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Statistical Quality Control Techniques in Semiconductor Manufacturing

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Abstract: Research addresses Statistical Quality Control (SQC) techniques designed specifically for semiconductor manufacturing processes. Packaging, test, and assembly steps normally receive little SQC analysis although proper control is equally important. Steps assigned high defect rates require special attention to offset the effect on product yield. SQC tools directly influence semiconductor production yield, for both internal process yield and wafer-scale yield.
The SQC solutions incorporate process capabilities, control charts, and sampling strategies. Recommended charts and control limits for all critical processing steps are provided by data from a major electronic product manufacturer. Special CUSUM and EWMA charts assess subtle process drifts. Process capability indices for non-normal data address the unique nature of defect counts. Bayesian techniques allow prior information in the analysis of any semiconductor step and posterior updating improves decisions on unknown parameters such as process mean and variance. A full integration with yield and defect analysis quantifies the contribution of control on yield improvement. Further development of statistical techniques is supported as overwhelming volumes of process data made real-time monitoring possible.

Keywords: Data; Tax compliance monitoring; Public revenue systems; Decision support; Policy evaluation; Policy design; Administration arrangements; Policy instruments; Tax gaps; Revenue risk.

I. INTRODUCTION

The semiconductor industry is the backbone of modern society, generating trillions of dollars annually and having an outsized impact on the world economy. As transistors become smaller and smaller and more are manufactured onto each silicon wafer, the cost of making semiconductor devices increases significantly. Statistically-based methods are widely recognized as vital to reducing defect levels and improving yields. Statistical Quality Control (SQC) techniques, in particular, are well-established tools in the manufacturing environment that provide an effective means of reducing costs and improving yields. Unplanned disasters are detected early and corrective actions are taken on a timely basis by monitoring a manufacturing process. The Shewhart control chart, Cumulative Sum Control Chart (CUSUM) and Exponentially Weighted Moving Average (EWMA) control charts are used to detect small changes quickly.

Use of naturally stratified sampling plans or systematic sampling approaches makes it easier to form samples for Wafer-Level Test (WLT). Sampling plans are developed that identify criteria for wafer sampling from production that is representative of the complete lot. Sources of uncertainty that affect measurement results are addressed and procedures described to enable successful calibration of measurement procedures where measurement standards are available. These concepts and techniques have been implemented on appropriate parts of the production process within a semiconductor fabrication facility. Whenever possible, the proposed techniques take into account the natural stratification in the population of interest and also the specific type of measurement uncertainty that might affect the laboratory. The testing facility responsible for the WLT study has been awarded ISO17025 accreditation, ensuring that measurement results are reliable and support the manufacturer's quality claims.

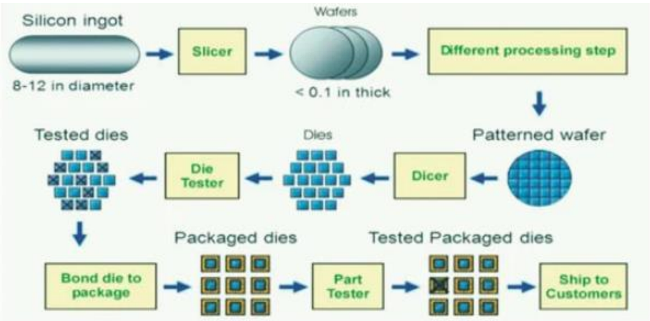

Fig 1: Statistical Quality Control

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1.1. Background and Significance

The semiconductor industry is a fast-evolving, capital-intensive business that manufactures micron- and submicron-scale products for an ever-widening range of applications. Nonzero defect rates are unavoidable because of inherent limitations of the manufacturing equipment and processes. Hence there are always defects present in the products even if the products still pass the final electrical tests. A framework to combine yield analysis with defect analysis has been established. For a given product, the relationships of yield and defect density for each manufacturing process step are modeled. Statistical process control (SPC) techniques are applied to the critical process steps of lithography, etching, and chemical-vapor-deposition (CVD) to achieve a lower defect density.

Defect reduction leads directly to an increase in yield. Yield and defect density are physically related, but the relationship may be complicated by the process and materials used in the semiconductor manufacturing. The relationship established allows the yield analyst to capture the potential change in yield as defect reduction is achieved. It can also be extended to study the correlation of the yield with defect reduction in other manufacturing process steps and facets of the product design beyond the immediate identification. The effects of the changes may be measured posthumously with production data. Quality control that integrates yield and defect analysis will become increasingly important as point defect densities are reduced to a level that allows such integration to take place.

1.2. Research design

Statistical quality control techniques in semiconductor fabrication processes offer great potential to reduce defects, improve yield, and thereby assure better quality on an ever larger wafer scale. A wide variety of industrial production data from different semiconductor process steps are synthesized and examined to establish capabilities, devices, and procedures to implement quality control and quality assurance with quantitative yield improvement. Description of statistical quality control usually starts with the selection of representative samples, the evaluation of measurement uncertainty, and the application of control charts. However, because of the direct correlation between flaws and yield loss in semiconductor production, it is logical first to analyze the main sources of variability and their effect on defect density. Measurements acquired during semiconductor production are also used to undertake process capability studies by incorporating statistical signal processing modified for non-Gaussian defect count data. The analysis is applied to both the short-term and long-term stability of a process from an SPC perspective, and the concepts can easily be extended to other process steps with similar non-Gaussian character. Support for making SPC decisions based on limited data using a Bayesian approach is provided.

Constant correlations should exist between yield and the different semiconductor processes because of the chain nature of adjustments. Once sufficient data have been collected to document these correlations, both the SPC results and the yield correlation structure can be synthesized to provide a global assessment of quality assurance. The result represents a logical extension to quality control. Rather than solely triggering modification of the manufacturing process once specific warning signals are detected, the approach combines the SPC approach with yield analysis and defect studies to quantify yield improvement allocations. The above research aspects form the basis for statistical quality control applications that can be integrated in a semiconductor fabrication environment. The initial focus is on Special-Purpose Production.

II. FUNDAMENTALS OF STATISTICAL QUALITY CONTROL

Control charts are tools for monitoring process capability and process performance by analyzing variable and discrete quality characteristics. Variable characteristics are monitored using Shewhart control charts, while discrete characteristics, such as the number of defects on a wafer, are monitored with Attribute Control Charts. A Cumulative Sum Control Chart (CUSUM) is utilized for detecting small shifts in the process mean, and an Exponentially Weighted Moving Average Control Chart (EWMA) serves the same purpose. Process Capability Indices (Cp and Cpk) are widely employed for determining the capability of critical steps in semiconductor fabrication.

Semiconductor manufacturing involves multiple process steps, from wafer fabrication to wafer test. The yield of a wafer is the percentage of good dice on the wafer after electrical test, and the yield is primarily affected by the number of defects per unit area on the wafer. Four processes—lithography, deposition, etching, and the combinations used in ion implantation or diffusion—are the major contributors to variability. The critical dimensions of the wafer, especially for lithography, must be controlled to avoid a large increase in the number of defects per unit area. Most of the processes' mean and dispersion values are within specification limits, but the specification limits for the critical dimensions of the product are very tight. Hence the Cp and Cpk values of these processes are very close to the specified value.

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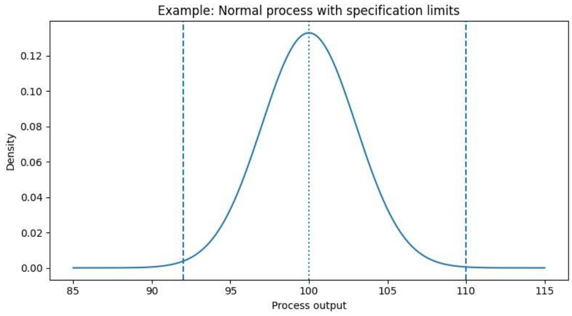

2.1. Overview of control charts

Control charts, introduced by Shewhart in 1931, are widely employed in Semiconductor Manufacturing Quality Control (SMQC). They help monitor random variability affecting both discrete and continuous data. To detect even minor shifts, Cumulative Sum Control (CUSUM) and Exponentially Weighted Moving Average (EWMA) control charts serve as alternatives to Shewhart charts. Satisfactory performance depends on effective construction, including the establishment of control limits.

Statistical quality control (SQC) entails using statistical methods to detect assignable causes of variability in a manufacturing process. This is especially vital in Semiconductor Device fabrication, where small shifts can have grave repercussions on Quality, Reliability, and Performance—potentially resulting in rework and oven testing of devices, expensive yield loss, diminished Reliability, and degraded Product Performance. A variety of SQC techniques—including process capability analysis, sampling plans, and control charts—have been developed to assist engineers in monitoring and controlling process variability. Control charts, originally developed by E. L. Horace P. Hughes and W. Edwards Deming, are employed in practically all Semiconductor Manufacturing Quality Control (SMQC) activities. Essential Quality Control (QC) tasks—monitoring Critical Dimension (CD) capability for lithography, evaluakting quality of deposits from plasma-enhanced chemical vapor deposition and chemical vapor deposition tools, and assessing line width roughness for etching operations—are invariably assisted by Shewhart charts.

Equation 1: Derive probability from log-odds (inverse-logit)
Start with the logit definition

$$\text{logit}(p) = \ln\left(\frac{p}{1-p}\right) = z$$

Exponentiate both sides

$$\frac{p}{1-p} = e^z$$

Solve for p

$$p = e^z(1-p) = e^z - e^z p \; p + e^z p = e^z \; p(1+e^z) = e^z \; p = \frac{e^z}{1+e^z} = \frac{1}{1+e^{-z}}$$

This is exactly what the paper shows.

3B) Odds-ratio interpretation (the “exp(beta)” rule)

Odds are:

$$\text{odds} = \frac{p}{1-p} = e^z$$

If X_i increases by 1, then z increases by β_i, so odds multiply by:

$$\frac{e^{z+\beta_i}}{e^z} = e^{\beta_i}$$

That supports the paper’s “odds change by exp(·)” interpretation.

2.2. Process capability and Cp/Cpk

Specification limits define the boundaries on critical parameters for the process. As the improved process cannot always meet the specification limits, Cp-index measures how well the process can potentially meet the specification limits if

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operating correctly. The Cp-index can be defined as the ratio of the width of the specification limits (understood as the USL—LSL) to the width of the process distribution (understood as 6σ, or the length of the interval, stretching from $\mu - 3\sigma$ to $\mu + 3\sigma$).
Thus,

$$Cp = (USL - LSL)/6\sigma.$$

A value of $Cp \geq 1$ would imply that the process is capable, whereas $Cp < 1$ would imply that the process is not capable for production. In applications, Cp cannot be used directly to conclude the capability conformity, as it does not take shifting and centering of the process distribution into account. This leads to the introduction of Cpk-index, which measures both precision and accuracy, and can be expressed as:

$$Cpk = \min(Cpu, Cpl)\text{ , where}$$

$$Cpu = (USL - \mu)/3\sigma \text{ and}$$

$$Cpl = (\mu - LSL)/3\sigma.$$

Based on the value of Cpk, proper inferences can be made while planning for production. If $Cpk \geq 1$, the process can be considered capable and acceptably centered. If $Cpk < 1$, the process is intolerable. However, if $0 < Cpk < 1$, it indicates that the process is tolerable but needs monitoring to check for possible shift.

III. COMMON VARIABILITY SOURCES IN SEMICONDUCTOR FABRICATION

Lithography, deposition, and etching are primary sources of process variability. In lithography, misalignment and focus contribute to wafer-level variation. A backscattering effect may also lead to CD variation, mainly in one-dimensional CD measurements. CD variation due to stepper optics is often small and can be neglected. Etch control affects CD's critical for junction leakage and performance. Random depth errors in etching or in siliciding affect junction leakage and may induce yield losses.

Random doping variation due to ion-implantation dose and energy may also limit yield. Ion-implantation process capability analysis usually considers four parameters: dose, energy, junction depth, and junction slope. Although the variance of the implant dose is small and often negligible, the variance of the implant energy affects yield and may be non-Gaussian. For shallow junctions encountered in deep-submicron CMOS devices, the implants' Gaussian profiles may be degraded by diffusion in the bank oxide; manual and microwave assistance may be used to improve the profile. Temperature quantum mechanical simulations may also be used to clarify bolometric response speed in biological areas.

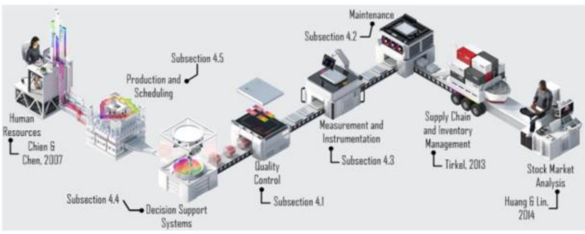

Fig 2: Variability Sources in Semiconductor Fabrication

3.1. Lithography, deposition, and etching processes

Lithography, deposition, and etching processes introduce significant variability into the fabrication process and, by extension, into the quality of the fabricated wafer. Critical dimensions for each of these processes can have a major impact on the final defect count of a wafer, as they are tied directly to pattern fidelity. In lithography, deviations from the design critical dimension can lead to image distortions and the eventual loss of pattern fidelity. In deposition, the layer thickness must be controlled within narrow tolerances to control not only the expected yield but also the defect density. In etching, variations of the critical dimension can allow undesirable photoresist undercutting, resulting in particles on the wafer surface, and can also partially etch the silicon layer, leading to defects as well.

Ion implantation and diffusion are non-occurrence processes that set the dopant profile within the device structure. The major sources of variability in these two steps are dose, energy, and the resulting concentration profile. The dose must not only be controlled for electrical performance but also to ensure that the required thermal budgets are sufficient to

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deactivate the dopants. If the dose is lower than required, there is a risk of incomplete junctions, resulting in an electrical defect, while excessive concentrations may lead to dislocations, degradation of minority carrier lifetimes, and poor latch-up characteristics.

3.2. Ion implantation and diffusion

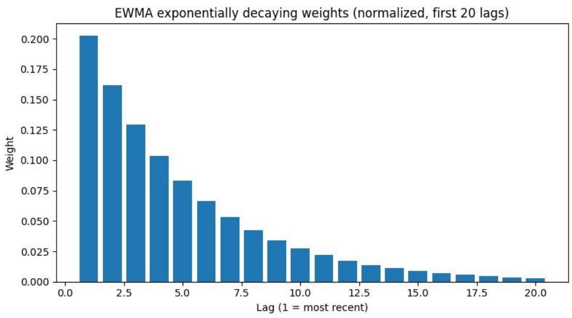
Variability in ion implantation and diffusion steps also has considerable influence on yield. For implanted layers, variability in the continuum parameters—the incorporated dose, energy and ion concentration profile—degrades the features of some devices directly: for example, short-channel MOSFETs with insufficient or poorly-doped drains, or TE-TI diodes suffering from depletion enrichment of the base region. Such features occur with non-negligible probability even when the parameters are inside the manufacturing limits, and their impact on yield depends on how critical the devices are for production. A first measure for this impact can be established by examining the behaviour of a simple function, F, with respect to the net dose and energy—ND and NE, respectively—assumed as continuum variables, recognising that the probability of operation within specification is given by P (F(ND, NE) > 0) and that, generally, the normal approximation to the binary distribution offers a good fit. Nevertheless, such an approximation cannot be used carelessly, because it requires that F(ND, NE) does not assume extreme values with any probability. The above formulation neglects any dependence of F on the other continuum parameters and any dependence not captured by normal approximation.

The role of drift, in terms of the process of displaced inversion, can also be expressed similarly using a function (E) that varies with time t and quantity D—the range of the diffused dopant—such that P (E(t) < 0) is an indication of deterioration of the structure. The same concept holds for other types of drift also, although in practice such drift might vary much more rapidly than that caused by diffusion and bipolar devices may end up being in-asymmetric joint conditions before the diffused layers are completed.

IV. DATA ACQUISITION AND MEASUREMENT SYSTEMS

Data for statistical quality control applications may be obtained from sampling plans or other data-acquisition systems. These plans may be stratified, selecting representative wares from the lots being processed in a given tool, or systematic plans, selecting and pooling data from lots and/or stages being processed in a given tool. The key is to select measurement data for quality-control purposes that are representative. Another important consideration is the measurement uncertainty of the sampled measurements. Potential sources of measurement uncertainty should be identified, and, if needed, measurement systems should be calibrated to minimize these sources of uncertainty. Wherever possible, some measure of the measurement uncertainty associated with the sampled measurement data should be included in the quality-control analysis. Measurement data that are traceable to standards can have characteristics similar to data from integrated devices and provide the capability of assessing potential process changes before they occur.

Measurement systems are subject to systematic error (bias), random error, loss of sensitivity for detecting defects, or other problems that may not appear in the measurement uncertainty evaluation and that can significantly affect the quality-control analysis. The measurement systems used in QC applications should be checked regularly or before each application, with the results being included in the quality-control analysis. Various types of checks are possible, including regular calibration to minimize systematic error, independent confirmation to detect loss of sensitivity, periodic comparison of the measurement result with those of other measurement systems to identify systematic differences.



4.1. Sampling strategies and sample size determination

Statistical quality control (SQC) methods applied during the fabrication of ICs require analysis of a large number of measured variables. For practical reasons, it is seldom possible to monitor all these variables on a complete wafer set.

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Sampling plans are thus required. The simplest type of sampling plan is random sampling to obtain a small number of wafers from every lot, assuming that each wafer is a representative sample of the entire lot. Stratified random sampling divides the population of wafers into different strata and, if feasible, a random sample of wafers is drawn from each stratum, ensuring that the set of wafers used for the analysis is representative.

Other ways to ensure representative sampling of the population of openings on a wafer is through systematic sampling or sampling in unequal proportions. If different levels of representativeness are assigned to different features, systematic sampling can be performed by simply picking every kth opening in a row or column or by implenting the method on the 2D plane. For example, if wafers are to be sampled from a population of panels built in production and measured in a laboratory and if the process into which the final products enter has severe consequences on the remaining production, then it might be prudent to sample more wafers from that population. There are usually sources of uncertainty in measurements. These undesirable effects can come from calibration, measuring devices or environments, transport, storage and many others. Quantifying this uncertainty is necessary when using data-experimentally derived to make decisions.

To obtain data originating from high-quality measurements, calibration should adhere to the ISO guidelines for its respective type. All calibration subtasks must be properly documented and when possible they should be managed using a dedicated tooling. Traceability of quality-related measurements to traceable international standards should be preserved. This should be followed throughout the entire life cycle of the calibration standard or calibration equipment.

4.2. Measurement uncertainty and calibration Quantifying the uncertainty of measurements is essential for drawing reliable conclusions from quality control studies. Sources of uncertainty include the measurement procedure itself, the precision of the measuring devices, environmental conditions, the influence of other variables, and so forth. In order to achieve comparable measurements and reduce uncertainty, it is necessary to select well-established protocols, calibrate the measurement systems regularly, and establish a procedure for tracking the origin of each measuring device.
In semiconductor fabrication, measuring resources are seldom used independently. A common practice is to send the measurement results to a measurement uncertainty database. When the measurement result enters the quality control stage, the uncertainty analysis load can be very light. The main tasks include reviewing the measurement uncertainty database and confirming the uncertainty linked to those resources that are unique to the current quality control task. At this stage it may become apparent that a measurement is indeed very important and that a new measurement without the current limitations would be helpful, even if the new measurement carried a larger measurement uncertainty.
The credibility of a measurement is ensured if traceability is established. The measurement results must therefore contain information on who did the measurement, when it was done, the conditions under which it was done, how it was done, its uncertainty, how the measurement uncertainty result is calculated, and when and how the measuring device(s) was (were) last calibrated and/or checked.

Equation 2: EWMA recursion and exponentially decaying weights

Given data X_t, smoothing parameter $\lambda \in (0,1)$, initialize Z_0 (paper notes common initialization choices).
Recursive update:

$$Z_t = \lambda X_t + (1-\lambda) Z_{t-1}$$

Substitute Z_{t-1}:

$$Z_t = \lambda X_t + (1-\lambda)(\lambda X_{t-1} + (1-\lambda) Z_{t-2}) \ Z_t = \lambda X_t + \lambda(1-\lambda) X_{t-1} + (1-\lambda)^2 Z_{t-2}$$

Repeat expansion:

$$Z_t = \lambda X_t + \lambda(1-\lambda) X_{t-1} + \lambda(1-\lambda)^2 X_{t-2} + \cdots$$

So the weight on X_{t-k} is:

$$\lambda(1-\lambda)^k$$

which is geometric decay, matching the paper's statement.

The paper references the standard form with an in-control stdev and a multiplier $k \approx 3$.
A common textbook expression is:

$$UCL_t = \mu_0 + k\,\sigma\sqrt{\frac{\lambda}{2-\lambda}(1-(1-\lambda)^{2t})} \ LCL_t = \mu_0 - k\,\sigma\sqrt{\frac{\lambda}{2-\lambda}(1-(1-\lambda)^{2t})}$$

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V. CONTROL CHART APPLICATIONS IN SEMICONDUCTOR MANUFACTURING

Control charts monitor process stability and performance. They are one-dimensional graphical representations of data sequences plotted sequentially over time against control limits. Three very popular control charts are Shewhart, Cumulative SUM (CUSUM), and Exponentially Weighted Moving Average (EWMA). Shewhart controls monitor sudden shifts in the process and are based on the assumption that quality characteristics fluctuate in a random way about a constant mean. CUSUM and EWMA control charts are used to detect small shifts from the target, enabling identification of deviations from the ideal manufacturing condition at the earliest possible moment. CUSUM seeks to detect shifts by summarizing past observations, while the EWMA control chart accomplishes a similar purpose by attaching varying weights to past observations. Control charts are implemented in quality-control systems that automate decision making and thus minimize reliance on human judgment.

In semiconductor manufacturing, critical fabrication steps, such as lithography, etching, and deposition, are monitored using Shewhart control charts. A capability index is calculated based on the last four completed production lots, and the process is considered stable when the index for the last lot satisfies specific criteria. Out-of-control signals are investigated and corrective measures implemented. CUSUM and EWMA control charts are applied to monitor drift in critical fabrication steps. Designers of these control systems must consider the expected number of false alarms per lot, the detection performance required by manufacturing, and the resources available to respond to alarms. Ultimately, these control schemes enhance defect control in the semiconductor manufacturing environment.

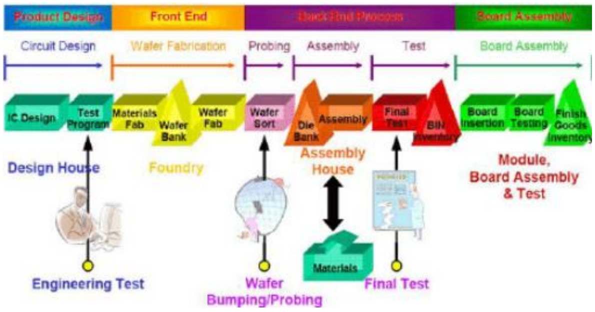

Fig 3: Overview of semiconductor manufacturing processes

5.1. Shewhart control charts for critical process steps Shewhart charts are detailed for use in critical technology steps. Shewhart limits are generated from statistical analysis of in-house historical data. Possible special causes, indicated when data exceed control limits, require immediate investigation and corrective measures. As such signals may arise due to sporadic events, decisions for such cases have also been formulated for the process steps of lithography exposures and etchings.

Lithography exposure is among the most critical steps in a state-of-the-art semiconductor fabrication process, especially for advanced nodes. Using about 1676 lots of mask–layer data over a period of seven years, a Shewhart chart has been constructed around the critical dimension of the photolithographic layer. The company-performance requirements dictate a three-sigma limit based on the Shewhart chart, with the upper and lower control limits set at ± 3 sigma from the center line. In-house company protocols prescribed by the applied-data division have been utilized for deciding on out-of-control conditions. For any out-of-control data point, a special cause must be established. If confirmed, the layer–mask pattern condition is relaxed, and the exposure is repeated (on the same wafer). If the cause is not special, a review of the entire set of wafers is undertaken.

5.2. Cumulative sum and exponentially weighted moving average charts

Cumulative sum (CUSUM) and exponentially weighted moving average (EWMA) charts extend process monitoring capabilities in fabrication steps where small shifts warrant sensitivity beyond that of Shewhart charts. CUSUM charts signal small deviations by evaluating sequential data point differences with respect to a specific target. Positive and negative CUSUMs are considered separately according to the step limits. Unlike Shewhart charts, these estimates are not independent and have memory properties. Control decision-making requires a minimum CUSUM resetting rate; CUSUMs are reset post-investigation or cause correction. Control action timing considers residual drift items and control cost.

EWMA charts, as rolling averages, provide apparent smoothing while retaining memory, placing greater weight on recent observations. The smoothing factor governs the time-to-detection speed–sensitivity trade-off, with low values requiring longer time to detection. Generally, CUSUM charts are sensitive to abrupt shifts, while EWMA is better for gradual drifts

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into the neighbouring error zone; hence analysis priority should be assigned. Only those process steps supported by a comprehensive SPC framework should have drift detection systems incorporated; inappropriate monitoring incurs unmanageable reaction overheads.

VI. PROCESS CAPABILITY ASSESSMENT AND OPTIMIZATION

Samples taken from semiconductor processes vary from cycle to cycle. Consequently, it is crucial to determine if a process has met requirements for a specific lot (short-term capability) and is capable of meeting requirements over a period of time (long-term capability). Both the Cp and Cpk indices for the critical dimensional processes (lithography, etching, and deposition) need to be evaluated, since the performance of these processes has a first-order effect on the defect density (and hence the yield) of the devices. The defect distribution is non-Gaussian; therefore, the capability indices must be modified accordingly and adapted to defect counts.

Short-term capability considers variation over a small number of production cycles (e.g. a lot), while long-term capability considers stability over larger time frames, for example process drift due to tool wear and aging. Use of Shewhart control charts for the critical steps, along with a knowledge of tool aging and stability of the upstream nodes, should assist in understanding long-term process capability for yield.

Equation 3: Shewhart "3-sigma" control limits
Step-by-step derivation
Given observations $x_1, \dots, x_n$.
Step 1: Estimate process mean

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

Step 2: Estimate process standard deviation (one common estimator)

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

Step 3: Apply 3-sigma rule
Center line:

$$CL = \bar{x}$$

Upper control limit:

$$UCL = \bar{x} + 3s$$

Lower control limit:

$$LCL = \bar{x} - 3s$$

6.1. Capability indices for non-normal distributions

For non-normal data distributions, the general approach is to use a transformation to attain normality or to approximate a specific non-normal distribution. There are also capability indices specifically tailored to non-normal distributions. Since many of the nonconformances recorded in semiconductor processes are counts of defects or failed devices and the underlying distribution is often Poisson, it is possible to outline a non-negative capacity index based on the Poisson distribution.

When nonconformances are counted and the counts are designated as Y, then Y ~ Poisson(μ). The capability index for a Poisson count model is defined as Cλ = λ assuming that the upper spec limit is infinite, the index is defined as C+ = λ. For a kill ratio, E(Y) K , the index is Ck = K λ . If the kill ratio with upper and lower specification limits is given by E(Y) K − λ , the index is Ck = K − λ . However, care is needed when applying these indices since the Poisson distribution is of diminishing variance.

Unfortunately, the distributions of Cp and Cpk for the short-term case are generally not known because, for most defect processes, a Wang-type approximation involves a non-central Chi-square distribution. Nevertheless, because it can be shown that the Y process is a martingale for the short-term case, it is possible to form estimates of Cp and Cpk that are consistent and asymptotically have an approx Chi-square distribution.

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Capability indices are also available for short-term and long-term SPC. The main difference in the models is the use of drift terms in the latter case. Long-term and short-term capability indices are not the same. The process capability during long-term variations might differ from the short-term stability shown during lot-to-lot variations. A decrease in capability during long-term variations might be due to the aging of equipment or drifts in the environment or in the materials during periods of time.

6.2. Short-term versus long-term capability

A discussion of capability indices in the previous section focused on the standard situation where the underlying distribution of a quantity of interest approaches a normal distribution. Existing literature also addresses the case of explicitly non-normal data using alternative capability indices based on percentiles, with Cp and Cpk adapted for non-Gaussian distributions suitable for defect counts.
Most capability indices consider a single process setting. However, semiconductor production is subject to variability arising from differing lot compositions, gradual changes of sensor readings detected only by powerful methods, and tool aging. In an optimal process, these effects should be small enough for only the short-term capability of critical steps to matter. Increasingly variable long-term performance will express itself through diminished long-term capability, becoming evident in Cp and Cpk ratios trending below one across production lots rather than individual steps. Further decay should be detectable by tracking changes of the product of Cp ratios between correlated process steps using a bagplot on an appropriate multidimensional kernel. Such formulations thus yield a process alerting in a successive panel-correlation fashion, supporting deeper monitoring of critical joint process settings. A new form of the capability indices can provide estimates of non-normal distributions. These indices use a kernel approach to providing non-parametric probability density functions and are applicable to others detection counts.

VII. ADVANCED ANALYTICAL TOOLS AND TECHNIQUES

Bayesian statistics offers a method for estimating distribution parameters when only limited amounts of data are available. Many decision-support and control techniques require the specification of a probability distribution for the quantity of interest, and a Bayesian procedure enables this specification even when limited actual measurements exist. The basic idea is simple: if some process was measured many times in the past, Bayesian methods can result in a prior distribution that takes into account this prior information. In particular, if previous measurements indicate that a certain parameter can be modeled by a normal distribution, then a Bayesian approach will allow someone to make a decision with a distribution that is weighted by the observations of that parameter. Rather than relying on one’s personal judgment alone, the decision is statistically measured with probabilities. After one’s process has accumulated many measurements, the Bayesian method can and should be dropped in favor of the classical statistical testing approach.

Several important advances have taken place in the area of statistical quality control, especially in describing the capability of processes. The capability indices Cp and Cpk are widely used to provide estimates of the actual performance of a manufacturing process. Cp is defined for a process that is assumed to be stable and in control. A typical semiconducting manufacturing process, however, is not stable. The process capability may vary from lot to lot because of aging of the tools, equipment, materials, operator, or other reasons. Short-term capability studies using techniques such as Cumulative Sum (CUSUM) and Exponentially Weighted Moving Average (EWMA) provide estimates of the capability of the process in the short-term.

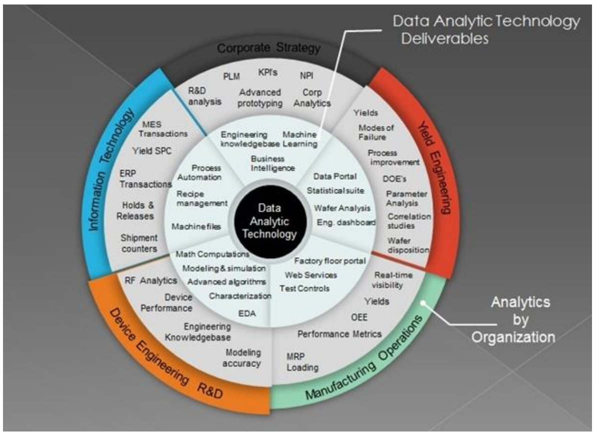

Fig 4: Advanced Data Analytics in Semiconductor Manufacturing

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7.1. Bayesian methods in quality control
Incorporating prior information, Bayesian methods allow one to update the information with data. It is possible to introduce a decision rule that minimizes the risk function. An SPC scheme can be set up that incorporates posterior probabilities derived from the binomial or Poisson distributions. These methods have found favor wherever prior information about failure rates can be reasonably established and where problems with high costs, low frequencies, and long cycle times have occurred.
The methods of Bayesian statistics can be profitably utilized whenever prior information is available, wherever there is a significant amount of data collected. The Bayesian mentality recognizes that the world is in constant change; it therefore insists upon a willingness to constantly update. A Bayesian SPC scheme permits the incorporation of all such evolving information into a coherent risk minimization decision rule. The Bayesian decision rule can rapidly assimilate SPC observations on extremely small samples and dynamically change the SPC setting depending on the accumulating in control or out"of"control observations. Data can also be integrated from company-specific databases to yield ever more reliable SPC information.

7.2. Statistical process control for yield and defect analysis
Statistical process control can be extended beyond straightforward monitoring to other applications where probability models of variables are either known or can be obtained. One of these situations concerns the monitoring of wafer probed in an integrated circuit (IC), particularly information gathered from the test probe wafer and other known posterior distributions of the total number of failure and yield for a lot of wafers. Commonly, the identification of failure ICs has high cost in time and expenses. The strategies to take decisions related defects detection are more complex, particularly when hidden failure are developed in the field. Bayesian methodology can be used for give more robust control charts and allow the users take better decisions. This enrich the space of prior distributions of these total-defect-yield variables, such information could then be readily incorporated into a Bayesian prior.
Layer by layer yield structural modeling can establish the correlation between process steps of yield and defects in the IC. The decision trees obtained from the structural model can relate process step variations with defect density and subsequently device yield. The correlation among input and output for the wafer measured in the last test can guide users to monitor and anticipate the worst condition of the production. These decisions allow anticipate the probability and part of the cost associated for Fermi Alert or Bare Panel problem, furthermore by analyzing the monitoring wave the users could monitor the long-term process.

VIII. CONCLUSION

The trends in quality control at semiconductor fabrication facilities point toward tighter and more efficient integration of information and knowledge across the different process steps. Quality assessment will become more extensive and tighter through greater implementation of process-sensitive sampling and the measurement of variables that affect production and yield. Early detection of abrupt shift and gradual drift will be practiced in a more adaptive manner that exploits knowledge of the process. Mechanistic explanations of the fabrication processes will be integrated with quality control schemes and statistical models. Model consistency checks will be used to identify crucial steps that deserve special attention. The new concept of capability will be applied to accommodate non-normal data. The capability of semiconductor manufacturing processes will be assessed on both short-term and long-term bases. Bayesian procedures will help to incorporate prior information and develop more effective decision rules. Yield analysis and automatic-quality-control decisions will be more closely translated.
Cheung et al. demonstrated how combining Statistical Process Control with yield analysis, using yield as a quality characteristic, can considerably enhance the decision-making capability of quality control systems. Links between stages can determine involvement in the overall yield and should be reflected in concentrated gauging. Such approaches can be expected to result in important advancement in high-volume production fabrication processes. Developments in the detection of shameful performance should reduce the number of unplausibly good lots. As known by those who have worked in these fab environments, the nature of defects, their creation and their effect on the circuit yield should reveal the true impact of the quality-control capabilities over time.

8.1. Future Trends
Future trends in Statistical Quality Control (SQC) decision-making processes in semiconductor manufacturing reside both in datacenter and in Fab processes to monitor yield and quality of products. Data integration between different departments such as yield, process, and operation should be further enhanced for better quality monitoring. With advanced services and capability of ML and AI computation, decision support solution will also be enhanced to perform real-time quality management and monitor products for quality assurance. AI methods will provide intelligent inference mechanism based upon historical results.

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Anticipated capacity and yield improvement will rely on process monitoring and controlling. Similar to SQC approaches, development of data monitoring and analysis framework will provide information by learning from processes instead of yield follow-up using historical data only. Process configuration will be adjusted according to high potential risks induced by quality-monitoring of critical quality indicators monitoring.

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