# Integrated applications of inspection data in the semiconductor manufacturing environment

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## ABSTRACT

As integrated circuit fabrication processes continue to increase in complexity, it has been determined that data collection, retention, and retrieval rates will continue to increase at an alarming rate. At future technology nodes, the time required to source manufacturing problems must at least remain constant to maintain anticipated productivity as suggested in the International Technology Roadmap for Semiconductors (ITRS). Strategies and software methods for integrated yield management have been identified as critical for maintaining this productivity. Integrated yield management must use circuit design, visible defect, parametric, and functional test data to recognize process trends and excursions so that yield-detracting mechanisms can be rapidly identified and corrected. This will require the intelligent merging of the various data sources that are collected and maintained throughout the fabrication environment. The availability of multiple data sources and the evolution of automated analysis techniques are providing mechanisms to convert basic defect, parametric, and electrical data into useful prediction and control information. Oak Ridge National Laboratory and International SEMATECH have been working to develop new strategies and capabilities in integrated yield management based on technologies such as Automatic Defect Classification (ADC), Spatial Signature Analysis (SSA), and Automated Image Retrieval (AIR). In this paper we will discuss a survey of these image-based technologies and their application to the ITRS issues that are driving the need for integration and data reduction.

**Keywords:** semiconductor manufacturing, integrated yield management, automatic defect classification, spatial signature analysis, content-based image retrieval

## 1. INTRODUCTION

Semiconductor manufacturers invest billions of dollars in process equipment, and they are interested in obtaining as rapid a return on their investment as can be achieved. Rapid yield learning is thus becoming an increasingly important source of competitive advantage in the complex environment of semiconductor device fabrication. The sooner an integrated circuit device yields, the sooner the manufacturer can generate a revenue stream. Conversely, rapid identification of the source of yield loss can restore a revenue stream and prevent the destruction of material in process [1]. The 1999 International Technology Roadmap for Semiconductors (ITRS) states that: *in the face of this increased complexity, strategies and software methods for integrated yield management (IYM) have been identified as critical for maintaining productivity* [2]. Figure 1 represents this statement as a function of two critical parameters that are highlighted in the ITRS: *critical particle size*, and *defect sourcing complexity*. Critical particle size refers to the minimum size of

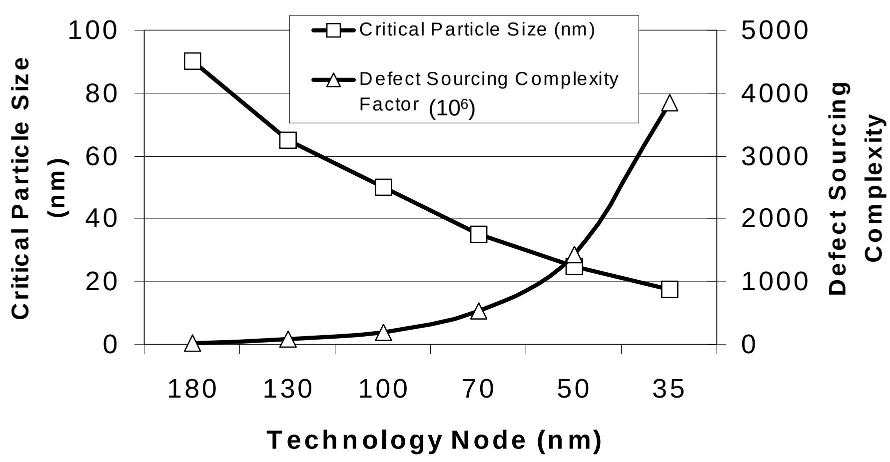


**Figure 1 – Graphical representation of the "needle in the haystack" regarding the detection of small defects on complex semiconductor devices.**

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particles that can cause electrical faults in an integrated circuit, whereas the complexity factor is the product of the number of transistors in a micro-processor by the number of process steps required to manufacture the device. These two parameters work against each other as manufacturers strive to meet future productivity goals in the industry. The challenge has been described as looking for a "needle in a haystack" [3].

Figure 2 demonstrates the current financial impact of the need to develop higher accuracy metrology capabilities and to reduce metrology information rapidly for the purpose of making accurate assessments and predictions of the causes of yield loss. Revenue spending for test and metrology (the bulk of which is wafer inspection) approached $10B in 2000 and is projected to increase. This corresponds to an increase in defect inspection expenditures for equipment, software, and support from around 1% of revenues in the early 1990's to over 3% in 2000. The issues driving these trends are the direct result of decreasing line widths (and therefore increased sensitivity to smaller particles), increasing device complexities, and increasing wafer dimensions.

To address these complex manufacturing issues, the Image Science and Machine Vision (ISMV) Group of the Oak Ridge National Laboratory (ORNL), and the Yield Management Tools (YMT) Program of International SEMATECH (ISMT) have been developing new technologies for automating the analysis of defects found in semiconductors. In this paper we will survey our work in this area over the past decade covering the topics of Automatic Defect Classification (ADC), Spatial Signature Analysis (SSA), Automated Image Retrieval (AIR), and the integration of these methods in the manufacturing environment, both as independent methods and in support of each other in the process of data reduction and yield learning.

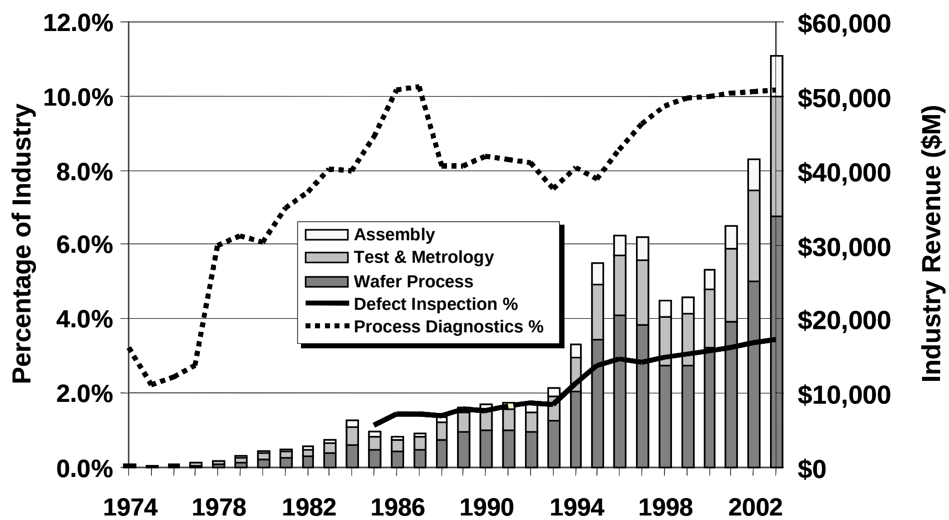


**Figure 2 – Semiconductor industry expenditures of revenues for various components of manufacturing. Note the increase in spending on test and metrology and in particular, defect inspection.**

## 2. YIELD MANAGEMENT

Semiconductor device yield can be defined as the ratio of functioning chips shipped versus the total number of chips manufactured. Yield management can be defined as the management and analysis of data and information from semiconductor process and inspection equipment for the purpose of rapid yield learning coupled with the identification and isolation of the sources of yield loss. The worldwide semiconductor market experienced chip sales of $144 billion in 1999 increasing to $234 billion in 2002 [4]. Small improvements in semiconductor device yield of tenths of a percent can save the industry hundreds of millions of dollars annually in lost products, product re-work, energy consumption, and by the reduction of waste streams.

It is in the area of yield management that ORNL and ISMT have been developing technologies that are impacting the manufacturers ability to rapidly isolate yield loss mechanisms and learn about yield issues for predictive and management purposes. Figure 3 depicts a simplified fabrication flow diagram. This diagram of production (including front-end and back-end processing), data management, and yield analysis, in Fig. 3a-d respectively, encapsulates the major components of the manufacturing environment where process and product data are generated, maintained, and accessed for yield management.

For our discussion we will focus on data that is generated from the wafer product itself, i.e., as opposed to process information such as tool condition data, temperature, pressure, etc. Figure 3a and 3b shows the process area in the fab where bare wafers enter the process, are printed and tested in-line, producing integrated circuits ready for packaging and sale. Metrology and defect data that are generated from the wafer are maintained in a variety of databases within the data management system (DMS). Wafer defect, parametric, and electrical measurement data are typically maintained in a small group of databases (DBs) that are accessed as a virtual repository to facilitate data correlation between what is sensed on the wafer in terms of defectivity (e.g., optical or laser scanned images), parametric data (e.g., line widths and film thickness), electrical function (e.g., binmap and bitmap), and device yield. This data is accessed and analyzed by the failure analysis laboratory during off-line review and by the yield management team - i.e., engineers whose job is to improve current and future yield through yield learning and process improvement. During failure analysis, the wafer can undergo additional physical testing off-line to gain a better understanding of pattern, particle, or parametric fault mechanisms by high-resolution optical imaging, scanning electron microscopy (SEM), focused ion beam (FIB) cross-section analysis, atomic force microscopy (AFM), etc. (Fig. 3d). This image-based information augments the product-based DB therefore providing a historical record for current and future learning and yield prediction. It is the accumulation and manipulation of this in-line and off-line image data that is the basis for our work in yield management automation and the subject of the remainder of this paper. Further discussion of the semiconductor fabrication DMS architecture, function, and future needs can be found in references [5, 6].

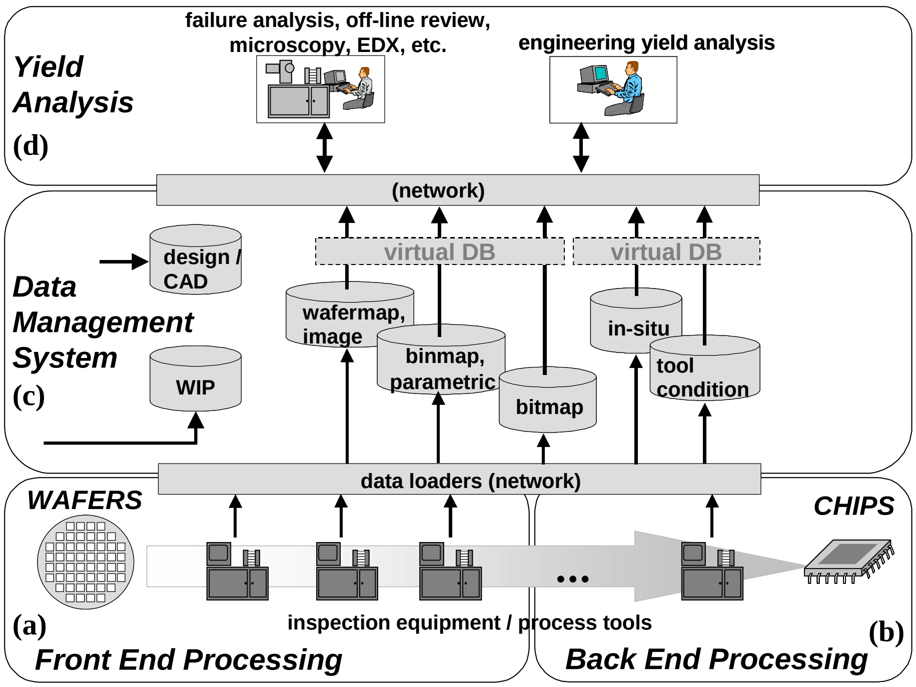


**Figure 3 – Stylized representation of the three major components of the semiconductor fabrication environment: (a) and (b) front-end and back-end processing, (c) data management, and (d) yield analysis.**

## 3. WAFER DATA ANALYSIS AUTOMATION

It has been estimated that up to 80% of yield loss in the mature production of high volume integrated circuits can be attributed to visually detectable random, process-induced defects (PIDs) such as particulates in process equipment [7, 8]. Yield learning can therefore be closely associated with the process of defect detection and reduction. In this section we will review our work in the automatic analysis of defect image data from in-line inspection and off-line review spanning the topics of ADC for individual defect classification, SSA for the classification of populations of defects, and AIR for the management of very large image repositories. Fig. 4 gives an example of the level of information reduction that is to be achieved in yield management through automation. This flow diagram is based on ITRS specifications for inspection equipment at the current technology node (i.e., 180 nm features) and

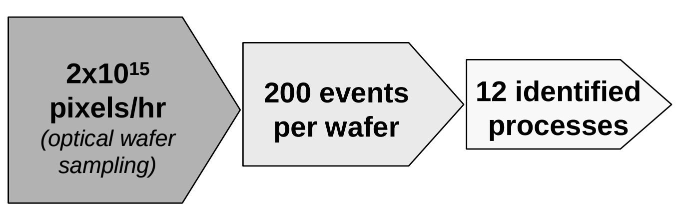


**Figure 4 – Typical information reduction target based on ITRS specifications for yield learning.**

200 mm diameter wafers at 150 wafers per hour per tool. In essence, the need is to reduce on the order of $10^{15}$ data samples per hour to around one dozen potential process sources. ADC, SSA, and AIR provide automation capabilities that support this goal.

## 1. Automatic Defect Classification

ADC was initially developed in the early '90s to automate the manual classification of defects during off-line optical microscopy review [9, 10, 11]. Since this time, ADC technologies have been extended to include optical in-line defect analysis and SEM off-line review [12]. For in-line ADC, a defect may be classified "on-the-fly", i.e., during the initial wafer scan of the inspection tool, or during a re-visit of the defect after the initial wafer scan, usually at higher resolution. During in-line detection the defect is segmented from the image using a die-to-die comparison or a method as shown in Fig. 5 [13, 8]. This figure shows an approach to defect detection based on a serpentine scan of the wafer using a die-to-die comparison; first showing A compared to B, B compared to C, etc., ultimately building a map of the entire wafer as shown in Fig. 5c. This electronic wafermap forms the primary data record that is maintained in the DMS and provides defect information for off-line review and spatial analysis. During off-line review the defect is re-detected using the specified electronic wafermap coordinates and die-to-die methods. The classification decision derived from the ADC process is maintained in the electronic wafermap for the wafer under test and will be used to assist in the rapid sourcing of yield impacting events and for predicting device yield through correlation with binmap and bitmap data if available.

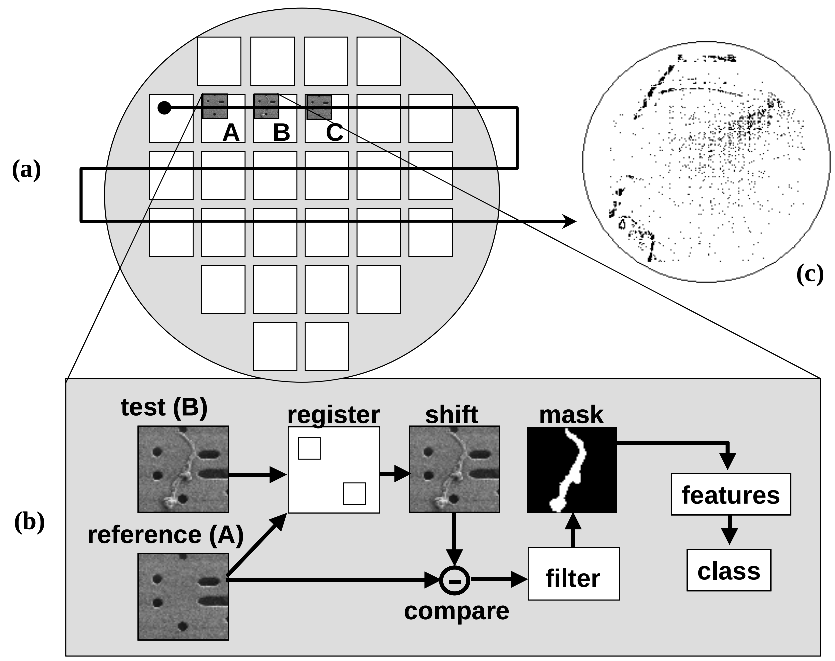


**Figure 5 – Schematic representation of the typical serpentine defect scanning process in (a) resulting in the detection of defects (b), and ultimately in the generation of the wafermap in (c), an electronic record of wafer defectivity that is maintained in the DMS.**

In semiconductor applications, the methods used for classifying defects vary greatly, although they are primarily feature-based. There are two broad categories of classifier in use: rule-based classifiers with a fixed number of pre-defined classes (pre-defined by the system developer), and trainable classifiers that are trained in the field by the end-user. Fixed-class systems have come into popularity for in-line applications since the resolution of these systems is generally less than off-line review microscopes. The reduced sensitivity of the in-line systems results in simple classification schemes that classify defects, for example, by size or brightness. There is no user training of a fixed-class system. The result is ease-of-use. The down side of this approach is that the system cannot easily be trained to accommodate new defect classes that are manufacturer-specific. A trainable system (e.g., based on distance-based classifiers such k-nearest neighbor or neural networks) can accommodate the wide range of defect types associated with different inspection points in the process, various process layers, or products, but can be cumbersome to train and maintain. The concept of having a classifier system that is ready to use has prompted the extension of the fixed-classifier concept to some off-line review systems but the lack of classification flexibility is considered to be an undesirable limitation by yield engineers. Ultimately there will likely be a fusion of these two approaches that allows the yield engineer to use the system immediately to classify basic categories of defects, while fine-tuning these categories through a training process over time [14].

## 2. Spatial Signature Analysis

A spatial signature is defined as a unique distribution of wafer defects originating from a single manufacturing problem [15]. The analysis of spatial patterns of defects across whole wafers can be described as a means to facilitate yield prediction in the presence of systematic effects. We have developed an automated whole-wafer analysis technique called SSA to address the need to intelligently group, or cluster, wafermap defects together into spatial signatures that can be uniquely assigned to specific manufacturing processes and tools [16, 17, 18]. This method results in the rapid resolution of systematic problems by assigning a label to a unique distribution; i.e., signature, of defects that encapsulate historical experience with processes and equipment. Standard practice in the industry has been to apply proximity clustering to defects that results in a single event being represented as many unrelated clusters. SSA performs data reduction by clustering defects together into extended spatial groups and assigning a classification label to the group that reflects a possible manufacturing source. Figure 6 shows examples of clustered and distributed defect distributions that are isolated by the SSA technique for both randomly occurring defect patterns and systematic patterns. SSA technology has also been extended to analyze electrical test binmap data (i.e., functional test and sort) to recognize process-dependent patterns that result from visible and non-visible (e.g., parametric) problems on the wafer [19].

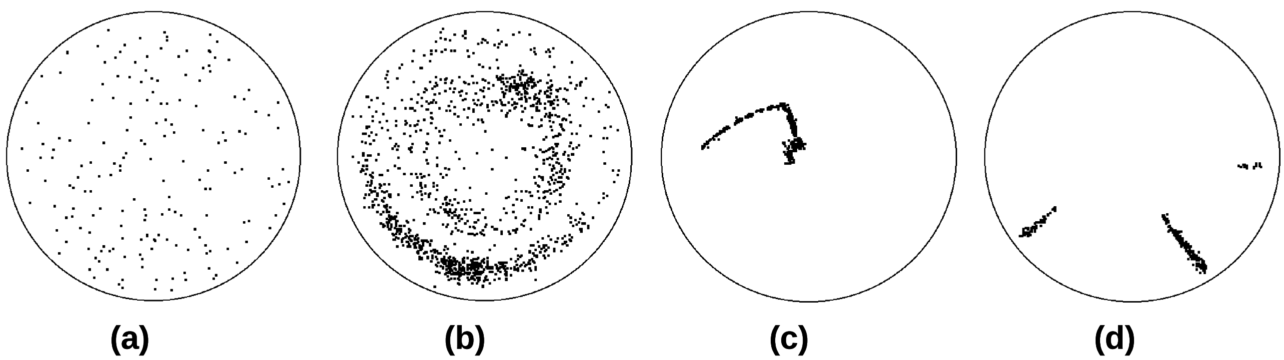


**Figure 6 – Examples of spatial signatures isolated by the ORNL SSA technology. In (a) a random population of defects, in (b) a systematic (non-random), non-clustered distribution, in (c) a complex scratch, and in (d) a spin coater streak pattern. SSA classifies each of these distinct patterns even when they overlap on a single wafermap.**

SSA is a feature-based system built upon a fuzzy k-Nearest Neighbor (k-NN) classifier [20]. In the manufacturing environment, electronic wafermap data is collected from in-line inspection tools and defect signatures are segmented for analysis. For semiconductor inspection, a signature object is defined as a unique pattern of individual optical defects or electrical bin codes that were generated by an errant process. Approximately 30 features are extracted from the segmented object and are sent to the classifier where a class label is assigned to the result based on user training. The user-defined class result then indicates the specific tool or process that must be corrected [21], e.g., the "spin coater streak" in Fig. 6d.

For industrial pattern recognition problems non-parametric classifiers such as the classical k-NN [22] apply well since information about the shape of the distribution of features in the multi-dimensional space of the classifier is not required. It is difficult to ascertain a statistical parameterization for the large variety of class types encountered. Also, in an industrial setting it is often required that the classifier system begins to classify new data with few training examples while providing reasonable accuracy. Bayesian classifiers [23] and neural networks [24] generally require large sample populations to estimate the appropriate statistics and are therefore difficult to implement in general for industrial applications. This is primarily due to the diverse nature of the patterns that arise for different manufacturing processes and facilities, coupled with the length of time required collecting large sample populations. Also, over the period of time required to collect large sample sets, acceptable process variations can occur that confuse the boundaries between classes. The fuzzy k-NN classifier training set can readily be maintained over time (e.g., by including and excluding examples based on time and date), can be modified often, and can operate with relatively few examples for each class.

## 3. Automated Image Retrieval

The ability to manage large image databases has been a topic of growing research in many fields. Imagery is being generated and maintained for a large variety of applications including remote sensing, architectural and engineering design, geographic information systems, and weather forecasting. Content-based image retrieval (CBIR) is a technology that is being developed to address these needs [25]. CBIR refers to techniques used to index and retrieve images from databases based on their pictorial content. Pictorial content is typically defined by a set of features extracted from an image that describe the color, texture and/or shape of the entire image or of specific image regions. This feature description is used in CBIR to index a database through various means such as distance-based techniques, approximate nearest-neighbor searching, rule-based decision-making, and fuzzy inferencing [25, 26].

CBIR addresses a problem created by the growing proliferation of automated defect review and ADC technologies; i.e., the management and reuse of the large amounts of image data collected during review. For semiconductor yield management applications we have denoted CBIR technology as AIR [27, 28]. Digital imagery for failure analysis is generated between process steps from optical microscopy and laser scattering systems and from optical, confocal, SEM, AFM, and FIB imaging modalities. This data is maintained in a DMS and used by fabrication engineers to diagnose and isolate manufacturing problems. The semiconductor industry currently has no direct means of searching the DMS using image-based queries, even though many thousands of images are collected on a weekly basis [29]. Current abilities to query the fabrication process are based primarily on product ID, lot number, wafer ID, time/date, process layer, engineer classification, or ADC class, etc. Although this approach can be useful, it limits the user's ability to quickly locate historical examples of visually similar imagery, especially for data that was placed in the database over one or two weeks prior. Data much older than this is nearly irretrievable since retrieval is dependent on human memory and experience. Without the addition of datamining capabilities such as AIR, this large image repository will remain virtually untapped as a resource for rapidly resolving manufacturing problems.

For AIR to be practical and useful in the yield management environment, the image data must be associated with the process conditions that caused the defect image to be generated by the review tool. The AIR system maintains this information in a relational database as shown in Fig. 7. The relational database manages standard wafermap information that is typically found in the wafermap file generated by the inspection tool such as defect data (e.g., X and Y coordinates, defect size, cluster number, etc.), wafer data ( e.g., Lot ID, wafer ID, Die pitch, etc.), and class data (e.g., engineer or ADC class labels for SEM inspection, optical inspection, cluster class, etc.). The primary starting point for AIR-based searches is the image feature data that is maintained in the image feature tables. These tables contain feature descriptions of the images (i.e., color, texture, shape, etc.) for the defect and substrate regions and file paths and names for the image directory that is maintained on the fab DMS side of the system. Once a query has been completed, the ranked list of similar imagery that is returned can be further analyzed to determine any number of statistical distributions, e.g., tool commonality, die location, wafer location, engineering classification, etc.

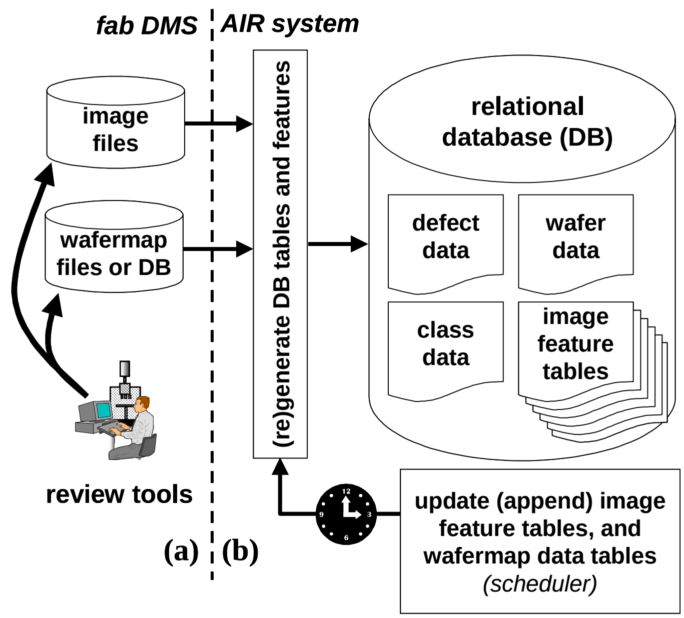


**Figure 7 – The fab DMS in (a) provides image and process data to the AIR system in (b) where it is maintained in a relational database.**

An example screen shot of the user-interface for the ORNL AIR system is shown in Fig. 8. This retriever interface represents the basic GUI for retrieving images based on several different criteria including image content. Images can be imported as query images using a cut-and-paste operation or file open browser dialog boxes. Once an image is imported into the system, a mask is generated for the defect that provides a localization of the defect region. Queries are performed by simply selecting the image areas of interest (e.g., defect texture, defect color, background color, etc), and optionally a set of layers or lots, which limits the query to images with these characteristics. Returned images are displayed in ranked order in a gallery. Clicking each returned image shows its lot, layer, file name, classifications, etc. The returned gallery can be exported to an

HTML file. In addition, Paretos are presented for the returned results that correlate the image list with processes. These Paretos can be exported to comma-separated value files for use with other analysis tools.

## 4. INTEGRATED ANALYSIS

Integrated analysis of DMS data goes beyond database infrastructure and merging issues and will encompass new methods that attribute informational content to data, e.g., the assignment of defect class labels through ADC, or unique signature labels in the population of defects distributed across the wafer using SSA. These methods put the defect occurrence into a context that can later be associated with a particular process, material characteristic, or even a corrective action. For example, a defect coordinate in a wafermap file contains very little information, but a tungsten particle within a deposition signature is placed in the context of a specific manufacturing process and contamination source. Later reporting of this information can lead to rapid yield learning, process isolation, and correction.

Figure 9 shows the image-based technologies that have been surveyed in this paper and where they apply in the manufacturing environment that was described through Fig. 3. To begin the discussion of integrated analysis, we will focus on merging SSA and ADC technologies as in Fig. 9a. These technologies are being combined to facilitate intelligent wafermap defect sub-sampling for efficient off-line review and improved ADC classifier performance [30, 31, 32]. The integration of SSA with ADC technology can result in an approach that improves yield through manufacturing process characterization. It is anticipated that SSA can improve the throughput of an ADC system by reducing the number of defects that must be automatically classified. For example, the large number of defects that comprise a mechanical scratch signature that is completely characterized by SSA will not need to be further analyzed by an ADC system. Even if a detected signature cannot be completely characterized, intelligent signature-level defect sampling techniques can dramatically reduce the number of defects that need to be sent to an ADC system for subsequent manual or automated analysis (e.g., defect sourcing, tool isolation, etc.).

The accuracy of an ADC system can potentially be improved by using the output of the SSA wafermap analysis to perform focused ADC. Focused ADC is a strategy by which the SSA results are used to reduce the number of possible classes that a subsequent ADC system would have to consider for a given signature. SSA signature classification can be used to eliminate many categories of potential defects if the category of signature can be shown *a-priori* to consist of a limited number of defect types. This pre-filtering of classes reduces the possible alternatives for the ADC system and, hence, improves the chance that the ADC system will select the correct classification. It is anticipated that this will result in improved overall ADC performance and throughput.

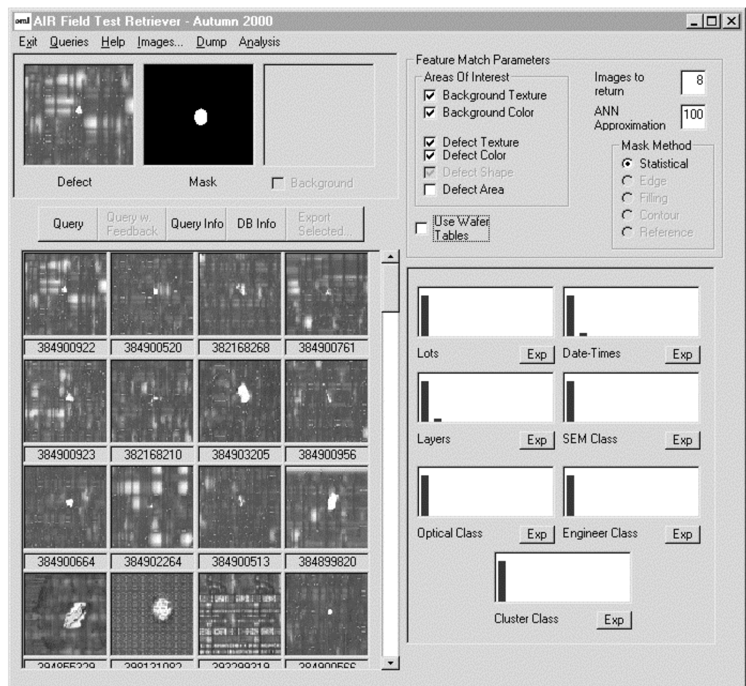


**Figure 8 – Screen shot of the user interface for the ORNL AIR system showing the query (upper left) and returned list of similar images (lower right) and associated process statistics (lower right).**

Integrating AIR with ADC will enable easier compilation of example libraries for ADC training purposes. A common frustration with ADC systems is the work required to train them. Using AIR should enable easier retrieval of relevant imagery to assemble appropriate sets for defining ADC classes. In addition, AIR technology can help determine if an ADC system is operating within its original defined class range. For example, subclasses can arise in a particular defect type that ADC cannot discern due to its static training. Applying AIR to these defect images can help the operator determine if new subclasses of defect images are appearing, and if these subclasses are significant enough to warrant new training of the ADC. An automatic set of AIR queries could serve to validate ADC performance and monitor trends; for example, an AIR query that retrieved 100 images could show that 75 of them had the same ADC label. A later query that showed only 50 of them had the same label could indicate changes in the process line.

Finally, the integration of SSA signatures and AIR (i.e., as in Fig. 9c) becomes a beneficial extension of the retrieval technology when we consider that the spatial signature is a collection of features. These features are directly applicable in the AIR environment as a descriptive search and retrieval mechanism analogous to the features used to describe individual defects. The storage of signature images (e.g., as simple binary bitmaps) will facilitate the viewing of retrieval data, but as with individual defect images, the greatest benefit is derived from the collection and analysis of associated process information. These process statistics help the yield engineer to isolate and source problems to tools and equipment.

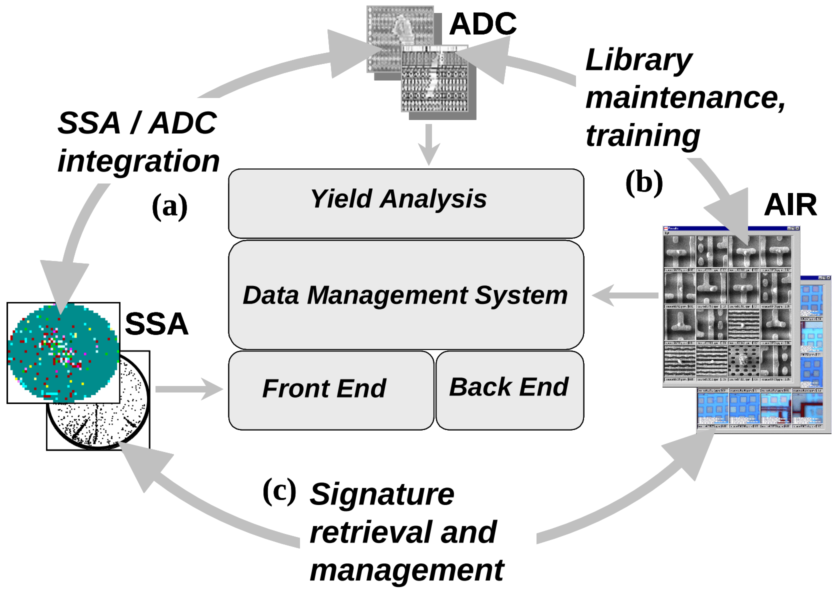


**Figure 9 – The integration of these technologies in the yield management environment are resulting in the rapid isolation and correction of problems in complex semiconductor fabrication processes.**

## 5. CONCLUSION

Integrated yield management strategies will have to accommodate the ever-increasing volume of manufacturing data that is being sampled from the manufacturing process as the complexity trend continues to increase. This increasing volume of data is necessitating the development of automation tools that can ultimately relieve the analysis burden placed on the yield engineer thus making him/her more efficient in the sourcing and correction of yield impacting events and trends. While network bandwidth, database storage capacity, database retrieval rates, information transfer protocols, and other data standards must continue to evolve to meet these needs, automation technologies that take raw manufacturing data and convert it to useful information will provide the greatest advantage. In this paper we have surveyed several technologies that have been developed by ORNL and ISMT that take human expertise and encapsulate it such that it can be applied to the decision-making process in an automated fashion. ADC and SSA take wafermap defect data and place it in the context of specific manufacturing events that impact yield. Integrating these technologies can lead to in-line yield prediction that can assist in the rapid prioritization of these events. AIR technology has the potential to provide an efficient query window into the historical record of the manufacturing environment, allowing search and retrieval capabilities currently unavailable to the semiconductor manufacturer. The integration of AIR with SSA and ADC will facilitate the management, training, and accessibility of these various systems and data types as the yield engineer continues to deal with an ever-increasing mountain of manufacturing data while striving to meet ITRS productivity goals.

## 6. ACKNOWLEDGEMENTS

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