

## **IMPACT OF CONTROL PLAN DESIGN ON TOOL RISK MANAGEMENT: A SIMULATION STUDY IN SEMICONDUCTOR MANUFACTURING**

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### **ABSTRACT**

In this paper, we analyze the impact of control plan design of defectivity inspections for tool risk management. Defectivity inspections are performed on products and can reveal the yield loss produced by contaminations or structural flaws. The risk considered in this paper concerns the exposure level of wafers on a tool between two defectivity controls. Our goal is to analyze how control plans can impact the manufacturing robustness from the point of view of wafer at risk on tools. A smart sampling strategy is considered for sampling lots to be measured. Actual data from the Rousset fab of STMicroelectronics are used. The simulation experiments are performed using the S5 Simulator developed by EMSE-CMP. Results show that not only the number and positions of controls operations have an important impact on tool risk management, but also how each control operation covers process operations.

### **1 INTRODUCTION**

In order to keep pace with the constant demand for more powerful and faster devices, the technology to produce them is always changing. During the past two decades, the level of integration has vastly increased. Semiconductor integrated circuits have become more complex and expensive to produce. In consequence, great control challenges arise. The need to find defective products or tools before they consume precious production resources is critical. Actually, the economic benefit of maintaining efficient and dynamic control increases with the complexity of manufacturing processes (May and Spanos 2006).

In semiconductor manufacturing, control methods to reduce risks are present at different levels: At product, process, tool and organizational levels (Bassetto and Siadat 2009). In this paper, we focus on the process and tool levels. In particular we concentrate on the wafer at risk (W@R), i.e., the number of wafers processed between two defectivity control operations. The W@R represents a virtual risk because of a potential defectivity issue.

Defectivity inspections can reveal several kinds of problems, such as contaminations or structural flaws. In order to ensure the high quality of finished products, regular inspections during manufacturing cannot be substituted (May and Spanos 2006). Since metrology capacity is limited and inspections directly affect production cycle times, efficient strategies to measure lots that provide the most relevant data are necessary. Previous work has been conducted in this direction. A static sampling plan usually consists of selecting the same number of lots to measure (Lee 2002). Adaptive Sampling varies the number of selected lots according to the actual production state (Boussetta and Cross 2005). Smart Sampling is a new approach that aims at minimizing the wafer at risk on tools dynamically (Dauzère-Pérès et al. 2010). This approach takes measurement capacities into account.

The process control plan provides a summary description of the methods used to minimize process and product variation (Le Saux 2006). Inspections of the control plan are placed between critical operations for the product. Processes are considered critical when possible defects can cause the dice structure to fail and produce a killer defect (May and Spanos 2006). Control plans and sampling strategies are highly related. Nevertheless, few methods link risk analyses and actual control plan strategies in a detailed manner (Bettayeb et al. 2010). In this paper, we aim at analyzing the impact of control plans for defectivity inspections on the wafer at risk in a fab.

The structure of the paper is as follows. The problem is defined in Section 2. Section 3 is devoted to the experimental study and analysis of the results. Section 4 presents the conclusions and outlines our future research work.

## 2 PROBLEM DESCRIPTION

Our problem focuses on the Wafer at risk ( $W@R$ ) on tools.  $W@R$  is the number of wafers processed on a tool since the process of the latest lot measured in defectivity (Dauzère-Pérès et al. 2010). When a lot is inspected at a control step, the risk on tools where the lot was processed is reduced (wafer at risk reduction). Thus, the  $W@R$  of a tool depends on the tool throughput and the time to get the results of the measurement. In this study, only the defectivity inspections are considered.

Let us consider a group of serial machines with identical throughput. The time to go from one process to another is also similar. Thus, the minimum wafer at risk of the tools depends on the delay to get the results of the measurement, see Figure 1. If new inspection operations are added, the delay to get this measurement result is reduced, and the wafer at risk could thus also be reduced. In this study, we analyze how the configuration of new control plans can have a positive or a negative effect on wafer at risk levels.

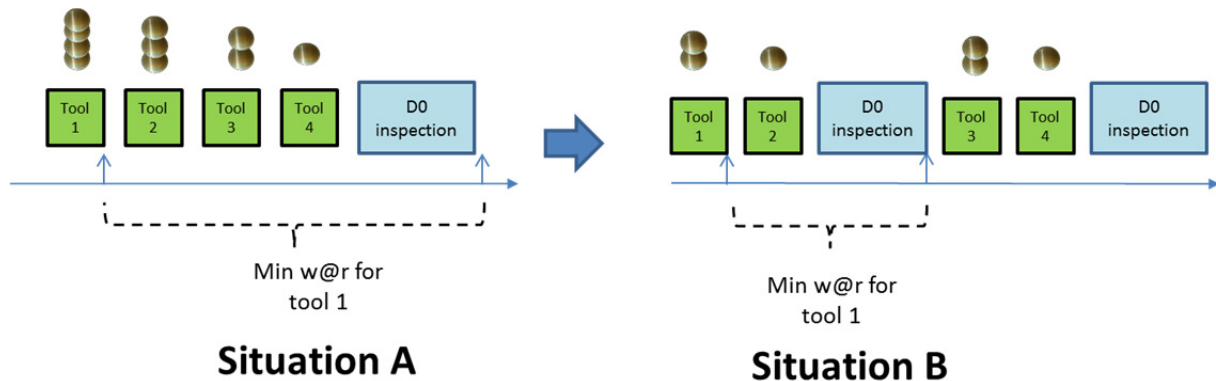


Figure 1: Minimal  $W@R$  representation

This study is based on a smart sampling strategy. Sampling a lot is based on how much is gained on risk reduction if the lot is measured. Metrology capacity is also considered. The control plan defines the set of process operations that can be controlled with an inspection and after which process operations a lot is available to be sampled. A control plan per technology is considered.

The original control plans have  $X$  inspections. We have created some control plans with additional operations ( $X + 20$  and  $X + 50$ ). Technical restrictions were not considered in the modifications of control plans. Figure 2 represents the strategies for adding new defectivity controls. With the so-called “No overlapping” strategy, the set of process operations is divided into the number of inspections. With the “Overlapping” strategy, the original control plan is maintained and additional inspection operations are included. In other words, the impact of the original inspection plan is kept.

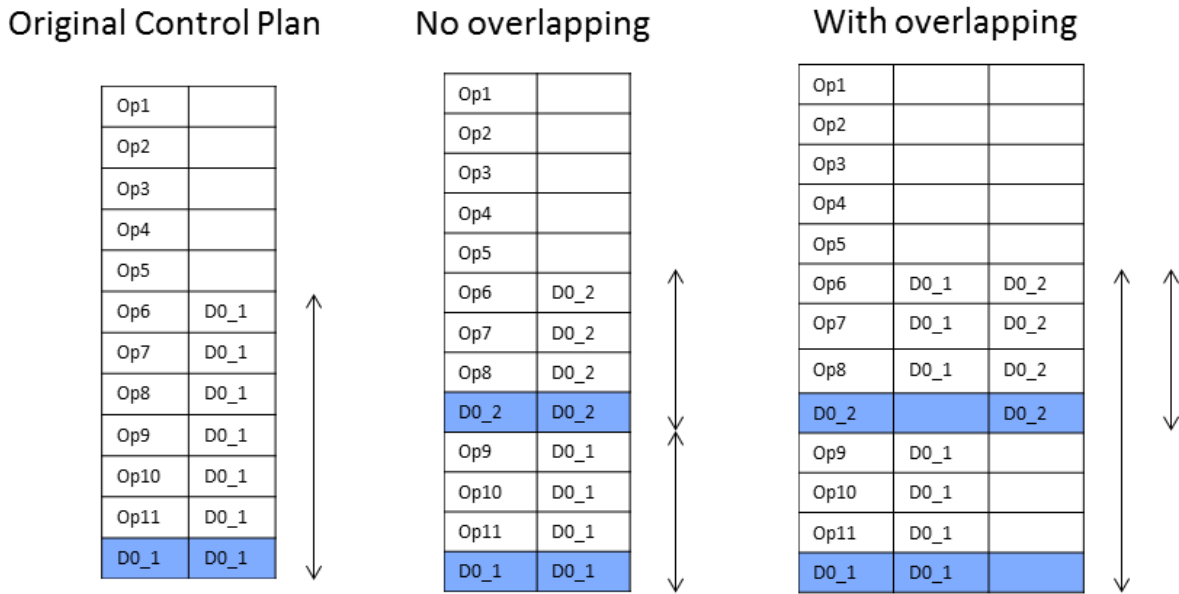


Figure 2: Control plan with and without overlapping

### 3 EXPERIMENTAL STUDY AND RESULTS

Experiments are performed with the Smart Sampling Scheduling and Skipping Simulator (S5) developed by the Department of Manufacturing Sciences and Logistics of EMSE-CMP. Simulations were conducted on real data from the 200mm fab of STMicroelectronics in Rousset, France. The data set includes around 5500 lots processed on more than 100 production tools. For confidentiality reasons, all results are normalized. For comparison with the fab sampling case, all performance measures are set to 100%. The selected performance measure is the “max W@R average,” i.e., the average of the maximum wafer at risk for each process tool in the fab. Different capacity values in the defectivity area are considered. Capacity A corresponds to the current capacity to conduct the defectivity controls in terms of the number of measured lots per hour. For the analysis of the different strategies the reduction of the wafer at risk (W@R) is considered.

#### 3.1 Number of Control Operations and Overlapping vs. No Overlapping

In this section, we analyze the impact of controls with and without overlapping as illustrated in Figure 2. Tables 1, 2 and 3 present the experimental results for different control plans where capacity A is the current defectivity control capacity, and capacities A2, A3, A4 and A5 correspond to a reduced number of measurement machines. In order to analyze the wafer at risk reduction with additional control operations, two control plans are tested. X+20 and X+50 correspond to control plans with 20 and 50 new control operations, that cover the same process operations as the initial control plan.

Table 1 presents the percentage of measured lots for each sampling capacity, i.e., number of measurement machines, when smart sampling is used. The defectivity capacity is an important aspect to take into account when adding new inspection operations. Since we select lots with the smart sampling strategy, the limited capacity at metrology is considered. That is the reason why the percentage of measured lots is similar for a given capacity value.

Table 1: Number of measured lots and control plans with and without overlapping

| Number of measures   | Start S. Capacity A | Smart S. Capacity A5 | Smart S. Capacity A4 | Smart S. Capacity A3 | Smart S. Capacity A2 | Smart S. Capacity A | Infinite Capacity |
|----------------------|---------------------|----------------------|----------------------|----------------------|----------------------|---------------------|-------------------|
| X control operations | 100.0%              | 27.4%                | 51.7%                | 68.5%                | 79.0%                | 84.0%               | 288.3%            |
| X+20 no overlap.     | 100.0%              | 27.5%                | 51.6%                | 68.4%                | 79.3%                | 84.7%               | 290.3%            |
| X+50 no overlap.     | 100.0%              | 27.5%                | 51.1%                | 68.2%                | 77.2%                | 82.0%               | 286.2%            |
| X+20 with overlap.   | 100.0%              | 27.6%                | 51.7%                | 68.7%                | 79.1%                | 84.5%               | 290.3%            |
| X+50 with overlap.   | 100.0%              | 27.6%                | 51.6%                | 69.1%                | 79.0%                | 85.0%               | 290.3%            |

Table 2 presents the experimental results on the maximum W@R average. As already mentioned, all values are compared with the Start Sampling strategy and the control plan with X number of control operations. The results are presented in percentage and represent the maximum W@R average obtained according to the parameters: Sampling strategy, capacity in the defectivity area, number of control operations in the control plan and configuration of control operations.

Table 2: Maximum W@R average and control plan with and without overlapping

| Maximum W@R average  | Start S. Capacity A | Smart S. Capacity A5 | Smart S. Capacity A4 | Smart S. Capacity A3 | Smart S. Capacity A2 | Smart S. Capacity A | Infinite Capacity |
|----------------------|---------------------|----------------------|----------------------|----------------------|----------------------|---------------------|-------------------|
| X control operations | 100.0%              | 140.3%               | 95.4%                | 78.8%                | 74.3%                | 72.6%               | 57.7%             |
| X+20 no overlap.     | 100.0%              | 142.5%               | 95.1%                | 78.9%                | 73.6%                | 72.6%               | 57.0%             |
| X+50 no overlap.     | 100.0%              | 155.2%               | 104.2%               | 86.5%                | 81.7%                | 80.6%               | 66.0%             |
| X+20 with overlap.   | 100.0%              | 139.3%               | 92.5%                | 78.0%                | 73.4%                | 71.6%               | 56.3%             |
| X+50 with overlap.   | 100.0%              | 140.1%               | 93.3%                | 77.8%                | 73.3%                | 71.8%               | 56.3%             |

Let us focus on the results for capacity A and a control plan with X number of operations. The maximum W@R average obtained with the Smart Sampling strategy is 72.6%. Hence, with similar capacity at the defectivity area, the maximum W@R average can be reduced 27.4% by only changing the sampling strategy. The process flows in modern high-mix semiconductor manufacturing facilities are known to be highly complex. For that reason, when lots to be measured are selected at the beginning of the process, an optimal control of the tools in terms of W@R cannot be guaranteed (see Nduhura Munga et al. (2011) for more details).

Results obtained when the capacity is reduced (Capacity A4 and A5) show that the maximum W@R average increases when using control plans with additional operations and no overlapping (155.2% and 104.2% with X+50 controls respectively). The reason is that the capability of a control to reduce the W@R on tools decreases when there is no overlapping. As described in Figure 2, with the original control plan the control operation D0\_1 validates six process operations. An additional control (D0\_2) will only validate three process operations. Thus, the maximum W@R average has been degraded.

Table 3 presents the difference in terms of W@R reduction between the control plan with and without overlapping. With the case of capacity A5, we observe that an additional reduction on W@R is obtained when overlapping is considered, 3.2% and 15.0% with X+20 and X+50 control operations respectively. Thus, when the number of control operations increase and the capacity is reduced, the influence of the overlapping on controls becomes more important.

Table 3: Difference of W@R reduction between control plan with and without overlapping

| <b>Delta between control plan with and without Overlap.</b> | Smart S. Capacity A5 | Smart S. Capacity A4 | Smart S. Capacity A3 | Smart S. Capacity A2 | Smart S. Capacity A | Infinite Capacity |
|---|----------------------|----------------------|----------------------|----------------------|---------------------|-------------------|
| X+20 control operations                                     | 3.2%                 | 2.6%                 | 0.9%                 | 0.3%                 | 1.0%                | 0.7%              |
| X+50 control operations                                     | 15.0%                | 10.9%                | 8.7%                 | 8.3%                 | 8.8%                | 9.7%              |

The results in Table 1, 2 and 3 show that, when overlapping is considered, the risk on tools can be reduced without increasing the number of sampled lots. Let us recall that these results are obtained when the Smart Sampling Strategy is used to choose the lots to measure. Conclusions concerning the control plan design could be different according to the sampling strategy. Therefore, the design of control plans should not be separated from the definition of the sampling strategy.

### 3.2 Impact of Control Operations Position

In this section, the position of control operations is studied. Table 4 shows the results for the control plan with X+20 and X+50 operations with different configurations. The throughput of some tools have been considered but not in an exhaustive way in Configuration 1. Let us focus on the control plan X+20. We observe that, with the same number of controls, different reductions on the maximum W@R average are obtained. In particular, in Configuration 1, some controls are placed near some tools with high throughput, thus leading to larger reduction on the W@R when lots are measured. When the distance between controls and tools with high throughput is reduced, the maximum W@R for these tools can also be reduced.

Let us focus on the control plan with X+50 control operations and Configuration 2. Results show that the maximum W@R average is sometimes worse compared to Configuration 1 of the X+20 control plan. These results show that more controls do not always mean less risk. Because lots are going to be controlled more often, the workload of metrology tools increases, and consequently waiting times in front of metrology tools can also increase. Concerning the scenario with “Infinite Capacity”, it refers to the case where all selected lots can be measured. This scenario give us an idea of the lower bound of the maximum W@R average. Note that, according to the control positions, the maximum W@R average will not be lower than 42.0%.

Table 4: Maximum W@R average and positions of control operations

| <b>Maximum W@R average</b> | Smart S. Capacity A5 | Smart S. Capacity A4 | Smart S. Capacity A3 | Smart S. Capacity A2 | Smart S. Capacity A | Infinite Capacity |
|----------------------------|----------------------|----------------------|----------------------|----------------------|---------------------|-------------------|
| X control operations       | 100.0%               | 140.3%               | 95.4%                | 78.8%                | 74.3%               | 72.6%             |
| X+20 Configuration (1)     | 139.3%               | 92.5%                | 78.0%                | 73.4%                | 71.6%               | 56.3%             |
| X+20 Configuration (2)     | 167.5%               | 109.4%               | 86.2%                | 75.3%                | 70.1%               | 46.4%             |
| X+20 Configuration (3)     | 140.1%               | 93.4%                | 78.0%                | 73.0%                | 71.6%               | 56.3%             |
| X+50 Configuration (1)     | 140.1%               | 93.3%                | 77.8%                | 73.3%                | 71.8%               | 56.3%             |
| X+50 Configuration (2)     | 197.5%               | 128.9%               | 95.5%                | 81.1%                | 72.4%               | 42.0%             |
| X+50 Configuration (3)     | 140.1%               | 93.2%                | 77.5%                | 73.3%                | 71.9%               | 56.3%             |

### 3.3 Impact of the Coverage of Control Operations

The impact of additional controls in the control plan with overlapping and different positions has been studied in the previous sections. However, the coverage of new process operations was similar to the original control plan. As illustrated in Figure 3, the risk on tools that were not covered has not been impacted with the new control operations. Since the analysis is based on the average maximum W@R, the impact of new control operations was limited. In this section, the coverage of new process operations is included in the control plan design.

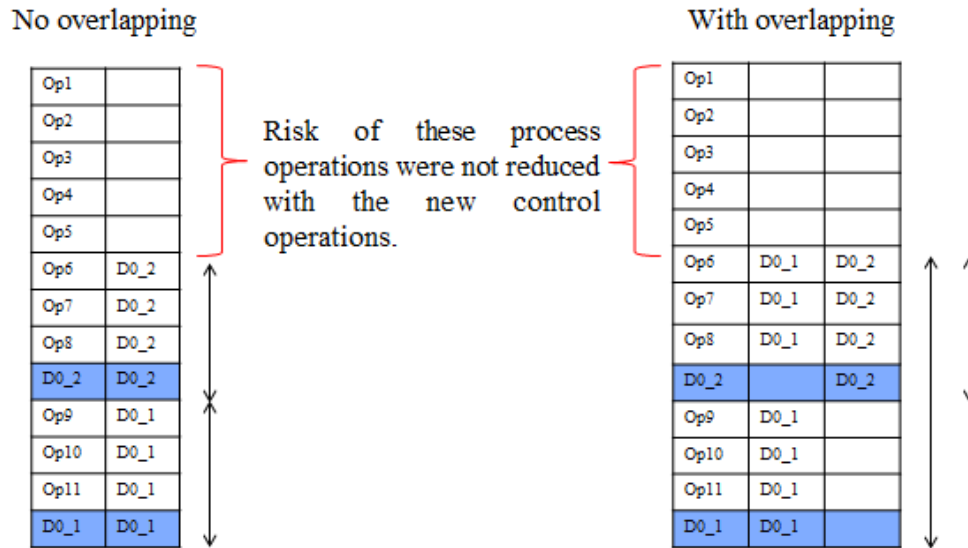


Figure 3: Coverage of control operations

Table 5 presents the maximum W@R average for a control plan with X+20 operations and a total coverage of process operations. The value of B represents the number of process operations covered by control. Thus, a control plan with B+6 covers more process operations than a control plan with B.

Table 5: Maximum W@R average with total coverage of process operations

| Maximum W@R average          | Start S. Capacity A | Smart S. Capacity A5 | Smart S. Capacity A4 | Smart S. Capacity A3 | Smart S. Capacity A2 | Smart S. Capacity A | Infinite Capacity |
|------------------------------|---------------------|----------------------|----------------------|----------------------|----------------------|---------------------|-------------------|
| X control operations         | 100.0%              | 140.3%               | 95.4%                | 78.8%                | 74.3%                | 72.6%               | 57.7%             |
| X+20 without overlapping (B) | 100.0%              | 156.7%               | 102.7%               | 74.7%                | 62.6%                | 54.3%               | 26.2%             |
| X+20 with overlapping (B+2)  | 100.0%              | 146.6%               | 93.1%                | 73.9%                | 59.8%                | 53.0%               | 26.2%             |
| X+20 with overlapping (B+4)  | 100.0%              | 143.7%               | 90.9%                | 69.9%                | 61.2%                | 52.5%               | 26.0%             |
| X+20 with overlapping (B+6)  | 100.0%              | 137.4%               | 89.1%                | 70.0%                | 58.7%                | 51.2%               | 25.9%             |

Let us focus on the results with infinite capacity. We observe that, when new process operations are covered, the impact of the additional control operations is significant. The wafer at risk obtained decreases from 57.7% with the original control plan (X control operations) to 26.2% having a control plan with X+20 control operations. Hence, when capacity is increased, the factor that enables the reduction of W@R is the number of operations. Let us focus on the results with capacity A4. The results show that, when the capacity is reduced, the overlapping is an important factor that helps to reduce the overall wafer

at risk. The maximum W@R average obtained with the original control plan is 95.4%, compared with an average maximum W@R of 102.7% without overlapping and 89.1% with overlapping.

#### 4 CONCLUDING REMARKS

In this paper, we presented an analysis for control plan design based on the tool wafer at risk (W@R) reduction and a smart sampling strategy for choosing lots. We focus on how the design of control plans for defectivity inspections impacts the reduction of the wafer at risk at the tool level. Experiments on actual data have been conducted with the S5 simulator developed at EMSE. Results show that more inspections in the control plan do not always reduce the overall wafer at risk. The wafer at risk reduction highly depends on the positions of control operations and how they cover process operations. In addition, when metrology capacity is reduced, the overlapping of controls can enhance the wafer at risk reduction. When metrology capacity is increased, the number of controls is a key factor to consider. Since metrology capacity must be considered, decisions on the control plan design cannot be done independently of the sampling strategy.

Future work will be conducted to study the optimization of the number and positions of the control operations in the control plan. The identified criteria are the throughput of process operations, the delay to get measurement results and the number of process operations covered by a control operation.

#### ACKNOWLEDGMENTS

This study has been done within the framework of STMicroelectronics and the Centre Microélectronique de Provence-George Charpak at Ecole Nationale Supérieure des Mines de Saint-Etienne in Gardanne, France. This work is supported by the IMPROVE ENIAC European Project.

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