Immersion induced defect SEM-based library for fast baseline improvement and excursion


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ABSTRACT

Immersion lithography offers great benefit for advanced technology nodes but at the same time poses a great challenge. Along with hyper NA values, which increase the scanner resolution, new types of imaging process related defects emerge. These new defects are related to water, top coating, resist and BARC in the litho process. Root cause analysis of the so-called wet defects (immersion) versus the so-called dry defects (non immersion-related) becomes crucial in any immersion lithography related defect reduction program. Manual and eventually automated classification of defects can be used to analyze the data and monitor baselines. Furthermore, a robust Automatic Defect Classification (ADC) increases productivity and decreases the wafer cycle time.

This article outlines a methodological approach for wet and dry defect classification that employs rule-based ADC and enables the generation of an immersion induced defect library for fast baseline improvement and excursion monitoring. The work described in this article has been performed at ASML using Applied Materials’ SEMVision G3 FIB automated defect review and analysis tool.

Keywords: Immersion, defects, DRSEM, ADC, signatures, inspection, Litho-Cell

1. INTRODUCTION

Immersion lithography has introduced a considerable number of complexities such as 1. leaching of low molecular weight components (mainly PAG and photo acid species) into the immersion fluid, 2. water penetration into the resist film, 3. ensuring compatibility between topcoat design and resist/topcoat, 4. control of the contact angle between the fluid meniscus and the moving surface, and 5. controlling wafer edge phenomena due topography effect on the immersion process. All these aspects potentially impact overall defectivity. Understanding the relationship of all these parameters to defectivity is therefore crucial for successful introduction of immersion lithography into production (1).

Close and continuous inspection of immersion lithography wafers and redetection and characterization of defects related to the immersion lithography processing is required but will provide large amounts of defectivity data that need to be analyzed using some type of classification method. Manual classification of a full dataset is typically an extremely time consuming and tedious approach. A novel methodology to create robust baseline monitoring and an effective defect root cause analysis program are proposed in this paper. The approach outlined consists of three main steps following the initial wafer inspection step using an advanced bright-field inspection system and subsequent upload of the defect file generated by the inspection system into the Defect Review SEM (DR-SEM). The different steps on which the proposed methodology is based are first briefly summarized below.
Step1 - Expert defect gallery preparation:

The main objective in the first step of the process is to create an initial library of defect classes on the DR-SEM. This consists of two phases. In Phase1 a defect gallery is generated based on possible defect root causes. In the subsequent Phase2 a defect “reduction” is carried out by grouping defects into new bins based on defect resemblance.

Step2 - Defect classification

Phase3 consists of the tuning set creation and learning. Based on expert manual defect selection and classification of representative defects taken from a larger defect set, a defect classification library is generated. The selected defects are processed based on a radial basis function (RBF) algorithm and a set of classifiers (descriptors), which represents each defect class, is produced [2]. The next phase (Phase4) consists of defects class verification; a Probabilistic Neural Network (PNN) algorithm uses the descriptors from the tuning set creation and learning phase to determine final defect classes using the full defect set [2]. If necessary, manual user rules can enforce desired results which must subsequently be verified again by executing the PNN algorithm. The final phase of step 2 (Phase5) is referred to as implementation. In this phase, the set of rules resulting from the previous step are tested for various (different) sets of defects to confirm robustness.

Step3 - Monitoring and root cause analysis

In the final step a daily manual classification is performed to obtain bins of interest (BOI, e.g. an immersion bin) to create baseline monitoring defect paretos (Phase 6A). In the subsequent and last phase (Phase6B), a manual classification of the BOI based on Phase 1 is done to trace defect root causes.

In addition to the steps outlined here to create a defect library on the DR-SEM, an initial rough binning step and defect signature analysis on the wafer inspection system (i.e. step 0) can support the methodology described above. The advantage of using this capability is that fewer classes need to be classified on the DR-SEM ADC, thereby further shortening required baseline monitoring cycle time.

2. DEFECTS AND SIGNATURES CLASSIFICATION AND RESULTS

The main elements of the three step / six phase methodology are illustrated in the following sections. Preliminary SEM ADC results obtained on defect data sets following the completion of the three step process demonstrate promising productivity gains. The resist and imaging conditions that are being evaluated are changing on a regular basis so no particular experimental details on these aspects are provided here. The methodology that has been described in the previous section has been extensively tested and turns out to work for various resist and imaging conditions. All considered targets consist of 100 nm lines and trenches with 1:1 ratio. When the technology node size is significantly decreased (e.g. going from 100 to 45 nm lines), step 2 would need to be repeated. Any new type of defects discovered at later stage in the process also requires restart of step 1 and 2.

2.1 Step1 phase1: Basic defect library creation by root cause

The SEMVision G3 review system has three complementary components integrated that are being used to support root cause analysis of defects: Automated Energy Dispersive X-ray (EDX) analysis (with element auto defect classification capability), Auto Focused Ion Beam (FIB) and Wafer Edge Imaging (WEI).

Based on the analysis performed so far, the range of defects is divided into thirteen main bins by an expert as illustrated by the SEM images in Figures 1-3 (also refer to [3]). In Figure 1, images of defect types that are related to the immersion lithography process are shown. Defect types that might or might be related to the immersion process are shown in Figure 2 whereas defect types that are not related to immersion are summarized in Figure 3.
Figure 1  
Overview of defect bins specifically associated to immersion lithography.

Figure 2  
Overview of defects bins that might or might not be specifically related to immersion lithography.

Figure 3  
Overview of examples of defect bins containing defects which are expected to be non-immersion lithography related.
2.2 Classification methodology

2.2.1 Step 1 phase2: Defect reduction
Defect reduction is a term used in this paper to describe the process of grouping together similar defects into the same bins (classes) thus reducing the number of bins of interest (BOI). This step in the overall process of building a defect library is essential to ensure robust SEM ADC performance. Underlying the SEM ADC process is a probabilistic neural network (PNN) algorithm, which is an information processing step based on a connectionist approach to computation (2). The PNN is an adaptive system that changes its structure based on external or internal information that flows through the network (see Figure 4).

![Figure 4](image.png)

**Figure 4** PNN dependency graph. The final class, or random variable $F = f(G)$ depends upon the random variable $G = g(H)$, which depends upon $H = h(X)$, which depends in turn upon the input defect descriptors or random variable $X$.

Grouping defects based on their resemblance and not necessarily on their suspected root cause simplifies greatly the computational efforts based on the PNN algorithm. The implication of this approach is a higher confidence level for each defect class. The thirteen immersions and non-immersion related bins originally identified were reduced to a total of only six by using resemblance as selection criterion (See Figure 5). As can be seen in Figure 5, the defect bin labeled “patterned”, includes all immersion related defects (attenuation and inverse attenuation) as well as two additional classes, originally referred to as pattern expansion and deformed pattern. For immersion specific defects, the regrouping implies a reduction from 13 to 5 classes (i.e. four patterned classes and one printing particle class). Final manual classification is typically performed on the patterned and printing particle bins to confirm the validity of the regrouping. Other bins, in this case, will not improve the statistical significance of the immersion related defect source. Therefore, the productivity benefits can be quantified by measuring the reduction in manual classification cycle time.
**Patterned**

(Former: Pattern expansion, attenuation, inverse attenuation and deformation)

**Printing particle**

(Same as former)

**Non printing Particle**

(Former: non-printing particle, embedded particles)

**Residues**

(Former: residues, BARC, μ-bridge)

**Missing pattern**

(Former: missing pattern, pattern shrinkage)

**Bridges**

**Figure 5**

*Overview of six (6) defect bins resulting from regrouping defects based on their resemblance.*
2.2.2 Steps 2 and 3: Automatic Defect Classification (ADC) and manual expert classification

The SEM ADC based classification vs. expert final classification is typically represented by a so-called confusion matrix which shows the agreement between the automatic review and the expert manual classification. A better agreement implies higher accuracy and purity percentage scores. Accuracy reflects the SEM ADC capability to successfully capture all defects belonging to the same class while purity represents the homogeneity of each class (see Figure 6).

An agreement matrix, on the other hand, contains only the elements of agreement of the reviewed vs. expert decisions as well as the total accuracy and purity scores. The agreement matrix based on the preliminary results obtained at ASML (based on verification of 2000 defects) is shown in Table 1.

**TABLE 1**  Normalized SEM ADC preliminary results obtained on a special test wafer. The results demonstrate good purity and accuracy for the majority of defects in the pattern and nuisance bins. The former contain 4 classes, including all immersions related defects.

<table>
<thead>
<tr>
<th>Review</th>
<th>Pattern</th>
<th>Printing</th>
<th>Particles</th>
<th>Residues</th>
<th>Missing</th>
<th>Bridges</th>
<th>False</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expert</td>
<td>Pattern</td>
<td>particle</td>
<td></td>
<td></td>
<td>pattern</td>
<td></td>
<td>Alarms</td>
<td></td>
</tr>
<tr>
<td>Pattern</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pattern</td>
<td>80</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>80%</td>
</tr>
<tr>
<td>Printing</td>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>67%</td>
</tr>
<tr>
<td>Non printing</td>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>65%</td>
</tr>
<tr>
<td>Residues</td>
<td></td>
<td></td>
<td>14</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>72%</td>
</tr>
<tr>
<td>Missing</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>38%</td>
</tr>
<tr>
<td>Bridges</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2</td>
<td></td>
<td>56%</td>
</tr>
<tr>
<td>False alarms</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>252</td>
<td>2</td>
<td>100%</td>
</tr>
<tr>
<td>Purity</td>
<td>98%</td>
<td>70%</td>
<td>35%</td>
<td>69%</td>
<td>26%</td>
<td>50%</td>
<td></td>
<td>99%</td>
</tr>
</tbody>
</table>
The results produced related to the statistically significant defect populations (nuisances and pattern) are acceptable (80% or above). In the current context, the most important defect bin is pattern which includes all immersion related defects and therefore has significant value for fast baseline monitoring. The number of defects for the other bins was not significant enough so the margin of error is more significant and further evaluation and ADC improvements are required.

### 2.2.2.1 Manual classification objectiveness

A benchmark is required to assess the overall ADC performance. Properties such as accuracy and purity are only meaningful if they are determined with respect to an objective classifier. The classification scheme needs to meet the following requirements for an objective manual classification:

1. Each class needs to be based on visual appearance of the defect using SEM review to prevent bias by the appraiser who might relate the defect to a suspected root cause,
2. The classes should cover the complete spectrum of possible defects,
3. The classes should be mutually exclusive.

Appraisers need to be properly trained and the complete measuring system, which includes the inspection tool, SEM review system, classification scheme and all appraisers involved, needs to be evaluated by performing a Gage R&R. Evaluation of a measuring system, which yields nominal data, can be carried out by means of an attribute referred to as Gage R&R. In an attribute Gage R&R $\kappa$ is used as a measure of reliability. $\kappa$ is a statistic in which the coincidental level of agreement is corrected for based on the following formula:

$$\kappa = \frac{P_{obs} - P_{exp}}{1 - P_{exp}}$$

Where $P_{obs}$ ($P$ observed) is the proportion of agreement between classifiers and $P_{exp}$ ($P$ expected) is the expected proportion of agreement, based on the individual choices of classifiers (e.g., suppose two classifiers classify 10 objects in 2 classes. $P_{obs} = \frac{\text{the number of objects which were put in the same class by both classifiers}}{10}$. If classifier A puts 60% of all objects in class 1, while classifier B puts 50% of all objects in class 1, then $P_{exp} = 0.6\times0.5 + 0.4 \times 0.5$. ).

As a rule of thumb:

- If $\kappa = 1$ the classification method is excellent.
- If $0.8 \leq \kappa < 1$ the classification method is acceptable.
- If $\kappa < 0.8$ the classification method is considered unreliable.

A manual classification system with $\kappa \geq 0.8$ for all classes can serve as a benchmark for evaluation of an ADC.
2.2.3 Step 0: Inspection signatures and rough bins ADC

The inspection tool can be used to further enhance the above described defect reduction methodology performance by narrowing down the defects range of interest through signatures and rough binning. As defect signatures can be easily identified and separated from random and systematic defects distributions, rough binning (i.e. inspection ADC) can further separate particles and pattern expansions (immersion and non-immersion related) from the smallest process residues with high accuracy and purity (see Figure 7). The advantage of this capability is that a pre-selection of defects can be done which avoids SEM ADC on defects that are not necessarily relevant for baseline monitoring.

<table>
<thead>
<tr>
<th></th>
<th>Protrusions + micro bridges</th>
<th>Particles + Pattern</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Protrusions + micro bridges</td>
<td>260</td>
<td>4</td>
<td>98%</td>
</tr>
<tr>
<td>Particles + Pattern</td>
<td>6</td>
<td>62</td>
<td>91%</td>
</tr>
<tr>
<td>Purity</td>
<td>87%</td>
<td>86%</td>
<td></td>
</tr>
</tbody>
</table>

Figure 7 Preliminary inspection rough binning results for two major bins: small process defects vs. immersion and larger defects.

In the process of setting up a defect library a new process residue class protrusion (Figure 8) has been identified using the UVision inspection system which has been added to the micro bridge bin to form a \(< 60 \text{ nm}\) defect bin (Figure 9).

![Figure 8](image-url) Newly identified 40 nm protrusion defect during wafer inspection using an UVision system (SEM image field of view is 1\(\mu\)m). This defect type has been added to the micro bridge defect bin to form a new “< 60 nm” defect bin.

The data in Figure 9 demonstrates the ability to sort the bins of interest from the Pareto on the inspection tool before exporting the defects to a review system. In this example, the newly discovered protrusions and micro bridges were successfully sorted prior to export of the defect file (for immersion base line monitoring purposes). This implies that only the immersion bin (pattern and surface particle), bridges, pattern shrinkage, missing pattern and embedded particles would be exported. The exclusion of the \(< 60 \text{ nm}\) bin (385 defects in total) significantly reduces the review and SEM ADC cycle time (by an additional 50%).
3. SUMMARY

Based on a three step methodology of smart defect binning, the approach described in this paper is considered as an efficient way to deal with a massive amount of defect data (in the current work to monitor an immersion lithography process). Preliminary data reduction results were presented and a reduction of at least 50% is achieved by using Applied Materials’ SEMVision G3 review tool for binning of immersion related defects. The gain in productivity is significant and can be quantified. Further efficiency gain can be achieved by utilizing the rough binning capabilities available on the UVision bright-field inspection tool prior to defect classification on the DR-SEM. More work is ongoing to further improve the performance of this methodology in order to establish the most efficient baseline monitoring and root cause analysis for tracking of immersion-related defects.

REFERENCES