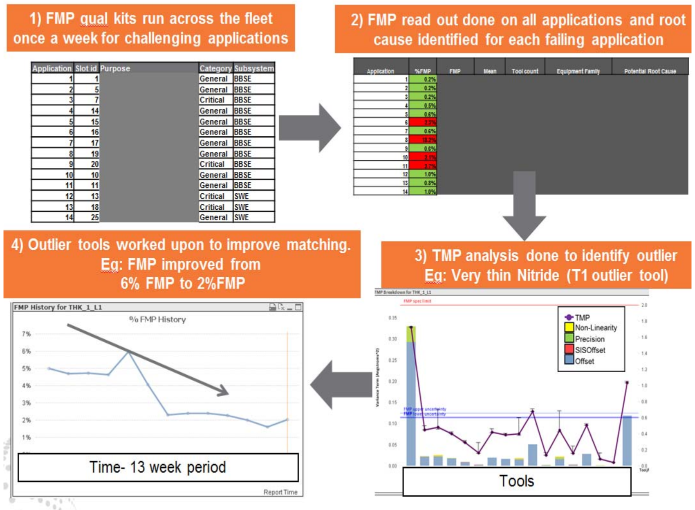


Fig. 6: A comparison of FMP vs 3 Sigma Limits on a set of data. a) 2% FMP limits applied to a dataset consisting of 6 tools. We can see that directly implementing these limits will result in 3 tools violating the limits. b) 3 Sigma limits result in no failing tools, however these limits equate to 6% FMP. c) A compromise of 4% FMP keeps all tools in spec, but when paired with FMP reporting can help to drive the matching down to the desired 2% limits.

Using our set of critical FMP wafers, we have established a control method using control limits back calculated using FMP in conjunction with traditional SPC charting. Based on the nominal measurement value and the variances calculated using the desired FMP %, we are able to create control charts to actively monitor and highlight potential FMP failures based off of data from a single tool. This methodology improves our MTTD (Mean Time to Detect) from 1x per weekly report to as soon as the FMP wafer finishes measurement and also allows us to operate the fleet well beyond standard supplier matching specifications.

The business process illustrating the steps from identifying key applications to driving hardware improvements can be seen in Figure 7.



1) FMP qual kits run across the fleet once a week for challenging applications

Application	Slot id	Purpose	Category	Subsystem
1	1	[redacted]	General	BBSE
2	5	[redacted]	General	BBSE
3	7	[redacted]	Critical	BBSE
4	14	[redacted]	General	BBSE
5	15	[redacted]	General	BBSE
6	16	[redacted]	General	BBSE
7	17	[redacted]	General	BBSE
8	19	[redacted]	General	BBSE
9	20	[redacted]	Critical	BBSE
10	10	[redacted]	General	BBSE
11	11	[redacted]	General	BBSE
12	13	[redacted]	Critical	SWE
13	18	[redacted]	Critical	SWE
14	25	[redacted]	General	SWE

2) FMP read out done on all applications and root cause identified for each failing application

Application	%FMP	FMP	Mean	Tool count	Equipment Family	Potential Root Cause
1	0.2%	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
2	0.2%	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
3	0.2%	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
4	0.5%	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
5	0.6%	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
6	2.3%	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
7	0.6%	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
8	18.2%	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
9	0.6%	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
10	2.1%	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
11	2.7%	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
12	1.0%	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
13	0.8%	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
14	1.0%	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]

3) TMP analysis done to identify outlier Eg: Very thin Nitride (T1 outlier tool)

4) Outlier tools worked upon to improve matching. Eg: FMP improved from 6% FMP to 2%FMP

Fig. 7: Business process for driving continuous improvement. Applications with failing FMP are highlighted and TMP is used to drive hardware improvement.

V. Additional Fleet Health Monitoring

After using the FMP methodology to drastically improve the health of our measurement fleet, we were able to notice additional signals became visible identifying new problem areas. In addition to improving measurement health through FMP, a parallel effort to improve system health, identify software issues, and improve overall uptime was performed. With the noise from some of our bigger issues accounted for through the standardization of our key hardware knobs, identifying trends from tool alarms and FDC became our next goal. By looking at the tool Mean Time Between Interrupt (MTBI) and creating a pareto of interrupt types to guide us with actions, we were able to drastically reduce on tool alarms, and increase available productive time on the tools (Fig. 8).

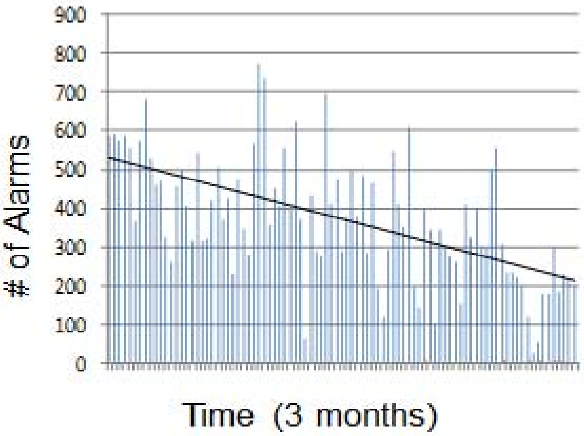


Fig. 8: 3 Month tool Alarm trend during the CIP time period

VI. Conclusion & Future Work

Through the use of weekly FMP reporting we have been able to demonstrate nearly a 30% reduction in fleet matching range on critical applications in a five month period. With this matching improvement we have also realized increases in our tool MTBI and decreases in on tool alarms. Eliminating key failure modes allows us to shift our focus from a day to day reactionary mindset to more of a proactive and predictive maintenance approach.

Although we have noticed significant improvements in tool uptime due to improved fleet health, we must keep in mind that we can continue to streamline this process. Since our initial finding on our ellipsometer fleet, we have continued to adjust our set of critical wafers to keep our most critical and sensitive applications as a part of this qual. The more quals we run, the less productive time we have available on tools. Because of this, we have removed wafers that provided duplicate signals. Additionally, we need to continue to improve our understanding of the “hardware knobs” and draw stronger correlations between FMP failure modes, FDC, tool alarms and the tool hardware. In doing this we will have a fewer number of and a faster turnaround on our scheduled repairs. This methodology is not limited to the thickness metrology toolsets; it is encouraged to apply this same methodology to other metrology toolsets to drive continuous improvement across the fab. Lastly, this demonstrates the untapped potential realized by using this methodology allowing significant capital savings that otherwise might have been used to purchase next generation tools.

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