Efficiency and Throughput Improvement on Defect Disposition through Automated Defect Classification

Lin He[a], Noel Corcoran[a], Danping Peng[a], Vikram Tolani[a], Hsien-Min Chang[a], Paul Yu[a], Kechang Wang[a]
C.J. Chen[b], T.H. Yen[b], Rick Lai[b], B.H. Ong[b], Laurent C.C. Tuo[b]
[a]Luminescent Technologies, Inc., 2471 East Bayshore Road, Palo Alto, CA, USA 94303;
[b]Taiwan Semiconductor Manufacturing Co. Ltd., 25, Li-Hsin Rd., Hsinchu Science Park, Hsinchu, Taiwan, 300-77, R.O.C.

ABSTRACT

The routine use of aggressive OPC at advanced technology nodes, i.e., 40nm and beyond, has made photomask patterns quite complex. The high-resolution inspection of such masks often result in more false and nuisance defect detections than ever before. Traditionally, each defect is manually examined and classified by the inspection operator based on defined production criteria. The significant increase in total number of detected defects has made manual classification costly and non-manufacturable. Moreover, such manual classification is also susceptible to human judgment and hence error-prone.

Luminescent's Automated Defect Classification (ADC) offers a complete and systematic approach to defect disposition and classification. The ADC engine retrieves the high resolution inspection images and uses a decision-tree flow based on the same criteria human operators use to classify a given defect. Some identification mechanisms adopted by ADC to characterize defects include defect color in transmitted and reflected images, as well as background pattern criticality based on pattern topology. In addition, defect severity is computed quantitatively in terms of its size, impacted CD error, transmission error, defective residue, and contact flux error. The final classification uses a matrix decision approach to reach the final disposition. In high volume manufacturing mask production, matching rates of greater than 90% have been achieved when compared to operator defect classifications, together with run-rates of 250+ defects classified per minute. Such automated, consistent and accurate classification scheme not only allows for faster throughput in defect review operations but also enables the use of higher inspection sensitivity and success rate for advanced mask productions with aggressive OPC features.

1. INTRODUCTION

As optical lithography extends to sub-0.35 k1 regime, many resolution enhancement techniques (RET) have been adapted to increase sub-wavelength resolution. These techniques include the use of more aggressive sub-resolution assist features (SRAFs), inverse lithography technology (ILT), and source mask optimization (SMO) masks. Together with higher MEEFs, these solutions have obviously made mask patterns much more complicated and therefore made mask inspection much more challenging. Generally, mask inspection tools are selected with sensitivity recipes to detect defects in any geometry that have some specified lithographic impact, say 8% CDE (CD error) as measured on a wafer print or AIMS™ simulation. It has always been true that these inspection setups do detect nuisance or false defects. The number of nuisance and false defects has increased significantly in sub-28nm node mask inspections. Figure1 shows an example of a 28nm mask with 1000+ false or nuisance detections due to aggressive OPC features. In this product case, most of the defects are not similar in both defect severity and pattern environment. So it takes a long time to classify all the defects manually or even by using ReviewSmart^{TM} to assist with defect classification. Therefore, to achieve efficient defect classification for the cases shown in the example Figure 1, it became necessary to find another efficient methodology that can analyze each defect individually instead of previous grouping-based disposition methods.

In this study, the performance of an automatic defect classification system called ADC is investigated. The first step is to align ADC with the existing defect judgment criteria used in original production line by operators. Then the defect classification results from ADC and operators are compared. The goal is to verify that ADC performs reliable defect disposition with no error classification that may cause quality impact and that ADC efficiency rate for false and nuisance defects is equal or better to existing operator efficiency rate. The final goal of this investigation is to show that implementation of ADC on mass production of advanced mask manufacturing is able to reduce human-induced judgment errors and reduce workload of human operators. The clear challenge for the ADC system is to provide a higher quality and more efficient approach for defect disposition on low-k1 technology masks given the large increase in nuisance defect detections.

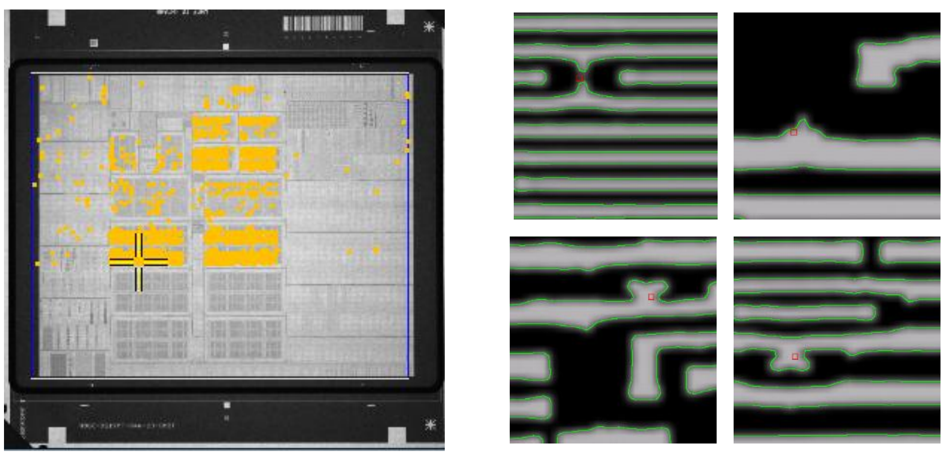

Figure 1: Example of high false count mask inspection due to aggressive OPC features

2. ADC TECHNOLOGIES

2.1 What is ADC?

The ADC engine retrieves high resolution inspection images and uses a decision-tree flow based on the same criteria human operators use to determine how to disposition and classify a given defect. By offering a systematic, automated, and offline review of results, ADC provides a much more direct production flow as opposed to the traditional manual method. Figure 2 shows a comparison between a traditional review flow and the proposed flow with ADC. In the traditional flow, every defect detected by the inspection system needs to be reviewed by an operator. As part of this review, the operator has to judge the potential lithographic consequence of each defect; distinguishing between nuisance, tool artifact, etc. and real critical defects, and classify them into specific bins for yield tracking and further repair purposes.

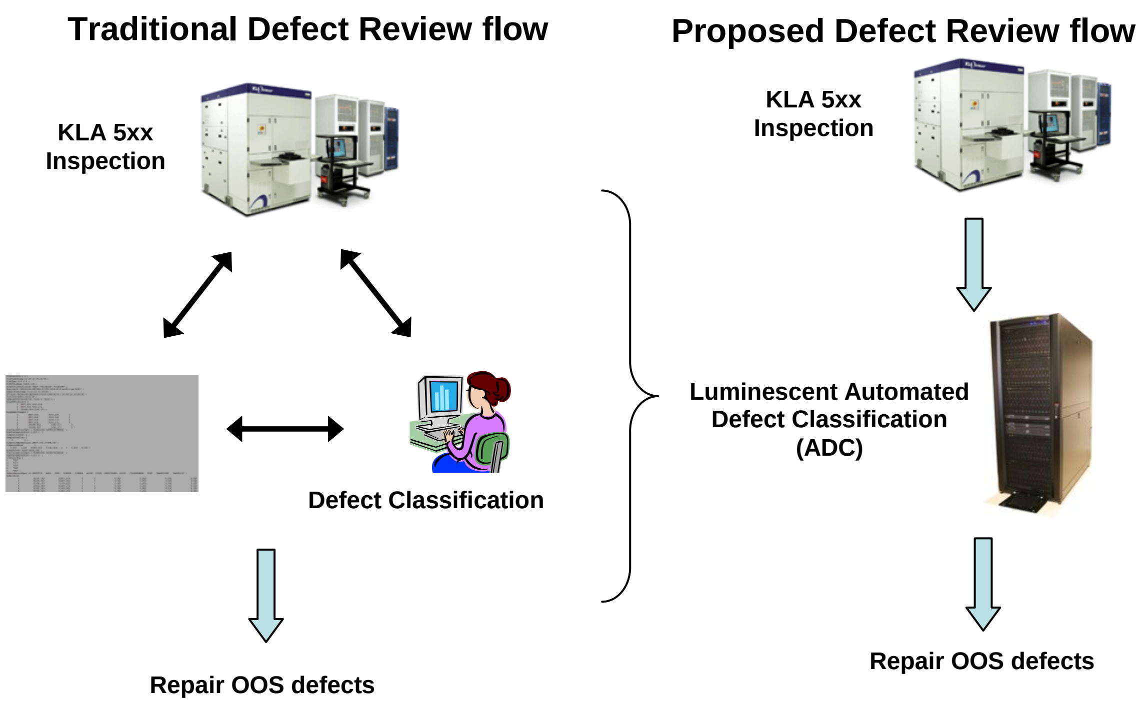

Figure 2. ADC replaces inspection defect review and classification.

2.2 ADC Engine Flow Overview

The Luminescent ADC engine flow begins with basic input from the inspection tool which includes test and reference images from both transmitted and reflected light settings. The general flow has 3 major steps: image preparation, defect classification, and final ADC report which ultimately bins the defect site into a “type” and “status”. The type defines the category into which the defect will be binned into and status provides the pass or fail decision provided by the tool. Figure 3 shows the ADC flow in general terms on top and in more specifics on the bottom part of the diagram.

2.3 Image Preparation

The high resolution inspection images have coarse pixel sizes and are often not aligned between reference images and defective images. However, many defects (such as contaminated particles) are only clearly visible in the difference images, i.e., subtraction between defective and reference images. The use of difference images to detect defects and other traits of defects (such as defect disposition and defect color) relies on the reference and defective images to be correctly aligned for both transmitted and reflected light images. Therefore ADC initially refines all four images: the reference transmitted image (refT), the reference reflected image (refR), the defective transmitted image (defT) and the defective reflected image (defR). And then alignment is done between defT and refT, and, defR and refR.

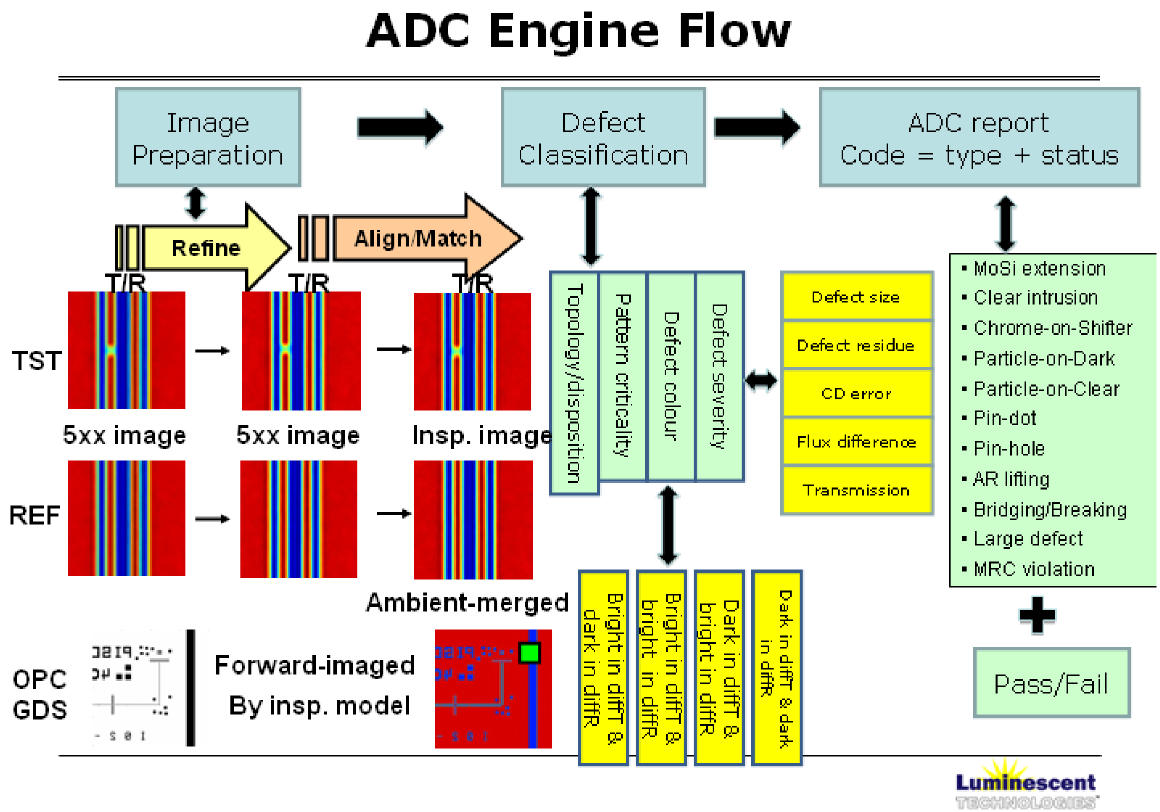

Figure 3. ADC process flow from image prep to final ADC disposition report

2.4 Classification Decision Tree

The ADC engine uses difference images to detect defects and applies a decision-tree flow based on the same criteria human operators use to classify a given defect. Some identification mechanisms adopted by ADC to characterize defects include defect dispositions based on pattern topology, pattern criticality, defect color in transmitted and reflected images and defect severity.

In addition, different defect severity methods are computed quantitatively depending on defect disposition, pattern criticality and defect color. The ultimate classification uses a matrix decision approach. ADC uses several kinds of severity methods: defect size, defective residue, impacted CD error, contact flux error, transmission error, edge placement error (EPE) and shift distance. For example, for defects which touch edge contour, we compute defect residue and CD error between reference images and defective images. Another example is for defects which are far away from edge contour, for which we compute either defect size or transmission error depending on defect color in transmitted and reflected images.

One of the critical components to this classification matrix is properly placing defects in the correct topology environments. To accomplish this important task, the ADC engine places topology marks on the incoming background reference pattern. Figure 4 shows an illustration both topology markers and some of the corresponding defect metrics.

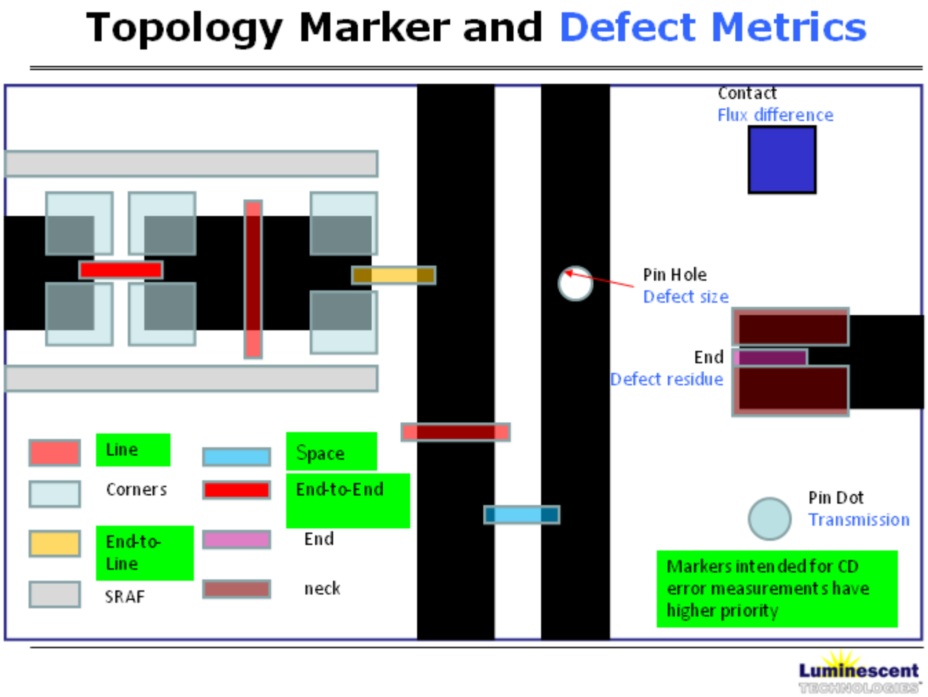

Figure 4. ADC Topology markers and defect metrics.

2.5 Severity Matching between ADC and Inspection Tool

For each severity judgment method, (i.e., CD error, defect size, defect residue, transmission, energy flux difference, edge placement error, etc) ADC values were directly compared to inspection tool values. For example, many defect sites of mask products have been studied to compare the energy flux difference values and the defective residue values in transmitted light between ADC and the inspection tool. Figure 5 and 6 below shows some correlation data mapping the ADC energy flux error and defective residue values to inspection tool. In the figures all the cases are within 2 GS (gray-scale) from each other in defective residue, and within 0.2% from each other in energy flux error.

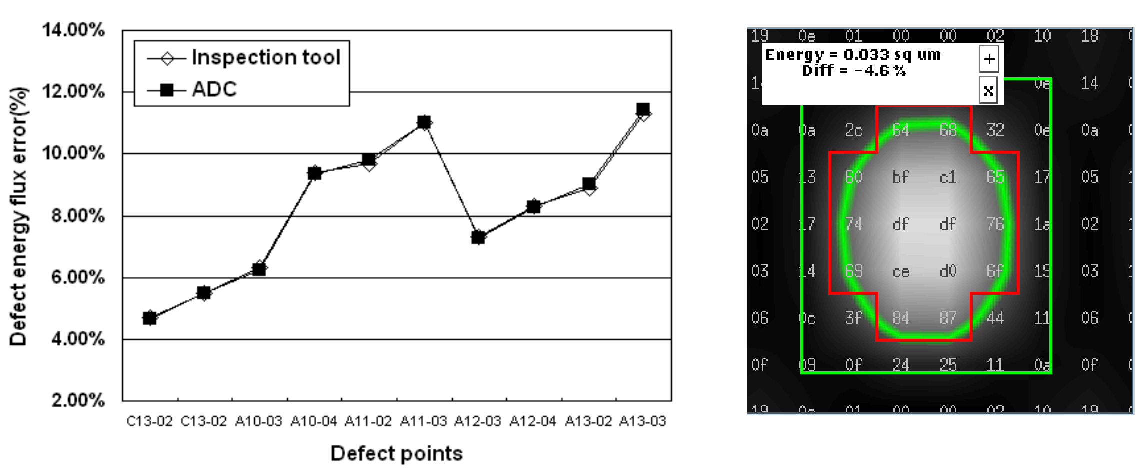

Figure 5. Energy flux difference values comparison between inspection tool and ADC for hole layer masks

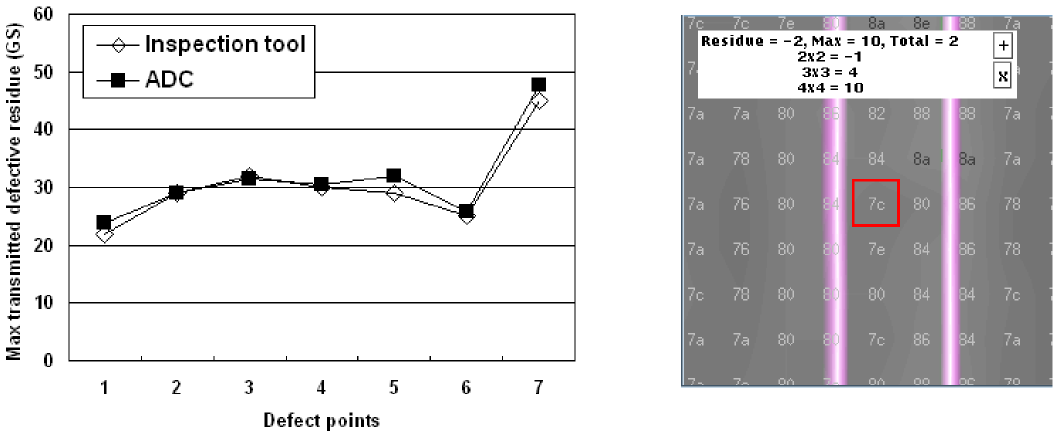

Figure 6. Transmitted image defective residue comparison between inspection tool and ADC

2.6 WebGUI Functionality and ADC Output Report

The overall system is made both operator and engineering user-friendly by providing job management submission, and defect review functionalities available through an intuitive web-GUI. Figure 7 shows screen captures of this GUI. Defects and defect summaries can be reviewed, and visualized in many possible ways to make it easier for routine operator use and engineering investigation.

Final classification is based on topology, defect metrics, severity, and specific properties (e,g,, protrusion or intrusion). The final ADC report is very customized to meet each customer's specific requirements. Generally, ADC will report defect type and defect status, which can include pass, fail, or warning output bins.

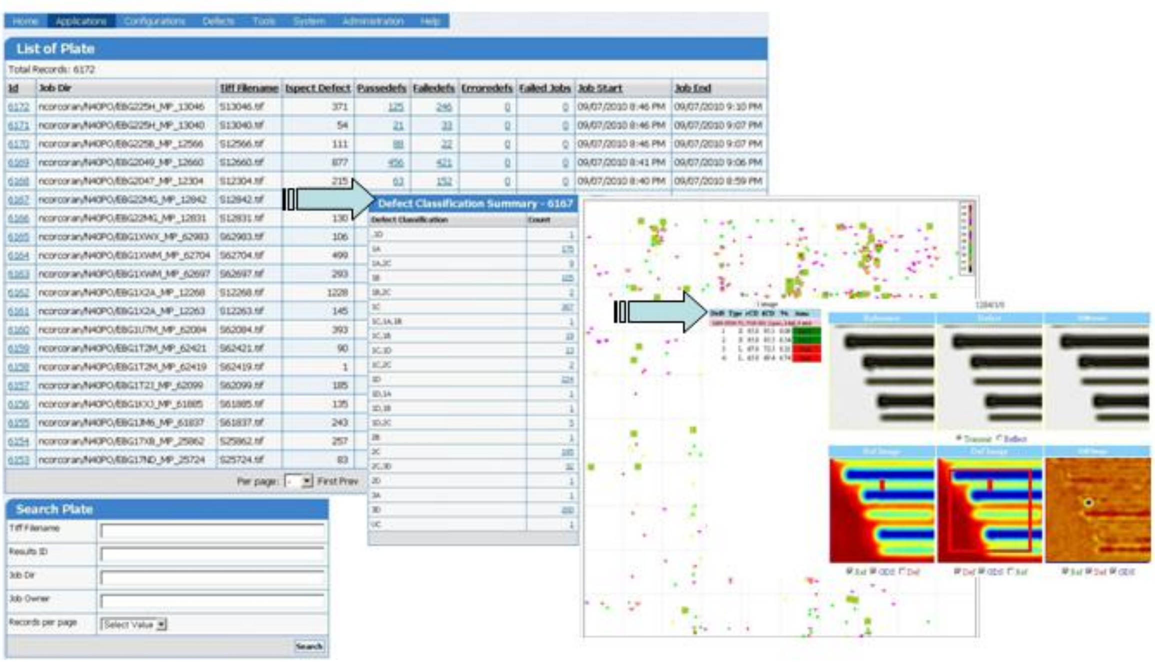

Figure 7. ADC WebGUI interface provided for job management and defect review.

3. RESULTS AND DISCUSSION

3.1 The Verification on Programmed Defect Masks

The ADC flow was first qualified on 40nm node programmed defect masks of critical logic layers, i.e., poly, contact, and metal. For each layer, more then 800 different defect types and sizes were chosen in different geometry (line, space, end-to-end, line-to-line, etc.) and pitches. The defect codes classified by ADC were compared to the codes classified by operators. The defect codes defined here refer to the severity and character of defects. For example, 1B refers to intrusion defect and needed to go through AIMS check or defect repair. Figures 8 and 9 show the defect codes comparison between what ADC performed and what operators classified for metal layer and contact layer programmed defect masks respectively. The results confirmed that ADC performed consistently with operator classification.

Pindot						-5%	-7%	-9%	-13%	-24%
						1C	1D	1D	1D	1D
						1C	1D	1D	1D	1D
Mis-sized					18%	26%	32%	39%	49%	53%
					1D	1D	1D	1D	1D	1D
					1D	1D	1D	1D	1D	1D
Intrusion	10%	14%	21%	26%	29%	37%	39%	47%	53%	58%
	1B	1B	1B	1B	1B	1D	1D	1D	1D	1D
	1B	1B	1B	1B	1B	1D	1D	1D	1D	1D
Pinhole	-3%	-5%	-7%	-7%	-10%	-8%	-15%	-24%	-31%	-54%
		1C	1D	1D	1D	1D	1D	1D	1D	1D
		1C	1D	1D	1D	1D	1D	1D	1D	1D
Protrusion				-12%	-24%	-28%	-38%	-54%	bridge	bridge
				1A	1A	1A	1A	1D	1D	1D
				1A	1A	1A	1A	1D	1D	1D
Pindot					-14%	-58%	bridge	bridge	bridge	bridge
					1C	1D	1D	1D	1D	1D
					1C	1D	1D	1D	1D	1D

AIMS CD error
Defect code by operator
Defect code by ADC

Figure 8. The comparison of classified defect codes by ADC and operators for metal programmed defects mask

Mis-sized		13.0%	20.2%	25.8%	30.5%	37.0%	38.3%	45.1%	54.7%	58.3%
		4B	4B	4B	4B	4B	4B	4B	1D	1D
		4B	4B	4B	4B	4B	4B	4B	1D	1D
Shift	7.8%	5.1%	-0.6%	4.2%	3.7%	5.4%	7.7%	5.6%	9.1%	10.7%
					1D	1D	1D	1D	1D	1D
					1D	1D	1D	1D	1D	1D
Intrusion				4.8%	4.1%	9.7%	8.5%	10.9%	14.7%	15.4%
				1B	1B	1B	1B	1B	1B	1B
				1B	1B	1B	1B	1B	1B	1B
Pinhole						-4%	0%	1%	1%	0%
						1C	1C	1C	1C	1C
						1C	1C	1C	1C	1C
Pindot						-9%	-77%	blind	blind	blind
						1D	1D	1D	1D	1D
						1D	1D	1D	1D	1D
Protrusion				-6%	-11%	-17%	-21%	-23%	-40%	-47%
				1A	1A	1A	1A	1A	1A	1A
				1A	1A	1A	1A	1A	1A	1A

AIMS CD error
Defect code by operator
Defect code by ADC

Figure 9. The comparison of classified defect codes by ADC and operators for contact programmed defects mask

3.2 Verification on Mass Production

ADC performance was further investigated on 40nm masks in mass production. Basically, defects can be differentiated into two categories. One category are defects which need post AIMS check or defect repair. The other category are defects which do not need AIMS check or defect repair, for example, false defects and nuisance defects. Here we define defect "classification efficiency" for a single mask product as the number of total false and nuisance defect counts classified by ADC divided by the total number of false and nuisance defect counts classified by operators. Higher classification efficiency with no error in classification (especially for cases needing AIMS check or defect repair) is required.

In figure 10, the summarized results of 250+ plates of mask products reveal that defect classification efficiency of over 95% has been achieved when comparing ADC final classifications to operator defect classifications. Moreover, no critical defect has been missed. Therefore, ADC performance was proven to be qualified for the application of mass production.

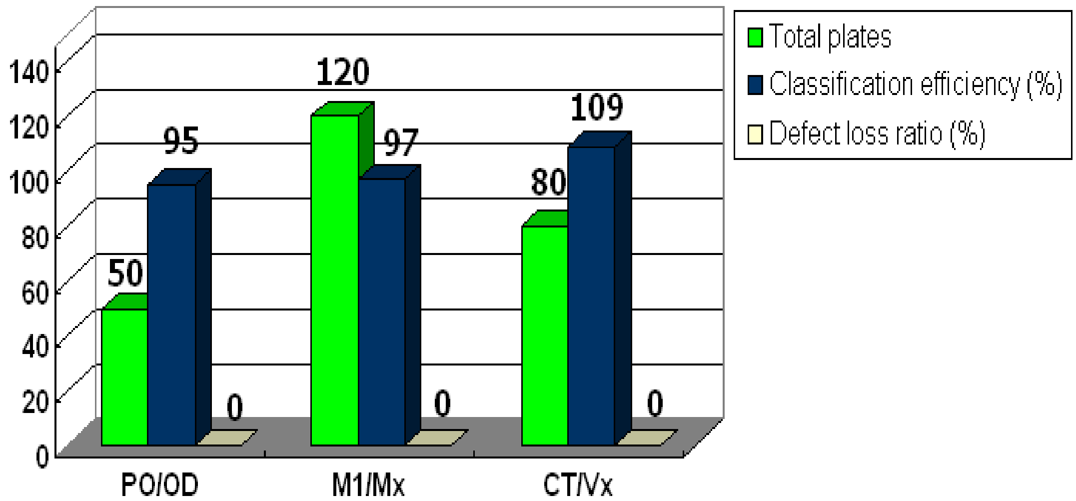

Figure 10. General result of ADC on 40nm mass production

〔Classification Efficiency = total false and nuisance defects per ADC / total false and nuisance defects per operator〕

4. CONCLUSIONS

In summary, ADC retrieves high resolution inspection images and uses a decision-tree flow based on the same criteria that human operators use to determine how to disposition and classify defects. ADC offers a fast and systematic approach to defect classification. Together with run-rates above 250ea defects classified per minute, ADC provides a fast, automated, consistent and accurate classification scheme that not only allows for faster throughput through mask inspection and defect review operations but also enables use higher inspection sensitivity and yield on complicated mask patterns. It provides good matching to operator classification with no critical defects missed and excellent matching with inspection tool defect severity values. Therefore, it is believed that ADC is potentially the best solution to improve defect classification efficiency in real mass production line.

5. REFERENCES

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