Original Research Paper

Optimal Pareto Solutions of a Dynamic *C* Chart: An Application of Statistical Process Control on a Semiconductor Devices Manufacturing Process

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Abstract: The present paper proposes a novel economic-statistical design procedure of a dynamic *c* control chart for the Statistical Process Control (SPC) of the manufacturing process of semiconductor devices. Particularly, a non-linear constrained mathematical programming model is formulated and solved by means of the ε-constraint method. A numerical application is developed in order to describe the Pareto frontier, that is the set of optimal *c* charts and the related practical considerations are given. The obtained results highlight how the performance of the developed dynamic *c* chart overcome that of the related static one, thus demonstrating the effectiveness of the proposed procedure.

Keywords: Statistical Process Control, Dynamic *C* Chart, Multi-Objective Design, ε-Constraint Method, Semiconductor Devices Manufacturing

Introduction

The quality control of a manufacturing process represents a crucial and critical issue in every modern manufacturing context. Statistical Process Control (SPC) and Process Capability Analysis (PCA) applications and procedures are widely considered to perform quality control of a manufacturing process (Lupo, 2015a). These strategies appear to be important in the globalized business environment (Di Trapani *et al*., 2014; Sgroi *et al*., 2014a; 2014b; Lupo, 2015b).

Referring to SPC operations, control charts represent the main tool to analyze the inherent variability of a process output and to achieve and maintain the in-control process state (Woodall and Montgomery, 2014). Many charts schemes are available with reference to peculiarities of the under control process output (Montgomery, 2013). For example, considering the manufacturing process of semiconductor devices, the SPC operations mainly concern the evaluation of not-functioning devices in a production run (Qin *et al*., 2006; Lee *et al*., 2006) and, in such a condition, the control chart for non-conformities numbers in inspection units, also called *c* chart, is typically considered.

In the present paper, a novel multi-objective design procedure for an enhanced scheme of the *c* chart is developed. In particular, a dynamic *c* chart is considered,

i.e., a chart scheme whose parameters can be changed during SPC operations to adapt chart characteristics to different process situations, in order to improve the chart effectiveness (Zimmer *et al*., 2000; Inghilleri *et al*., 2015). In detail, the developed design procedure takes into account two objectives to be optimized:

- The statistical one, to indirectly optimize the immeasurable or even hard to evaluate quality cost part, which is strongly related to the statistical performance of the employed chart (Lupo, 2014)
- The economic one, to also take care of the measurable quality cost portion

More in detail, the considered goal is to determine the parameters of a dynamic *c* chart in order to minimize both the hourly total quality costs (economic objective) and the out-of-control average run length of the chart (statistical objective), i.e., the expected number of points required by the chart to indicate an out-of-control state of the process. A non-linear constrained mathematical model is formulated to solve the treated multi-objective problem whereas the optimal chart configurations, that is the Pareto frontier, are obtained by means of the ε-constraint method. Finally, the effectiveness of the proposed procedure is shown in a numerical application as regards to SPC operations related to a manufacturing process of semiconductor devices.

The reminder of the paper is organized as follows: The theoretical aspects of the treated problem are presented first, followed with the description on the model to evaluate the economic performance of control charts; the multi-objective mathematical model is formulated next. Meanwhile, the application of the proposed procedure is presented in detail. Hence, conclusion of this study is provided as well.

Fundamental Definitions

A dynamic c chart to monitor the non-conformities number x of a manufacturing process output is considered. In detail, in such a type of chart the zone within the control limits [–k, k] is divided into three strips. Two zones are defined: *The central zone*, [–w, w] and *the warning zones*, [–k, –w) U (w, k] (Fig. 1). If the point representative of the tth sample statistic c is plotted within the central zone, then the next one will have a sample size of n_1 and will be taken h_1 time unit after the tth one. On the contrary, if the point representative of the tth sample c is plotted within the warning zone, then the next one will have a sample size of $n_2 > n_1$ and will be taken $h_2 < h_1$ time unit after the tth one. Finally, if the point representative of the tth sample is plotted outside of the control limits, then the out-of-control signal has to be considered as a false alarm or as a consequence of the occurrence of an out-of-control cause.

As well known, the under control non-conformities number x follows the Poisson probability distribution with parameter $\bar{c} > 0$, which represents its mean and variance. However, when such parameter exceeds 10, the normal distribution $N(\bar{c}, \bar{c})$ can be considered as a satisfactory approximation of the Poisson distribution with parameter $\bar{c}$. Therefore, in such a condition, the c chart can be plotted considering the standard normal distribution $Z \sim N(0,1)$ and, in particular, the following sample statistic can be considered:

$$Z_i = \frac{x_i - \bar{c}}{\sqrt{\left(\bar{c}/n\right)}} \tag{1}$$

In which, x_i is the observed average non-conformities number in the sample i composed by n inspection units. Finally, the process in-control time is assumed to be exponentially distributed with mean $1/\lambda$ and the of out-of-control condition occurrence determines an instantaneous and persistent shift magnitude δ in the process mean $\bar{c}$.

Cost Model

The total quality costs C_T arising from the employment of a control chart can be expressed as:

$$C_T = C_{LR} + C_Q(\delta) \tag{2}$$

where, C_{LR} and $C_Q(\delta)$ are the hourly labor resource and quality control costs over a system functioning cycle, respectively. In the next section, the system functioning cycle is defined and all the durations of its periods are evaluated, whereas computations of C_{LR} and C_Q costs are formulated next.

System Functioning Cycle

The process functioning cycle is supposed to be constituted by the following fundamental periods (Duncan, 1956):

- The in-control period P_{in}
- The out-of-control period P_{out}
- The time T_1 required to detect the assignable cause and the time T_2 to restore the system
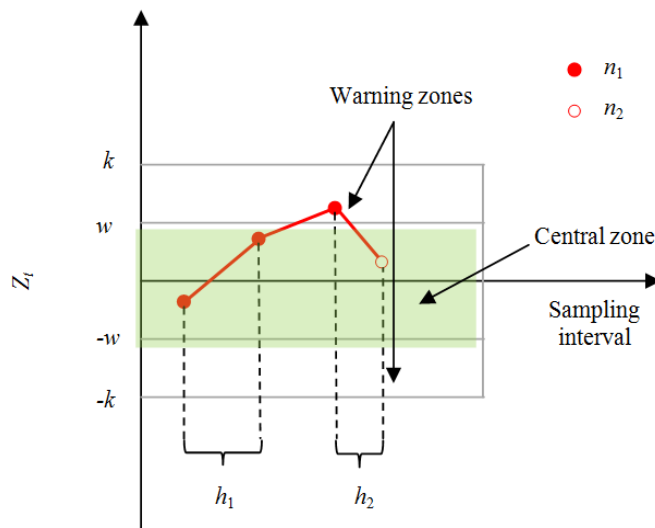

Fig. 1. Dynamic c chart with two zones

The expected length of a system functioning cycle $T(\delta)$ represents the period between two successive starting of the manufacturing process, after detecting the out-of-control assignable cause and solving its related problems.

The in-control period length P_{in} is given by:

$$P_{in} = \frac{1}{\lambda} + \frac{(1-d_1) \cdot s \cdot T_0}{ARL_0} \qquad (3)$$

where, λ is the failure rate of the manufacturing system, while the second term takes into account the false alarms effects over the in-control period. Let d_1 be a binary variable that takes 1 if the production continues during assignable cause searches and 0 otherwise, T_0 the expected search time associated to a false alarm of the chart, ARL_0 the in control average run length, i.e., the expected number of points plotted on the chart before a point indicates a false out-of-control condition and s the expected number of samples taken during the in-control period.

To the contrary, the out-of-control period has a time duration P_{out} given by the following equation:

$$P_{out} = \left(E_\delta(h) - \zeta \right) + E_\delta(h) \cdot \left(ARL_\delta - 1 \right) + \frac{E_\delta(n)}{r_{IN}} \qquad (4)$$

where, $E_\delta(h)$ is the out-of-control expected value of sampling interval, ARL_δ is the out-of-control average run length of the chart and the last term represents the time to inspect the sample providing the out-of-control signal, i.e., the last sample in the system functioning cycle. $E_\delta(n)$ is the expected value of the sample size while the process is out-of-control and r_{IN} the sample inspection rate. Thus, according to Equations 3 and 4, the expected length of the system functioning cycle $T(\delta)$ assumes the following expression:

$$T(\delta) = \frac{1}{\lambda} + \frac{(1-d_1) \cdot s \cdot T_0}{ARL_0} + ATS_\delta + \frac{E_\delta(n)}{r_{IN}} + T_1 + T_2 \qquad (5)$$

The functions of s, ARL_0, ARL_δ, ATS_δ, $E_\delta(n)$, $E_0(h)$ and $E_\delta(h)$ are given with more details in Lupo (2014).

Labor Resources Cost C_{LR}

For the adaptive aforementioned policy, the needed labor resources capacity can vary at two levels, LR_1 and LR_2, according to the chart parameters stated at each sampling epoch. In particular, let i be the zone of the control chart which the point representative of the $(t-1)^{th}$ sample has been plotted in under the assumption that the entire sampling interval h_i is used to inspect the sample of size n_i. The amount of labor resources needed to inspect the next t^{th} sample can be obtained by:

$$LR_i = \frac{n_i}{h_i \cdot r_{IN}} \quad for \ i = 1,2 \qquad (6)$$

Therefore, the expected amount of Labor Resources $E(LR)$ can be evaluated as the weighted sum of LR_1 and LR_2 by the related in-control probabilities that a point is plotted on the chart within the zone 1 or 2 (Lupo, 2015c). Consequently, the expected labor resources cost C_{LR} can be computed by the following Equation 7:

$$C_{LR} = E(LR) \cdot c_{LR} \qquad (7)$$

Being c_{LR} the hourly labor resources cost.

Quality Control Costs $C_Q(\delta)$

The hourly quality control cost related to the out-of-control shift δ, $C_Q(\delta)$, can be obtained by dividing costs arising from the quality control in a system functioning cycle C_δ by the system cycle time $T(\delta)$, that is:

$$C_Q(\delta) = \frac{C_\delta}{T(\delta)} \qquad (8)$$

The costs C_δ can be computed by means of the following Equation 9:

$$C_\delta = C_1 + C_2(\delta) + C_3 + C_4(\delta) \qquad (9)$$

Where:
C_1 and $C_2(\delta)$ = The costs arising from the non-conforming products manufactured during the system in-control and out-of-control periods, respectively
C_3 = The cost due to the false alarms, the detection and the removing of out-of control causes
$C_4(\delta)$ = The cost arising from the sampling activities required by the control chart

The costs C_1 and $C_2(\delta)$ represent the economic loss due to the deviation of the production output from its target value T. As suggested by Wu *et al.* (2004), such an economic loss can be effectively estimated by the quadratic representation of the quality loss function via the following relationships:

$$C_1 = P_{in} \cdot r_{PR} \cdot \int_T^{+\infty} c_{nc}(x-T)^2 f(x)dx \qquad (10)$$

$$C_2(\delta) = P_{out} \cdot r_{PR} \cdot \int_T^{+\infty} c_{nc}(x-T)^2 f_\delta(x)dx \qquad (11)$$

In which $f(x)$ and $f_\delta(x)$ are the probability density functions of normal distributions $N(\bar{c},\bar{c})$ and $N(c_\delta, c_\delta)$

when the process is in-control and out-of-control respectively. The term r_{PR} is the production rate (*units/h*) and c_{nc} is a constant depending on the external cost associated with the production of non-conforming parts.

The cost C_3 in Equation 9 is given by the following Equation 12:

$$C_3 = \frac{s \cdot Y}{ARL_0} + W \qquad (12)$$

In which Y and W are the costs associated with the false alarms of the chart and the detection and the removal of out-of-control causes, respectively.

Lastly, the sampling cost $C_4(\delta)$ is given by:

$$C_4(\delta) = (a + b \cdot E_0(n)) \cdot s + (a + b \cdot E_\delta(n)) \cdot s' \qquad (13)$$

where, a and b are the sampling cost components, $E_0(n)$ is the expected value of the sample size while the process is in-control and s and s' are the expected number of samples taken during the system in-control and out-of-control periods, respectively. The formulation of s' and $E_0(n)$ are detailed in Lupo (2014).

Multi-Objective Problem Formulation

Aiming at optimizing the dynamic c chart parameters, the following mixed integer non-linear constrained mathematical model is formulated:

$$\min C_T(n_1, n_2, h_1, h_2, w, k) \qquad (14)$$

$$\min ARL_\delta(n_1, n_2, h_1, h_2, w, k) \qquad (15)$$

Subjected to the following constraints:

$$ARL_0 \geq L \qquad (16)$$

$$LR_{\min} \leq LR_1 \leq LR_2 \leq LR_{\max} \qquad (17)$$

$$n_{\min} \leq n_1 < n_2 \leq n_{\max} \qquad (18)$$

$$h_{\min} \leq h_2 < h_1 \leq h_{\max} \qquad (19)$$

$$k_{\min} \leq w < k \leq k_{\max} \qquad (20)$$

In detail:

- (16) ensures a minimum required in-control average run length of the chart
- (17) implies that a minimum part of the available labor resource should be employed to perform the SPC and, at the same time, that the labor resource does not exceed the available resource capacity

- (18)-(20) assure the adaptive capability of the dynamic c chart and limit the sampling effort

The considered objective functions (14) and (15) contrast one each other so that it is not possible to find out a single optimal solution corresponding to the best result for both the considered objectives. Thus, in Multi-Objective Optimization Problems (MOOPs), as that one considered here, the concept of solutions dominance has to be applied. More in detail, a generic solution X_1 of a MOOP dominates the generic solution X_2 if X_1 is non-worse than X_2 for each objective and X_1 is strictly better than X_2 for at least one objective (Erfani and Utyuzhnikov, 2011).

In the literature, various resolution methods have been developed to point out optimal solutions of a MOOP (Certa *et al.*, 2014). The simplest and probably the most widely used approach to solve a MOOP is the ε-constraint method (Marler and Arora, 2004). The latter consists in reformulating the considered MOOP by taking into account only one of its objectives and restricting the remaining ones within user-chosen values of the parameter ε. By applying this resolution method, the MOOP is thus reduced to a single-objective optimization problem and the set of non-dominated solutions can be obtained in more than one optimization steps. Particularly, in order to describe the Pareto frontier for the MOOP here considered the Lexicographic Goal Programming (LGP) method (Deb, 2001) is initially used to find out the extreme Pareto frontier solutions. For example, these sequential steps allow to find out the extreme solution (A) of the minimum total quality costs (Fig. 2):

- Minimizing C_T function (Equation 14) as a single objective optimization problem obtaining $C_{T,\min}$
- Minimizing ARL_δ function (Equation 15), by imposing that C_T has to take a value not greater than $C_{T,\min}$, obtaining $ARL_{\delta,\max}$

This procedure is analogously applied changing the objectives hierarchy to find out the other two bounds ($ARL_{\delta,\min}$, $C_{T,\max}$) of the extreme solution (B).

Once the extreme points of the Pareto frontier are determined, the ε-constraint method has to be recursively applied. In the first step, the C_T function is minimized and the ARL_δ is forced to take a value smaller than the $ARL_{\delta,\max}$ previously obtained. In this way, the optimal solution (1) ($ARL_{\delta,1}$; $C_{T,1}$) belonging to the Pareto frontier can be found. In the next step, such a procedure is repeated minimizing the C_T function and imposing that the ARL_δ function has to take a value smaller to that one corresponding to the solution previously found. The procedure is repeated until the other Pareto frontier extreme (B) is obtained. In such way, the ε-constraint method ensures the determination of the whole Pareto frontier (Certa *et al.*, 2011; Lupo, 2015d).
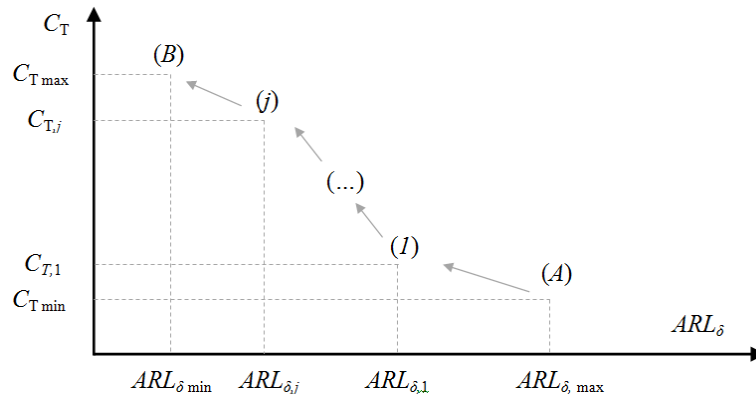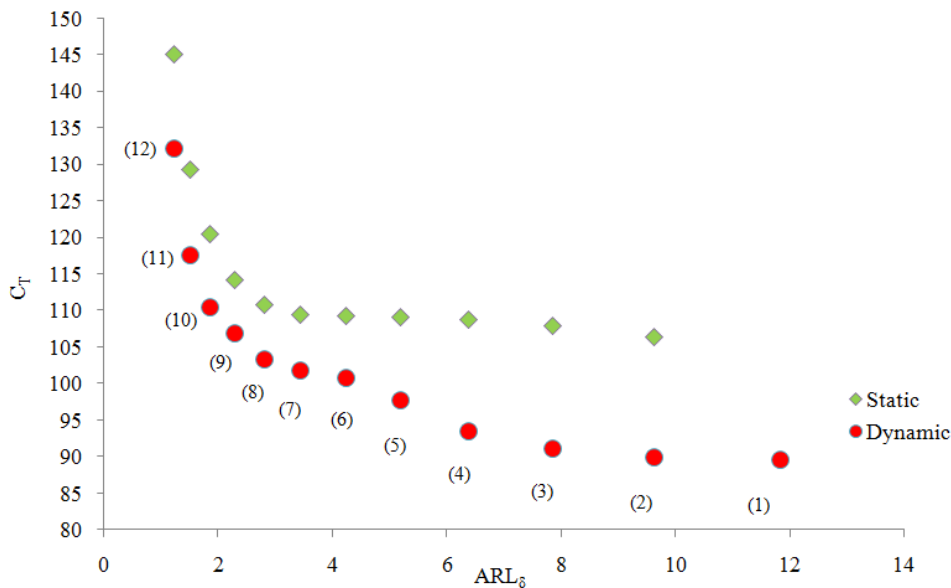
Fig. 2. ε-constraint multi-step optimization procedure

Fig. 3. Optimal Pareto frontiers of dynamic and static c chart schemes ($ARL_0 = 600$; $\delta = 1$)

Application: Control Quality of Manufacturing Process of Semiconductor Devices

The manufacturing process of semiconductor devices, such as diodes, transistors, integrated circuits, microprocessors and different kind memories (RAM and ROM), follows a multi-step sequence of photo lithographic and chemical processing steps during which electronic circuits are gradually created on a wafer made of pure semiconducting material. Normally, the fundamental process parameters are monitored during manufacturing operations to promptly diagnose incipient process faults or malfunctions and SPC operations are performed on the process output by monitoring the non-conformities number in the whole production outcome or in its samples. Such an activity, which is considered a significant overall measure of manufacturing process

effectiveness, is commonly performed by means of the classical static c control chart (Cubberly and Bakerjian, 1989; Bhatt, 2000; May and Spanos, 2006).

In this section, the multi-objective design procedure previously developed is adopted to point out the optimal configurations of the dynamic c chart. In particular, a firm working in the memories manufacturing field for Solid State Devices (SSD) in herein considered. Table 1 reports the related operating and costs parameters.

The non-linear Generalized Reduced Gradient Algorithm (GRG) implemented by the Microsoft Excel® solver has been used to solve the multi-objective optimization problem. By minimizing both objective functions, namely the total quality costs C_T (Equation 14) and the expected out-of-control average run length ARL_δ (Equation 15), the chart parameters have been obtained.

Table 2 the Pareto frontier compared with the one related to the typical static scheme of the c chart is shown in Fig. 3.

Table 1. Numerical application data

a ($)	0	T_0 (h)	0.083
b ($/measure)	0.001	T_1 (h)	0.083
c_{nc} ($/non-conforming part)	20	T_2 (h)	0.750
c_{LR} ($/h)	10	d_1	1.000
r_{PR} (units/h)	100	d_2	0.000
r_{IN} (measures/h)	5	Y ($)	2.000
λ (failure/h)	0.05	W ($)	700.000
ARL_0	600		
$\bar{c}$	10	δ	1.000
Bounds of the design variable			
n_{min}; n_{max}	1; 50		
h_{min}; h_{max}(h)	0.1; 50		
w_{min}; w_{max}	1; 5		
K_{min}	$w + 0.2$		
LR_{min}; LR_{max}(Resource number)	0.01; 3		

Table 2. Optimal dynamic c chart configurations ($ARL_0 = 600$; $\delta = 1$)

Optimal solution	Chart parameter value					
	n_1	n_2	h_1	h_2	w	k
1	1	8	0.32	0.32	1.79	3.14
2	1	9	0.36	0.36	1.70	3.14
3	1	11	0.44	0.44	1.69	3.14
4	1	12	0.48	0.48	1.56	3.14
5	1	14	0.56	0.56	1.46	3.14
6	6	6	1.24	0.36	1.86	3.14
7	7	7	1.48	0.41	1.92	3.14
8	8	8	1.73	0.46	1.93	3.14
9	10	10	2.12	0.58	2.09	3.14
10	11	11	2.62	0.50	1.84	3.14
11	14	14	3.21	0.57	1.95	3.14
12	20	20	4.31	0.80	2.09	3.14

From Fig. 3, the Pareto frontier regarding the herein proposed dynamic c chart dominates that one corresponding to the related typical static configuration. In detail, from the economic point of view, the optimal dynamic c chart scheme is represented by the solution (1) with $ARL_\delta = 11.83$ and $C_T = 89.58$ \$. To the contrary, from the statistical performance point of view, the optimal solution (12), with $ARL_\delta = 1.23$ and a $C_T = 132.2$ \$, represents the related best one. In addition, Table 2 shows that with the increasing of the statistical performance required to the optimal chart configurations, from solution (1) on, also the sample sizes (n_1 and n_2) and the sampling intervals (h_1 and h_2) increase with no severe changes in the chart control limits w and k. Finally, if the Pareto optimal frontier includes lots of solutions, the decision maker could be supported by a decision multi-criteria method as the Analytic Hierarchy Process (AHP) (Saaty, 1990) or the ELimination Et ChoixTRaduisant la REalitè (ELECTRE) (Roy, 1978) in order to select the chart configuration that represents the best compromise among the considered objectives.

Conclusion

A multi-objective design procedure for a dynamic c chart has been developed with the aim to point out the suitable optimal chart configurations to perform SPC operations on a manufacturing process of semiconductor devices. The problem has been formulated by a non-linear constrained mathematical model and the ε-constraint method has been employed to describe the Pareto frontier. The knowledge of this frontier will provide useful information to the decision maker about the decisional process that cannot be directly obtained by the typically considered design procedures. For instance, if a budget constraint is added, the sub-set of the optimal feasible solutions on which restricting the selection can be immediately individuated. Moreover, the frontier analysis could address the decision maker to discard some solutions which imply small cost reductions with meaningful statistical performance decreases (such as solutions (1), (2) and (3)) or, to the contrary, small statistical improvements with significant cost increments (such as solutions (11) and (12)). Finally, the developed approach is simple to be used, it is fully supported by an Excel macro and it requires short computational time.

Author's Contributions

This study is a result of the full collaboration of all the authors.

Toni Lupo: Wrote paragraphs Fundamental Definitions, Multi-Objective Problem Formulation and Conclusion.

Filippo Sgroi: Wrote paragraphs Introduction and Application: Control Quality of Manufacturing Process of Semiconductor Devices.

Ethics

The authors have no conflicts of interest in the development and publication of current research.

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