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Knowledge-Based Process Control For Fault Detection and Classification

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PROCESS: FAULT DETECTION

Knowledge-Based Process Control For Fault Detection and Classification

By John Scanlan, Mike Hopkins and Kevin O'Leary, Straatum

ABSTRACT

Increasingly, semiconductor manufacturing is looking for innovative solutions beyond statistical process control (SPC) to improve fab yield and tool productivity and reduce manufacturing costs. Fault detection and classification (FDC) is an emerging process control technology focused on detecting real-time tool and process excursions and identifying the root cause. In this paper we suggest a novel approach to FDC, using a knowledge-based approach rather than a statistical one. A fingerprint of the process is compared in real time to a library of known fault fingerprints. If a match is detected, the fault is both detected and classified and the magnitude of the fault reported. Comparison of the fault magnitude to the process window allows the user to determine impact on yield immediately.

INTRODUCTION

Rapid detection of process and tool faults is the key to maintaining high product yields in semiconductor fabs. Identifying the root cause of such faults is the key to maintaining high factory productivity levels. Historically, the fab has often relied on either end-of-line quality checks or regular process quality checks using *ex situ* metrology and/or short loop test structures to detect faults. Fault root cause identification or fault classification has very often relied on the expertise of fab engineers analyzing trace data from the manufacturing tools and analytical tools [1].

In an effort to speed the detection of tool or process faults, fabs have also used statistical process control (SPC) on tool-state sensors and, if available, on process-state sensors. For example, plasma etch tools will have data streams available for power, pressure, gas flows and so on and may have data streams available from optical, RF or other process-state sensors. The traditional approach is to apply statistics to this data, either as univariate SPC or, more recently, multivariate SPC [2]. Possible faults are detected by monitoring deviations outside normal limits from the statistical mean.

One limitation of this approach is that the underlying sensor data does not usually have a normal distribution, as is assumed by the SPC approach. This results in a trade-off between low control limits (for example 3-sigma), resulting in a lot of "false positive" alarms, and high limits (for example, 6-sigma or greater), resulting in too many "missed faults." This is represented graphically in Figure 1. The dashed vertical line represents the control limit, chosen with respect to sensor variance. "Missed faults" appear in the upper left quadrant, "false positives" appear in the lower right quadrant.

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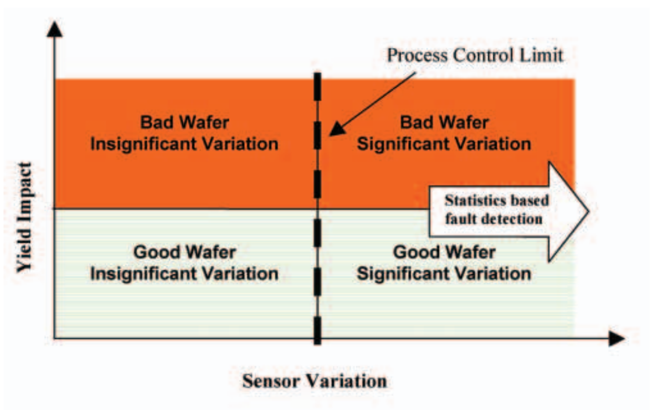
FIGURE 1

Statistics-based fault detection



A NEW APPROACH TO FDC

Figure 2 is a graphic representing the ideal fault detection system. Faults are detected based on yield impact and not on sensor variation. This is the knowledge-based approach. There are no false positives and all known faults are detected. So how is such a system achievable?

One approach to developing the system of Figure 2 is to construct a multi-dimensional fingerprint of the process and continually compare it in real time to a set of known fault fingerprints. A fault is detected if and only if a match is determined. This is the first step in ensuring there are no false positives. The question of sensitivity to real fault conditions then becomes a function of the underlying sensor data and the resolution set by the user. In general, the underlying sensor should be sensitive to very small changes in the process conditions and the user can then set alarm or warning limits based on the process window.

Imprint MX from Straatum uses this knowledge-based approach to FDC. A set of fault fingerprints constitute a fault library, which is populated generally in two ways. Firstly, through a set of simulations defined by the user which can include normal process inputs as well as known fault scenarios for a particular tool type. Secondly, new faults can be added as they are encountered. The fault library is thereby expandable and is also transferable to other tools in the fab. Once the user has a fault library, the system can run and there is no necessity to collect a statistical model-set to define control limits.

Figure 3 shows sensor data as a function of wafer number. Notice the non-normal data distribution: the data trends with time as tool parts wear and chamber wall conditions change, and a preventive maintenance (PM) event at approximately wafer number 1300 shows a typical discontinuity. The circled region represents a real fault condition, illustrating the difficulty in isolating such an event.

The knowledge-based approach is shown in Figure 4. The data is continually monitored and compared to known fault fingerprints. Therefore, data trends and discontinuities are ignored since they are not fault conditions. When the fault condition appears, beginning at approximately wafer number 1200, the fingerprint match alerts the user to a real fault condition. The edge of the process window, defined by the user, appears as ±1 on the control screen. It is possible to report the

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FIGURE 2

Knowledge-based fault detection

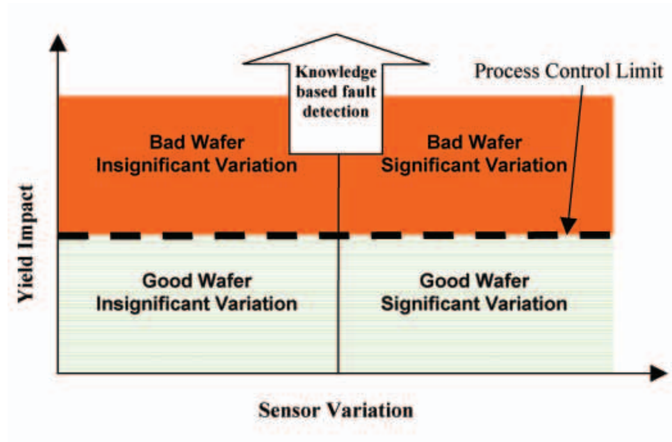


FIGURE 3

Fault condition on raw sensor data

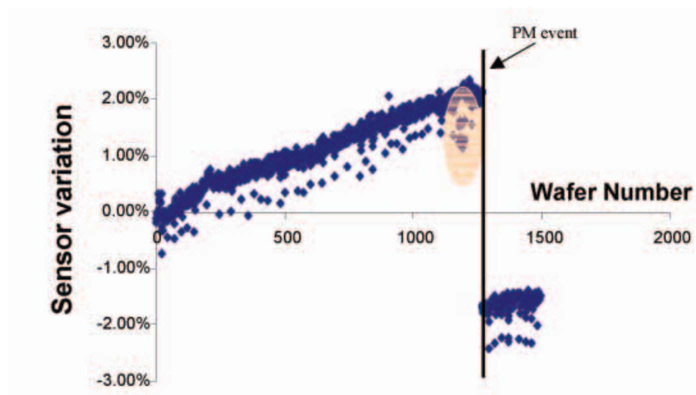
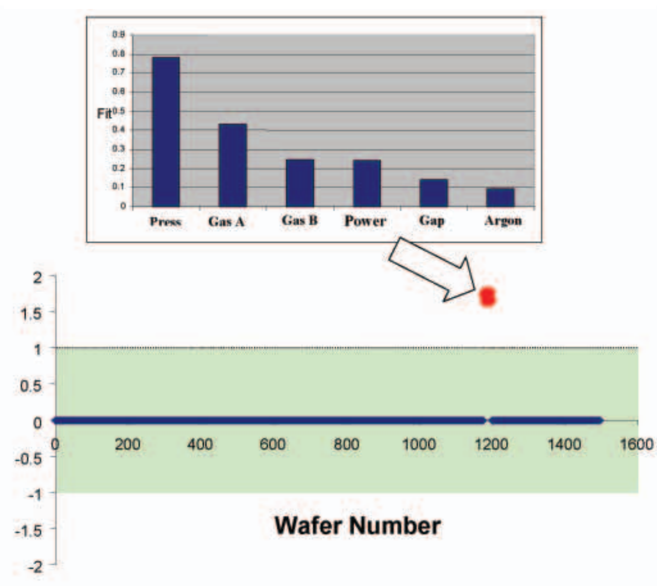


FIGURE 4

Fault condition with fingerprint approach



Faults are detected based on yield impact and not on sensor variation. This is the knowledge-based approach.

magnitude of the fault because the fault condition is compared to an absolute fault fingerprint, whose magnitude is known.

Since fault detection is based on matching the process condition to a known fault condition, classification is instantaneous. In fact, in this technique, classification precedes detection. Thus, Figure 4 also shows a Pareto of best fit fault fingerprints to the detected fault. The user is therefore simultaneously flagged on a fault and the root cause of the fault.

FDC SPECIFICATIONS

The knowledge-based approach to FDC described above is very similar conceptually to defect detection systems currently found in fabs. Defects are classified as part of the detection process and pattern recognition concepts are used. In this case, product specifications are based on correctly detecting and classifying defects with certain defined resolution [3]. We suggest the same specification concept be used for *in situ* FDC. For example, we could define detection accuracy as the percentage of known faults correctly detected, classification purity as the number of detected faults correctly classified and resolution as the smallest detectable limit. The advantage of this approach is to give the fab engineers the same confidence with *in situ* fault detection that they currently have with *ex situ* particle defect monitoring.

CONCLUSIONS

A novel approach to tool-side FDC has been suggested. The method uses a fingerprint recognition scheme as the basis for fault detection, thereby making classification instantaneous. Disadvantages of the statistical approach, such as missed faults and false positives, are avoided. The approach also allows the user to access the impact of faults since the magnitude if the fault is reported.

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Kevin O'Leary graduated from Dublin City University (DCU) in 1991 with a first-class degree in Electronic Engineering. After working in computer vision research at DCU, he joined Applied Materials in 1993 and was employed in field service and process engineering positions in Ireland and the U.S. In 1997, he joined the Teltec research centre in DCU as a project manager, coordinating EU-funded telecoms research projects. He moved to Straatum in 2001 as applications engineering manager. He holds one U.S. patent.

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