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ECONOMIC SUSTAINABILITY OF THE $\bar{X}$ IMPLEMENTATION IN UNCAPABLE PROCESSES

Abstract: *This study aims to evaluate the economic viability of SPC implementation in an out-of-specification production system in order to find the most sustainable point to change from the 100% inspection to sampling inspection. It can prevent losses with false alarms and, or, excessive inspection. It was a computational simulation study through the application of Duncan's (1956) model for the economic design of control charts. The model was optimized using a simulated annealing algorithm to find the parameters' values — a comparative study realized with a real case and a decision flow chart for SPC implementation provided. The results have several relevant practical implications, since the correct decision concerning the inspection type to be adopted based on the proportion of defective items allows its operation with lower costs, eliminating wastes in unnecessary inspections. The optimization of resources also contributes to focusing efforts on continuous process improvement.*

Keywords: *Sustainability; Economic Design; Control Chart; SPC Implementation*

1. Introduction

The capacity of sustaining or maintaining an operational system in equilibrium depends on simultaneously meeting technical-economic requirements that incorporate minor losses, less material use, and lower energy expenditure. Smith and Sharicz (2011) define sustainability as the result of an organization's activities, which demonstrates the organization's capacity to maintain its production and commercial operations viable (including financial viability depending on the case), even though it does not affect negatively on the ecological and social systems. Gunasekaran et al. (2013) present the concept of Sustainable Operations Management (SOM) as operational strategies, tactics, techniques, and operational policies to support an organization's economic and environmental objectives and goals. Thus, the idea of sustainability strongly relates to the dynamics in businesses and their adaptive capacity needed for better production system management (Voinov & Farley, 2007). In this context, priority given to manufacturing costs, product quality, process flexibility, product innovation, and delivery. Nevertheless, considering the level of complexity involved in this type of analysis, results that reflect in detail the ecological, economic and social dimensions are hardly found in the same study (Govindan et al., 2013).

Total quality is considered a lean practice that influences the three sustainability dimensions (Govindan et al., 2014). Also, due to the increase in competitive pressure, today's

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managers view quality improvement as a means to improve and sustain organizational performance (Meftah Abusa & Gibson, 2013). Monitoring quality standards play an essential role in organizations' sustainability in competitive markets (Kasarapu & Vommi, 2013). The techniques used for monitoring inserted in the statistical process control (SPC). The seven SPC tools, once well developed in a firm, resolve most product and process quality issues. Related with lean practices and SPC, Korzenowski et al. (2013) propose the use of endogenous variables in predictive models aimed at overcoming the multiple setup and short production runs problems found.

In the context of production management, SPC tools utilized by companies. The SPC's pioneer, Walter Shewhart, whose studies aimed to improve quality and productivity. This system of controlling variations and the increase of process capacity, based on continuous improvement, had a positive impact on Japanese manufacturers (Montgomery, 2009). Korzenowski et al. (2015) show this improvement with two new proposals of self- start statistical process control procedures for implementing quality control charts in mass customized production environments. Including, starting in the 1970s, Ohno and Shingo implemented the concept of "seven wastes", reducing costs and consequently increasing profits in a continuous improvement environment, having SPC as technical support for its success (Kausalya et al., 2013). Nowadays, determine which mass customization characteristics prioritized in mass-customized service design it is hard, but Vidor et al. (2015) show in his research the method.

SPC provides a way to reach the maximum levels of productivity and has contributed to several economic benefits in different industry sectors (Amir et al., 2014). However, to do so, attention to decision errors regarding the use of control charts is required since such errors may generate undesirable costs - tangible as well as intangible ones. For instance, the chart may signal the occurrence of an alteration in the process, which did not occur. It may generate costs associated to the unproductive investigation of the supposed issue. If the decision in the SPC strategy is to stop the production line, these costs could be even higher. On the other hand, there is still the possibility that the process undergoes a significant alteration, and the chart does not signal this occurrence. For example, such alteration increases the production of defective items without noticing them, causing future expenses with warranty, replacement and rework, besides intangible costs associated with losing client's trust.

The aim of using control charts is to propose a strategy of monitoring quality standards with lower costs, and this occurs at the moment that a complete inspection does not take place and is replaced by sampling inspection, reducing costs associated with data gathering, sample size, information registration and evaluation costs (Engi˙n, 2008). When searching for a definition or the choice of applying a chart, the intention is to choose a chart which has the highest performance possible, that is, with a lower number of errors, which will then minimize non-detection costs, which will cause failure and/or false alarm costs, contributing to a rise in evaluation costs (Montgomery, 2009; Zhang et al., 2011).

Economic sustainability investigated in association with SPC in the study of Engi˙n (2008), which combines traditional charts with equipment efficiency parameters. From the assessment of the number of events in which equipment stop or present some failure, the time spent to finish the inspection, to solve the issue, and the number of equipment assigned to each operator considered. In this case, economic sustainability sought through the combination of control charts and the sum of individual equipment efficiency.

The case studied here reflects the reality of a firm that currently faces quality issues in its production line. The fraction of defective items was 60,000 per million (ppm) and, after some improvement efforts, such number reduced to 5,000 ppm. The company still utilizes a quality evaluation system through complete (100%) inspection. The costs of this type of assessment system are becoming deterrent due to the production volume, once the reached improvement in this process has reduced the volume of rework until then. In this context, considering 100% inspection costs and the current quality level of the production process, the following question is highlighted: can we affirm that the current stage, from the company's economic sustainability point of view, is appropriate for the implementation of statistical process control through monitoring charts? The literature points that, for SPC implantation, a stable process required (Korzenowski et al., 2014) and, a priori, the fact that the process does not meet the specifications is not a limiting factor for its implantation. Note that, according to Montgomery (2009), a process with Cp = 1, potential capacity presents a rate of 2,700 ppm.

This case study aims to evaluate, through the application of Duncan's (1956) model for economic design, the economic viability of SPC implantation, in addition to sensitivity analysis in error costs associated with a control chart decision. Due to the process characteristics, the implantation of a control chart for averages ($\bar{X}$ Chart) used as a reference. The results demonstrate that the decision to implant $\bar{X}$ control charts was directly impacted by the SPC operational cost in an out-of-state control, as the out-of-specification production volume increases. The contribution of this study is in the evaluation of which process conditions (considering production volume and the ppm of defective ones) make the 100% inspection more preferable concerning the use of a process control chart. The subsequent sections present the theoretical review of Duncan's Economic Model, the optimization method chosen for this study, the methodology itself, the analysis of the results, and final remarks.

2. Theoretical Background

2.1. Duncan's Economic Design

Duncan (1956) was the first to work with an economic model using Shewhart charts and to incorporate an optimization method to determine $\bar{X}$ control chart parameters. Through such a proposition of an economic model for optimal economic planning, his article was a stimulus for several subsequent studies in this area, such as de Magalhães et al. (2002); Mortarino (2010); Pan et al. (2011); Korzenowski and Werner (2012); Mohammadian and Amiri (2012).

Duncan (1956) utilized as a reference to the work of Girshick and Rubin (1952), which uses a net income per time unit maximization criterion. Duncan admits that a $\mu 0$ stable control state characterizes the process and that after the occurrence of a random attributable cause at a δ magnitude, a change of $\mu 0$ mean to $\mu 0 + \delta\sigma$ or $\mu 0 - \delta\sigma$ occurs.

Process monitoring occurs through an $\bar{x}$ chart with a central line in $\mu 0$ and $\mu 0 \pm k\sigma/\sqrt{n}$ control limits. The samples must be extracted in intervals of h hours, and only when a point surpasses control limits the $\mu 0 \pm k\sigma/\sqrt{n}$ searches begin. Posteriorly, studies such as Panagos et al. (1985), modeled the system with a stop as soon as an attributable cause signalized.

In Duncan's (1956) model, adjustment costs or repairs not considered in this search of net income process. It is supposed that the $\mu 0$, δ, and σ parameters are known and sample size n, amplitude of control interval k, and interval between samples h (in hours) must be determined so as to minimize control chart operational costs, investigation costs of attributable cause as well as eventual costs associated with the non-detection of process anomalies.

The model proposed by Duncan (1956) is detailed as follows. According to the author, the attributable cause expected time (τ) might define as in Equation (1).

$$\tau = \frac{\int_{jh}^{(j+1)h} e^{-\lambda t}\lambda(t-jh)dt}{\int_{jh}^{(j+1)h} e^{-\lambda t}\lambda dt} = \frac{1-(1+\lambda h)e^{-\lambda h}}{\lambda(1-e^{-\lambda h})} \quad (1)$$

Where λ is the attributable cause expected frequency per hour, h is the interval between samples and j e (j+1) determine the interval between samples when there is an occurrence of an attributable cause. The probability of a false alarm (λ) obtained in Equation (2).

$$\alpha = 2\int_{k}^{\infty} \varphi(z)dz \quad (2)$$

where k is the distribution probability value which defines control limits, and φ(z) is the standard average density. The probability of an attributable cause detected, when it occurs, is determined by Equation (3).

$$1-\beta = \int_{-\infty}^{-k-\delta\sqrt{n}} \varphi(z)dz + \int_{k-\delta\sqrt{n}}^{\infty} \varphi(z)dz \quad (3)$$

where β is the probability of a type II error, δ is the size of the deviation to be detected, n is the sample size adopted in-process monitoring, and φ(z) is the density of standard normal distribution, defined as

$$\varphi(z) = (2\pi)^{-1/2}\exp(\frac{-z^2}{2})$$

The interval between the beginning of the production and the adjustment for the detection and elimination of an attributable cause defined as a production cycle. This cycle classified in four periods: a) under control period; b) out-of-control period; c) time for sample extraction and analysis and d) time to find the attributable cause. Thus, the objective function with (n, k, and h) decision variables defined as in Equation (4).

$$E(L) = \frac{a_1+a_2 n}{h} + \frac{a_4\left[\frac{h}{1-\beta}-\tau+gn+D\right]+a_3+\frac{a'_3\alpha e^{-\frac{\lambda}{h}}}{1-e^{-\lambda/h}}}{\frac{1}{\lambda}+\frac{h}{1-\beta}-\tau+gn+D} \quad (4)$$

where:

α depends on k according to equation (2);

E(L) = expected wasted time incurred in the process;

a1 = sampling cost fixed component;

a2 = sampling cost variable component;

a3 = cost of determining an attributable cost;

a'3 = cost of investigation of a false alarm;

a4 = hourly cost of the penalty associated with the out-of-control production state;

g = required time for sampling and interpretation of results; and

D = required time to find the attributable cause after an action signal.

Tannock (1997) notes that control charts may be relatively ineffective due to the use of incorrect parameters, leading to an insensibility to process alterations. Another possible issue which may occur is when a stable process (but with insufficient capacity) results in manufacturing non-conforming items due to the excessive variety of common causes, and these items may not be detected and still delivered to the client. These scenarios have adverse economic outcomes and may generate a false sense of safety, while changes in the process are occurring, or waste time and money through signaling false alarms. Based on this, Tannock (1997) makes an economic comparison of control charts with other control quality methods, presenting a simulation model which proves to be capable of providing a view of the standard comparative costs associated with control charts for variables and alternative inspection strategies.

Due to the preoccupation with the difficulty in estimating model parameters and to avoid unnecessary costs in the process, several authors utilized metaheuristics as an optimization method for x¯ control charts. Shiau et al. (2006) utilized the Genetic Algorithm, while Yu and Low (2005) utilized Simulated Annealing, in which numeric examples demonstrate more precise and reliable optimal values in comparison to published values. Ganguly and Patel (2012) developed an application of Simulated Annealing for Duncan's (1956) control chart optimization method, comparing its results with the ones proposed by Montgomery

(2009). Sultana et al. (2014) performed this same comparison with their version of this algorithm with the option of (n) sample number as a continuous variable. The same authors even present a version of a Genetic Algorithm for the optimization of control charts. It was opted to use Simulated Annealing for the optimization in this study due to its simplicity in implementation, with applications to the issue of control chart optimization, which allows the validation of the utilized method to be more consistent.

2.2. Simulated Annealing

Simulated annealing is a local search metaheuristic algorithm, developed to solve several optimization issues, mainly combinatory ones, through the simulation of the annealing process. Its main advantages are the capacity for escaping from optimal locals and easy application (Chibante, 2010; Soares et al., 2013).

Annealing is the metallurgical process of altering physical material properties, obtained through heating the material until its fusion temperature followed by slow cooling until the crystallization of its structure. Since the heating allows the atoms to move randomly, the cooling process must be sufficiently slow to allow the atoms to move to positions with the lowest energy possible inside the structure. Considering this procedure as an optimization issue, if the atom arrangement obtained in the process is the lowest energy possible one, such arrangement is an optimal solution for the issue of minimizing energy in the structure (Soares et al., 2013). Simulated annealing uses this analogy in the search for an optimal solution for a determined optimization issue (Michalewicz & Fogel, 2013). Kirkpatrick et al. (1983) and Černý (1985) demonstrated this analogy between combinatory optimization issues and large physical systems studied in statistical mechanics. These authors demonstrated that the statistical mechanics model to simulate annealing processes, initially proposed by Metropolis et al. (1953), could be extended to resolve statistical optimization problems in general, mainly those of combinatory origin. Simulated annealing utilizes Metropolis' (1953) algorithm to simulate the search for thermal equilibrium. An analogy assumed between the physical process and

combinatory optimization process based on the following equivalences (KORST, 1990):

- The value of the optimization problem objective function is equivalent to the energy of the solid in the cooling, physical process towards thermal equilibrium;
- Intermediate solutions for a combinatory optimization problem are equivalent to the matter cooling stages;
- The selection of a neighbor solution in an optimization problem is equivalent to the disturbance of a physical state;
- The global optimum of a combinatory problem is equivalent to the fundamental state of a particle system;
- An optimal local location of a combinatory problem is equivalent to a fast cooling of a physical system, maintaining atoms in high energy positions.

The algorithm, when applied to a discrete optimization problem, compare in each iteration the values for both solutions (the current solution and a recently selected neighbor solution. The acceptance of solutions which worsen the objective function is tolerated, in the hopes of escaping from optimal locations during the search for the global optimum. The probability of accepting worse solutions depends on a temperature parameter, which normally undergoes a decrease in every algorithm iteration, to enable the exit of local optima. As the temperature parameter is reduced, reaching close to zero, the ”mountain climbing” (acceptance of worse solutions) occurs with less frequency, concentrating the search on the globally optimal solution (Gendreau &

Potvin, 2010). The pseudocode of Simulated Annealing demonstrated in Algorithm (Figure 1), where

T0 = Initial temperature;

Tf = Final temperature;

α = Cooling speed;

L = Temperature cycles;

nbsc = Number of best solutions found;

nic = Number of consecutive iterations;

f oc = best local solution; and

f o∗ = optimal solution.

Algorithm 1 *Simulated Annealing*

```
Obtains an initial solution fo
Defines T_0 and T_f temperatures
Defines the (α) cooling speed
Defines nlim e nbsc
Defines i e L
while (t > T_f or nbsc < nlim) do
    repeat
        Searches for a solution in the nighborhood
        Calculates fo^c
        if fo^c − fo ≤ 0 then
            fo = fo^c
            if fo − fo* ≤ 0 then
                fo* = fo
                nbsc = nbsc + 1
        else
            Obtains X ~ U(0, 1)
            if X > e^{−(fo^c − f)/t} then
                fo = fo^c
        i = i + 1
    until i = L
    t = α × t
return fo*
```

Figure 1. Algorithm – Simulated Annealing

3. Method

For the validation of the proposed algorithm, an instance proposed in example 9-5 of (Montgomery, 2009, p.309) was used, which was also used by Ganguly and Patel (2012) and Sultana et al. (2014) for the validation of their algorithm proposals for Duncan's (1956) optimization model of control charts. The results obtained by the algorithm were compared to the ones obtained by the two authors, validating the efficacy of the algorithm.

Later, the algorithm applied in a real setting - a metal mechanic factory located in Southern Brazil. This company had been dealing with considerable variability in the process, which caused it to opt for a 100% inspection in the production of a specific production line. The company made several investments and is conducting a series of improvements in its process, recently reducing its failure rates from 60,000 ppm to 5,000 ppm. Due to this improvement and the continuous effort in this sense, quality managers began to deal with the following questions: (i) In what moment 100% inspection should be replaced by a sample inspection, in order to avoid losses by an excess of inspections? (ii) Moreover, once the sample inspection is adopted, what are the (n, h, k) parameters which must use to guarantee quality security, minimizing inspection costs?

The algorithm set with data originated from a real instance, being them a1 = $30.00, a2 = $0.004, a3 = $1000.00, aj3 = $1000.00, a4 = $450, g = 0.083, D = 2, δ = 2 e λ = 4.205. The fixed sampling cost (a1), was obtained by dividing the monthly fixed cost by the number of hours worked. In the fixed cost, costs of the inspection control structure considered, which includes labor and infrastructure. Dividing this value by the number of monthly worked hours, on an average of 357 hours, equals a1 = $30. The variable sampling costs (a2), are those related to energy and material consumed during the sampling, inspection, and interpretation of results, were related without $3,61, dividing this value by the production of the factory of 841 per hour, obtaining a2 = $0.004.

To determine the investigation costs of (a3) attributable cause, it was taken into consideration the average hourly cost of the team comprised of people working in the quality and engineering departments - responsible for performing the investigation of detected out-of-control points - reaching a value of $1000,00. Once that in this context, the investigations do not involve destructive tests; only labor costs considered in this study. According to the procedure performed in the company, the investigation of an attributable cause and a false alarm present insignificant differences concerning labor. Therefore, it assumed that both have the same cost (aj3 = a3).

The costs of not detecting a failure, (a4) out-of-control operation, were estimated based on the costs of rework to correct the out-of-specification produced items, obtaining a cost of $450,00. In these contexts, opportunity costs due to lost sales as a consequence of unavailability of conforming items not considered. Although it is known that these costs may be significant to businesses that operate with small inventories, this was not the case of the company studied here, and therefore they were not considered at that moment.

The required time for sampling and result interpretation (g) obtained through the analysis of the company's inspection records, with an average of 5 minutes for the complete operation. This time, expressed as a fraction of an hour, results in g = 0,083. These same company records contributed to obtaining the average time for concluding an investigation which points to an attributable after a sign of action, with an approximate time of two hours (D = 2). The magnitude of the deviances which must be detected is δ = 2.

The production volumes of defective items were utilized to obtain the λ parameter. Once λ is the expected frequency of occurring attributable causes per hour, from the proportion in ppm and the production volume per hour, the frequency of the occurrence of defective items may be estimated, which is the last analysis, must be pointed as attributable by the control chart. Thus, the λ value was determined, in ppm, by the Equation (5).

$$\lambda = PPH \times \frac{ppm}{1.00.0000}$$

Where PPH is the production per hour, the determination of the hourly cost of the 100% inspection was performed using the total monthly cost of inspection operation and quality control, divided by the average quantity of working hours in a month (357 hours/month), reaching a cost of $33.61 per hour.

After defining the cost parameters for the optimization, a sensitivity analysis in ppm performed in order to analyze how its behavior impacts on the parameters, and, as a consequence, on SPC operating costs. This procedure also allowed the identification of the maximum ppm value, which allows management to utilize sampling inspection, which in turn will allow cost reductions without generating losses due to out-of-specification production. The defective items rate varied approximately from 0 ppm to 1,500 ppm, in 50 ppm intervals. It permitted the evolution of the evaluation of the E(L) cost function. In the analysis of the results, a direct relationship between the out-of-control operating cost (a4) and the λ observed. Because of this, we proceeded a scanning of out-of-control operating costs seeking to identify in which λ values the convergence of the objective function value for out-of-control operating costs occur. It enabled a calibration model to identify, based on the PPM, in which out-of-control operating cost the SPC implantation is more advantageous from an economic perspective.

The analysis was performed based on the company's current situation, repeating this procedure with the data from Montgomery's (2009) study (example 9-5, p.309), in order to corroborate with the results found. The validated algorithm applied in the actual ppm instance (5,000 ppm), to obtain the (n, h, k) decision values to begin the SPC implantation. The following section presents a detailed description of the company's data in addition to the results found in this study.

4. Results

In order to answer the questions regarding the right moment of change from 100% inspection to SPC use, a sensibility analysis was performed in the optimization method adopted in this study and applied in the company's data. The proportion of defective manufactured items varied in this procedure in order to evaluate the behavior of SPC operating costs. Note that, the alteration of the defective items proportion values (ppm) directly affects the λ value, as demonstrated in Equation (5).

The first results point to the fact that, as the proportion of defective items increases, the inspection costs through SPC converges to out-of-control production costs, according to Figure 2. This convergence may be noted starting from 500ppm.

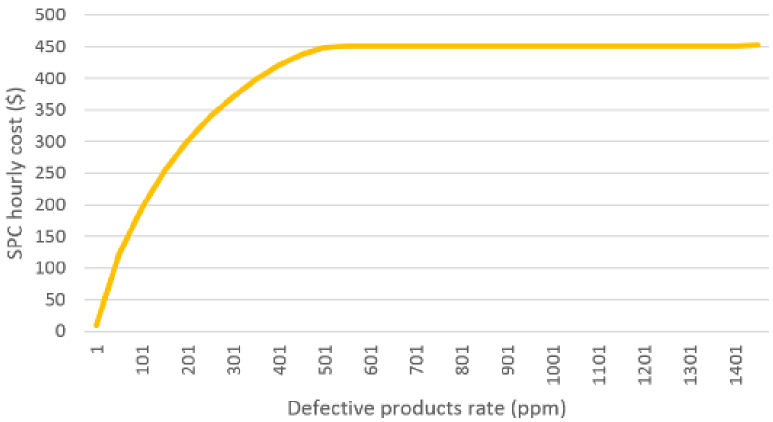

Figure 2. Inspection hourly cost in function of ppm

Once there is a proportion of defective items higher than 500 ppm, the hourly costs to maintain a 100% inspection program against the out-of-control operating cost must be evaluated (OC Cost in the figure). Note that a proportion of defective items higher than 500ppm is equivalent to a Performance Index of Pp ≈ 1.16. The implementation of improvement strategies suggested in order reducing the variability of the process. However, in case the proportion of defective items is lower than 500ppm, which is equivalent to an index of Pp ≥ 1.16, the SPC hourly operating cost must compare with the 100% inspection cost for the decision-making process of which quality monitoring system is better to be adopted.

These results have several relevant practical implications, since the correct decision concerning the inspection type to be adopted based on the proportion of defective items allows its operation with lower costs, eliminating wastes in unnecessary inspections. The optimization of resources also contributes to focusing efforts on continuous process improvement.

The tendency to convert SPC operating values in higher levels of defective items confirmed with the data from Montgomery's (2009) study (example 9-5, p.309). The same analysis procedure repeated in this instance. Figure 3 presents the behavior of the cost function converging to the out-of-control operating cost when the λ value is above 3.50. It may observed in Figure 3 that the λ value obtained through Equation 2 - where such convergence occurs - is not the same as the company's current instance (λ ≈ 0.46). This is because the λ is dependent not only on the manufactured volume but also on the ppm value of defective units. The example 9.5 of Mongomery's (2009) study describes a process of bottle production which presents a higher production volume in comparison to the situation in this study, due to its high automation degree, which directly reflects on the λ value.

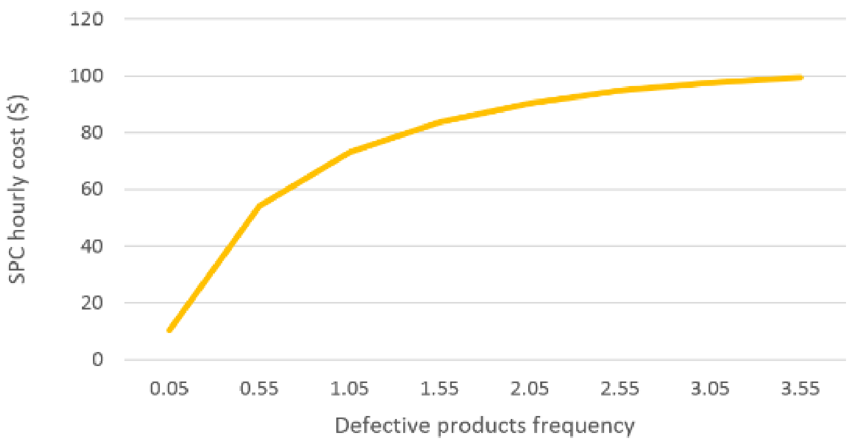

Figure 3. Inspection hourly cost in function of λ

At last, according to the results presented in this study, the decision to implement SPC must follow the criteria shown on the flow chart in Figure 4, so that such implantation occurs in an economical and safe manner, which guarantees the rationalization of the company's resources and security in exchange for product quality warranty. The fl describes the function from the calculation of the Pp indicator, and in case the index is higher than 1.16, we must evaluate if the SPC operating costs are higher than 100% inspection costs. If negative, SPC implementation must ow proceed and start monitoring the quality level of the productive system. In cases where 100% inspection are lower costs, it adopted rand; an improvement program must become a priority in this process with the aim tor reducing operating costs of a future SPC implantation. In cases where the Pp index presents lower levels than 1.16 ones, we must evaluate if the out-of-control operating costs are lower than 100% inspection costs. In case it is negative, 100% inspection must be implemented and give priority to an improvement program in the system to turn the index into Pp > 1.16. If positive, where out-of-control operating costs are lower than inspection ones, SPC must be adopted to maintain the monitoring of the (λ) frequency of defective items, since the out-of-control operating cost depends on this variable. Under these conditions, the prioritization of measures to promote improvements in the productive system becomes urgent, in order to reduce inspection costs and elevate the Pp value.

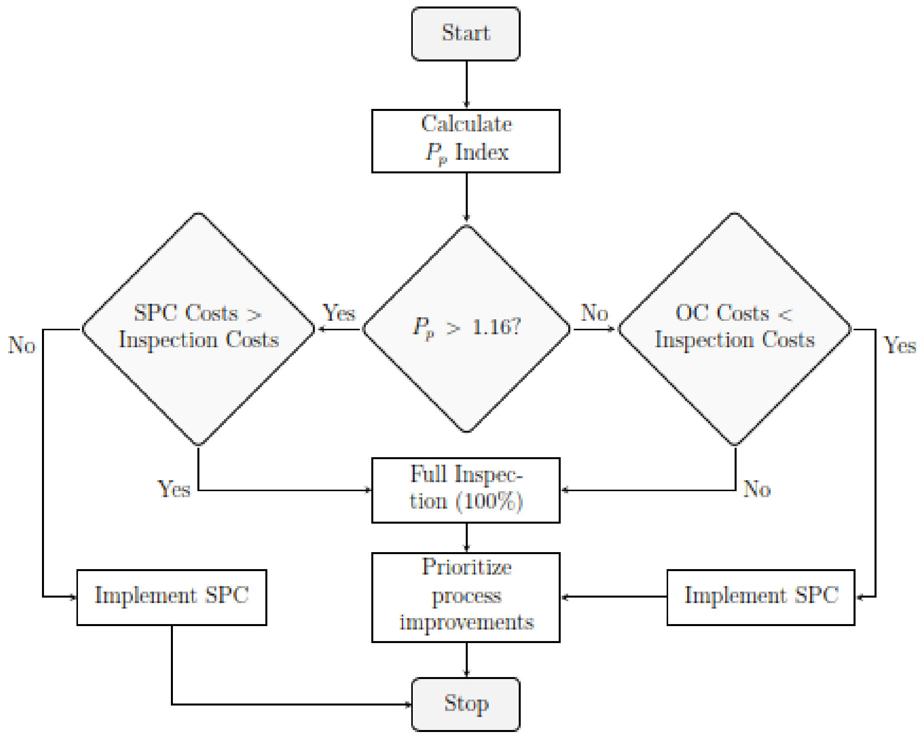

Figure 4. Decision fluxogram for SPC implantation

The decision made based on the proposed flow chart must have a continuous aspect since improvement programs cause alterations in the variables involved, which may cause further alterations on the decision to be made. Eventual system worsening, independently of its origin, must also induce this type of alteration. Furthermore, the decision making the process at the right moment will incur in lower costs related to excessive or insufficient inspections.

5. Conclusion

Quality improvement in organizations has a long way to go, with economic sustainability being a critical factor for the maintenance of the obtained improvements throughout this process and its continuous amelioration. The optimization of the efforts, as well as the adequation of a quality control strategy and the selection of adequate tools to the reality of the company, are factors which may strongly influence the economic sustainability of a continuous improvement process. In this sense, this paper presented Duncan's (1956) model as an option for the optimization of control parameters for monitoring quality through SPC. Due to the combinatory nature of this issue and with the aim of obtain- ing better results, the model was optimized through Simulated Annealing metaheuristics based on the studies of Ganguly and Patel (2012) and Sultana et al. (2014). The sensitivity analysis, based on the model applied in a real instance and example 9.5 in page 309 of Montgomery (2009), revealed that as the frequency of (λ) defective item production level increases, SPC operating cost converges to an out-of-control operating cost. This type of behavior enables the decision-maker to opt for a 100% inspection in case its cost is lower or strategically irrelevant if compared to the out-of-control operating cost producing defective items with a (λ) frequency. This convergence point reveals itself as a crucial factor in the decision-making process for which inspection type adopted by the company. Based on the results, the flow chart presented in figure 4 enables decision-makers to comprehend quickly and analyze fast when opting for a product quality inspection strategy. The constant evaluation of this decision through the proposed flow allows the company to utilize the adequate strategy under its circumstances in regards to quality levels. It also allows the elimination of unnecessary costs with 100% inspection as the frequency of defective item production decreased. Right below the point where the SPC operating cost converges to an out-of-control cost, 100% inspection abandoned and the company may begin to operate with exclusive monitoring through SPC.

Even though the flow indicates 100% inspection not being adopted in cases where the costs of this inspection are higher than an out-of-control operation, it indicates the prioritization to improvements in the production process for all cases, except when Pp > 1.16 and SPC costs are not superior to 100% inspection costs. It understood that in only this situation the productive system is mature enough in the quality system to fully operate using an SPC without the need of other interventions, and in all the other cases efforts must be performed in the process aiming to reach this same condition.

The incorporation of strategic elements to the decision-making process may provide higher robustness in practical applications in other market segments. The incorporation of related variables to the environmental impact due to rework might be a considerable contribution to the optimization model when uniting environmental sustainability factors to economic sustainability ones in the evaluation of companies' quality levels.

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