Optimisation of the process control in a semiconductor company: model and case study of defectivity sampling

M. Shanoun\textsuperscript{a}; S. Bassetto\textsuperscript{a}; S. Bastoini\textsuperscript{b}; P. Vialletelle\textsuperscript{b}

\textsuperscript{a} Grenoble Institute of Technology, Grenoble, France \textsuperscript{b} STMicroelectronics, Crolles 300, France

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Optimisation of the process control in a semiconductor company: model and case study of defectivity sampling

M. Shanouna, S. Bassettoa*, S. Bastoinib and P. Vialletelleb

aGrenoble Institute of Technology, Lab. G-SCOP, CNRS, 46, Avenue Félix Viallet 38000, Grenoble, France; bSTMicroelectronics, Crolles 300, France

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This article studies the skip, under some assumptions, of process control operations. The case of one tool, one enhanced buffer and one metrology tool of a monotonic parameter is analysed. This article presents circumstances in which control plan can be optimised due to the buffer’s behaviour. After discussing the industrial issue of defectivity, this article presents a literature review followed by the model and steps towards industrial development. Then demonstrator, which is applied at a case study of defectivity sampling, is presented. A test of over a 300-mm wafer fabrication data set shows serious improvements – around 35% of defectivity controls have been skipped compared to the static sampling plan.

Keywords: process control; dynamic control plan; risk measurement; defectivity measurement

1. Introduction

The industrial problem underlying this study finds its roots in front-end semiconductor facilities. Particles control is performed over products and tools. After manufacture, products can be connected to control devices to collect information about their purity. The result is used to qualify the production system and the product itself. Using data to monitor both products and processes is a common practice in statistical process control and acceptance controls. These measurements are the heart of defectivity and yield control (Kumar et al. 2006).

Let us consider an oversimplified example: the dust control of a manufacturing equipment T, like an etching tool. The level of contamination, D, increases with the number of items produced. If a product is manufactured using tool T, it adds particles and can be contaminated by residues. It is controlled after being processed. T is considered fouled if the level of D, measured on the product, is higher than a threshold limit ULDust. In that case, the product is also labelled defective and it can be either washed or scrapped. Below this limit, both the product and the tool are considered as clean. Consider a sequence of 10 products from P1 to P10, produced with T and the associated sampling plan: to-control P1 and P10. P1 is then produced and controlled. If P1 is clean, then the production plan goes on. If it is measured as defective, a clean operation has to be performed on T and P1 (if possible). If the cleaning is successful, then the production can be restarted. When P10 is controlled, if the level of D does not reach ULDust, as dust has a...
property of accumulation throughout the production, one can say that P2, P3, P4, P5, P6, P7, P8 and P9 are also clean. If P10 is dirty, then no conclusion can be inferred about previous productions.

Let us change the previous control plan for a 100% one. The travel between the manufacturing and the control system can follow a stochastic law as illustrated in Figure 1. B is made of the tool’s output buffer, transportation buffer and entrance buffer of the control tool C. The buffer B can behave in a range of stochastic laws. Following Figure 1, the product P1 is manufactured first and controlled in the fourth position due to the buffer’s behaviour. Some products can be controlled in sequence with the manufacturing of products. However, as the dust deposition is an increasing phenomena, it is obvious that if product P4 has been released, product P1 is also clean and it is not necessary to control it anymore.

This observation is the basis of this article.

In the semiconductor industry, at each point of production, easy implementation and the ability to release controls, without losing information help increase the productivity in a steady state mode and also in the ramp-up mode. Then this article, contributes towards this goal by providing an algorithm to perform this task. A particular measure of operational risks at a tool level and the potential that a measurement has to reduce it has been introduced in order to be able to operationally implement this concept. A model of this case is presented revealing potential gains of this problem.

Section 2 presents a brief literature review. Section 3 presents the model and associated development to implement it operationally. Section 4 presents a case study and discussion.

2. Literature review

Spanos (1991) introduces the concepts of process control in the semiconductor industry. A detailed overview of process control tools and practices can also be found in the book by May and Spanos (2006). The work of Montgomery (2004) is recommended to understand the concept of statistical process control (SPC), generalised in this industry. In order to design controls and adapt them throughout a technology lifecycle, economic design of control charts and adaptive control chart are the two grounding fields of statistical control.

The first one has been initiated by Duncan (1956). Major drawbacks have been pointed out (Woodall 1986) towards this design mode, especially the lack of robust results. However, grounded with a true problem of balancing controls and their costs, developments have followed. For example, a historical article has been found about quality control skipping (Hsu 1977). This article is concerned with reduction of sample size
and decrease in the control frequency, compared to a 100% or screening plan. It aims at identifying the right control frequency regarding a particular cost model. In the field of economic design of control charts, the model proposed by Lorenzen and Vance (1986) seems to be a milestone with the development of Vommi and Seetala (2007).

A second development is the adaptation of a control plan regarding events observed. Varying sampling intervals, sampling frequency or changing of control limits are common actions taken for data collection. The systematic analysis of this subject began with the publication of Reynolds et al. (1988). They demonstrated that two levels of controls (sampling size, frequency and limits) is a better solution to control and detect faster issues while minimising the cost of errors. Adaptive process control has been reviewed by Tagaras (1998). More recently, De Magalhães et al. (2009) presented an outstanding overview of these techniques, which is a key paper in this field.

In the semiconductor industry, several authors focussed on control adaptation, yield impact and risks. Based on an economic model, which takes into account the reuse of SPC data during yield and scraps investigations, Baud-Lavigne et al. (2009) presented how quality controls can be released due to learning curves. Bousetta and Cross (2005), Mouli and Scott (2007) and Purdy (2007) presented industrial development aiming at adaptive control of measurement, regarding yield evolutions, measurement capacity and risks. Among these three papers, the first paper presents a sampling strategy by counting the number of wafers passed on metrology tools. The second provides a mechanism to update control regarding process excursions. The third presents a generic architecture to update control regarding risks encountered during production. The latter presents an entire development, which seems to improve quality control performances. Key to their development is the concept of a lot environment, named Partition, which is used to compute a risk index. However, they do not provide further explanation of the manner in which they identify the risk index and its representativeness.

Literature pertaining to design economic and adaptive sampling are measured by the velocity of control chart detection. The reason why control charts have been settled is hardly or never studied in any of those papers. One of them presents a grounded approach of adaptive quality controls based on yield improvement. Another presents a generic approach to risk evaluation but not in detail the reason why these risks are modelled so and consequences of such a model. None of them is concerned with control skip due to operation control.

The problem presented in this article can be seen as an inspection re-allocation problem due to the buffer’s behaviour and the variable monitored. Inspection devices can be used to monitor products other than those defined in a static control plan, due to updated information about products.

The field of inspection allocation has been investigated since the publication of Lindsay and Bishop (1964). They studied a cost function per unit produced, taking into account the inspection cost and its location in the process. The minimum cost has been found for none of the inspections or entire batch inspected. Since their paper, several studies have been performed. Close to the authors concern, in the field of printed circuit board, Villalobos et al. (1993) present flexible inspection systems for serial and multi-stage production systems. They provide an algorithm based on a Markov Chain model to optimise global goals (like costs) and local constraints like inspection tool availability. Verduzco et al. (2001) present an interesting case of information-based inspection allocation. They modelled a cost function taking into account the type I and type II errors linked at each measurement. They simulate their algorithm with a knapsack formulation. They yield that
the information-based solution showed better performances in terms of classification
errors than static inspections. Their paper has been a source of inspiration for authors as
they introduce the fact that the control strategy can be modified based on its gain. In his
master thesis, in MIT, Bean (1997) presents the development of an inline, dynamic
inspection plan, based on the probability of excursions, due to measurement. His work
also presents the notion of material at risk (MAR) as each product between two samples
can be impacted by defects. In order to be complete, in the field of inspection allocation,
authors recommend the surveys of Raz (1986) and Tang and Tang (1994). Close to the
subject is development about automatic control and the position of sensors in the
manufacturing process, in order to reduce uncertainty. These models are tightly coupled
with diagnosis approaches of Zamaï (1997). It is assumed that the more the process goes
on, the more is the uncertainty accumulated, and if it crosses the threshold, a control has
to be performed.

To our knowledge no papers have been published related to the release of measurement
or inspection due to operations management.

As presented in Section 1, measurement of operations can be strongly influenced by
operations management and especially by the way the buffers production tool and control
tool behave. Authors share the view of Colledani and Tolio (2009) that models of quality
and quantity are rare in the literature. Hsu and Tapiero (1989) pioneered this field by
proposing a link between operations management and SPC control charts. Gershwin and
Kim (2005) and Colledani (2008) present academic investigations on how quality and
operations control can be linked. Especially, Colledani (2008) designs the buffer size
regarding quality and cycle time expectation. It is based on the Markov chain model of a
production system, allowing a multiple failure behaviour mode. However, none of these
works models a possible release of measurements, due to operations management, nor
models impact towards risk monitoring.

At the boundary of this research are risk management and production ramp-up. As it
inspires authors, the literature goes through – very quickly – these domains.

During the production ramp-up of a transfer or a new technology, the ability to release
control is crucial in order to produce in time. Readers are referred to the paper of Bousetta
and Cross (2005) as an introduction to controls management practices, during ramp-up.
Also, we recommend the academic works of Tapiero (1987), Fine (1988), Terwiesch and
Bohn (2001).

At the same time, almost all semiconductor industries have to provide updated failure
mode effects and criticality analysis (FMECA; Department of Defense 1980, Villacourt
about their tools, processes and products in order to ensure their production ability to the
customer. These analyses cover operational risk management, which can be defined as the
elicitation, evaluation – often through ranking techniques – mitigation and follow-up of
‘fearsome event, regarding stakes’ (De Choudens et al. 2000). A general survey of modern
methodologies to master risks can be found in Tixier et al. (2002). Measurements are
performed over products, processes and tools in order to detect drifts and other possible
operational risks that occur. However, very few articles truly link risk analysis and
detection. Even in the field of adaptive controls, risks are not explicitly mentioned. Only
monitored process excursions (out-of-control events), which are precursors or conse-
quences of operational risks, are analysed (Bean 1997). Pillet et al. (2007), pioneered the
work of linking control plan at risks. An impact matrix has been presented linking risks
and their elicitation at associated control. Ozouf (2009) following Pillet, provides a deeper
analysis of the link between risk analyses type and control plan. Bassetto (2005) proposes an enterprise model joining risks elicitation, their evaluation and associated control activities. The central idea is that controls (charts, inspections . . . etc.) are required due to the fact that tools, processes or products can have or produce failures. For each occurrence, a revision of risk analysis has to be performed and associated control plans revised. The more the risk, the more the control has to be performed. This framework has been applied by Mili et al. (2009) for defining maintenance priorities and improvement actions. Application of these models have been tested over a photolithography workshop. This research remains at management level and neither provides details about the way to update controls, nor ensures that no instabilities can emerge from this looped system. This problem has also been pointed out by Bean (1997).

At joints of process control – or inspection – risks management and operations management, the research seems very promising, while surprisingly it has received less attention from researchers. Some papers are akin to this present article, however, the authors have not retrieved any of those papers for the purpose of this article. The quality control release seems to be hardly studied yet and especially its impact in terms of information. Of course, industries can practise an adaptive control, regarding specific risks and their operations without having published their methods other than internal reports, which are unaccessible to the researchers. Maybe such practices can also be kept confidential, as part of their operational excellence.

3. Model of the dynamic release of some sampling operations

The purpose of this section is to model and understand the phenomenon presented in Section 1 in order to move towards a dynamic quality control plan, applied at particle measurement.

Assumption 1: The models under consideration is the case of one production tool, one buffer (made of the output buffer of the manufacturing tool, the transportation buffer – within the plant – the input buffer of the metrology tool) and one control device. This model oversimplifies the reality but allows initial developments.

Assumption 2: The problem of why products are rescheduled into the buffer is not taken into account in this article. Several factors are involved, especially, control plan, measurement capacity, transportation and type of information related to products. The waiting time of the product between manufacturing operation and control operation, is only modelled with a random law $l$.

Assumption 3: The metrology tool behave perfectly regarding the phenomenon observed over the product: type I and type II errors are neglected in this first model. The measurement time is considered as constant, $t_{\text{Ctrl}}$. The information about the wafer’s purity is assumed to be immediately available after the measurement.

Assumption 4: The metrology is performed over only one parameter, which behaves in a monotonic manner exclusively with products. In the developments given below, it is considered as an increasing phenomenon of particle deposition, grease or painting deposition. The more the goods produced, the more the contamination for new products. When possible, decreasing phenomenon are presented in quotes.
Assumption 5: Data obtained on product variables allow to infer information about product functionality and about the way the manufacturing tool behaves. It is the case of contamination (dust, ionic, grease, etc.) for clean products like wafers or medical devices.

Assumption 6: The test, $C$, compares the value of a parameter named $Def$, measured on the $i$th product named $P_i$, with a limit labelled $UL_{Def}$. A product is considered as non-defective if its measure is below (or higher) $UL_{Def}$ (resp. $LL_{Def}$). $C$ is a function from the product space in real $C: \{\text{products}\} \rightarrow \text{Real}$.

Notations: $k, j, i$, three production indices $k < j < i$.

A clearing event is an action like cleaning, a washing of the tool, or every action that can requalify $T$ for production. This includes maintenance actions and the dissipation of related effects (Waddington effect, for example).

Property 1: The consequence of the variable’s monotonicity is that if a product $P_i$ is tested and labelled as non-defective, then considering every products $P_j$, manufactured since the last non-defective product $P_k$ or the last clearing event, can be considered as correct. Demonstration: if there is a $j | j < i$ and $C(P_j) > UL_{Def}$, by the monotonicity of the phenomenon monitored by $C$, $C(P_j) > C(P_i) > UL_{Def}$, which contradicts with the measurement of $C(P_i) < UL_{Def}$. The demonstration follows the same pattern for a decreasing phenomenon with $LL_{Def}$.

If assumption 3 cannot be assumed, then this property has to be modified for a stochastic approach.

As a consequence of this property, if the information retrieved by the measurement is to compare these products towards $UL_{Def}$ (resp $LL_{Def}$), it is unnecessary to control them and the measurement can be skipped. When a product is scrutinised and considered as clean, the products manufactured since the last qualification operation (maintenance or following bad production detection) are also labelled clean. In contrast, if a product is measured as faulty or fouled, an investigation has to begin for every product before it is contaminated. In a sceptic perspective, when a product is not measured, it joins the set of potentially bad products.

Mixed with a stochastic behaviour of the buffer $B$ (Figure 1), $P_i$ has a non-null probability to be measured before $P_j$. The previous property can generate release of controls, and by the way gains.

However, these developments only point out possible improvement. Let us go further in the investigation of behaviour and system performances (Li and Meerkov 2009), by introducing some complementary notations and assumptions.

Assumption 7: The model is made between two qualification actions or clearing events. The time elapsed between these two actions is named as production cycle and denoted $PC$. Indices of product within a Process Cycle, start at 1.

Assumption 8: For the sake of simplification, $T$ produces goods in a regular manner for every $\tau$ second, and follows a non-stochastic behaviour. We consider that $\tau \propto PC$. During $PC$, $T$ produces $PC/\tau$ products.

Assumption 9: The control plan is set at 100%. Every manufactured product has to be measured.
**Assumption 10:** The probability that an $i$th product is clean depends on the number of products produced before, since the last clearing event, and due to assumption 7, the beginning of the process cycle.

\[ p(P_i \text{ is clean}) \propto \left(1/\text{number of items produced since last clearing event}\right)^\alpha, \]

where $\alpha$ is a parameter

\[ p(P_i \text{ is clean}) \propto (1/i)^\alpha \]

as a consequence of assumption 7.

The buffer $B$, follows a stochastic law, noted as $l$. The probability that a product goes out of $B$ $t_B$ time after being entered, is given by the formula:

\[ p = \int_0^{t_B} l(x) \, dx. \]

Let us note that $t_C(P_i)$, the time where the information about $P_i$ is available, $t_P(P_i)$, the time when $P_i$ is manufactured, and $t_B(P_i)$, the time elapses by $P_i$ within the buffer $B$.

Property 1 can be transformed as follows:

\[ 8(i,j) \in \{1,PC\}; (i,j) \neq c_0(c_28) \]

Condition 1: $t_C(P_j) \leq t_C(P_i)$
Condition 2: $P_j$ is clean

Let us now evaluate the probability that these two conditions are true for a particular product.

**Probability of condition 1:**

\[ t_P(P_i) = i \ast \tau, \quad t_P(P_j) = j \ast \tau \]

the buffer $B$ behaves as a delay generator.

\[ t_C(P_i) = t_B(P_i) + t_P(P_i) = t_B(P_i) + i \ast \tau + t_{Ctrl} \]

\[ t_C(P_i) = t_B(P_i) + t_P(P_i) = t_B(P_i) + j \ast \tau + t_{Ctrl} \]

Condition 1 is verified \iff $t_C(P_j) \leq t_C(P_i)$ \iff $t_C(P_i) + t_B(P_j) + j \ast \tau \leq t_B(P_i) + i \ast \tau + t_{Ctrl} \Rightarrow t_B(P_j) \leq t_B(P_i) - \tau \ast (j-i)$

In terms of probability that these events occur for the product $P_i$,

**Case 1:** $\tau \ast (j-i) > t_B(P_i)$; (*) cannot be verified and $p(t_C(P_j) > t_C(P_i)) = 0$, $P_i$ cannot be released for control.

**Case 2:**

\[ \tau \ast (j-i) = t_B(P_i); \quad p(t_C(P_i) = t_C(P_j)) = p(t_B(P_j) = 0), \quad L(0) = \int_0^0 l(x) \, dx. \]

**Case 3:** $\tau \ast (j-i) < t_B(P_i)$; the probability that the time elapse by $(P_i)$ within the buffer is below $t_B(P_i) - \tau \ast (j-i) \iff \tau \ast (j-i) < t_B(P_i)$; $p(t_C(P_i) > t_C(P_j)) \Rightarrow p(t_B(P_j) < \int_0^{t_B(P_i) - \tau \ast (j-i)} l(x) \, dx$.

Cases 1–3 are valid for every product manufactured within the Process Cycle.
Probability of condition 2:

P_j should also be clean. However, the last clearing event has to be anterior to i. In contrast, nothing could be inferred from the cleanliness of P_i.

\[ p(P_j \text{ is clean}) \propto \frac{1}{\text{number of items produced since last clearing event}} = \frac{1}{j^\alpha} \]

Probability for a particular product P_j to verify conditions 1 and 2, and to be released:

Let us note R, the set of products which can be released. During production, R increases as products verify conditions 1 and 2. After a Process Cycle, \( R = \{ P_i/i \in [1; PC/\tau] \text{ and } \exists j \in [1; PC/\tau]/j > i \text{ and } t_B(P_i) < f_{\text{m}}(P_j)-\tau(j-i) \cdot 1(x)dx \text{ and } P_j \text{ is clean} \} \).

A particular product P_j belongs to R, if there is at least one product, produced after P_i that is measured before and if it is clean. These products can be \( P_{i+1}, P_{i+2} \ldots P_{k*} \), where \( k^* \)

- the last product is produced within the Process Cycle; \( k^* \leq PC/\tau \)
- the time elapse between \( P_i \) and \( P_k^* \) is at the limit of \( P_i \)'s waiting time within the buffer:
  - \( t_B(P_i) > \tau(k^* - i) \)
  - \( t_B(P_i) \leq \tau(k^* + 1 - i) \)

The probability that \( P_j \) belongs to \( R = p(P_j \in R) \)

\[ p \left( [P_{i+1} \text{ reaches C before } P_i \text{ and } P_{i+1} \text{ are clean}] \text{ or } [P_{i+2} \text{ reaches C before } P_i \text{ and } P_{i+2} \text{ are clean}] \ldots \text{ or } [P_{k^*} \text{ reaches C before } P_i \text{ and } P_{k^*} \text{ are clean}] \right) \]

\[ \sum_{m=i+1}^{k*} p(P_{i+m} \text{ reaches C before } P_i \text{ and } P_{i+m} \text{ are clean}) \]

\[ \sum_{m=i+1}^{k*} p(t_B(P_m) < f_{\text{m}}(P_j)-\tau(m-i) \cdot 1(x)dx) \cdot p(P_{i+m} \text{ is clean}) \]

In order to consider the equivalence, let us take the case where \( p(P_j \text{ is clean}) = \frac{1}{j^\alpha} \)

\[ \sum_{m=i+1}^{k*} p(t_B(P_m) < f_{\text{m}}(P_j)-\tau(m-i) \cdot 1(x)dx) \cdot \left(\frac{1}{i+m}\right)^\alpha \]

Algorithm: This formulation is generic for every product being produced within a process cycle. In order to determine Card R, this probability has to be evaluated for every product manufactured in a cycle. This sum, can be simulated knowing 1, \( \alpha \). Of course, \( t_B(P_i) \) are defined when the simulation reaches the ith step. The algorithm is presented in Annex 1.

As the buffer behaves in a stochastic manner, there is no reason that this probability is systematically null, then Card R \( \geq 0 \). As the initial control rate was 1 considering that Card (R) \( \geq 0 \), the new sampling rate is \( [1-\text{card } R/(PC/\tau)] \).

Several problems are encountered at this level:

- To determine Card R in an exact manner.
- The evaluation of \( p(R_i \text{ is clean}) \) depends heavily on the way the risk monitored behave. Other probability functions could have been chosen.

Illustrative example, based on the simulation:

From the first product to the first control, the control plan is set at 100%, \( \alpha = 0, 5 \), and \( \tau = 1 \). In this simulation, \( t_c(P_i) \) is known, leading at a ranking of product behind measurement tool.

The product 1 is produced at 1 and controlled at time 58. The product 2 is produced at 2 and controlled at time 5. It is clear that in this list, the second product is the first to be measured. Its probability of being clean follows the law of assumption 10, which leads at 0.7. As the measurement retrieves a value below this limit, the product is considered as clean. By the way, the first product is also declared as clean and skipped from control.
3.1 First measurement

The buffer’s output is reordered for the second control (Table 1).

3.2 Second measurement

According to Table 2, the fourth column, the second measurement occurs on eight products. Its probability of being clean equals 0.35. As the measurement retrieves 0.3, it is declared as clean by its predecessors also. This involves:

- Products 9 and 10 are moved from respectively from the 4th and 7th position to the 3rd and 4th ones.
- Controls of products 3–7 are skipped.

### Table 1. First measurement.

<table>
<thead>
<tr>
<th>Product</th>
<th>$t_B(P_i)$</th>
<th>$t_C(P_i)$</th>
<th>Buffer output rank</th>
<th>Cumulative production since last control</th>
<th>Probability of being clean</th>
<th>Measurement</th>
<th>Result of control</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>57</td>
<td>58</td>
<td>6</td>
<td>1</td>
<td>1</td>
<td></td>
<td>Clean</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>5</td>
<td>1</td>
<td>2</td>
<td>$0.7 = (1/2)^{0.5}$</td>
<td>0.1</td>
<td>Clean</td>
</tr>
<tr>
<td>3</td>
<td>84</td>
<td>87</td>
<td>9</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>87</td>
<td>91</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>15</td>
<td>20</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>73</td>
<td>79</td>
<td>7</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>7</td>
<td>47</td>
<td>54</td>
<td>5</td>
<td></td>
<td></td>
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<td>8</td>
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<td>9</td>
<td>28</td>
<td>37</td>
<td>4</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>76</td>
<td>86</td>
<td>8</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Table 2. Second measurement.

<table>
<thead>
<tr>
<th>Product</th>
<th>$t_B(P_i)$</th>
<th>$t_C(P_i)$</th>
<th>Buffer output rank</th>
<th>Cumulative production since last control</th>
<th>Probability of being clean</th>
<th>Measurement</th>
<th>Result of control</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>57</td>
<td>58</td>
<td>Skipped</td>
<td>1</td>
<td>Not computed</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>5</td>
<td>Done</td>
<td>2</td>
<td>$0.7 = (1/2)^{0.5}$</td>
<td>0.1</td>
<td>Clean</td>
</tr>
<tr>
<td>3</td>
<td>84</td>
<td>87</td>
<td>7</td>
<td>1</td>
<td>N/A</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>87</td>
<td>91</td>
<td>8</td>
<td>2</td>
<td>N/A</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>10</td>
<td>20</td>
<td>2</td>
<td>3</td>
<td>N/A</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>73</td>
<td>79</td>
<td>5</td>
<td>4</td>
<td>N/A</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>47</td>
<td>54</td>
<td>4</td>
<td>5</td>
<td>N/A</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>9</td>
<td>17</td>
<td>1</td>
<td>6</td>
<td>$0.35 = (1/8)^{0.5}$</td>
<td>0.3</td>
<td>Clean</td>
</tr>
<tr>
<td>9</td>
<td>28</td>
<td>37</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>76</td>
<td>86</td>
<td>8</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
3.3 Third measurement

For this measurement, the ninth product is measured and its probability of being clean is 0.31. The measurement retrieves 0.6, which leads at a clearing event.

- Controls of products 3–7 are skipped.

The third measurement reveals a fouled tool (Table 3). A cleaning action is performed and the process cycle is restarted. The probability of being clean is now $(1/9)^{0.5} = 1$.

3.4 Fourth measurement

The fourth measurement is then made for a new cycle, as the clearing event occurs at the third measurement (Table 4).

Table 3. Third measurement.

<table>
<thead>
<tr>
<th>Product</th>
<th>$t_B(P_i)$</th>
<th>$t_C(P_i)$</th>
<th>Buffer output rank</th>
<th>Cumulative production since last control</th>
<th>Probability of being clean</th>
<th>Measurement</th>
<th>Result of control</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>57</td>
<td>58</td>
<td>Skipped</td>
<td>1</td>
<td>1</td>
<td>0.1</td>
<td>Clean</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>5</td>
<td>Done</td>
<td>2</td>
<td>$0.7 = (1/2)^{0.5}$</td>
<td>N/A</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>84</td>
<td>87</td>
<td>Skipped</td>
<td>1</td>
<td>N/A</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>87</td>
<td>91</td>
<td>Skipped</td>
<td>2</td>
<td>N/A</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>10</td>
<td>20</td>
<td>Skipped</td>
<td>3</td>
<td>N/A</td>
<td></td>
<td></td>
</tr>
<tr>
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<td>79</td>
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<td>4</td>
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<td></td>
<td></td>
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</tr>
<tr>
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<td>28</td>
<td>37</td>
<td>1</td>
<td>1</td>
<td>$0.31 = (1/9)^{0.5}$</td>
<td>0.6</td>
<td>Dirty</td>
</tr>
<tr>
<td>10</td>
<td>76</td>
<td>86</td>
<td>2</td>
<td>Not computed</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4. Fourth measurement.

<table>
<thead>
<tr>
<th>Product</th>
<th>$t_B(P_i)$</th>
<th>$t_C(P_i)$</th>
<th>Buffer output rank</th>
<th>Cumulative production since last control</th>
<th>Probability of being clean</th>
<th>Measurement</th>
<th>Result of control</th>
</tr>
</thead>
<tbody>
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<td>0.1</td>
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</tr>
<tr>
<td>2</td>
<td>3</td>
<td>5</td>
<td>Done</td>
<td>2</td>
<td>$0.7 = (1/2)^{0.5}$</td>
<td>N/A</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>84</td>
<td>87</td>
<td>Skipped</td>
<td>1</td>
<td>N/A</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>87</td>
<td>91</td>
<td>Skipped</td>
<td>2</td>
<td>N/A</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>10</td>
<td>20</td>
<td>Skipped</td>
<td>3</td>
<td>N/A</td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>
In this example, six products have been skipped, over 10, without loss of information.

This section presents, under some assumptions, that some controls can be skipped due to properties of the underlying phenomenon, without impacting information generation. A general formulation has been presented and a fake example illustrates the purpose. However, in order to provide exact solutions, further investigations have to be carried out. The probability presented in this section is hardly obtained in real situations. It can be used for estimating a potential return on investment.

4. Towards an industrial application

In order to operate properties presented above, another decision tool is introduced. As mentioned previously, while a product has not been measured, it is considered as suspect, and so is the tool. A 100% sampling plan is often ideal for process control activities. Sampling involves that some products are not controlled and can be revealed as defective after having followed their production plan. A risk estimator is employed to ensure operational understanding sampling impact. At operation level, the main focus is on the amount of product processed and potentially impacted by a fault. This estimator counts the number of potentially bad products. It measures the risk of impact. It is not an estimator of the behaviour of the monitored phenomenon, in this case, the defectivity. The probability that a product has been contaminated is independent of this indicator. An illustration of this indicator is provided in Figure 2. This counter is also known as MAR (Bean 1997), and named operationally wafers-at-risk.

This concept is threefold:

- From T point of view, each time it operates a product, a counter, named $IR(T)$ is increased. It is the number of products potentially impacted by the drift of the tool. In the remainder, it will also be named ‘risk indicator for the tool T’. It depends on the number of products manufactured.
- From the product, when it is manufactured, it sees the value of the risk at the time it is processed, $IR(P_i) = IR(T_i)$. Each time a product is controlled, due to assumption 5, this indicator evolves.
Let us note that $IR(P_i)$ is the amount of $IR(T)$ reduction, associated at a measure and release of $P_i$. This measure is a pivot to evaluate the information held by the product.

With such definitions, there is a direct correspondence between information added by a product and risk taken by production or control. This indicator has been and centrally remains the communication with operational teams about the skipping action, as easier to manipulate than probabilities.

At time $i$, if the product is immediately controlled after being produced, if it is declared as clean, and if it is the first product to be measured since the last tool T qualification, then products produced before are released: $IR(P_i) = IR(T)$. Considering that a product $P_i$ adds to $IR(T)$, $f(P_i)$ (typically $f$ is a step 1 function, if the tool operates one product per operation). $IR(T)_{i+1} = IR(T) + f(P_i)$ As $IR(P_{i+1}) = IR(T)_{i+1}$, $IR(P_{i+1}) = IR(P_i) + f(P_i)$. Until a measurement is performed, values of risk reduction remain unchanged. By recurrence for the $h$th product (implicitly produced at time $h$, and not notified here):

$$IR(T)_h = IR(P_h) = IR(P_i) + \sum_{z=i,...,h} f(P_z) = IR(T)_i + \sum_{z=i,...,h} f(P_z)$$

This equation links a risk reduction potential at a time $h$, at the risk indicator of the tool at a predefined passed time $i$, in function of the production during $i$ and $h$. While $P_h$ has not been controlled, it enters in the risk reduction calculation for forthcoming products.

As each measurement progresses, the system evolves. Let us introduce some complementary notations:

$t_c(P_i)$ is noted as $k$.

The measurement of $P_h$ is available at time $k$: $C(P_h, k)$.

$..._k$ for values just before the measurement at time $k$;

$..._k$ for values just after measurement at time $k$. For example,

$IR(P_i)_k$ for $IR(P_i)$ before the measurement at time $k$ and

$IR(P_i)_k$ for $IR(P_i)$ just after the measurement at time $k$.

When a measurement occurs:

**Case 1:** If the product $P_i$ is measured before product $P_h$, at time $k (k/h > i)$, and if $C(P_h, k) < ULD$ it is declared as clean. This will modify the equation given above.

$IR(P_h)_k = 0$ and $\sum_{z=i,...,h} f(P_z)_k = (\sum_{z=i,...,h} f(P_z))_k$ remain unchanged as these products have been manufactured after $P_i$.

$$IR(P_h)_k = 0 + \sum_{z=i,...,h} f(P_z)_k = (\sum_{z=i,...,h} f(P_z))_k = IR(P_h)_k = IR(P_i)_k$$

The risk indicator is decreased by the value of $IR(P_h)_k$ and $IR(P_i)_k > 0$. This case is presented in Figure 2.

**Case 2:** If the product $P_h$ is measured first and $C(P_h, k) < ULD$. If $P_h$ is declared ‘clean’, then due to the property demonstrated before, every product produced and not measured before can be released.

In the example of 10 products, the release of $P_{10}$, also validates $\{P_2, \ldots, P_9\}$, 8 products. Thus, $IR(T)$ is decreased by 8, $IR(P_{10})_{10+} = 8$. After this measurement, $IR(P_2)_{10+} = IR(P_3)_{10+} = \ldots IR(P_9)_{10+} = 0$. 

IR_h(P)_k+ = 0 and IR(T)_k+ = 0, if h is the first product to be measured since the beginning of the production. This situation is presented in Figure 3, where product 3 is measured before product 2, releasing it for production.

The skip action: the action of case 2, for product P_h, is named as ‘skipping’. It is the drop of a control action, as the operation will not modify this indicator.

This indicator helps in clarifying the manner to operationalise previous property. Case 1 can be used to choose among a list of products to be measured, the one which will induce the highest risk reduction. Case 2 induces the skip of a measurement.

5. The application and discussion

The case study takes place in a research on a semiconductor production plant of STMicroelectronics in France. This facility is a Front-End Semiconductor 300-mm wafer fab. The case considers defectivity control, for etching tool. Defectivity is performed over several measurement devices, which will be assimilated at one single tool. The risk indicator is a counter of wafers, manufactured by the tool. Due to handling operations (automatic or manual) and priorities of the products, the time spent between the end of the manufacturing operation and the measurement is highly variable. It may happen that some lots produced after noon are measured before the lots produced in the morning, and case 2, mentioned above seems to occur frequently.

Case study assumptions: The case is limited at one manufacturing device, one defectivity tool. Products are assimilated here at lots of products, often made of 25 wafers. A lot intended for the defectivity carries only one information about the manufacturing tool which is the ‘wafer at risk reduction’, \( IR_r \).

A test computes \( IR \) in real time and performs the skip where the possibility that has been realised central to this algorithm is the computation of conditions 1 and 2 for each product observed. It uses real data from STMicroelectronics (Figure 4). In this figure, the reader can see two X axes for the time. The upper axis is based on production’s time.
It is not linear and depends only on the times when products are manufactured. The second axis represents the actual time. In this axis, measurements are denoted by circles.

The interface, presented in Figure 4, shows a real-time graphical representation of the movement of lots in production, those waiting for the defectivity measurement and the evolution of $IR$.

In the first test, a data set has been prepared in order to run the algorithm. Over a 12-day-period, one case, which is allowed to skip has been introduced. Lots intended to be measured and their true entrance into measurement devices are presented in green. Lots intended to be skipped are flagged with a red line, as illustrated in Figure 5. Lots actually skipped are represented with a white circle.

The test has been successful. The lot fulfilling conditions 1 and 2 has been identified and skipped as presented in Figure 5.

The algorithm has been used for over 2 months of production. During that period, 14,292 wafers have been flagged for defectivity measurement. The application of this algorithm showed that 5024 wafers could have been released for production as they did not add any new information. The algorithm released 35% of lots flagged for defectivity compared to the static sampling plan. Card $R/(PC/\tau) \approx 35\%$. This means that 35% of these lots have been controlled, without adding any information and have costed in terms of measurement capacity, due to the fixed sampling.

The industrial application of the property demonstrated in this article, is more concerned with the evaluation of the number of potentially infected wafers. However, results are promising as Card $R$ is far from 0. The real case shows potential improvement and actual cost reduction of defectivity measurement.
Then there is a deep interaction between manufacturing scheduling and buffer behaviour’s lead at the release of controls, without loss of information.

Particular ongoing developments are as follows:

- The impact of the stochastic behaviour of the buffer allows release of some controls, as they will not add any information regarding risks. However, regarding the buffer’s characteristics (mean time, variability, behaviour law, etc.) and regarding a specific production plan, the gain of capacity could be calculated.
- The impact of some assumption modifications as variable monotonicity and metrology tool behaviour.

Even if the semiconductor industry generated the case study, every situation, which fit assumptions presented for the model could apply the skip algorithm.

6. Conclusion

This article presents a tool, a buffer and a measurement device production system. It investigates a particular property of this system under 11 assumptions, in order to raise a class of problems, and especially the variation of sampling rate, without the loss of information due to the stochastic behaviour of the buffer. In order to operationalise this concept, a risk index is introduced and a case study is presented in a semiconductor manufacture process. The measurement is defectivity control. This article ends with a special opening concerning the quantification of gains, in advance, by identifying the buffer’s behaviour and its impact on capacity release.
Acknowledgement

Authors are warmly grateful to STMicroelectronics for providing data and support for their research.

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References


Department of Defense, 1980. *Procedures for performing a failure mode, effects, and criticality analysis*. MILSTD 1629A.


Annex 1. The simulation’s algorithm

// Initialize variables
Initialize E(tE)
Initialize PC
Initialize R
Initialize a
Card R = 0
// computation of times and buffer order
For each product $P_i$ manufactured within PC
    If $P_i$ is flagged for control
        $t_B(P_i) \leftarrow$ Randomize(1)
        $t_C(P_i) \leftarrow i + t_B(P_i)$
    Else
        End If
        $i \leftarrow i + 1$
End For
Sort the output buffer of control, regarding $t_C(P_i)$ values

// computation of Card $R$
For each product $P_j$ within the control’s stack (ordered from the 1st to be controlled to the last)
    Compute the probability that $P_j$ is clean: $\left(1/(j - (E(t_E) + 1))\right)^a$
    and compare it with a randomized value.
    If it is higher,
        then the product is dirty, nothing can be inferred about previous product (if any)
        $E(t_E) \leftarrow j$
    Else
        It is clean, since the last clearing event, which occurs before it.
        List every products produced before and skip their controls.
        Card $R \leftarrow$ length of this list.
    End If
End For
This algorithm works is not a real time. It is employed to evaluate the gain only.

Annex 2. The prototype algorithm
For each product produced
    • compute $IR(T)$
    • store time at which a cleaning event occurs
    • each time a measurement occurs, evaluate $Ir(P_i)$, for product waiting for measurement since the last clearing event
        • if $Ir(P_i) = 0$, then release the product.
        • else let the product in the control buffer.