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Title: A broader view of the economic design of the X-bar chart in semiconductor industry.

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Abstract: This paper starts from a notice made in semiconductor industry: process control system and especially control charts provide information that can be exploited for correlation analyses during process investigations. In this industry, key and costly investigations are made for improving yield and reducing scraps. Daily, engineering teams are working at manufacturing improvements. Without process data, their work could take much more time and lead to weak improvements. Nevertheless, design of process control systems and in particular control charts lacks from taking into account this remark. As there is no sound application to infer optimal control chart depending on « business parameters » like yield, scraps, customer audits... Meetings between several engineering teams (process control, quality, process integration, industrial engineering and production) occurs frequently to find an affordable quantity of controls for each operations. The literature point of view doesn't provide more recommendations to take into account the reuse of data into these costly investigations.

The paper investigates then this issue. For this first investigation, works have been focused on the design economics of control charts for a simplified process model. The paper translates into the Lorenzen and Vance model this concept. It simulates the design economic of control chart taking into account this new model and infers new optimal SPC set points. An analysis of this new link is made in a context of yield improvement, providing reference for knowing optimal quantity and frequency of controls.

Key words: economic design of control chart, scrap investigation, learning, ramp-up

1 Introduction

Semiconductor industry has to cope with severe environment, drifting processes, and sensitive products at any process disturbance. Information coming from tools and process measurements is a central element for learning how to master manufacturing systems. For each new semiconductor technology a learning process is followed, enabling the fine tuning of specifications, operating modes, control positions, etc. This process is followed to master operational risks before increasing the volume of production. Often, it is admitted by manufacturing teams that during early phases of this learning process, the number of controls have to be high in order to learn faster. However, milestone after milestone processes are expected to be more robust and stable. Progressively, it becomes possible to release controls as the process is better mastered. Maintaining high level of controls is then a nonsense [1] and the pressure to release controls increase drastically as the ramp-up process is going on.

Nevertheless, releasing controls remains an high risky action for managers. As studied by Gershwin and Kim [2], and Colledani [3], it increases the number of wafers produced between two control and by the way increases the risk of massive scrap. Often decision of affordable quantity of controls for each operations are taken during engineering meeting between several teams: process control, quality, process integration, production management... This can lead at sticking the level of control close to a predefined value reasonable in the organization, often far from an optimum. For example, it is a common practice in semiconductor industry to measure over 200 points of control, each wafers during first phases then to decrease near 50 points almost each lot and to reach less than 10 points per measured lots every 100 lots, when products are manufactured in volume. These control rates are not really linked at those provided by classical SPC design methods (either pure statistical design or economic design methods), which also fail to take into account business parameters like data reuse or global cost. There is then an opportunity to develop a decision aided tool to help balancing optimal parameters depending on scrap rate. The design of control charts takes care of external parameters, usually considered by managers like scrap rate and the reuse of quality information.

The aim of this paper is to provide a framework to help this decision process by taking into account both statistical and informational issues. This paper proposes a two stages approach toward such a tool :

- The first step enhances the now classical Lorenzen and Vance's model [4]. The cost of one scrap is far more important than out of control ones and data collected from quality measurements are used during scrap analyzes for building root causes, curative and preventative action plans. It adds the influence between number of points, control frequency

1
2 and the necessary time to solve scrap issues.

- 3 ● The second fold consists in discussing the evolution (through the simulation) of sampling points and rates under the
4 condition of scrap rate evolution.

5
6 The paper is structured over five sections. In a first part, the paper goes through a literature review of economic design
7 of control chart. Then, the paper presents the model enhancing the Lorenzen and Vance's once. The paper presents how
8 simulations have been performed and several results. These two parts represent the first stage, discussed above. Then
9 the paper goes through the second stage, also aforementioned. The paper ends with perspectives.

10 11 12 **2 Literature review**

13 The questioning of interaction between quality and manufacturing operation has been addressed recently by Gershwin
14 and Kim [2], and Colledani [3]. Their works are first investigations of how quality considerations can modify the
15 production control.

16
17 The design of control charts involves the selection of three parameters: sampling size (n), control frequency (h), and
18 control limits (L) in order to detect earlier tools and processes shifts [5]. Economic design of control chart is a method
19 which aims at determining these parameters of a control chart in optimizing a cost function of the process monitored.
20 Usually, it considers parameters inner to the monitored process, such as the cost of sampling and analyzing, quality cost
21 and behavior of the machine.

22
23 Classical criteria as statistical properties can be considered as economic variables. Duncan, [6] proposes in 1956 the
24 economical optimization of a \bar{X} control chart of a process which is only shut down during repairing. Several works
25 around this model during the next 40 years have been interesting on the others types of control charts, adaptation to
26 specific situations and resolution methods. A breakthrough has been the generalization of all these models by Lorenzen
27 and Vance [4]. It is nowadays a reference in economic design, as it can be easily implemented and adapted.

28
29 Optimizing the design of control charts in an economic manner affords many opportunities to take into account external
30 parameters of the process. One example is the adaptation of the economic design to semiconductor industries by Jang et
31 al. [7]. This study details cost parameters of the Lorenzen and Vance's model, specifically the quality cost by using
32 opportunity cost of the non-conformities.

33
34 Several critics and enhancements have been performed over economic control chart design. Critics of this type of
35 design highlight a lack of statistical properties, and the difficulties to evaluate correctly the input parameters [8].
36 Improvements of the Lorenzen and Vance model have been done in adding statistical constraints [9], and by proposing
37 more robust implementation: in using multiple scenarios in the optimization [10] or in expressing the input parameters
38 in ranges of values [11]. Extensions of the economic design have also been done through adaptive control [12]. We
39 recommend the overview of Tagaras [13] for more details about adaptive control.

40
41 Another lack pointed by Deming and Edwards [14] and Woodall [8] in the economic design theory is the aim at
42 maintaining the process in its initial situation, without any emphasis on continuous improvement. Silver and Rohleder
43 [15] propose a dynamical optimization of the design parameters by reducing the out-of-control frequency at each cycle
44 during the expected improvement period. This reflect the fact that improvement is inherent to the process and should be
45 considered as it affect one design parameters. Weheba and Nickerson [16] consider the economic design of control chart
46 as a reactive process and have a proactive approach, by adding the cost function of improvement in the process. Instead
47 of considering improvement as a possibility to reduce costs, the targeted quality is imposed. The concept of "better
48 quality level" is implemented in their model as lower process drifts.

49
50 In the current literature, fact that controls retrieve data, which is employed to solve manufacturing issues, seems not
51 exploited. However, data coming from tools, process and product controls are re-employed during problem solving
52 sessions. An example is provided by a case study on the semiconductor industries [17]. This literature review has not
53 retrieved any article about links between the reuse of process control data and the design of control charts. This paper
54 investigates this link. Moreover, considering yield improvement, the paper discusses how quality control equilibriums
55 (number of points to be measured, sampling rates in particular) will be modified by the decrease of scrap rate due to
56 learning. Learning, as scrap rate or yield will be considered as exogenous factors of control chart design in this paper.

57 58 59 **3 Description of the model and the cost function**

60 This paper proposes an enhancement of the Lorenzen and Vance's economic design of control charts model, by
embedding a link between control plan definition (sampling rate and number of controls) and duration of scrap
investigation. This enhancement comes from literature review and authors experience in semi-conductor industry.

The manufacturing process is composed of N stages, as presented Figure 1, followed by a \bar{X} control chart. It is similar to the model of Colledani [3], which investigates the equilibrium between process control actions and line balancing ones.

Usually, SPC measurements are employed for monitoring processes drifts. Each out of control is followed by a local action. Most of the time, this action is a predefined procedure known to be a fast answer at the drift. These kinds of actions remain low cost and simple to perform, so that any operator can apply it. They are full part of local continuous improvement. Long run investigations are usually not allowed within this frame.

At the end of the process, the product is qualified by functional tests. These controls are employed to sort dices and wafers and to scrap those rejected. When a product is considered faulty, long run investigations are performed to detect faulty process stages. Data from the entire production line are used to investigate, through data analysis algorithms (commonalities, clustering for example). These actions are performed by high qualified technicians and engineers. They are time consuming and rely on available process data. Speeding this stage remains a major stake as it is at the heart of process learning and global continuous improvement [18].

In the remainder, the paper aims to determine parameters of each SPC controls that will minimize the costs of the whole model.

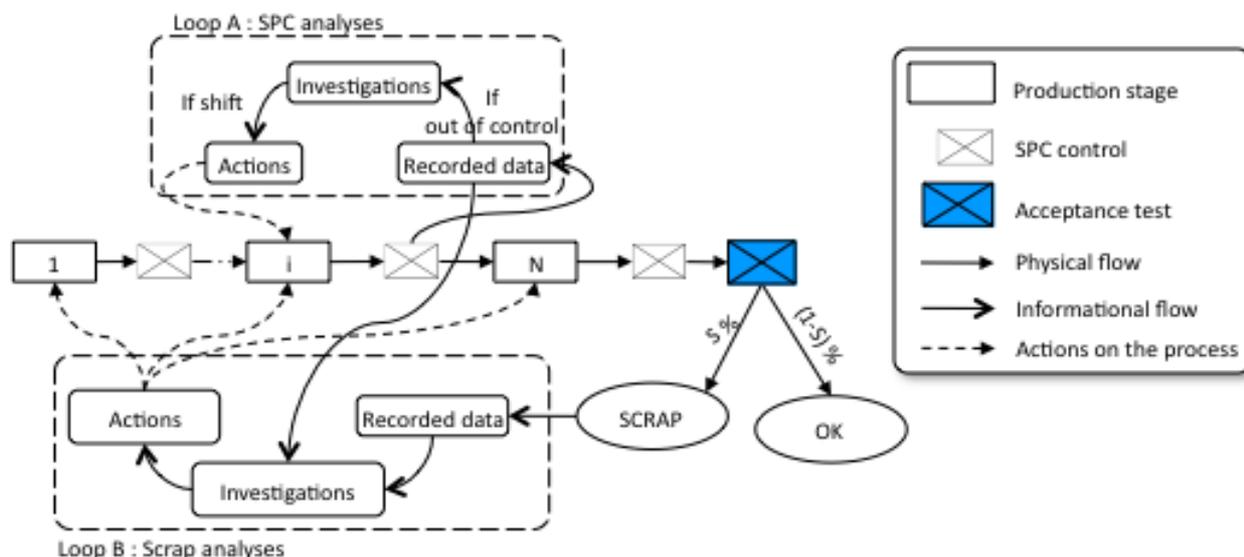


Figure 1: Modeling of the production line and the quality controls

In order to simplify the mechanism of the model, only the size (n) and the interval between two sampling (h) will be optimized, given control limit (L). In order to focus the analysis on the effect of the scrap investigation costs and to constrain the solution space, L is held at three in our optimization as presented by Weheba and Nickerson [16]. This assumption respects the “six sigma” method recommendations. When relaxing this assumption, constraints have to be added on the “average run length (ARL)” to ensure statistical properties of the optimization, as in the economical-statistical design of Saniga [9]. Besides, emphasis should be put in optimization methods to maintain a short time optimization.

The function to minimize is:

$$\min_{n_i, h_i} \left(\sum_{i=1}^N f_i(n_i, h_i) \right) + b\left(\frac{n_1}{h_1}, \frac{n_2}{h_2}, \dots, \frac{n_N}{h_N}\right)$$

Where f_i is the cost function of the i^{th} SPC control and b is the cost function of the scrap investigation.

The cost of the investigation (function b) has been formulated in function of the quantity of SPC control done during the production. At stage i , if n_i is the size of a sample and $\frac{1}{h_i}$ the frequency of sampling, then $\frac{n_i}{h_i}$ is the quantity of controls per hour. Each control is assimilated at one measurement retrieving data. As mentioned before, this amount of data is stored and used both for local and global improvement. The more information is available, the more analyses can

be driven without any extra test. Time of investigation is shortened and extra costs are reduced with high quantity of control.

In this model, **b** is two folded. It is made of a fixed cost C when no information are available and a function **-g()** which decreases the cost when available SPC data increases. As the problem has been formulated as an optimization process, C can be suppressed. In the remainder, only **g()** will be taken in account.

The function to minimize becomes then

$$\min_{n_i, h_i} \sum_{i=1}^N f_i(n_i, h_i) + b\left(\frac{n_1}{h_1}, \frac{n_2}{h_2}, \dots, \frac{n_N}{h_N}\right) = \min_{n_i, h_i} \sum_{i=1}^N f_i(n_i, h_i) + C - g\left(\frac{n_1}{h_1}, \frac{n_2}{h_2}, \dots, \frac{n_N}{h_N}\right) = \min_{n_i, h_i} \left(\sum_{i=1}^N f_i(n_i, h_i) - g\left(\frac{n_1}{h_1}, \frac{n_2}{h_2}, \dots, \frac{n_N}{h_N}\right) \right)$$

Model studied

For the sake of simplification, a model composed only of the *i*th stage and the scrap investigation has been implemented. It is presented Figure 2.

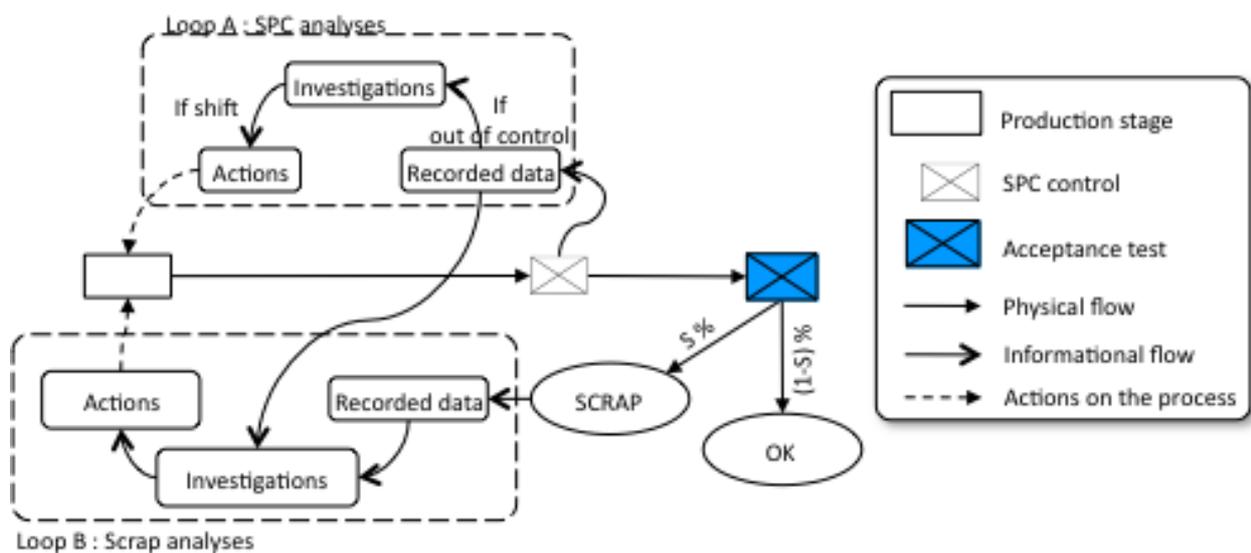


Figure 2: Simplified model

The function to minimize is simplified to:

$$\min_{n, h} \left(f(n, h) - g\left(\frac{n}{h}\right) \right)$$

Notations and the cost function of the economic design model are taken from Lorenzen and Vance model [4]. This function follow the classical control cycle detailed Figure 3, each parameter and cost are described Table 1.1.

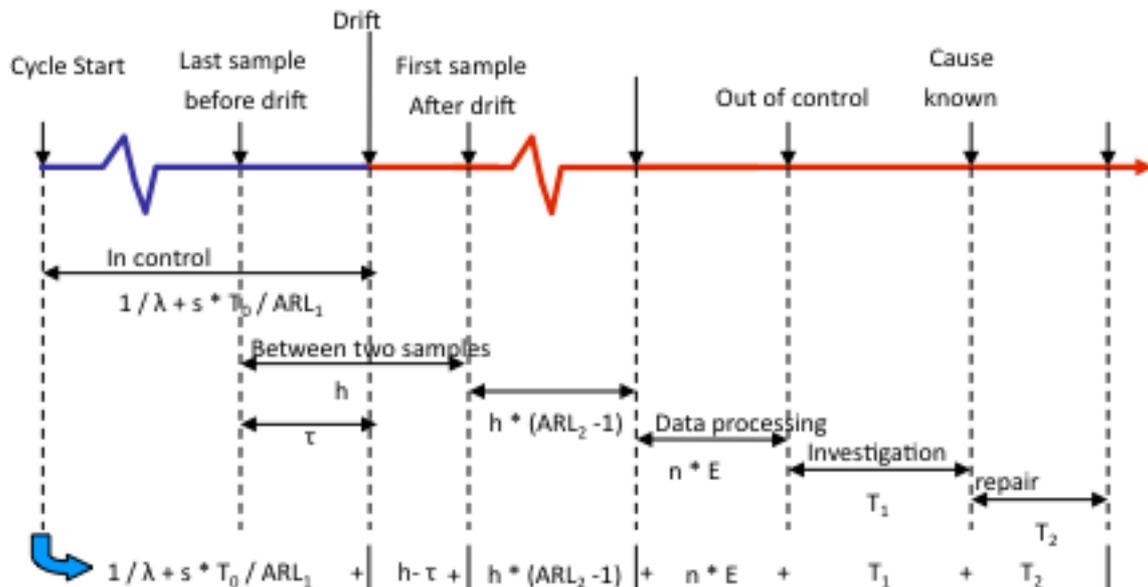


Figure 3: A control cycle

The cycle starts in control. There is a control before the drift. The duration of the « in control » state is $1/\lambda + s * T_0/ARL_1$. τ is the mean time between the last sample before the drift and the drift. h is the time between samplings. However, the control chart cannot detect immediately the drift. Then $h * (ARL_2 - 1)$ time passes until the sampling which will detect the out of control. Between the sample and the out of control signal, there is a data treatment duration: $n * E$. After the out of control, there is T_1 the investigation time, and T_2 , the repair time. At the end of T_2 , the issue is fixed and the process is released in control.

Type	Variable	Designation
Design Variables	n	sample size
	h	hours between samples
	L	number of standard deviation from control limit to center line
Process Parameters	λ	1/mean time process is in control
	Δ	number of standard deviation slip when out of control
	C_0	Quality cost / hour while In Control (IC)
	C_1	Quality cost / hour while Out Of Control (OoC)
Sample parameters	a	fixed cost per sample
	b	cost per unit sampled
	E	time to sample and chart on item
OOC Parameters	Y	cost per false alarm
	W	cost to locate and repair the assignable cause
	T_0	expected search time when false alarm
	T_1	expected time to discover the assignable cause
	T_2	expected time to repair the process
Calculated variables	s	mean number of sample while IC
	τ	mean time between last sample while IC and the drift
	ARL_1	mean number of sample between an out of control while IC
	ARL_2	mean number of sample between an out of control sample while OoC

Table 1.1 List of parameters

The hourly cost function of a classical economic design is: $f(n, h) = \frac{C_{NC} + C_{OoC} + C_S}{T_{cycle}}$

Where: T_{cycle} is the length of a cycle from the production beginning to the occurrence of an assignable cause, then its detection, and finally its repair.

$$T_{cycle} = \frac{1}{\lambda} + \frac{Y \cdot s}{ARL_1} - \tau + h \cdot ARL_2 + n \cdot E + T_1 + T_2$$

C_{NC} is the non-conformities costs for a cycle.

$$C_{NC} = \frac{C_0}{\lambda} + C_1(-\tau + n \cdot E + h \cdot ARL_2)$$

C_{OoC} is the false alarm and detection costs for a cycle.

$$C_{OoC} = \frac{Y \cdot s}{ARL_1} + W$$

C_S is the direct sampling cost for a cycle.

$$C_S = (a + b \cdot n) \frac{(1/\lambda - \tau + n \cdot E + h \cdot ARL_2)}{h}$$

For a detailed explanation of this classical model, authors recommend to read the paper of Lorenzen and Vance [4].

Expression of the gain function

$g()$ is the gain per hour on the scrap investigation. It is estimated by the following function:

$$g\left(\frac{n}{h}\right) = I \cdot C_{Inv}\left(\frac{n}{h}\right)$$

Where :

- I is the number of investigations per hour. I equals the Scrap rate (or mechanical yield) times Number of products per hour.
- $C_{Inv}\left(\frac{n}{h}\right)$ is the expected gain per investigation. It equals the maximum gain times $j\left(\frac{n}{h}\right)$
 - $j()$ expresses the impact of the quantity of available information, that is the quantity of control done, on the gain of investigation. $j\left(\frac{n}{h}\right) \in [0, 1]$
 - Several functions have been tested, such as linear, logarithmic or sigmoid ones. To translate the fact that the value of data is higher when we present a first order model: $j\left(\frac{n}{h}\right) = 1 - e^{-Q \cdot \frac{n}{h}}$, where is Q a constant which determines both the slope of the function and the maximum of profitable information.

Even if data are reused for scrap and yield improvement, the learning mechanism remains unknown and will be considered as a black box in this paper. As a consequence, scrap rate will be considered as exogenous parameters of control charts design.

4 Simulation and results

The case study used to test this model generalizes a typical process in the semi conductor industry [19] in a 300mm wafer fab. The maximum gain is estimated at 2500 € per investigation, and is reached when controls are about 200 units per hour, that is Q is around 0.029. We assume that the process drifts to 1 sigma every 24 hours in average. Costs are estimated upon a cost of a machine of 300 €/h. C_0 is roughly estimated at 160 €/h. C_1 reaches 640 €/h.

Sampling parameters considers a fixed cost per sample of 2 € (a 1000€ test wafer is used about 500 times), a time to sample 17 units takes about 5 minutes i.e. $5 \cdot 10^{-3}$ min/unit sampled. This leads to a variable cost of 1.4706€ (time to sample x 300€/h). The search time following an out of control is one hour, whenever the process is in control or not. So the cost of a false alarm is 300 € (1 hour x 300€/h). The time to repair the process is 4 hours, and the cost to locate and repair the assignable causes is 2000€ (5 hours x 300 €/h). Parameters are synthesized in appendix. ARL_1 , the mean number of sample between an out of control while IC is estimated at ___ and ARL_2 , the mean number of sample between an out of control sample while OoC is estimated at ___

The maximum gain over one scrap analysis is estimated at 2500€. The scrap rate (also named S) for this simulation is 50%. The manufacture processes 12 products per hour.

A synthesis of these parameters is presented Table 1.2

	Variables	Case study
Design variable	n	optimised
	h	optimised
	L	3
Process parameters:	λ	1/24
	Δ	1
	C_0	160 €/h
	C_1	640 €/h
Sample parameters	a	2 €
	b	1.4706 €
	E	.004902
OC parameters	Y	300 €
	W	2 000 €
	T_0	1 h
	T_1	1 h
	T_2	4 h
Calculated variables	s	$\frac{e^{-\lambda h}}{(1 - e^{-\lambda h})}$
	t	$\frac{[1 - (1 + \lambda h)e^{-\lambda h}]}{[\lambda(1 - e^{-\lambda h})]}$
	ARL_1 & ARL_2	Calculated following Lorenzen and Vance's formulation

Table 1.2: Model's parameters

The optimization is a systematic enumeration of the possible combinations of n and h, in a few steps: first, a rough step for n and h is used to determine the valuable scale (ie n is search between 1 and 1000 with a step of 10, h between 0 and 20 with a 0.1 step). Then the window is narrowed and the step is refined. Thanks to modern computers and the fact that we consider L given, the enumeration is fast and take less than five seconds for 40000 combinations tested on a Pentium M processor at 2.1 GHz with 1 Go RAM. The program has been made in C++ with graphic representation using Root¹ (CERN) libraries, and is available upon request from the authors.

¹ <http://root.cern.ch/>

The results are represented in Figure 4 and Figure 5:

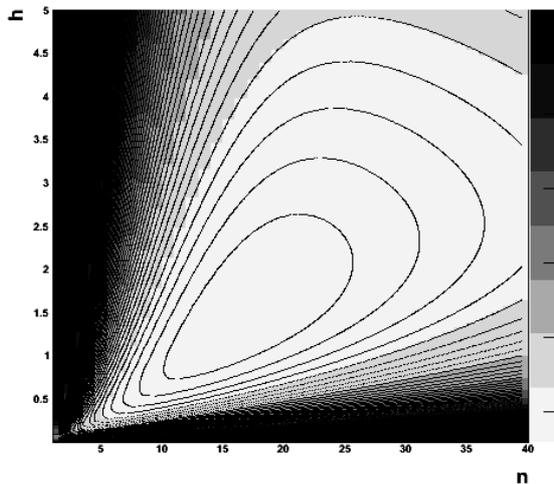


Figure 4: Cost per hour of the classical economic design

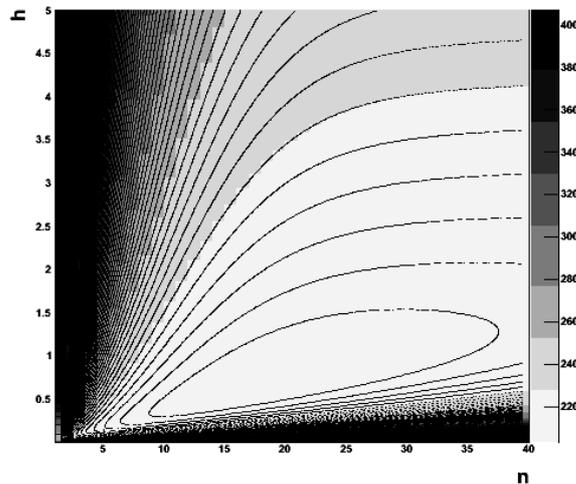


Figure 5: Cost per hour with integration of the scrap investigation costs

Curves represent « iso » values of $f(n, h) - g\left(\frac{n}{h}\right)$ depending on n and h . Costs are elevated when

- n is low, because of false alarm and scrap investigation costs
- h is low and n is high, because of out-of-control and direct sampling costs

The integration of the scrap investigation costs in the economic design of control chart modifies quantity of control optimum. Indeed, in our example, quantity of controls increases from 10.85 u/hour to 25.17 u/hour, the interval between two samples decreases from 1.475 hour to 0.715 hour and the sample size increases from 16 to 17 points. This result shows that: the reuse of SPC data for speeding scrap investigations has a clear impact on SPC parameter and tends to increase the number of controls. This connection proves that other sampling plan choices would lead at higher process control cost.

5 Discussions about the use of this model in a ramp-up context

During the ramp up phase of a new product, significant improvement in the process happens. Preventive actions improve yields, manufacturing stability and robustness. Therefore, production costs and scrap rate are decreasing rapidly [20]. In the semiconductor context, priority is to reduce ramp-up time and to achieve as soon as possible a good yield [21], because of the product life cycle, characterized by decreasing of the prices and short life time [7]. Experience on the past product and learning curves [20] can provide estimation of the scrap rate.

The model assumes that S is an exogenous parameter toward C_0 and C_1 . When the process is in control, the monitored tool produces nevertheless some scraps. Wafers can be scratched or broken, or contribute to the final yield reduction, without knowing clearly each process stage implication. As final scrap rate evolves during the manufacturing ramp-up or the technology lifecycle, there is a relation between C_0 and S . Nevertheless, as it is possible to know broken and scratches costs at each process stage, estimating the true contribution of each operation upon hundreds of them to the final yield is hard to perform. That is why learning is considered only through the evolution of S , while C_0 and C_1 are assumed to be fixed quality costs.

Following curves present the evolution of optimal n and h parameters depending on scrap rate.

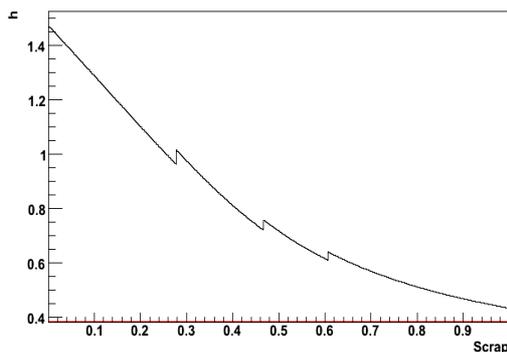


Figure 6: h , function of scrap rate

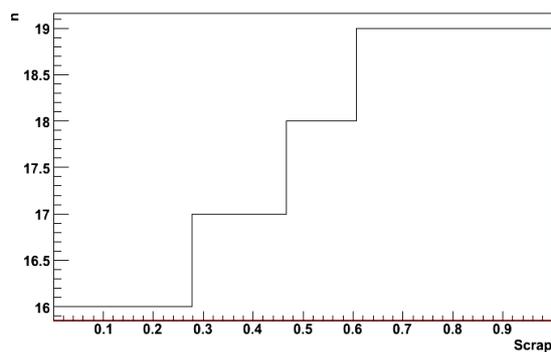


Figure 7: n , function of scrap rate

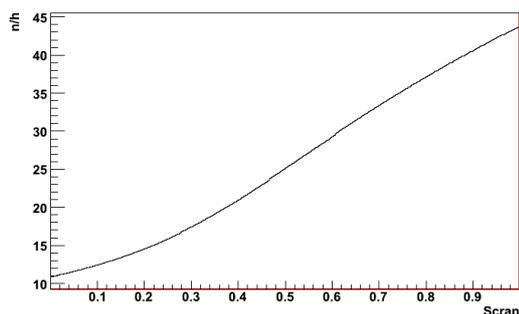


Figure 8: Evolution of the optimal quantity of control per hour depending on scrap rate

Figure 6 presents the frequency of control decreases dramatically, with slight peak augmentations when n increases.

Figure 7 presents number of units sampled is discrete. It increases slightly from 16 when scrap rate is below 28% to 19 above 62%.

Figure 8 combines the two previous ones. Figure 8 shows the optimal solution for n , h , and the quantity of control (n/h) in function of the scrap rate.

When the scrap rate is null, optimum values are the classical economic design optimum. The quantity of control considerably increases with the scrap rate. The more scrap there are, the more controls have to be performed. Moreover, two major phenomena appear on the latter graph:

- The influence of the gain on investigation is strengthened with scrap rate, as more investigations happen, and the derivate of the quantity of control increase with scrap.
- Then, the expression of the gain on investigation weaken the influence of the quantity of control when $n/h > 30$.

These two points are related to the gain function. Other gains would have provided other curves.

As practical application, by anticipating scrap rate, it is possible to evaluate accurately the quantity of information needed for both process control and process learning. It rationalizes extensive sampling early in the product life cycle to achieve faster learning.

A simulation of yield learning phenomenon, is presented Figure 9. Yield increases following a 1st order learning process from 5 up to 98% in 100 periods: minimum and maximum yield, yield evolution, and period length should be adjusted to the studied industry.

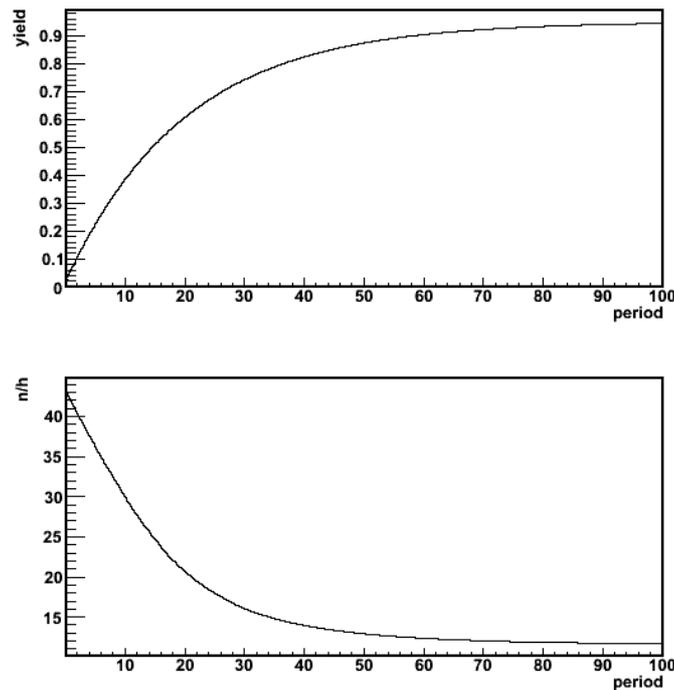


Figure 9: Impact of Yield learning curves on process control plans

In semiconductor industry, it is common to find such yield learning curves. Yield is just assimilated at (100-(Scrap rate)). Result presented Figure 9 can be used as a first tool for adjusting controls while yield increases, based on a economical approach.

6 Conclusion

In this paper, we presented an adaptation of the economic design of control charts by integrating that SPC measurements are valuable data for scraps analysis. Control charts are used for both monitoring locally the process and gathering information about each manufacturing steps. Scrap investigations duration are globally decreased by employing data analysis algorithms, which rely on SPC data.

The paper proposed a model enhancing the Lorenzen and Vance's Design economic model. The simulation leads at a new equilibrium of optimal sampling plan. Based on this model, the paper investigates also the impact of scrap rate evolution on optimal control plan. Several perspectives pursue this enhancement.

Final scrap rate and learning processes, locally and globally are considered as external variables of the model. In a next model, they could be considered as endogenous parameters.

Indeed, if (n,h) are modified, few data will be available for investigate scrap issues and related problems and then it could take more time to investigate. Lets' note t a discrete time period, It is understandable that change of $(n,h)_t$ leads at a change of $(S)_{t+1}$, which leads at a change of $(n,h)_{t+1}$ and so on. $(n,h)_t$ is then a function of previous n and h couples and scraps rate. $(n,h)_t = \Theta((n,h)_{t-1}, \dots, (n,h)_0, (S)_t, (S)_{t-1}, \dots, (S)_0)$. It is the same for C_0 and C_1 parameters. During this investigation, the stability of the model should be checked. The convergence toward an attraction pole should also be investigated.

A second investigation to lead is to take into account that process control has several layers of information [22], [23]: SPC, EPC, Run To Run, Alarms, Customer Feedbacks... Each of these layers generates data, which can be used for learning. It can be useful to take into account this new configuration to set control of each layer depending of its impact on yield learning.

A third extension of the paper could be N process stage instead of only one [24]. Stage correlations could be part of this extension. In this extension, the integration with WIP should also be taken into account.

Finally a full model: dynamic, multilayer and N process stage could be proposed.

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