KNOWLEDGE BASED PROCESS CONTROL

Improving productivity and increasing product yields

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Abstract

The semiconductor industry has long searched for a suitable answer to the questions of how to improve fab yield and maximize equipment productivity. For a number of manufacturers, automated process control is the light at the end of the tunnel and already many report improvements as a result of adopting solutions in this area. Challenges remain nonetheless.

This paper examines advanced process control (APC), critically evaluating its two arms – fault detection and classification (FDC) and run-to-run (R2R) control. It outlines the knowledge based process control approach developed by Straatum and highlights the reasons why tool and process optimization techniques are bolstered using it. It concludes that integrating advanced sensors with tool and process models is, ultimately, the way forward to achieve higher tool productivity and yield.

Introduction

How to improve capital equipment productivity and increase product yield? These are the questions constantly facing the semiconductor industry. Typically, fabs have approached the challenge by investing early in next generation tools and by using traditional process control methods. A technology culture rather than a manufacturing one has existed with tool and yield issues addressed on an as-need basis. Industry changes in the last few years, however, including rapid ramp requirements, greater fabrication complexity and higher costs have seen this traditional approach come under increasing pressure. The outcome is a growing realization that a move to a manufacturing culture is necessary to deliver those much sought-after improvements.

As a result, many manufacturers are now turning to advanced process control methods to address their fab yield and productivity issues. This increased focus on process control has also highlighted the need for better technology solutions from suppliers. Indeed, in many cases, fabs have developed their own solutions to fill the gap, be it perceived or real, between APC requirements and currently available solutions. These new solutions include *in-situ* sensors, integrated metrology, collection and analysis of tool-state and process-state data, fault detection, fault classification and run-to-run control. A number of recent case studies have backed up the experience of those fabs who are now reaping the benefits of adopting such technologies. The challenges that remain however are two-fold. Firstly, how to turn increased data flow into information and secondly, how to process that information to return a decision to the fab as rapidly as possible.

Advanced process control – two separate approaches

Advanced process control (APC) has two aspects – fault detection and classification (FDC) and run-to-run (R2R) control.

FDC refers to real-time or near real-time detection of tool faults and/or process excursions and rapid identification of the root cause. Tool uptime, yield and mean-time-to-repair are all positively impacted by a successful FDC program. R2R control is a method for adjusting process step n (closed loop control) and/or step n-1 (feed-back) and/or step n+1 (feed-forward) based on a measurement of the output of step n. Improved yield is the primary outcome.

In choosing to run with these new technologies, different fabs have sought or developed different responses. Some advocate FDC as being critical to reduce tool downtime and catch process excursions early. Others have adopted R2R control as a fab-wide enterprise in the effort to tighten process performance. There is a general acceptance, however, that APC is still developing but as the industry matures all fabs will need to adopt one or more of these solutions if they are to remain competitive.

R2R – the model based approach

R2R control is model based. Feed-back and feed-forward loops are based on *in-situ* or *ex-situ* metrology measurements and a model that links wafer-state data to the process recipe, as shown in Figure 1. For example, an in-situ thickness monitor may measure film thickness above required specification on a given wafer. Because the R2R controller includes a model that relates thickness to process input, the recipe for the following wafer can, for instance, be adjusted to include decreased power. The thickness is again measured after the power is reduced, and the adjustment repeated if necessary until the film is in spec. Alternatively, an etch or CMP step can be informed of the increased wafer thickness and be adjusted accordingly. Again, a model that relates etch or polish rate to process recipe is used to determine the appropriate change.

Are there any drawbacks?

One issue that arises with R2R control is that, in many cases, implementation of these schemes begins with local models. To use the above example, the film thickness is assumed to be driven by some set of process inputs. The model only contains information on the thickness and its relationship to the process recipe. It is generally unaware, for example, of what happens to the refractive index of the film or the film stress resulting from decreased power. To avoid introducing a new problem when fixing an existing one, the R2R controller tends to limit the control loop to within the process window.

Another factor that is potentially problematic is that the R2R model is blind. If the process has drifted due to a fault on the tool, the R2R controller adjusts the process input without considering this possibility. Again, to use the above example, problems with power delivery, process spacing, gas flow or any other process input may be responsible for the increased film thickness. The R2R controller cannot fix the problem but merely compensates for it.

For these reasons, it is generally accepted that while an FDC engine can exist without an R2R controller, R2R control is greatly empowered by a complementary FDC engine. Therefore, the first step towards APC should be the adoption of a fault detection and classification engine.

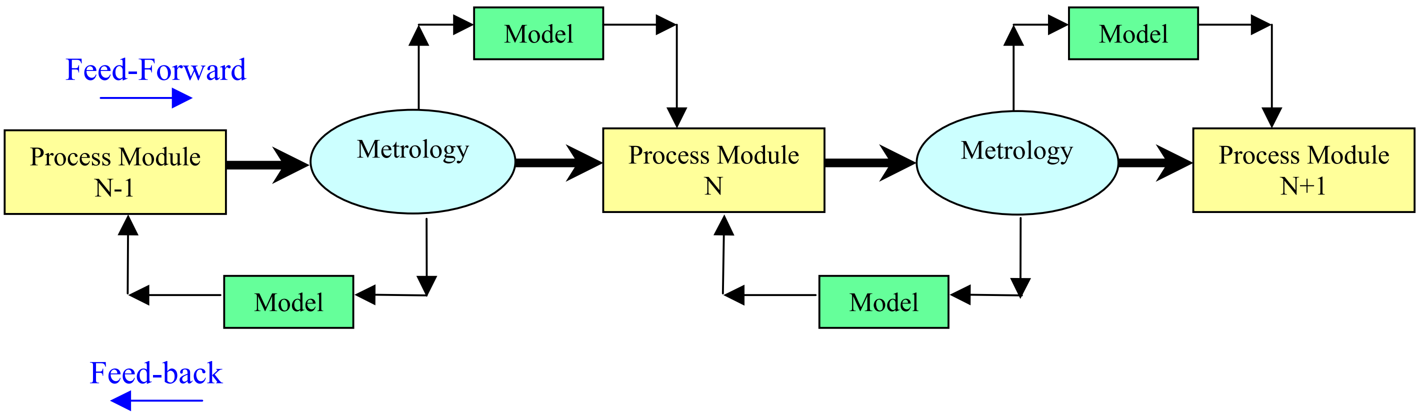


Figure 1: Schematic of integrated process modules and metrology tools as part of an APC infrastructure incorporating R2R control

Measuring performance

Many FDC solutions currently available are model-based. For example, multivariate statistical analysis (MVA) techniques have recently been upgraded to replace the univariate Statistical Process Control (SPC) used today by many fabs. These techniques are designed to reduce the number of SPC charts a user needs to control and also to include covariance in addition to the variance measurements used by SPC. Inclusion of covariance has helped remove many false positives which SPC techniques are susceptible to and catch those excursions they typically fail to spot.

MVA techniques have proven to add value to process control methods, particularly for fault detection. A common MVA implementation is data compression for many or all SPC charts to a single statistic, such as Hotellings' T^2. This statistic is a summary of all input performance relative to each individual variance and also the standard covariance between the inputs. Deviations from the defined process space are flagged as excursions. Because MVA is based on statistical analysis, a model, or rather a template, must be learned from known good performance. This is usually done by observations on real production data.

MVA techniques have also been used for fault classification. That is, having identified a fault condition, methods such as Principal Component Analysis (PCA) can help identify frequently occurring fault scenarios. Typically these techniques are template based, i.e. through repeated runs, the system is taught the probable contributors to certain faults, based on statistical analysis. There is no inherent knowledge present as templates are usually based on signals from process set-point actuators rather than from process sensors. Basing control on measurement of the process input rather than measurement of the process itself is inherently limiting.

Knowledge based process control

Straatum has pioneered an approach to advanced process control called Knowledge-Based Process Control. This differs from the model-based approach described above because it works as an intelligent process knowledge tool, rather than as a mere template. The solution's platform, shown in Figure 2, integrates advanced sensor data and tool/wafer data with tool and process models.

The core value of this approach lies in the model's ability to understand and manipulate data to provide corrective action. The key output of the solution is a decision that is designed to improve tool and/or process productivity.

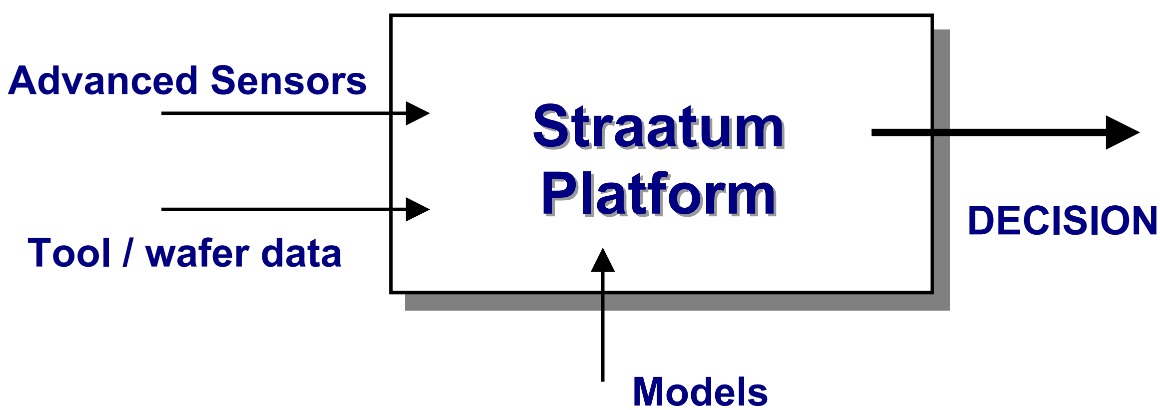


Figure 2: The Straatum platform integrates advanced sensor data and tool/wafer data with tool and process models.

Advanced sensors

The Straatum approach embeds an advanced sensor guaranteed to be tool and process sensitive. In this way, the process itself does much of the data compression, rather than having to rely on statistical algorithms compiled from the tool inputs. Because it works with a knowledge of the tool itself, built through observations of the sensor's data as it is forced to endure changes in tool and process conditions, data is used to construct a model upon which the FDC software engine is based. The initial focus is to isolate the fundamental tool or process health indicator and to use this to determine whether the tool or process is in control or not. Following an excursion, the knowledge-based model is then used to identify the root cause of the problem.

Detecting and classifying faults

An example of this knowledge-based process control is the Straatum FDC solution for plasma etch and CVD tools. Firstly, fault detection is done by compressing the sensor data to give a single state-of-health parameter, the Plasma Index. The chosen sensor is a plasma impedance monitor, selected for its sensitivity to process and hardware deviations. Figure 3 shows a typical Plasma Index from a commercial etch tool. When the tool is in control, the index is well behaved. However, faults in either tool or process result in the index moving outside the control limits. Examples are shown of induced power, pressure and gap variations in the range of 5-10%. Following an out-of-control excursion, the decision will be returned as "*Stop processing as index is out-of-control*". This universal index, much like a multivariate statistic, has the advantage of compressing all control charts into one master chart.

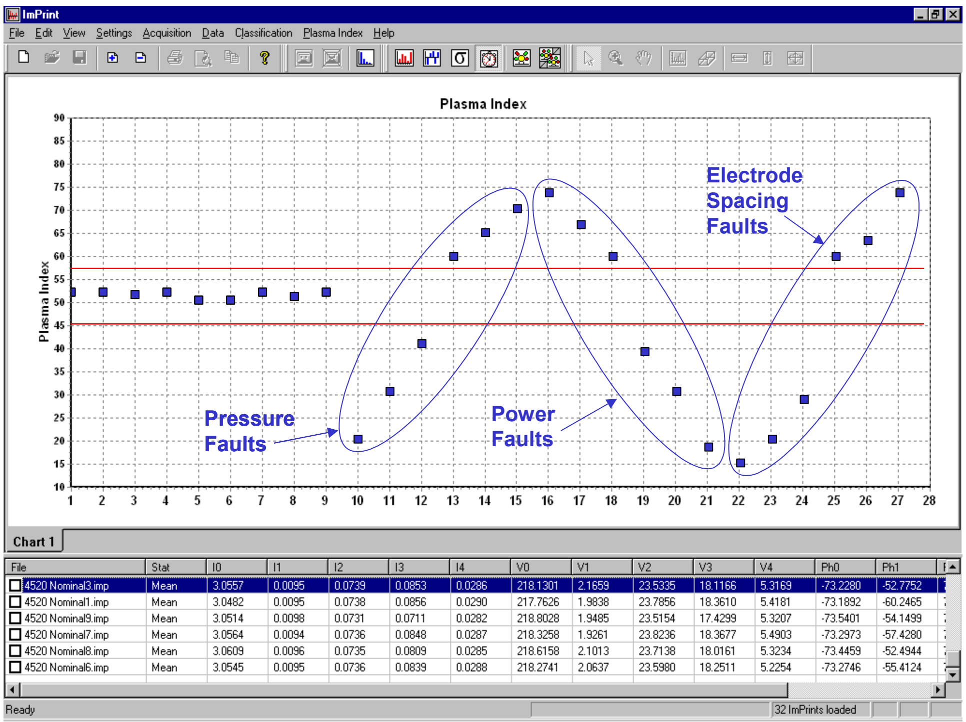


Figure 3: Single variable Plasma Index control chart indicating response of index to various induced faults

Resolving the problem

Following a decision to stop processing the problem needs to be resolved as quickly as possible to maintain high tool productivity. Hence the importance of fault classification. Again, using the advanced sensor and knowledge-based model, classification is possible.

In general a single parameter cannot be used to classify a fault, since many faults can lead to an identical response on a single parameter. The greater the number of individual components contributing to the Plasma Index, the more accurate will be the resulting fault classification. The Straatum solution for etch and CVD tools takes the Fourier components from the impedance sensor to classify the fault. Having learned how the Fourier spectrum varies with forced input changes, a particular process or tool fault can be identified when it occurs in those same Fourier components. Figure 4 shows a typical classification of a process fault. A knowledge-based model predicts that the change in Fourier Components is best ascribed to a power change. All other close fits are shown in Pareto format. Following this classification, the decision proffered *is "Power drift of +21W detected – check match unit and generator*".

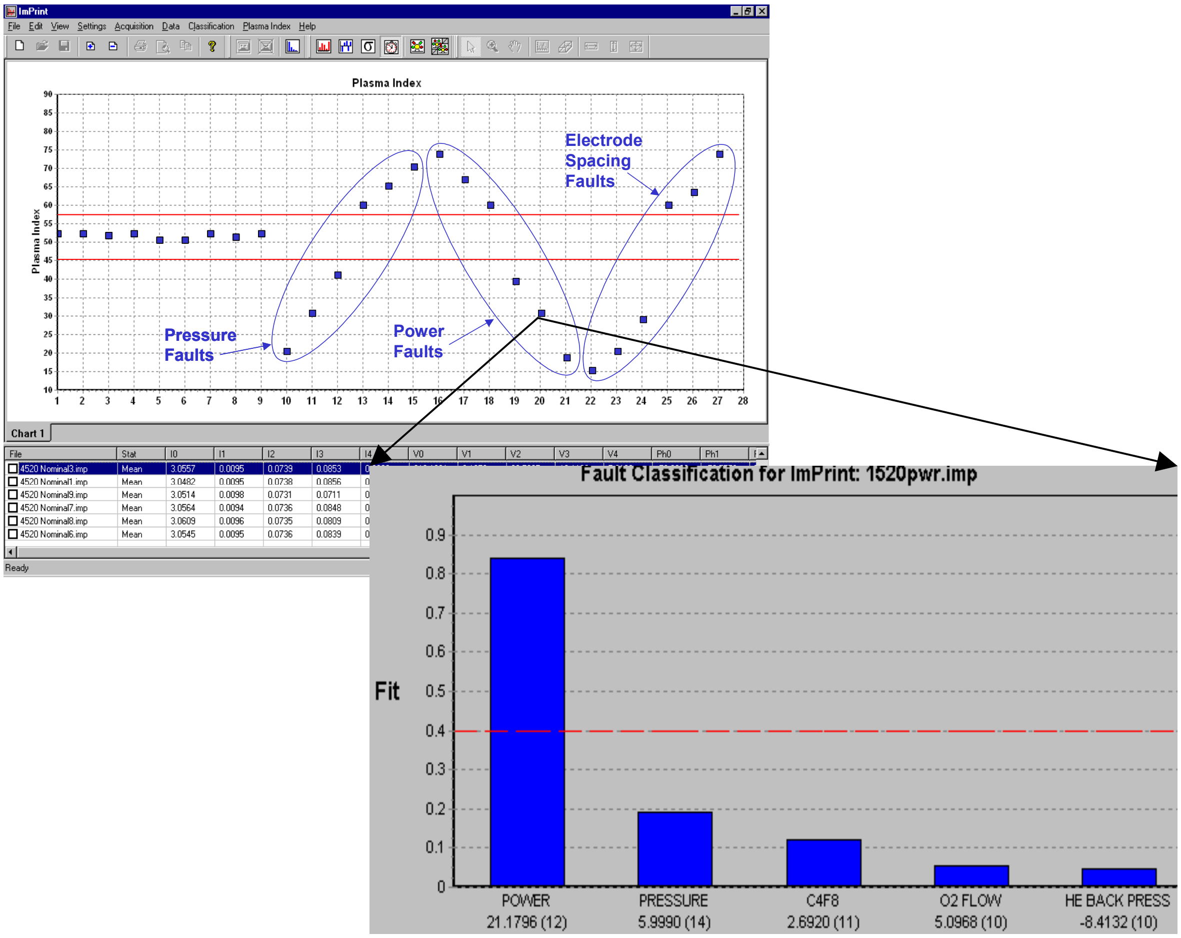


Figure 4: Fault classification algorithms identify the source of one Plasma Index excursion as an RF power drift.

Why integrate your R2R and FDC systems?

The benefits of R2R control and FDC solutions are optimized when they are both fab-integrated and connected to the MES and yield/data management systems. R2R control carries out recipe adjustments based on a metrology measurement. FDC identifies tool or process faults. If both are employed but not connected, R2R recipe adjustments will appear as faults to the FDC engine and R2R process recipe adjustments may mask faults that the FDC engine sees. Figure 5 shows a typical integration set-up. In this case the integration layer resides on the host rather than on an interim layer. The R2R controller, which talks to all tools and metrology stations, gets information from the MES and FDC engine. The FDC engine, which resides at the tool level, is aware of all activity by the MES and R2R controller.

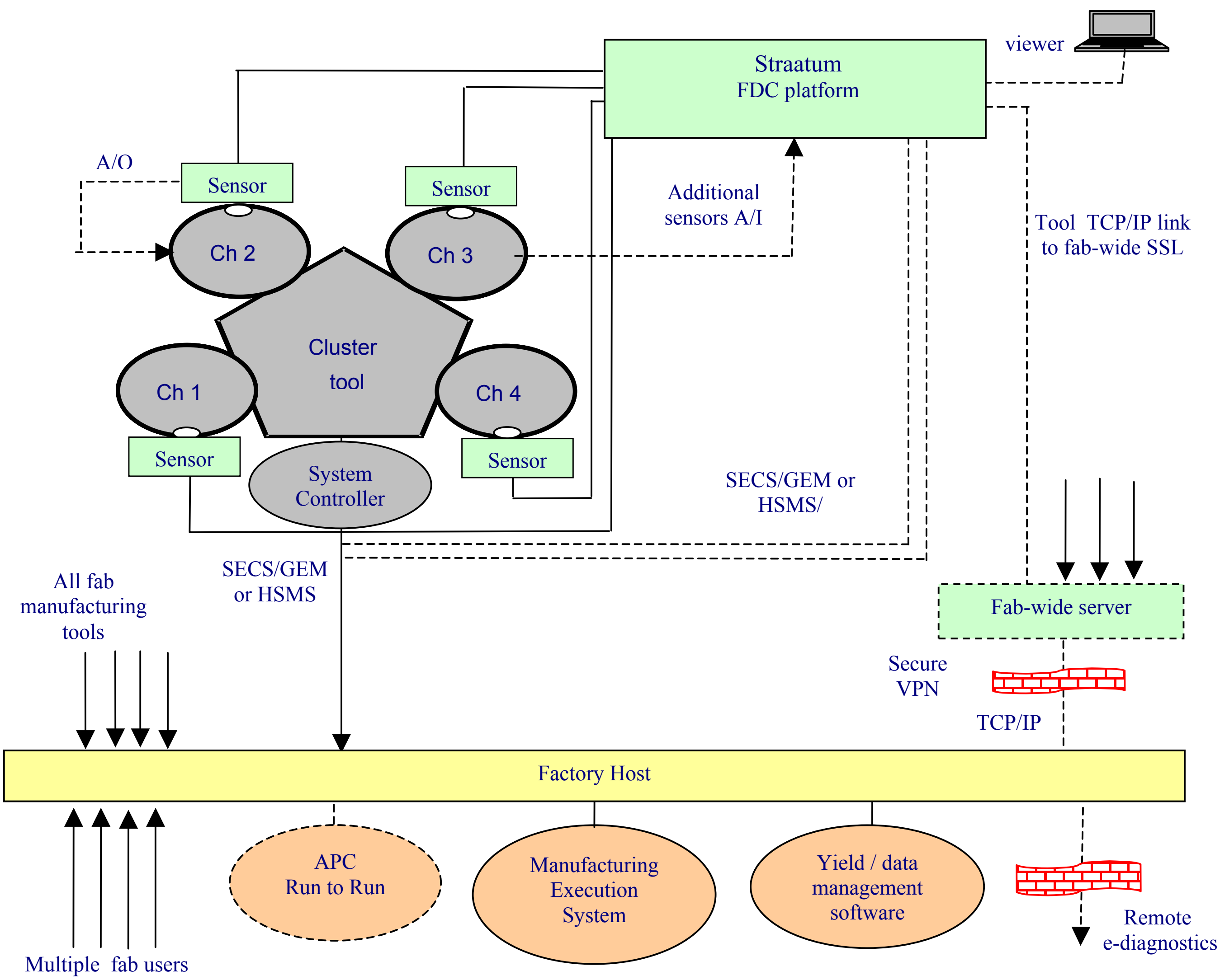


Figure 5: Schematic of fully integrated APC program incorporating R2R and FDC platforms into overall fab control systems.

Optimizing your tools

FDC deals with fault detection and subsequent root-cause identification. For the purposes of this paper, it is useful to divide all issues relating to productivity and yield into two categories – tool faults or process excursions. The former is generally a tool productivity issue whereas the latter is concerned with process optimization. Both impact on tool uptime and yield and both should be easily handled by an FDC engine, such as that previously described. Examples of typical tool faults and process excursions are outlined below.

Tool faults

Ideally tool faults should not occur, but in reality they can be quite frequent. They usually relate to problems with the tool itself, or with tool sub-systems or components. Examples include MFC drifts, match unit fails and wafer clamping issues among others. They also include chamber-to-chamber differences, despite the fact that these are technically engineered in the same way. An effective FDC engine handles these problems by registering deviations in the Plasma Index and subsequently classifying the fault.

If faults occur on the tool that the FDC engine has not seen before the Plasma Index will, for the most part, detect a problem, but classification of this 'new' fault will be impossible. In this instance, the FDC engine needs to be enhanced to allow the user to fault-find rapidly. Figure 6 shows how the Straatum FDC solution handles these cases. In effect, by leading the user through a decision-tree comparing baseline fingerprints to fault fingerprints it facilitates the classification of the fault into a pre-designated fault family. This, in turn, rapidly allows the user to narrow his search and hence identify root-cause more efficiently. In the example in Figure 6, one possible decision given could be "*Hardware fault detected – please check chamber build*".

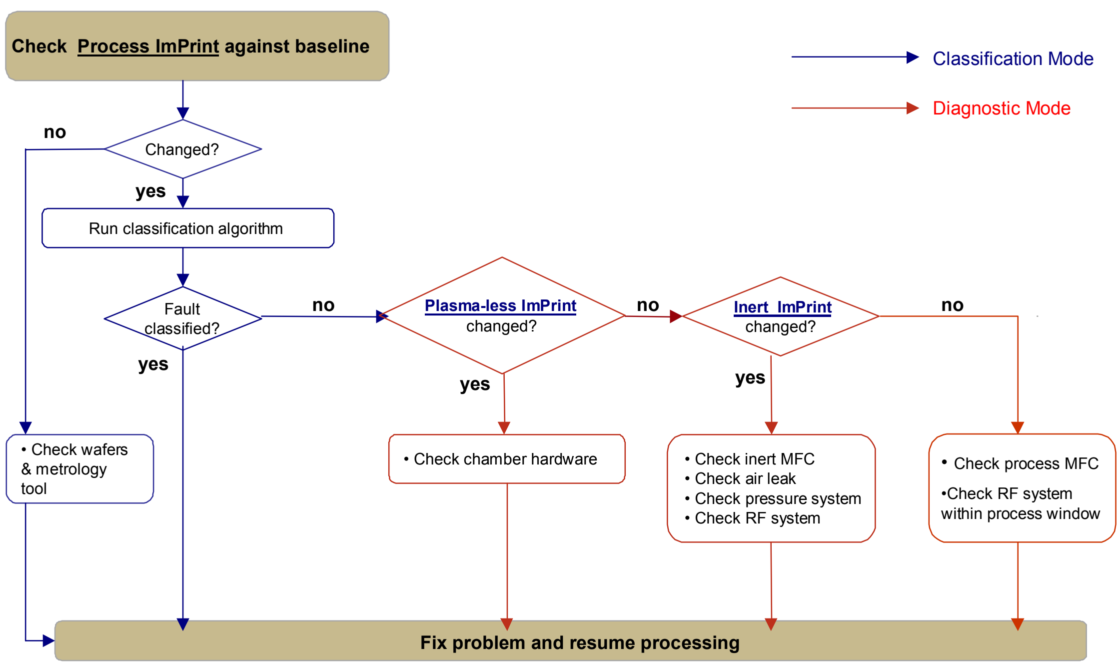
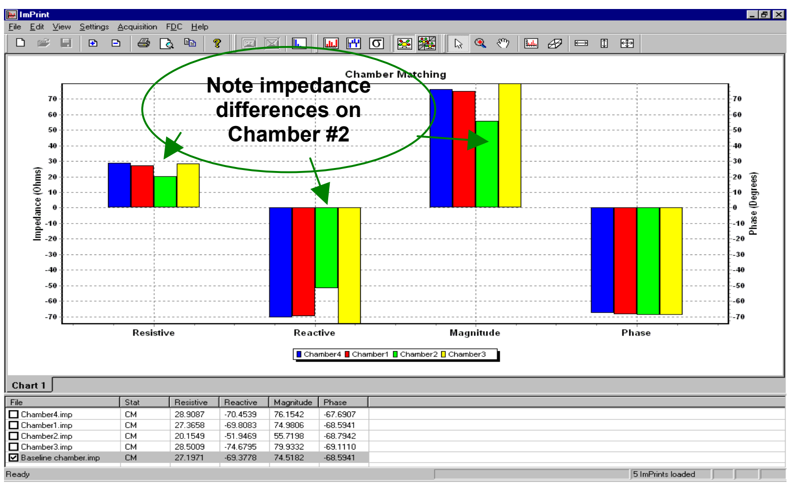


Figure 6: When the root cause of the fault cannot be immediately identified the Straatum FDC decision tree enables the classification of the fault into a pre-designated fault family.

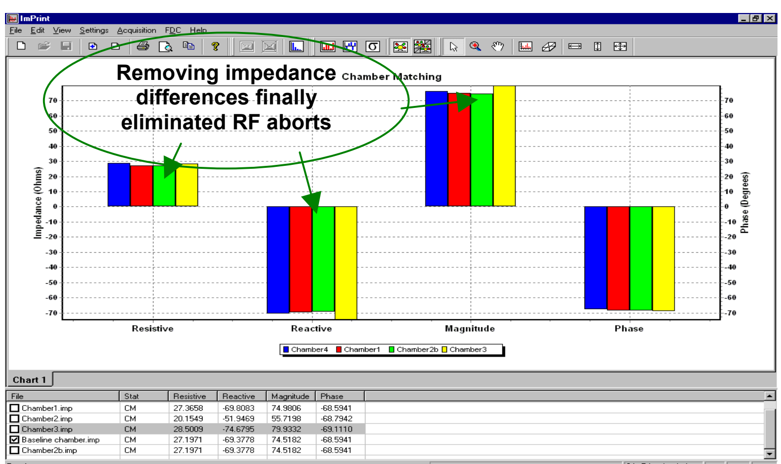
Chamber-to-chamber differences

To illustrate how this fault diagnostic function works in practice, consider the example of chamber-to-chamber differences. These differences are often manifested in the process output – CD bias / CD dispersion or etch rate differences, for example. They may also be manifested as differences in tool productivity, as would be the case if certain chambers need more maintenance than others for instance. Typically, there are insufficient methods available in the fab to solve these problems.

Figure 7a illustrates an impedance fingerprint of a set of four process chambers, three of which are well matched by output while one exhibits reduced yield and productivity performance. By following the methodology outlined in Figure 6 the root cause was classified and this chamber repaired. Figure 7b shows the fingerprint after the fix. Chamber productivity and yield performance are now similarly high across the board.



(a)



(b)

Figure 7: Impedance fingerprints of four chambers before (a) and after (b) identification of source of process differences from chamber 2.

Preventive Maintenance (PM) Issues

Another example of tool optimization relates to tool performance following a scheduled preventive maintenance (PM) procedure. Following a PM, such as a wet-clean, the procedure for re-qualification prior to hand-over to production usually includes running a set of chamber conditioning wafers, running test wafers, checking metrology performance and running some short-loop wafers to test functional performance.

Here, problems can occur which are not always picked up by the tests outlined above. The Straatum solution can, however, be used to enhance tool productivity following a PM by indicating state-of-health using the Plasma Index. Figure 8 shows the Plasma Index across a set of wafers pre and post PM. The first run after the PM shows deviation from SPC limits, indicating that the PM has not been carried out to specification. This implies that a fingerprint can in fact be taken prior to test wafer and short loop runs, and a pre-qualification fingerprint used to determine if a chamber is good to go.

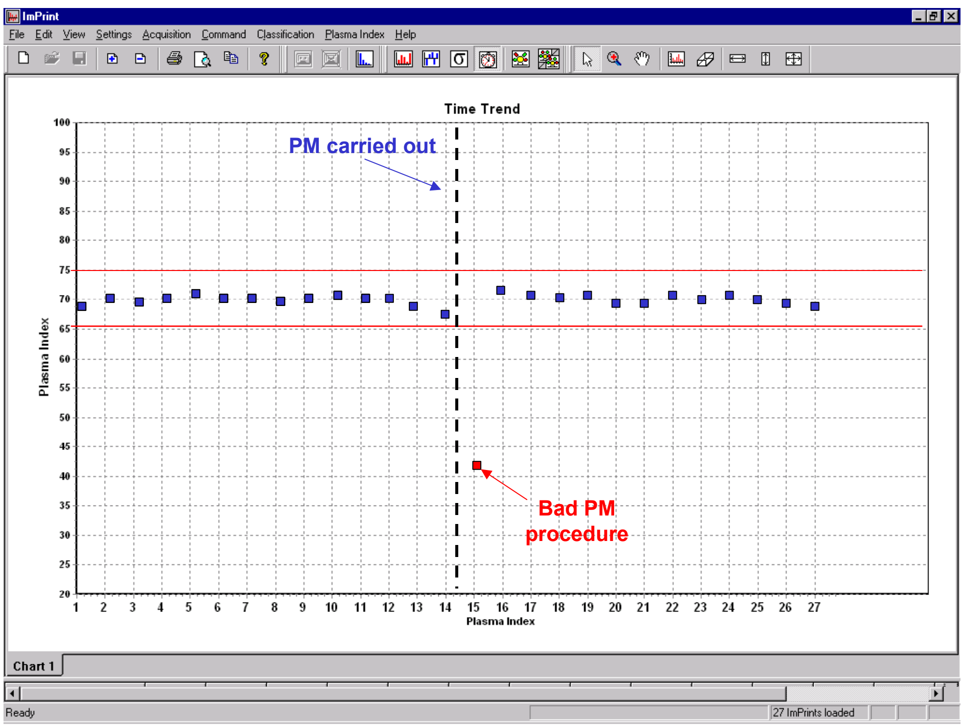


Figure 8: Plasma Index control chart indicating bad PM procedure detectable by out of control Plasma Index.

Process optimization

The second category, process optimization, can be very specific to the fab and the processes they run. Tools are typically supplied from the tool manufacturers with a set of "best known methods" (BKM's), which include standard recipes with typical process results. Very often fabs will design their own proprietary recipes and process flows as they need them. The FDC engine employed should therefore, be configurable to allow optimum results to be achieved from any new developments the user puts in place. A few examples of how the Straatum FDC platform handles these yield and productivity learning issues are outlined below.

Preventive maintenance – when do you need to carry it out?

The first example illustrates how PM timing can be optimized. Dry etch tools running typical process chemistries, such as HBr, Cl_2 and C_4F_8, need to be regularly cleaned. Dry cleaning is often employed but never obviates the need for wet cleans. Typically wet cleans can take up to 8 hours, a substantial hit on uptime. Optimizing this clean cycle can impact uptime, cycle-time and process ramp rate. Current maintenance techniques are often based on best known methods (BKMs). The typical approach has been to issue a BKM, indicating a clean cycle of 500RF hours for example. This is often based on previous particle monitoring data.

Straatum's approach to this is to use an advanced sensor with a process model to indicate when PMs should take place. Figure 9 illustrates how such a system can be used as a predictive trigger. The Chamber Clean Index shows a clear predictive trend across wet clean cycles. Based on product type, the system is programmed to call a wet clean without resorting to ex-situ monitors or BKMs.

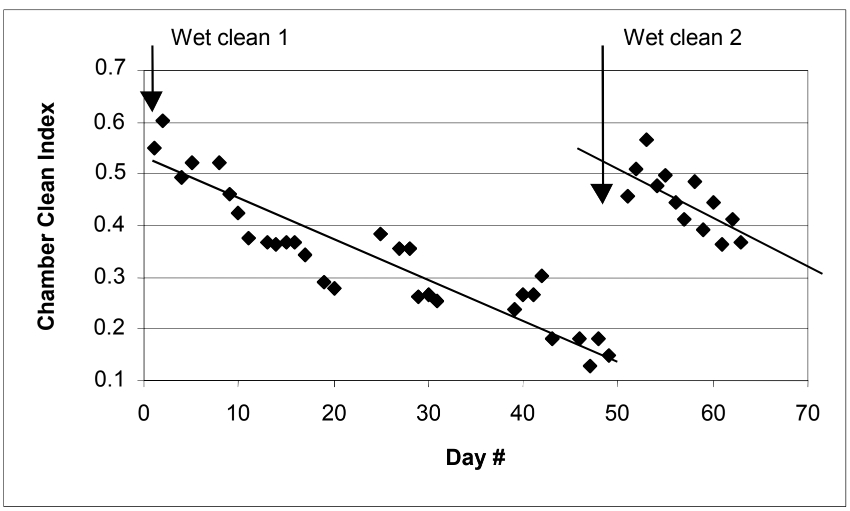


Figure 9: Plot of Chamber Clean Index through two wet clean cycles.

Chamber conditioning – monitoring real-time rates of change

The second example of the use of the Plasma Index in relation to PM issues illustrates how chamber conditioning, following chamber downtime, can be optimized. Usually, a BKM indicates the number of wafers needed to condition a chamber prior to production. The Straatum solution couples a sensor with a model that is adaptive to changing conditions. The system monitors the real-time rate of change of conditioning and predicts when saturation will occur. The output decision is a running indication of the number of additional wafers needed to complete conditioning. An example of such a predictive chamber conditioning model based on a Plasma Index is illustrated in Figure 10.

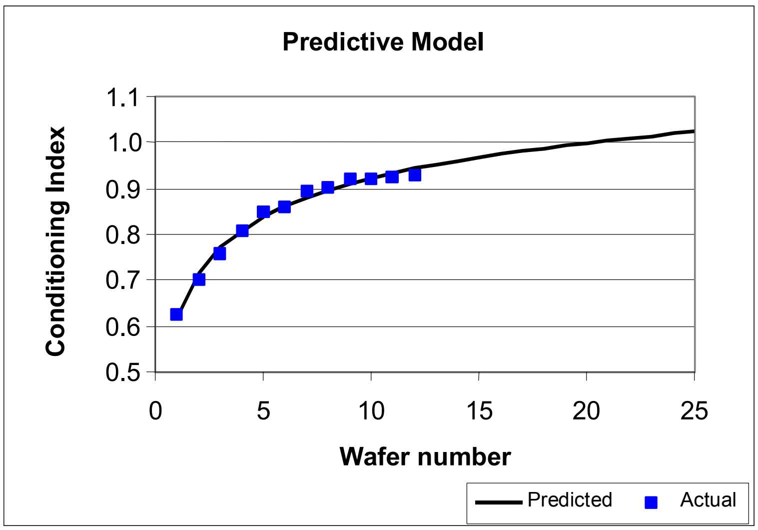


Figure 10: Predictive model for chamber conditioning based on Plasma Index indicating chamber conditioning occurring after wet clean.

Recipe development – improving yields

The third and final example of process optimization is in recipe development. As fabs move through device nodes or develop new designs, recipes must be developed to run the new process flow. The typical approach is to test new recipes based on output. That is, to test the recipe on pilot production runs and monitor device and yield performance. Repeats of this may be necessary to optimize the recipe. The Straatum approach again uses an advanced sensor to optimize performance. During design, the recipe is monitored for any adverse performance that would impact yield.

Figure 11 shows how the plasma strike step is optimized to improve yield using the Straatum platform. Prior to recipe optimization run-to-run repeatability was poor as a result of differing plasma strike conditions (red, blue and black traces). After the strike conditions and settings are optimized the voltage and other sensor readings, is much more repeatable run-to-run (gray, yellow and green traces)

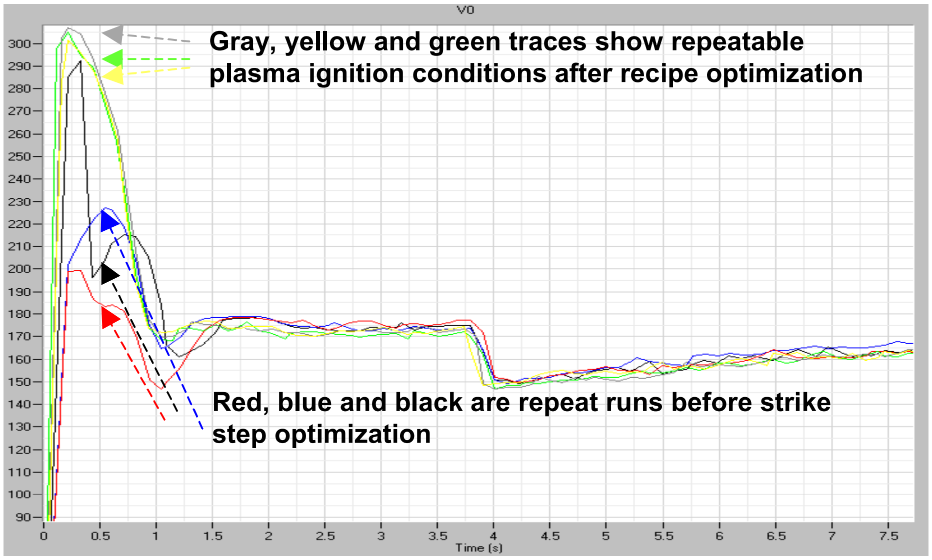


Figure 11: Plot of voltage versus time for a single step of a multi-step recipe. Optimized plasma strike step using Straatum platform gives more repeatable plasma conditions and process results run-run and ultimately enhances yield.

Summary

Knowledge-based process control integrates advanced sensors with tool and process models for enhanced FDC performance. Rather than using a statistical or template-based control model, the knowledge-based approach is developed around core information extracted from the process itself. The FDC engine, in this instance, is defined as real-time fault detection and near-real-time classification.

Tool faults are defined as any tool issues that result in unnecessary downtime, while process issues are those that directly impact yield and yield learning. The Straatum platform has been developed to return a series of key output decisions on tool and process efficiency, enabling the delivery of higher tool productivity and yield.

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